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Gender, Management Earnings Forecasts, and Critical Audit Matters

par
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Gender, Management Earnings Forecasts, and Critical Audit Matters

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Résumé

Cette thèse de doctorat est composée de trois articles. Dans les deux premiers articles, nous étudions comment la diversité des genres à la haute direction affecte la divulgation volontaire des entreprises. Le troisième essai examine l'association entre les questions d'audit critiques divulguées et la qualité des charges à payer des entreprises.

Le premier article examine la divulgation volontaire des prévisions de bénéfices par les femmes PDG. Nous constatons que les femmes PDG sont plus susceptibles de fournir des prévisions de bénéfices que les hommes PDG, et les prévisions des femmes PDG sont plus précises. De plus, nous constatons que les analystes financiers ont tendance à suivre les entreprises dont les PDG sont des hommes. Cependant, les efforts des femmes PDG pour publier des prévisions de bénéfices précises réduisent cet écart entre les femmes PDG et les hommes PDG.

Le deuxième article examine le conservatisme des prévisions de bénéfices par les femmes CFO et ses conséquences possibles. Nous trouvons que par rapport à leurs homologues masculins, les femmes CFO fournissent des prévisions de revenus moins optimistes. Étant donné que les prévisions optimistes conduisent à des attentes plus élevées des parties prenantes, les entreprises qui émettent des prévisions optimistes peuvent s'engager dans la gestion des bénéfices pour atteindre les critères de référence des bénéfices plus élevés. Par conséquent, les femmes CFO ont moins besoin d'ajuster leurs revenus à la hausse et avoir un risque de chute du cours des actions plus faible.

Dans le troisième article, nous étudions la relation entre les questions critiques d'audit (CAM) divulguées et la qualité des charges à payer de l'entreprise. Nous constatons que les entreprises avec plus de CAM ont tendance à avoir une qualité de comptabilité d'exercice inférieure et cette association négative est atténuée dans les entreprises avec un comité d'audit de haute qualité. Nous analysons plus en détail les sujets liés aux CAM et constatons que les CAM liés aux revenus et les CAM liés à l'estimation de la juste valeur sont les principaux moteurs de la mauvaise qualité des charges à payer.

Mots clés : Femme PDG; femme CFO; prévisions de bénéfices; Analyste ensuite; Prévisions des analystes; Risque de crash boursier; Questions d'audit critiques; Qualité des régularisations.

Méthodes de recherche : Archives, Analyse quantitative

Abstract

This doctoral thesis is composed of three essays. In the first two essays, we investigate how the gender to top management affects companies' voluntary disclosure. The third essay examines the association between critical audit matters disclosed and companies' accruals quality.

The first essay examines the voluntary disclosure of earnings forecasts by female CEOs. We find that female CEOs are more likely to provide earnings forecasts than male CEOs, and female CEOs' forecasts are more accurate. Moreover, we find that financial analysts tend to follow companies with male CEOs. However, female CEOs' efforts to issue accurate earnings forecasts narrow this gap between female CEOs and male CEOs.

The second essay examines the earnings forecasts conservatism by female CFOs and its possible consequences. I find that compared with their male counterparts, female CFOs provide less optimistic earnings forecasts. Since optimistic forecasts lead to higher expectations of stakeholders, companies issuing optimistic forecasts may engage in earnings management to meet the higher earnings benchmarks. Therefore, female CFOs may have less need to adjust their street earnings upward and have a lower stock price crash risk.

In the third essay, we investigate the relation between critical audit matters (CAMs) disclosed and company's accruals quality. We find that companies with more CAMs tend to have lower accruals quality and this negative association is mitigated in companies with a high-quality audit committee. We further analyze CAMs topics and find that revenue-related CAMs and fair value estimation-related CAMs are the primary drivers of poor accruals quality.

Keywords : Female CEO; Female CFO; Earnings forecast; Analyst following; Analyst forecasts; Street earnings; Stock price crash risk; Critical audit matters; Accruals quality.

Research methods : Archival, Quantitative analysis

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List of abbreviations

CAM	Critical audit matter
CEO	Chief executive officer
CFO	Chief financial officer
CSR	Corporate Social Responsibility
FRC	Financial Reporting Council
IAASB	International Auditing and Assurance Standards Board
ISA	International Standard on Auditing
KAM	Key audit matter
PCAOB	Public Company Accounting Oversight Board
SEC	Securities and Exchange Commission

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Introduction

This thesis is composed of three essays attempting to extend the literature on companies' financial reporting practices and quality. The first and second essays investigate the impact of the gender of top executives on companies' financial voluntary disclosures. The third paper examines the association between the disclosure of critical audit matters (CAM) and companies' accruals quality.

In the first essay, my co-authors and I examine whether female CEOs provide earnings forecasts more frequently and whether their earnings forecasts are more accurate. Since female CEOs are numerical minority in top management, they face greater scrutiny from the media and colleagues inside the organizations. Therefore, female CEOs may have a greater pressure to deliver strong performance and build a good reputation in front of investors. They are likely to put more effort into providing earnings forecasts. By constructing regression models controlling for firm and year fixed effects, we find female CEOs tend to issue more earnings forecasts than male CEOs, and those forecasts are more accurate. We next examine whether female CEOs who provide superior earnings forecasts enjoy higher analysts following. We find that analysts prefer to follow companies headed by male CEOs, probably because analysts hold a negative bias against female CEOs or have more privileged communication with male CEOs. However, this gap in analyst coverage can be mitigated by the female CEOs' efforts to provide more accurate forecasts. This study provides evidence that gender inequality still exists extensively in the top management. Not only the number of male CEOs is extremely higher than the number of female CEOs, but also female CEOs are placed in inferior positions and need to make much more efforts than male CEOs.

In the second essay, I investigate whether CFO gender affects corporate voluntary disclosure. Companies manage analysts' and investors' expectations by providing forecasts. Optimistic forecasts reinforce investors' confidence and boost corporate stock market performance in the short-term, but companies who fail to deliver the expected earnings eventually suffer stock price crash. The key responsibilities of CEOs and CFOs are different. Unlike CEOs, CFOs are not accountable for the companies' overall performance nor the reporting policy, but they are responsible for financial reporting and assist CEOs with forecasting. Since CFOs also exert significant influences on companies' earnings forecasts, I expect female CFOs who present different personalities may select different forecasting strategy.

According to previous literature, female CFOs are more accounting conservative and less likely to engage in earnings management. Because of these risk averse traits of female CFOs, I expect them to issue less optimistic earnings forecasts in order to reduce the risk of missing the forecasts. After examining several measures of forecast optimism and constructing both OLS regression and robust regression models, I find results that strongly support my hypothesis. I further investigate what consequences may be caused by male CFOs' overconfidence in forecasting. Since male CFOs provide more optimistic forecasts, they need to take more actions in order to avoid the failure of missing the forecasts. However, once companies are not able to meet the inflated shareholder expectations and maintain their overvalued equity, they will eventually experience a stock price crash. My study provides evidence that male CFOs inflate their "street earnings" by excluding more expenses, and companies with male CFOs are likely to have a higher risk of stock price crash.

In the third essay, my co-authors and I examine the association between the critical audit matters (CAM) disclosed and companies' accruals quality. Auditors are currently required to provide information about Critical Audit Matters they identify in the expanded audit reports. Regulators hope CAM/KAM disclosure helps enhance auditors' communication with financial reporting users, whereas some scholars argue that CAM/KAM disclosure does not provide any new information and is not useful to users. To contribute to this debate, we investigate whether CAM can be an indicator of poor accruals quality. Accruals quality is important as it reflects the reliability and credibility of companies' financial reports. We find that companies with a higher number of CAMs tend to have poorer accruals quality, and this negative association is mitigated in companies with effective audit committees. It shows that the number of CAMs can be used as an instrument for earnings quality, especially when audit committees perform poorly. We further find that CAMs that are related to revenue and fair value calculation are the main drivers of poor accruals quality, which means the presence of these CAMs can be a signal for poor accruals quality. In additional analysis, we also provide evidence that companies with more revenue-related CAMs are more likely to engage in revenue manipulation. This study provides insights on the informativeness and usefulness of CAM disclosure because we show that CAMs provide investors useful information about companies' accruals quality. Investors can easily form a preliminary perception of companies' accruals quality based on CAM disclosure.

Chapter 1
Earnings Forecasts of Female CEOs: Quality and Consequences*

Abstract

This study examines the voluntary disclosure of earnings forecasts by female CEOs. We find that in the backdrop of increased pressure to perform from investors and other stakeholders, female CEOs tend to issue more earnings forecasts than male CEOs, and those forecasts are more accurate. We also find that while financial analysts generally prefer to follow companies headed by male CEOs, female CEOs' efforts to issue accurate earnings forecasts pay off as these efforts help them close the analyst coverage gap. We provide complementary evidence on the disclosure efforts of female CEOs with regard to updates to the forecast and the 10-K report. Lastly, we show that financial analysts rely more on the earnings forecasts of female CEOs, possibly because they realize female CEOs' superior forecasting quality. Our results are robust to the use of alternative research designs, including difference-in-difference, propensity score matching, and entropy balancing. Overall, our study documents gender differences in voluntary disclosure by senior management.

Keywords: Female CEO; voluntary disclosure; management forecast; management forecast errors; analyst following; analyst forecast

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* Francoeur, C., Li, Y., Singer, Z., & Zhang, J. (2022). Earnings forecasts of female CEOs: quality and consequences. Review of Accounting Studies, 1-44. Reproduced with permission from Springer Nature.

1.1 Introduction

Even though the number of female executives has risen in recent decades, compared to men, women are still vastly underrepresented among top executives. According to the annual Women CEO report released by Gray and Christmas Inc., the share of women in new CEO appointments in U.S.-based companies was merely 18.4 percent in 2017. This gender gap in the largest companies is even wider, with only 5.4 percent of women CEOs in S&P 500 companies (Pew Research 2017).

This pronounced gender gap in top management has garnered the attention of researchers. A growing collection of work reports that female executives make a positive impact on firm performance. Female executives enhance firm innovation and create a collaborative work environment (Gaughan and Smith 2016). They also exhibit less overconfidence, i.e., they show better judgment when making important corporate decisions, compared to men (Huang and Kisgen 2013). With respect to financial reporting, companies led by female executives engage less in earnings management (Barua et al. 2010; Gull et al. 2017) and are more conservative in their accounting choices (Francis et al. 2015), probably because women are on average more ethical, more risk averse, and less aggressive than men (Valentine and Rittenburg 2004; Lund 2008; Ho et al. 2015). In part due to these distinctive traits attributed to women, researchers, activists, and regulators are calling for more female representation in top management (e.g., Dezsö and Ross 2012; Habib and Hossain 2013).

In this study, we examine the voluntary disclosure of management earnings forecasts by female CEOs. Management earnings forecasts play a key role in companies' information environment (Hirst et al. 2008) by representing a major channel through which firms communicate voluntary information to their stakeholders (Hilary and Hsu 2011), which has been shown to lead to capital market benefits (Baginski and Rakow 2012; Cao et al. 2017). This type of disclosure can be an ideal means for female CEOs to establish their reputation. More specifically, we examine two important aspects of earnings forecasts issued by female CEOs, compared to their male counterparts: 1) the relative likelihood of issuing a forecast, and 2) the relative accuracy of the forecast.

We expect important differences in the earnings forecasts between male and female CEOs for several reasons. First, important actors in the corporate world (such as investors and board members) are known to hold prejudicial views toward female CEOs (Eagly and Karau 2002; Atkinson et al. 2003; Lee and James 2007; Bohren and Strom 2010; Niessen et al. 2019). Male senior managers may also develop negative attitudes toward female CEOs, and as a result, may cooperate less with these CEOs (McDonald et al. 2018). Perceiving this prejudice, female CEOs may respond by extending efforts to demonstrate their competency. Issuing accurate management forecasts can be a good way for female CEOs to counter such negative attitudes toward them. Doing so can also help female CEOs establish their leadership at their companies and among other senior managers in particular.

Second, female CEOs are a minority in top management at large public companies; as a result, they face greater scrutiny. According to the well-known theory of tokenism (Kanter 1977), minority groups such as women are subjected to greater pressure to perform. Female CEOs also face greater media scrutiny. For instance, female CEO appointments attract three times as much media attention as appointments of their male counterparts (Gaughan and Smith 2016). Female CEOs can use management forecasts as a way to respond to this pressure.

Third, inherent gender characteristic and leadership style differences between men and women may lead male and female CEOs to use earnings forecasts differently. Women are known to be more risk averse (Croson and Gneezy 2009), more conservative (Ho et al. 2015), and more ethical than men (Weeks et al. 1999; Valentine and Rittenburg 2004; Lund 2008). Therefore, they may choose to issue earnings forecasts with a higher degree of accuracy in order to minimize risk and conform to ethical standards. Female CEOs are also more willing to communicate (Rosener 1990) and are more relationship oriented (Helegesen 1990). As a result, their interactive leadership style may improve corporate disclosure transparency. For all of these reasons, we expect female CEOs to be associated with a higher likelihood of issuing earnings forecasts, and with more frequent and more accurate earnings forecasts.

On the other hand, there are several reasons why we may not observe differences in management forecast behavior across genders. First, women are promoted mostly by men (Oakley 2000) in a male-dominated environment. Thus, women who were able to break through the glass ceiling and obtain leadership positions may behave in ways very similar to men, insomuch as they blend in with their male counterparts (Branson 2006; Adams and Funk 2012). Even if they initially differ from men, female CEOs may decide to adapt their leadership style to conform to masculine norms (Offermann and Beil 1992). This adaptation will contribute to minimizing gender differences among CEOs. Indeed, even though women are generally more risk averse than men (Croson and Gneezy, 2009), Adams and Funk (2012) find that female directors are not more risk averse than male directors. Second, CEOs, regardless of their gender, are expected to maximize shareholders' value and lead the organization to success. To succeed, CEOs must make rational and objective value-maximizing decisions. If both male and female CEOs use an objective cost-benefit analysis regarding the issuance of a management forecast, it is unlikely that there will be any gender difference in the likelihood of issuing earnings forecasts or in their properties.

Using a sample of U.S. public companies over the period from 2000 to 2018 and a research design with firm and year fixed effects, we find evidence that corroborates our predictions. Specifically, our findings show that female CEOs are 15.3 percent more likely to issue management forecasts than male CEOs, and that these forecasts are almost 40 percent more accurate.

Next, we examine whether the greater efforts that female CEOs put into forecasting earnings are rewarded by greater analyst following. This is important because an increase in analyst coverage is known to be associated with a positive investor reaction, a decrease in the cost of capital, and a faster incorporation of new information into stock prices (Irvine 2003; Chan and Hameed 2006; Derrien and Kecskes 2013). We expect female CEOs' greater efforts in forecasting earnings to lead to an increase in analyst following because analysts greatly benefit from more accurate management disclosure (e.g., Mikhail et al. 1999; Hong and Kubik 2003; Boivie et al. 2016). We observe that, in general, more financial analysts follow companies led by *male* CEOs. However, this gap disappears for female CEOs who provide more accurate earnings forecasts; thus, their efforts seem to pay off.

In supplementary analyses, we provide further evidence of female CEOs' greater efforts to address the needs of financial information users. We show that they provide more frequent earnings forecast updates that continue until a later time during the year. Female CEOs also provide 10-K disclosures that are longer, contain more visual data, and use more unique words. In addition, we examine whether financial analysts recognize the higher-quality forecasts made by female CEOs, and consequently, whether these analysts are more likely to rely on these forecasts. Consistent with analysts realizing the superior forecasts of female CEOs, we find that analyst forecast errors and analyst forecast dispersion are more sensitive to the management forecast errors of female CEOs than to those of male CEOs.

We conduct various tests to address the potential endogeneity problems of reversed causality and omitted correlated variables. First, we use a difference-in-difference approach in which we identify CEO transitions from male to female (treatment group) and CEO transitions from male to male (control group). We find that the likelihood of issuing an earnings forecast, and the forecast's accuracy increase significantly for the treatment group after the transition, compared to the control group. Second, we use propensity-score matching (PSM) and entropy-balancing methods to increase the comparability between companies with female CEOs and those with male CEOs, and our results continue to hold. Third, we do not find any difference between male and female CEOs regarding the likelihood of beating their forecasts. This rules out the possibility that male CEOs strategically choose to under-forecast in order to increase the likelihood of beating their forecasts, which would make their forecasts less accurate. Fourth, because CFOs are also known to affect earnings forecasts (Bamber, Jiang, and Wang 2010), we control for CFO gender and obtain similar results. Using the first (instead of the last) management forecast for a given prediction does not alter our results. Finally, the CEOs of struggling companies may work harder to gain the attention and trust of analysts and investors, regardless of their gender, by providing earnings forecasts with high accuracy. If female CEOs are more likely to be selected to run these sinking ships (also known as the ‘glass cliff’ hypothesis, e.g., Ryan and Haslam 2007; Cook and Glass 2014), and the CEOs of sinking ships make greater efforts to provide earnings forecasts that are of high quality, the better earnings forecasts of female CEOs could be due to the types of companies they lead rather than the greater efforts made by female CEOs. We compare the performance of companies prior to the appointments of a female CEO and a male CEO, and we fail to find evidence that the female CEOs in our sample are more likely to run ‘sinking ships’.

A concurrent paper by Cook et al. (2020) also examines some aspects of management forecasts by female CEOs. The common aspect of the two studies involves an examination of gender differences in the likelihood of issuing earnings forecasts. However, beyond this point, the two studies take different directions. Cook et al. (2020) mostly argue that innate personality trait differences between males and females, such as overconfidence, narcissism, and risk taking, will affect the forecast properties of the two genders. Accordingly, they hypothesize that the forecast precision[1] and bias of male and female CEOs will differ, but they fail to find such evidence. Neither of these properties concerns the accuracy of the forecasts.[2] We, on the other hand, argue that due to heightened pressure to perform, female CEOs put greater efforts into their forecasts, which results in greater forecast accuracy. Consistent with our prediction of greater efforts, we find evidence that the forecasts of female CEOs are more accurate and more frequently updated. Because our sample is larger,[3] we replicated Cook et al.’s tests of gender differences in forecast precision and bias. Similar to Cook et al. (2020), we do not find significant gender differences in those dimensions of the forecast (untabulated). This finding suggests that forecast accuracy is different from forecast precision and forecast bias. As a further divergence, we focus on the *consequences* of the greater quality of

[1] Forecast precision refers to the forecast range, where a forecast of earnings per share ranging between 0.74 to 0.76 cents is considered more precise than a forecast of earnings per share ranging between 0.72 to 0.78 cents. Forecast accuracy refers to the absolute difference between the forecasted and actual earnings.

[2] Precision is an ex-ante measure, and therefore is unrelated to the forecast’s accuracy. Moreover, a measure of bias might not capture accuracy. Forecasts can be very different than the actuals, but if they are over-optimistic in 50% of the cases and over-pessimistic in 50% of the cases, they will be unbiased yet inaccurate.

[3] We collect data from both the Execucomp and Boardex databases, whereas Cook et al. (2020) only use data from Execucomp.

forecasts issued by female CEOs. We find that female CEOs who provide more accurate forecasts are able to eliminate the gender gap in analyst following. This finding shows that greater efforts to provide higher-quality forecasts by female CEOs pay off. Cook et al. (2020), on the other hand, only show that both investors and analysts hold bias toward female CEOs, but remain silent on whether and how female CEOs make efforts to reduce such bias. Overall, we believe our study is comprehensive, consistent, and insightful regarding the greater efforts that female CEOs put into their earnings forecasts, and the benefits of their forecasting efforts.

Our study contributes to the literature in three ways. First, until recently, the literature has paid very little attention to gender differences in voluntary disclosure in general, and in management earnings forecasts in particular. The very few studies on this topic mostly examine small samples outside the U.S.[4] Our examinations regarding the decision to issue management forecasts, the accuracy of the forecasts, and their consequential impact on analyst coverage fill this gap in the literature. We provide consistent evidence of a gender difference between female and male CEOs. We show that companies led by female CEOs are more likely to issue earnings forecasts and provide more frequent forecasts; further, those forecasts are on average more accurate. Second, we contribute to the literature on how female leadership affects corporate behavior (Barua et al. 2010; Francis et al. 2015; Gaughan and Smith 2016; Gull et al. 2017). We argue that female CEOs put more efforts into issuing more frequent and accurate corporate voluntary disclosures, and that male CEOs can learn from this "feminine" leadership style. Third, our study contributes to the literature on gender perception and gender bias and how to mitigate both. We show that women can successfully correct perceptual biases through the provision of high-quality earnings forecasts, leading to the reduced preference for financial analysts to follow companies led by male CEOs.

The remainder of the paper is structured as follows. We review the literature and develop our hypotheses in section 2. In section 3, we describe the research design, sample

[4] Nalikka (2009) examines a sample of 108 Finnish companies; Alqatamin, Aribi, and Arun (2017) examine a sample of 201 Jordanian companies; and Lokani (2019) examines a sample of 930 observations from Thailand.

formation, and provide the descriptive statistics. Section 4 reports the main empirical results. The results of the supplementary analyses and robustness tests are presented in section 5. The final section summarizes and concludes this study.

1.2 Prior Literature and Hypothesis Development

Various studies have explored the benefits of improving female representation in upper-level management and boards of directors (e.g., Francoeur et al. 2008; Harjoto et al. 2015; Isidro and Sobral 2015). Their findings increase the legitimacy of hiring women as top executives, and numerous countries (e.g., Norway, Iceland, Spain, and France) and the State of California[5] have introduced legally binding measures to force corporations to nominate more female directors.

Investors have been shown to hold stereotypical views toward, and prejudicial bias against, women in leadership positions (Eagly and Karau 2002; Dobbin and Jung 2010). In line with this tendency to categorize women leaders, Lee and James (2007) find that the stock market reacts negatively to the appointment of female CEOs, and Bøhren and Strøm (2010) report a negative shareholder reaction to an increase in female board representation. Similarly, Jeong and Harrison (2017) report that female representation in the upper echelons is negatively related to short-term stock market returns, even though such representation is positively related to long-term stock performance. In addition, Atkinson et al. (2003) and Niessen-Ruenzi and Ruenzi (2019) report that even though female mutual fund managers do not underperform relative to male fund managers, investors are less likely to invest in their funds. A recent experimental study by Bloomfield et al. (2020) demonstrates that even highly experienced professional investors may hold biased views toward women. The authors show that the professional investors considered female analysts as less promotable to senior positions, compared with identical

[5] Some other states are also taking steps to increase female representation on the boards of directors. Colorado has passed a joint non-binding resolution for a minimum number of female directors on the board, depending on the board's size. Maryland and Illinois have passed laws focusing on the disclosure of female representation on the board, and Hawaii, Massachusetts, Michigan, New Jersey, and Washington are each considering mandatory board diversity legislation (Hutcher and Latham 2020).

male analysts.[6] Against this backdrop of a negative market bias against women in senior positions, new female CEOs start off their tenure in a disadvantageous position, compared with male CEOs.

In addition to investors' unfavorable attitudes, female CEOs face greater scrutiny from the media and their colleagues inside their organizations. Research on media coverage shows that female CEOs receive greater media attention due to their gender. Lee and James (2007) find that gender is frequently highlighted in the announcements of female CEO appointments, while rarely mentioned in those involving men. In addition, Gaughan and Smith (2016) find that, compared with male CEO appointments, female CEO appointments attract three times more media attention. Under this higher public exposure, female CEOs' performance during their tenure may have a larger influence on their reputation and their careers. Female executives are a numerical minority in top management. According to the theory of tokenism (Kanter 1977), minority individuals have higher visibility; they are subjected to greater performance pressure and, overall, face a less cooperative environment. McDonald et al. (2018) find that in the presence of a female CEO, white male senior executives tend to develop a diminished sense of organizational identity and consequently provide less help to the CEO. Studies show that even subordinates will subject minorities to hostility, resistance, and dislike (Nesbitt, 1997; Heilman et al. 2004). To be recognized as strong achievers, women have to be better qualified and demonstrate outstanding performance as top executives. As discussed in Eagly and Carli (2003), female leaders suffer from prejudice in masculine organizational contexts. Moreover, female leaders must be extremely competent to cope. Female CEOs also bear a higher risk of being dismissed (Gupta et al. 2018). Cook and Glass (2014) find that minority CEOs tend to be replaced by white men when firm performance declines. Another source of scrutiny derives from the fact that some companies may appoint women to senior positions for the sake of improving their CSR index score (Cook and Glass

[6] The authors created a scenario that manipulated whether a male or female analyst who is considered for a promotion persists in pitching a stock pick that has been voted down by a portfolio manager. The professional investors considered negative (less promotable) analysts that did not persist in pitching the stock, but only if they were female analysts. The authors attribute this gender-based evaluation to categorizing theory, which suggests that evaluators rely on stereotypes when assessing behavior.

2018).[7] These situations may cast doubt on the competency of women and may pressure them to prove themselves.

Therefore, in the environment where they operate, female CEOs may feel greater pressure to deliver strong performance and build their reputation. As a result, they are likely to make greater efforts than male CEOs to improve investors' attitudes, gain market participants' confidence, and earn managers' and employees' trust. Previous literature documents various ways to alter investors' perceptions and ultimately increase firm market value (e.g., Cohen and Dean 2005). One reliable way is by increasing voluntary disclosures and financial transparency. For instance, Kimbrough and Louis (2011) find that the market reacts more favorably to the merger announcements of companies holding conference calls. Field et al. (2005) find that preemptive bad-news forecasts help deter substantive lawsuits. Within this context, we investigate the relationship between CEO gender and corporate voluntary disclosure in the form of earnings forecasts.[8]

Earnings forecasts represent the manager's expectations of near-future profitability. Because managers have access to private information, their forecasts of future earnings send a valuable signal to outsiders, notably to investors (Patell 1976; Penman 1980; Nagar et al. 2003; Hilary and Hsu 2011). Management forecasts also guide analysts in preparing their own forecasts (Graham et al. 2005). The manager's decision to provide earnings forecasts depends on the benefits and costs of doing so. Managers issue earnings forecasts when the benefits exceed the costs. On the benefit side, earnings forecasts provide value-relevant input for analysts' forecasts that can ease the analysts' job and make their forecasts more accurate and less dispersed (e.g., Hassell et al. 1988). These forecasts will further increase analyst coverage, reduce estimation risk and information asymmetry, and lower the cost of capital (Lang and Lundholm 1996). On the cost side, once the issuance of earnings forecasts begins, investors would expect managers to maintain this practice; companies that stop providing earnings forecasts are likely to be

[7] In a survey of board members by Heidrick and Struggles (2012), 32 percent of female board members indicated that their gender was a significant factor in their appointment to the board, compared with only 2 percent of male directors making a similar claim.

[8] Ng, Tuna, and Verdi (2013) show that the market reacts more strongly to more credible management forecasts, suggesting that the market appreciates higher managerial efforts to predict earnings.

punished by investors (Graham et al. 2005). Furthermore, when actual earnings are less than what was forecasted, companies risk a decline in their stock price.

Meeting investors' and analysts' information needs is important to all CEOs.[9] However, we see two reasons why it may be more important for female CEOs to issue earnings forecasts. First, issuing such forecasts can help female CEOs build a reputation for transparent reporting (Hirst et al. 2008), which can help them gain investors and other stakeholders' confidence, and can lower the level of scrutiny they must deal with. Second, some inherent characteristics that are more common for women than for men also increase the likelihood that female CEOs issue earnings forecasts. Relative to men, women are on average more risk averse (Croson and Gneezy 2009), more conservative (Ho et al. 2015), and have greater ethical values (Weeks et al. 1999; Valentine et al. 2008). These behavioral traits are bound to extend to how female CEOs lead their organizations. In this regard, Barua et al. (2010) and Gull et al. (2017) find that companies led by female executives engage less in earnings management. Furthermore, Francis et al. (2015) find that companies led by female executives make more conservative accounting choices. We therefore expect female CEOs to report in a more transparent way, as more transparency reduces litigation risk (Field et al. 2005; Hilary et al. 2014) and is considered more ethical. Women also differ from men in their leadership style. It has been established that female CEOs are more willing to communicate (Rosener 1990; Francis et al. 2020) and are more relationship oriented (Helegesen 1990). This more interactive leadership style may improve corporate disclosure transparency, including earnings forecasts.

On the other hand, there are two main reasons why female CEOs may not differ from male CEOs in the likelihood of issuing management forecasts. First, female CEOs are appointed in a mostly male-dominated environment (Oakley 2000). Thus, women who have been able to break through the glass ceiling and reach the top executive suite may behave in ways similar to men (Branson 2006; Adams and Funk 2012): they may believe that their promotion is greatly due to their similarities with men. Second, if the decision of whether or not to issue a management forecast is solely based on an organizational

[9] Even though CEOs do not directly prepare forecasts, they are likely to be heavily involved in the process (Cheng and Lo 2006; Bolliger and Kast 2007; Baik et al. 2011).

cost-benefit analysis, there is no reason to expect female CEOs to behave differently. Nonetheless, we expect women in top leadership positions to be more likely to issue earnings forecasts to ease the great pressure they face. Therefore, our first hypothesis regarding gender differences in issuing earnings forecasts is as follows:

HYPOTHESIS 1*: Female CEOs are more likely than male CEOs to issue earnings forecasts.*

Our second hypothesis concerns the relative accuracy of earnings forecasts by female CEOs. As discussed above, female CEOs are under pressure to build their reputation and change the way they are perceived. Female CEOs can use the accuracy of their earnings forecasts to signal their competency (Baik et al. 2011). Forecast accuracy signals the manager's capacity to process information (Tan et al. 2002); it has also been shown to be associated with a lower likelihood of CEO turnover (Lee et al. 2012). By providing more accurate earnings forecasts, companies can better meet investors' demand and reduce analysts' workload (Graham et al. 2005). Managers who issue more accurate earnings forecasts build a forecasting reputation, which leads analysts to rely more on them (Williams 1996). Realizing that more accurate forecasting can help them overcome the many disadvantages they face, female CEOs are likely to put additional efforts into and pay more attention to their forecasting, which should lead to greater accuracy. Thus, our second hypothesis is as follows:

HYPOTHESIS 2*: Female CEOs issue more accurate earnings forecasts than male CEOs.*

Our third hypothesis investigates whether female CEOs' efforts in forecasting earnings help them establish their credibility and lead to certain benefits. Specifically, we examine whether female CEOs who provide high-quality earnings forecasts enjoy higher analyst following. We focus on analyst following because the number of analysts covering a stock has a significant influence on investors. Prior studies demonstrate that analyst forecasts can improve market efficiency and are closely related to the firm's information environment (Healy and Palepu 2001). Chan and Hameed (2006) find that the stock prices of companies with more analyst coverage incorporate new information faster. Derrien and Kecskes (2013) also find that a decrease in analyst coverage increases information asymmetry and the cost of capital, while the initiation of coverage is viewed positively by investors (Irvine 2003). Conclusively, analyst coverage has a significant effect on the company and its information environment. We therefore stipulate that when female CEOs provide more accurate earnings forecasts, this will convey a clear signal to analysts about their capabilities, which will lead to an increase in analyst following. Our third hypothesis is as follows:

HYPOTHESIS 3: *Female CEOs who provide more accurate earnings forecasts enjoy greater analyst following.*

1.3 Research Design, Sample Selection, and Sample Description

1.3.1 Research Design

To test our first hypothesis that female CEOs are more likely than male CEOs to issue earnings forecasts, we use the following Linear probability model (LPM) model[10]:

$$
\begin{aligned}
Pr\,(MF{=}1) = {} & \beta_0 + \beta_1 FCEO + \beta_2 ROA + \beta_3 LOSS + \beta_4 NEGCHG + \beta_5 VOLATILITY \\
& + \beta_6 DISTRESS + \beta_7 MB + \beta_8\, FOLLOW + \beta_9 SIZE + \beta_{10} BIG \\
& + \beta_{11} INST\_OWN + FIRM\ FE + YEAR\ FE + \varepsilon \qquad (1)
\end{aligned}
$$

The dependent variable in (1) is the likelihood of issuing a management forecast, *MF*, which is equal to 1 when a company provides an annual earnings forecast, and to 0 when it does not. The independent variable of interest is *FCEO*, which is set to 1 when the CEO is female, and to 0 when the CEO is male. According to the first hypothesis, female CEOs have a higher tendency to issue earnings forecasts. Accordingly, we expect the coefficient of *FCEO* to be positive.

[10] It is common to use a linear probability model with a binomial dependent variable when many fixed effects are included in the model. See, for example, Adams and Ferriera (2009), Hanlon and Hoopes (2014), Guo and Masulis (2015), and Fos et al. (2017). The use of a linear probability model does not impose potential bias or inconsistency on the coefficients and standard errors (Greene, 2004). Logit models, on the other hand, can result in a significant loss of observations and are less interpretable. We obtain similar results using a logit regression.

We include an array of control variables that may affect firms' voluntary disclosure decisions. We control for firm profitability using *ROA*, the return on assets, and *LOSS*, a binary variable equal to 1 if current earnings are negative, and to 0 otherwise. We control this latter variable, given that firms reporting negative earnings are more likely to stop providing earnings forecasts (e.g., Ajinkya et al. 2005; Graham et al. 2005). However, in order to forestall litigation, firms with a negative earnings change are more likely to disclose this information (Skinner 1994). Thus, we include *NEGCHG*, which is set to 1 if current earnings are smaller than those of the previous year, and to 0 otherwise. Firms with higher earnings volatility are less likely to provide forecasts (Waymire 1985) due to the greater difficulty in predicting earnings under high operational uncertainty. We therefore include *VOLATILITY*, the monthly stock return volatility over the past 12 months. Lang and Lundholm (1996) find greater analyst following for companies that provide more earnings guidance. We therefore include the variable *FOLLOW*, the number of analysts following the stock.[11] Companies audited by Big N firms tend to have better disclosures (Lang and Lundholm 1993). Thus, we use the indicator variable *BIG*, as a proxy for disclosure quality. We also control for the following firm-level characteristics: financial distress, *DISTRESS*, measured using Zmijewski's Z-Score; the ratio of the market-to-book value, *MB*; and firm size, *SIZE*, defined as the natural logarithm of total assets. Lastly, we add to the model *INST_OWN*, the percentage of shares held by institutional investors (e.g., Ajinkya et al. 2005; Baik et al. 2011). A list of all variable definitions is provided in the Appendix 1-1. All continuous variables are winsorized at the 1 and 99 percentiles to minimize the effect of extreme values. We also include here and in all of the other models firm fixed effects to account for potential missing time-invariant firm characteristics, and year fixed effects to account for systematic variations in the dependent variables across years. We cluster standard errors at the firm and year levels.[12]

[11] We consider companies not covered by IBES Academic as having no analyst coverage. All results we report in the paper remain unchanged if we use the natural logarithm of the number of analysts, or if we remove the observations with zero analyst coverage in IBES Academic (approximately 0.5 percent of the sample).

[12] Our results are similar if we cluster only at the firm level.

Our second hypothesis is that the earnings forecasts of female CEOs are more accurate than those of male CEOs. To test this hypothesis, we run the following OLS model using a sample of companies that issued management forecasts:

$$\begin{aligned} MFE = {} & \beta_0 + \beta_1 FCEO + \beta_2 ROA + \beta_3 ABILITY + \beta_4 LOSS + \beta_5 ABSCHG \\ & + \beta_6 VOLATILITY + \beta_7 DISTRESS + \beta_8 MB + \beta_9 FOLLOW + \beta_{10} SIZE \\ & + \beta_{11} BIG + \beta_{12} GAP\_MF + \beta_{13} ABSAEM + \beta_{14} ABSREM + \beta_{15} INST\_OWN \\ & + FIRM\ FE + YEAR\ FE + \varepsilon \qquad (2) \end{aligned}$$

The dependent variable *MFE*, management forecast error, is defined as the absolute difference between management-forecasted earnings per share and actual earnings per share, divided by the stock price and multiplied by 100. All forecasts included in the sample are either of a specific point or range, in which case we take the midpoint. Considering that earnings forecasts are estimated on a "continued operations" basis, and that managers and investors rely more on *street earnings*[13] than on GAAP earnings (Bradshaw and Sloan 2002), we use the street earnings reported by IBES to calculate the forecast errors. Because we expect female CEOs to provide more accurate earnings forecasts than male CEOs, their earnings forecast errors should be smaller, and we expect the coefficient of *FCEO* to be negative.

Baik, Farber, and Lee (2011) find that high-ability CEOs are likely to provide more accurate management forecasts; thus, we control for managerial ability (*ABILITY*) using two different proxies: 1) *ADJROA*, the average rank of the industry-adjusted ROA in the previous three years (Rajgopal et al. 2006; Baik et al. 2011),[14] and 2) *DEASCORE*, an efficiency score measure based on the data envelope analysis method (Baik et al. 2011; Demerjian et al. 2012). Prior research has shown that larger earnings changes are

[13] Street earnings are a non-GAAP measure of firms' actual earnings, excluding "non-recurring" items such as extraordinary items, earnings from discontinued operations, and other non-operating items. Street earnings are reported by analyst tracking services (e.g., IBES, First Call).

[14] If the specific CEO has been on the job for less than three years, we use the average ROA for the period she has been on the job. In this specification, we drop *ROA* from the model due to its high correlation with *ADJROA*.

associated with lower forecast accuracy (Lang and Lundholm 1996). We therefore control for the absolute difference between the current and previous annual earnings per share, *ABSCHG*. Following prior literature on earnings forecasts (e.g., Behn, Choi, and Kang 2008; Gul, Hutchinson, and Lai 2013), we control for the number of days between the issuance of the last management forecast and the end of the fiscal year, *GAP_MF*, which is found to have a negative relationship with forecast accuracy. Finally, previous studies show that managers may use accounting flexibility to meet their forecasts (Kim 2016). Female CEOs are less likely to manage earnings (e.g., Gull et al. 2017; Na and Hong 2017), which may affect earnings forecast accuracy. Thus, we add to the model the absolute discretionary accruals, *ABSAEM*, and the absolute abnormal cash flow from operations, *ABSREM*, calculated using the models of Kothari et al. (2005) and Roychowdhury (2006), respectively. All other variables are defined in Model (1).

Our third hypothesis is that greater efforts in providing earnings forecasts will reward female CEOs in terms of increased analyst following. We first examine whether companies led by female CEOs have more or less analyst coverage. For this, we run the following OLS model:

$$\begin{aligned} LEAD\_FOLLOW = {} & \beta_0 + \beta_1 FCEO + \beta_2 TRADE\_VOL + \beta_3 ROA + \beta_4 LOSS \\ & + \beta_5 ABSCHG + \beta_6 VOLATILITY + \beta_7 DISTRESS + \beta_8 MB + \beta_9 SIZE \\ & + \beta_{10} BIG + \beta_{11} INST\_OWN + \beta_{12} FOLLOW + FIRM\ FE + YEAR\ FE \\ & + \varepsilon \qquad (3) \end{aligned}$$

The dependent variable in Model (3) is *LEAD_FOLLOW*, the number of analysts following the company in the following year. We use analyst following in the subsequent year because it might take some time for the quality of the manager's forecasts to affect the analysts' stock coverage decision. Our variable of interest is *FCEO*. A negative coefficient of *FCEO* will indicate analyst preference toward companies with male CEOs. Alford and Berger (1999) find that stocks generating more trading volume, and thus leading to higher brokerage commissions have increased analyst following. Thus, we control for the annual trading volume, *TRADE_VOL*. We also include in the model *FOLLOW*, the number of analysts following the company in the current year due to the stickiness of analyst coverage. All of the other variables are defined above.

To examine whether female CEOs are rewarded with more analyst coverage for providing more accurate forecasts, we use the following OLS models:

$$
\begin{aligned}
LEAD\_FOLLOW = {} & \beta_0 + \beta_1 FCEO + \beta_2 MF + \beta_3 FCEO \times MF + \beta_4 TRADE\_VOL \\
& + \beta_5 ROA + \beta_6 LOSS + \beta_7 ABSCHG + \beta_8 VOLATILITY \\
& + \beta_9 DISTRESS + \beta_{10} MB + \beta_{11} SIZE + \beta_{12} BIG + \beta_{13} INST\_OWN \\
& + \beta_{14} FOLLOW + FIRM\ FE + YEAR\ FE + \varepsilon \qquad (4)
\end{aligned}
$$

$$
\begin{aligned}
LEAD\_FOLLOW = {} & \beta_0 + \beta_1 FCEO + \beta_2 LOW\_MFE + \beta_3 HIGH\_MFE \\
& + \beta_4 FCEO \times LOW\_MFE + \beta_5 FCEO \times HIGH\_MFE + \beta_7 TRADE\_VOL \\
& + \beta_8 ROA + \beta_9 LOSS + \beta_{10} ABSCHG + \beta_{11} VOLATILITY + \beta_{12} DISTRESS \\
& + \beta_{13} MB + \beta_{14} SIZE + \beta_{15} BIG + \beta_{16} INST\_OWN + \beta_{17} FOLLOW \\
& + FIRM\ FE + YEAR\ FE + \varepsilon \qquad (5)
\end{aligned}
$$

In Model (4), we test whether the mere provision of a forecast by a female CEO will lead to higher analyst coverage. Our variable of interest is the interaction variable, *MF x FCEO*. A positive coefficient will indicate that female CEOs' provision of earnings forecasts leads to a higher increase in analyst following, relative to that of male CEOs. In Model (5), we test whether the provision of more accurate earnings forecasts will benefit female CEOs in terms of greater analyst following. We add to the model *LOW_MFE*, an indicator variable equal to 1 if a company provides earnings forecasts (*MF* = 1) and the management forecast error (*MFE*) is below the sample median, and to 0 otherwise. Similarly, we add *HIGH_MFE*, an indicator variable equal to 1 if *MF* is equal to 1 and *MFE* is above the sample median, and to 0 otherwise. We then interact each of the variables with *FCEO*. If female CEOs' higher propensity to issue earnings forecasts of greater accuracy affects analyst coverage, we expect positive coefficients of *FCEO x LOW_MFE*.

1.3.2 Sample Selection and Description

Our sample covers the period from 2000 to 2018. We start in 2000 because only very few firms were headed by female CEOs before 2000. In addition, Regulation Fair Disclosure (Reg FD), a major regulatory change with respect to the communication between management and analysts, was passed in 2000. Gender identification mainly comes from Execucomp and is complemented by data from BoardEx, which also provides information on executive gender.[15,16] If there is more than one CEO during a fiscal year, we manually select the person who is the CEO for most of that fiscal year. We obtain data on management earnings forecasts from IBES Guidance, and on analyst forecasts and street earnings from IBES Academic. Fundamental financial information is obtained from Compustat; stock return-related data are from CRSP; and institutional ownership data are from Thomson Reuters Institutional Holdings. Observations missing the necessary data for the control variables are removed from the sample. After those steps, we have 49,595 firm-year observations to test H1.[17]

Testing H2 involves earnings forecast accuracy; thus, we only consider companies that provide management forecasts. We also require that management forecasts be released before the end of the fiscal year in order to exclude preliminary earnings announcements. Following prior studies (e.g., Waymire 1985; Hirst et al. 1999), we exclude open-ended

[15] For companies whose International Security Identification Number (ISIN) is given in BoardEx, we use that number to match the CUSIP in Execucomp. For those without an ISIN, we use fuzzy matching with Compustat, based on the similarity of the company names provided. All matches suggested by the software were manually checked and confirmed.

[16] If the gender information from the two sources is inconsistent, we further search the companies' websites and other websites (e.g. Google.com; Bloomberg.com) to confirm the CEO's gender.

[17] As Table 1 shows, some singleton observations are dropped from the models because we include firm and year fixed effects.

forecasts.[18] After those additional steps, our sample for testing H2 comprises 13,888 observations.

To test H3 regarding the consequences of providing management forecasts, we exclude from our initial sample observations without the necessary analyst information for the following year. The sample for testing H3 comprises 46,314 observations. Table 1 summarizes the sample formation and composition process.

[Insert Table 1-1 here]

Panel A of Table 2 presents the sample distribution across the sample period. The percentage of female CEOs increases from 1.54 percent in 2000 to 5.02 percent in 2018, which is similar to the time trend reported in other gender analyses (e.g., Catalyst Research of Women CEOs in the S&P 500). The number of female CEO observations is 1,568, which represents 3.16 percent of the total sample. Panel B of Table 2 presents the sample distribution by Fama-French's 12 industries. Female CEOs are relatively overrepresented in the Consumer Nondurables, Transmission, Utilities, Wholesale, and Healthcare industries, and are underrepresented mainly in the Consumer Durables, Energy, Business Equipment, and Manufacturing industries.

[Insert Table 1-2 here]

Panel C of Table 2 presents a univariate comparison of all variables in our main tests between female and male CEOs. The average *MF* is 0.353 for companies with female CEOs, which is significantly higher than 0.307, the average for companies with male CEOs. Thus, female CEOs are 15.0 percent more likely than male CEOs to issue earnings forecasts. These results provide preliminary evidence that female CEOs are associated with a higher tendency to issue earnings forecasts. *MFE* is higher for male CEOs than for female CEOs, but the difference between the two groups is not statistically significant. Thus, the univariate comparison does not show any difference in the management forecast accuracy between the two genders. We also observe significant differences in many firm characteristics between the two groups. In general, female CEOs are hired by less

[18] We obtain similar results if we do not exclude those observations.

distressed companies, companies with higher profitability, and higher growth prospects, as well as companies that are more likely to appoint a Big 4 audit firm. This finding supports the conclusion of Knippen et al. (2018) that companies with strong financial health are more likely to appoint a female CEO. Institutional ownership is higher for companies with male CEOs. The average *GAP_MF* of female CEOs is 11 (0.03 x 365) days shorter than that of male CEOs, which means that the last earnings forecast issued by a female CEO is closer to the end of the fiscal year than that issued by a male CEO. Lastly, the comparison of earnings management reveals that female CEOs are less likely to engage in accrual-based earnings management, while they are more likely to engage in real earnings management than male CEOs.

Table 3 provides Pearson correlations for the variables in the smaller sample used to test H2 and H3. The correlation tests are generally consistent with the univariate results. The correlations between the independent variables are relatively small. Nonetheless, we check the variance inflation factor (VIF) of each variable tested in each model, and none exceeds 3.5. The relatively low coefficients in the correlation matrix and the VIF results suggest that multicollinearity should not be a concern in this study.

[Insert Table 1-3 here]

1.4 Empirical Results

Table 4 reports the LPM regression results on the association between CEO gender and the likelihood of management forecast provision (H1). We see that the coefficient of *FCEO* is positive and statistically significant (0.046, t-value = 3.667). In economic terms, the relative likelihood of providing an earnings forecast is 15.3 percent higher for female CEOs. These results support our first hypothesis. With respect to the control variables, *LOSS* is negatively associated with *MF*, which is consistent with the argument that companies with negative earnings are more likely to discontinue the provision of earnings forecasts. *NEGCHG* is positively associated with *MF*, consistent with the observation that companies having bad news choose to disclose that information quickly. *VOLATILITY* has a negative and significant coefficient, which is consistent with the idea that it is more challenging to predict earnings under high uncertainty. The coefficient of *MB* is positive and significant, suggesting that companies with high-growth prospects are more likely to provide earnings forecasts. The coefficients of *FOLLOW*, *SIZE*, *BIG*, and *INST_OWN* are all positive and significant, suggesting that companies with more analyst coverage, larger companies, companies audited by Big 4 firms, and companies with higher institutional ownership are more likely to provide earnings forecasts. The remaining variables are insignificant.

[Insert Table 1-4 here]

Table 5 reports the OLS regression results on the association between female CEOs and management forecast accuracy. We control for the manager's ability using *ADJROA*, the average of the ranked industry-adjusted ROA in the previous three years in Column 1, and *DEASCORE*, the efficiency score measure based on the data envelope analysis method in Column 2. The results in both columns show that the coefficient of *FCEO* is negative and significant, which suggests that, after controlling for other factors that affect forecast accuracy, forecasts issued by female CEOs have smaller errors. In economic terms, relative to the forecast errors of male CEOs, female CEOs' forecast errors are 40.0 percent (39.2 percent) smaller when we control for CEO ability using *ADJROA* (*DEASCORE*).

With regard to the control variables, we first note that our two measures of CEO ability are negatively associated with forecast errors, suggesting that more able managers issue more accurate forecasts. Management forecast errors are larger for firms with high earnings changes, loss firms, distressed firms, and firms with high stock price volatility. The earnings forecasts disclosed by larger firms and more profitable firms are more accurate. The number of analysts following the stock has a significantly negative relationship with forecast errors, suggesting that the forecasts of firms with more analyst coverage are more accurate. This finding is consistent with the evidence in Graham et al. (2005) and Lang and Lundholm (1996). *GAP_MF* is positively associated with management forecast errors, which means that the forecasts issued closer to the end of the fiscal year are more accurate, given that they contain more recent information.[19] Finally, institutional ownership is negatively associated with management forecast errors.

[Insert Table 1-5 here]

The results related to our third hypothesis on the association between earnings forecasts by female CEOs and analyst following are in Table 6. Column 1 reports the results of Model (3). The coefficient of *FCEO* is negative and significant at the 5 percent level. This finding suggests that on average, analysts prefer to follow companies with male CEOs.[20] Column 2 reports the results of Model (4). We see that the coefficient of the interaction term *FCEO* x *MF* is insignificant, and that the coefficient of *FCEO* remains negative and significant. This finding suggests that on average, the mere provision of management forecasts does not alter analysts' preference for male-led companies. Column 3 reports the results of Model (5) and shows that, as expected, the coefficient of *LOW_MFE* is positive and significant, whereas the coefficient of *HIGH_MFE* is insignificant. These results mean that the provision of more accurate management forecasts (smaller forecast errors) is rewarded with more analyst coverage, whereas the provision of less accurate management forecasts is not rewarded. More important for our study, the coefficient of *FCEO x LOW_MFE* is significant at the 5 percent level, while the coefficient of *FCEO x HIGH_MFE* is insignificant. These results suggest that providing earnings forecasts of greater accuracy helps female CEOs to increase their analyst coverage, relative to male CEOs. Moreover, the sum of the coefficients of *FCEO* and *FCEO x LOW_MFE*, reported at the bottom of the table, is insignificant (p-value = 0.45). This finding indicates that the provision of more accurate management forecasts allows female CEOs to eliminate the gap in analyst following relative to companies with male CEOs. The insignificant coefficient of *FCEO x HIGH_MFE* suggests that the provision of less accurate

[19] Because we report in Table 2, Panel C that *GAP_MF* is shorter for female CEOs, and that *GAP_MF* is positively correlated with MFE, we repeat this test using the first earnings forecast. The coefficient on FCEO remains negative and significant, suggesting that the more accurate forecasts are not merely because they provide forecasts at later times.

[20] We consider two explanations concerning analysts' preference for companies headed by male CEOs. One possible explanation is that analysts hold a negative bias against female CEOs, and therefore refrain from following their companies. A second possibility is that male CEOs communicate privately with financial analysts more than female CEOs, which will incentivize analysts to prefer companies headed by male CEOs.

management forecasts does not help reduce the gap.[21] Overall, the results suggest that the high efforts of female CEOs to issue accurate earnings forecasts can help reduce the gender gap in analyst following.

[Insert Table 1-6 here]

1.5 Supplementary Analysis and Robustness Checks

1.5.1 Other Evidence on Female CEOs' Effort

We posit and find that female CEOs make greater efforts to meet the information needs of investors and analysts by providing more accurate management forecasts. We corroborate this finding by providing evidence on 1) the frequency of female CEOs updating their earnings forecasts, and 2) the content of their 10-K disclosures.

We follow Baik et al. (2011), and in addition to the likelihood of issuing earnings forecasts, we examine whether the frequency of issuing forecasts by female CEOs (which also includes updates to the original forecasts) is higher than that by male CEOs. A higher frequency of forecast issuance by female CEOs will further demonstrate that they make greater efforts to keep stock market participants informed.

Panel A of Table 7 provides a univariate comparison of the frequency of forecasts between male and female CEOs. Using the full sample (including companies not issuing earnings forecasts), the frequency is 1.437 for male CEOs and 1.776 for female CEOs; the difference is statistically significant. This finding indicates that female CEOs provide 23.6 percent more earnings forecasts. Because this test reflect the effects of both providing forecasts and revising them, we also report the results for the sample of companies issuing forecasts. Male CEOs provide on average 4.676 disclosures, including revisions, whereas female CEOs make on average 4.936 disclosures (a relative difference of 5.6 percent). Thus, female CEOs are more likely to issue forecasts and make more timely updates to those forecasts. Panel B provides the multivariate results of an OLS regression where we repeat Model (1), replacing the dependent variable *MF* with *FREQUENCY*, the number

[21] An alternative research design that only includes observations with management forecasts and uses a single indicator variable for management forecast accuracy (*LOW_MFE*) shows similar results.

of annual management earnings forecasts disclosed in one year, including forecast revisions. The results in Column 1 show that female CEOs provide more frequent forecast disclosures, and the relative difference is 18.0 percent. In Column 2, where we only consider companies that issued management forecasts during the year, the coefficient of *FCEO* remains positive and significant at the 10 percent level. The relative increase in the forecast frequency for female CEOs is 7.5 percent. This finding implies that female CEOs provide more frequent updates to their forecasts, informing investors more promptly about changes in their expectations of future profitability. In addition, as we already report in Table 2, Panel C, the variable *GAP_MF* is significantly smaller for female CEOs. This result means that female CEOs continue to update their forecasts until a later date before the end of the year than do male CEOs. In Column 3, we report the multivariate analysis on the relations between *GAP_MF* and CEO gender. Consistent with the univariate results, the coefficient of *FCEO* is negative and significant, suggesting that the number of days between the issuance of the last management forecast and the end of the fiscal year is shorter for female CEOs.[22] Overall, our findings of higher forecast updates during the year and of updates that last until a later point by female CEOs complement each other and paint a complete picture of female CEOs making greater efforts to keep the users of forecasts informed.

[Insert Table 1-7 here]

We also analyze the content of 10-K reports to provide further evidence on female CEOs' efforts. While this report is mandatory, managers can exercise some judgment over its content. We examine three aspects of the report: its length, use of graphics, and use of unique words. We complement this analysis by examining the Gunning Fog index (Gunning 1952), the SMOG Fog index (McLaughlin 1969), and the average length of the sentences.

We use the natural logarithm of the file size, *FILESIZE* (Loughran and McDonald 2014), and the natural logarithm of the number of words, *WORD* (Li 2008), to measure the length

[22] In untabulated results, we further find weakly significant evidence that the timespan from the first earnings forecast to the last forecast update is longer for female CEOs.

of 10-K reports. The univariate results reported in Panel A of Table 8, and the multivariate results reported in the first two columns of Panel B show that the 10-K reports of female CEOs contain more words, and their file size is larger than that of male CEOs. This finding may suggest that female CEOs provide more valuable information to financial information users. However, Li (2008) and Loughran and McDonald (2014) argue that longer reports may indicate lower readability, as longer reports take longer to read and process. As a result, the length of the report can be used strategically to make the report less transparent and to conceal unfavorable information by overflowing the report with irrelevant information. We therefore examine other aspects of the report.

We examine the use of exhibits in the 10-K because the SEC recognizes the potential benefits of graphics in communicating financial information to users in a manner that is easier to read and understand (SEC 1998).[23] Moreover, Loughran and McDonald (2016) assert that non-textual materials enhance the reader's ability to understand the information. Consistent with the ability of data visualization to facilitate the effective communication of relevant valuation information to 10-K users, Christensen et al. (2021) find significantly positive associations between infographics and the magnitude of both 10-K filing abnormal returns and analysts' forecast revisions. The results in Column 3 of Panel C show that female CEOs make greater use of infographics, suggesting that they are more attentive to the needs of information users. We also examine the use of unique words, using the variable *UNIQUE*, the natural logarithm of the number of unique words in the 10-K report. If the intent is to mislead investors, we would expect to see more repetition in the reports. However, as shown in Panel A and in Column 4 of Panel B, female CEOs use more unique words. This again suggests that female CEOs provide more information in 10-K filings than male CEOs.

We complement this analysis by calculating the Fog index (either the Gunning Fog index or the SMOG Fog index) and the average sentence length, *AVE_LENGTH* (which is one of the two components of the Gunning-Fog index). The univariate results in Panel A show

[23] To facilitate the use of graphics in regulatory filings, in 2000, the SEC updated its Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system to allow HTML files containing embedded tags for graphic or image files (SEC 2000).

higher values for female CEOs. However, as Lougharn and McDonald (2016) show, differences in the Fog index between groups can be statistically significant without having a meaningful difference. This seems to be the case here, as the univariate results suggest a difference of only 0.2 years in education in terms of readability. Even more importantly, after controlling for firm characteristics, the multivariate results reported in Panel C of Table 4 show no statistical difference between the two genders on all measures. Considering all evidence together, we conclude that female CEOs provide more useful information to 10-K users without making 10-K reports more complex.

[Insert Table 1-8 here]

1.5.2 Earnings Forecast Errors and Analyst Forecast Errors

Research has shown that forecast accuracy has a significant effect on financial analysts' careers. For example, Mikhail et al. (1999) find that analysts who issue less accurate forecasts are more likely to be replaced. According to Hong and Kubic (2003), analysts who are more accurate forecasters are more likely to move up to a high-status brokerage house. Consistent with analysts wanting to forecast accurately, Williams (1996) shows that they tend to rely more on the forecasts of managers who have established a reputation for accuracy. These arguments suggest that financial analysts will rely more on the earnings forecasts of female CEOs than those of male CEOs if they believe the female CEOs' forecasts are more accurate. On the other hand, similar to investors, analysts may also hold negative attitudes toward female CEOs and may downplay their capabilities. This in turn may cause them to discount, or at least not appreciate the forecasts of female CEOs, despite their higher accuracy. To assess whether analysts recognize the higher-quality forecasts of female CEOs, we use the following model that focuses on the association between management earnings forecast errors and analyst earnings forecast errors and dispersions.

To test this hypothesis, we run the following OLS models:

$$AFE\ /\ AF\_DISP = \beta_0 + \beta_1\, FCEO + \beta_2 MFE + \beta_3 FCEO \times MFE + \beta_4 ROA + \beta_5 LOSS$$

$$+ \beta_6 ABSCHG + \beta_7 VOLATILITY + \beta_8 DISTRESS + \beta_9 MB + \beta_{10} FOLLOW$$

$$+ \beta_{11}SIZE + \beta_{12}BIG + \beta_{13}ABSAEM + \beta_{14}ABSREM + \beta_{15}GAP\_AF$$

$$+ \beta_{16}INST\_OWN + \beta_{17}LAFE / LAF\_DISP + FIRM\ FE + YEAR\ FE + \varepsilon \qquad (6)$$

In Model (6), the dependent variable is either *AFE* or *AF_DISP*. *AFE* is the absolute value of the difference between the analyst consensus earnings forecast per share and the actual earnings per share (street earnings), divided by the stock price and then multiplied by 100. *AF_DISP* is the standard deviation of the analyst forecasts per share, divided by the stock price. Our interest lies in the interaction variable *FCEO x MFE*. A positive (negative) coefficient estimate for β_3 in each of the models will suggest a greater (smaller) association of analyst forecast errors and dispersions with the management forecast errors of female CEOs, and therefore greater (smaller) reliance of analysts on female CEOs' forecasts. Because analyst forecasts issued close to the earnings announcement date are likely to be more accurate, we control for the average time between the issuance of analysts' forecasts and the end of the fiscal year, *GAP_AF*. To account for analyst forecast consistency (Hilary and Hsu 2013), we control for the previous year's average analyst forecast errors, *LAFE*, and the previous year's average analyst forecast dispersion, *LAF_DISP*. All other variables are as defined in Model (2).

Table 9 reports on the association of analyst forecast errors (Column 1) and analyst forecast dispersion (Column 2) with management forecast errors. The very high correlation of the dependent variables with *MFE* is evidence that management forecasts are an important input for analyst forecasts. We find that the coefficient of the interaction variable *FCEO x MFE* is positive and significant in both columns, which indicates that analyst forecast errors and forecast dispersion are more strongly correlated with the management forecast errors of female CEOs. These results are consistent with analysts placing more weight on the forecasts of female CEOs than those of male CEOs. One explanation for these results is that analysts rely more on female CEOs' forecasts when preparing their own forecasts because they recognize female CEOs' higher accuracy. However, we must acknowledge that the lower association of analyst forecast errors with the management forecast errors of male CEOs can happen if analysts who follow companies with male CEOs derive more information from other channels.[24] We also observe that analyst forecast errors and forecast dispersion are positively associated with *LOSS*, *ABSCHG*, *DISTRESS* , and *GAP_AF*.

It is realistic to expect that analysts will need to take some time to recognize the superior forecasts of female CEOs. We therefore expand Model (6) to incorporate the indicator variable *FIRST*, which is set to 1 for the first year the company is covered by analysts (no analyst followed the company for at least three years), and to 0 otherwise. We then interact *FIRST* with *MFE* and with *MFE* x *FCEO*. A negative coefficient of *FCEO* x *MFE* x *FIRST* will suggest that the stronger reliance on the forecast of female CEOs does not occur right away, and will add credibility to our model. We report the results of the expanded model in Column 3. As can be seen, the coefficients of *FCEO* x *MFE* x *FIRST* are negative and significant in both columns.

[Insert Table 1-9 here]

1.5.3 Difference-in-Difference Research Design

Even though we include firm fixed effects in all of the models, to further mitigate the correlated omitted variable problem and to ensure the robustness of our results, we also use a difference-in-difference approach. We first construct a treatment sample of companies that changed their CEOs from male to female, and a control sample of companies with male-to-male CEO transitions. We identify all cases of CEO transitions that meet the following criteria. First, both pre- and post-transition CEOs must be in that position consecutively for at least three years. Second, if the company has several same-gender CEO transitions (e.g., from male to male, and then from male to male again), we only keep the latest transition. Third, we exclude observations of the transition year. Fourth, there must be at least one observation pre- and post-transition to ensure that the sample is balanced. We include observations up to five years before and after the

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[24] For example, it is possible that male CEOs communicate privately with financial analysts more than female CEOs. Even though the private communication between firms and analysts is prohibited under Reg FD, some studies show that analysts continue to derive some private information from companies (Ajinkya et al. 2005; Fang and Huang 2017). Because females are deemed more ethical than men (Bernarda and Arnold 1997; Valentine and Rittenburg 2004; Lund 2008; Gupta et al. 2019), they are more likely to adhere to Reg FD and avoid the private disclosure of information to analysts.

transition and control for CEO experience by controlling for their tenure. Under this research design, the sample size drops by more than 70 percent. Table 10, Panel A summarizes the number of transitions and related observations for the sample and control groups separately for hypotheses H1 and H2.

Then, we construct the following difference-in-difference regression model:

$$Dependent\ Variable = \beta_0 + \beta_1 F\_TRANS \times POST + \beta_2 Control\ Variables$$
$$+ FIRM\ FE + YEAR\ FE + \varepsilon \qquad (7)$$

where *POST* is an indicator variable equal to 1 (0) for firm-year observations after (before) CEO transitions. *F_TRANS* is an indicator variable equal to 1 for observations in the treatment sample (male-to-female transitions), and to 0 for observations in the control sample (male-to-male transitions). Our variable of interest is the interaction variable *F_TRANS x POST*.[25] The difference-in-difference regression results are presented in Table 10, Panel B. Consistent with the results of H1 that female CEOs are more likely to issue earnings forecasts, Column 1 reports a positive and significant coefficient of *F_TRANS x POST*, suggesting an increase in the likelihood of providing management forecasts after a transition from a male-to- female CEO, relative to a transition from a male-to-male CEO. Consistent with the results of H2, in Column 2, the coefficient of *F_TRANS x POST* is negative and significant, suggesting a decrease in management forecast errors after a male-to-female CEO transition, relative to a male-to-male CEO transition. Overall, the difference-in-difference regression results are consistent with our results on forecasts by female CEOs.

[Insert Table 1-10 here]

1.5.4 Propensity Score Matching and Entropy Balancing

As a robustness check, we use both propensity score-matching (PSM) and entropy-balancing methods in a further attempt to rule out the impacts of confounding effects. For

[25] We do not include *F_TRANS* or *POST* in the model as standalone variables due to the inclusion of firm and year fixed effects.

the PSM procedure, we match female CEO observations with the nearest 10 male CEO observations within a distance of 0.05. Observations are matched on the firm characteristics controlled in Models (1) and (2), industry and year. We also use the entropy-balancing method to construct a balanced sample. All observations with male CEOs are reweighted to match observations with the female CEOs based on the same variables used in PSM. Then, we rerun Models (1) and (2) with the matched samples generated by PSM and entropy balancing. Columns (1) and (2) of Table 11, Panel A report the results of the sample matched on propensity scores. Columns (3) and (4) present the results of using the entropy-balancing approach. Our variable of interest, FCEO, continues to yield a positive coefficient when testing H1 and a negative coefficient when testing H2. We check the rebalancing of the matched samples after PSM and report the results in Panels B and C. The results show that there is no significant difference in firm characteristics between observations with female CEOs and male CEOs, which indicates that the PSM-matched samples are well balanced.

[Insert Table 1-11 here]

1.5.5 Alternative Explanation for H2

Studies have shown that on average, managers issue pessimistic quarterly earnings forecasts (Matsumoto 2002; Kross et al. 2011). Thus, an alternative explanation to the smaller management forecast errors of female CEOs (H2) is that male CEOs (more often than female CEOs) strategically choose to provide pessimistic earnings forecasts. Doing so will increase the likelihood of beating their forecasts, thus allowing those managers to establish a reputation as capable CEOs who exceed expectations. This practice, if more common for male CEOs than for female CEOs, will lead the management forecast errors of male CEOs to be higher. To rule out this possibility, we construct the dependent variable, *BEAT*, which is set to 1 if the actual earnings exceed the manager’s forecast. We then regress *BEAT* on *FCEO* and the other controls. The results reported in Table 12 show that the coefficient of *FCEO* is insignificant (t-value = -1.002). This finding suggests that there is no gender difference in the likelihood of actual earnings exceeding the forecasted earnings, which rules out the alternative explanation.

[Insert Table 1-12 here]

1.5.6 Other Robustness Tests

Glass cliff theory predicts that female executives are more likely to be promoted to leadership positions in companies that are struggling and have a high risk of failure (e.g., Ryan and Haslam 2007; Cook and Glass 2014). In the case of a sinking ship, CEOs may work harder to gain the attention and trust of analysts and investors, regardless of their gender. If female CEOs are more likely to be selected to run these sinking ships, and the CEOs of sinking ships make greater efforts to provide earnings forecasts that are of high quality, the better performance of female CEOs with regard to earnings forecasts could be due to the types of companies they lead rather than the greater efforts made by female CEOs. We therefore compare company performance prior to male-to-female CEO transitions and male-to-male CEO transitions. As shown in Table 13, female CEOs are more likely to be hired by larger companies and companies whose monthly stock returns are less volatile. The results of the financial performance and stock market performance for the three years before the CEO transitions show that the return on assets, *ROA*, and the market-adjusted abnormal return, *AR*, of companies with male-to-female transitions are similar to those of companies with male-to-male transitions. For the other firm characteristics, we examine (*LOSS*, *VOLATILITY*, *DISTRESS* and *MB*); the results show no significant difference between firms hiring female CEOs and firms hiring male CEOs. Thus, we conclude that female CEOs are not hired by companies under financial distress.

CFOs also play an important role in the provision of earnings forecasts (e.g., Bamber et al. 2010). A potential explanation for our results is that the differences in earnings forecasts are driven by gender differences involving the CFO. Given that controlling for CFO gender will reduce our sample size by approximately 40 percent, we report the regression results after controlling for the CFO's gender (*FCFO*) as a robustness test. In untabulated results, we find that *FCFO* is insignificant in the tests of H1 and H2, and its interaction with *MFE* is insignificant in the test of H3. At the same time, our results for *FCEO* are consistent with those previously reported. These results indicate that the association between female CEOs and earnings forecasts cannot be attributed to the

CFO's gender, and also reinforce the idea that CEOs play a decisive role in the provision of earnings forecasts.

To rule out the possible impacts of other CEOs' individual characteristics, we control for CEO age and network size. As the inclusion of these variables greatly erodes the sample size, we do not include them in the main tests. In the untabulated results, the coefficients of *FCEO* remain significant after controlling for CEO age and network size.

1.6 Conclusion

In this paper, we examine the voluntary disclosures of female CEOs, which until recently has received very little attention in the literature. In particular, we focus on management earnings forecasts, a major channel involving the communication of voluntary information (Hirst et al. 2008; Hilary and Hsu 2011). We consider not only the intrinsic traits of women, but also the unfavorable view and high scrutiny from shareholders and other parties that female CEOs face, which may lead them to behave differently than male CEOs with regard to earnings forecasts.

Using a research design that includes firm and year fixed effects, we find that, compared to their male counterparts, female CEOs are more likely to provide earnings forecasts, a major form of voluntary disclosure concerning financial information. We also show that their forecasts are significantly more accurate than those of male CEOs. These results suggest that female CEOs improve the disclosure environment of their companies by providing high-quality earnings forecasts. We also find that on average, analysts are less likely to follow companies led by female CEOs, which is an unfavorable outcome for them, given the many benefits of enhanced analyst coverage. However, we show that the greater efforts that female CEOs put into forecasting accurate earnings pay off, as these efforts help them increase analyst coverage. We provide supplementary evidence that female CEOs make other efforts to provide valuable information to investors and analysts. We show that they provide more frequent earnings forecast updates until later during the end of the year. They also provide 10-K disclosures that are longer, contain more exhibits, and use more unique words. Finally, we find that financial analysts rely more on the management forecasts of female CEOs than on those of male CEOs when formulating their own forecasts. One possible interpretation of this result is that financial analysts recognize the superior accuracy of earnings forecasts issued by female CEOs. To this end, we show that analysts' greater reliance on management forecasts does not begin right from the beginning, which suggests that analysts gradually recognize the superior performance of female CEOs. Our results are robust to numerous robustness tests and alternative research design methods, including a difference-in-difference research design, PSM, and entropy balancing.

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Table 1.1: Sample Construction

This table describes our sample selection process for the tests of Hypotheses 1, 2, and 3.

	N
Firm-year observations with CEO gender information	98,910
Less: Missing fundamental information from Compustat	-36,024
Less: Missing fundamental information from CRSP	-12,775
Less: Singleton observations in the fixed-effect model	-516
Number of observations for testing H1	49,595
Less: Observations without a management forecast	-34,302
Less: Observations with an open-ended management forecast	-620
Less: Missing information from IBES Analytics	-310
Less: Singleton observations in the fixed-effect model	-475
Number of observations for testing H2	13,888
Number of observations for testing H1	49,595
Less: Missing analyst forecast data for the following year	-3,033
Less: Singleton observations in the fixed-effect model	-248
Number of observations for testing H3	46,314

Table 1.2: Sample Distribution and Descriptive Statistics

This table presents a comparison between the subsamples of companies with female CEOs and male CEOs. Panel A presents the distribution of subsamples by year, and Panel B presents the distribution by Fama-French's 12 industries. Panel C provides descriptive statistics and univariate comparisons of the variables used in the analysis between female and male CEOs. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. Significance at the 10 percent, 5 percent, and 1 percent levels is indicated by *, **, and ***, respectively.

Panel A: CEO Gender Distribution by Year

	Male		Female		Total	
	Number	Percent	Number	Percent	Number	Percent
2000	2,501	98.46%	39	1.54%	2,540	5.12%
2001	2,718	98.12%	52	1.88%	2,770	5.59%
2002	2,742	97.96%	57	2.04%	2,799	5.64%
2003	2,781	97.82%	62	2.18%	2,843	5.73%
2004	2,809	97.67%	67	2.33%	2,876	5.80%
2005	2,872	97.52%	73	2.48%	2,945	5.94%
2006	2,811	97.60%	69	2.40%	2,880	5.81%
2007	2,735	97.26%	77	2.74%	2,812	5.67%
2008	2,685	97.18%	78	2.82%	2,763	5.57%
2009	2,556	96.82%	84	3.18%	2,640	5.32%
2010	2,441	96.25%	95	3.75%	2,536	5.11%
2011	2,419	96.45%	89	3.55%	2,508	5.06%
2012	2,371	96.50%	86	3.50%	2,457	4.95%
2013	2,345	96.34%	89	3.66%	2,434	4.91%
2014	2,397	95.96%	101	4.04%	2,498	5.04%
2015	2,419	95.42%	116	4.58%	2,535	5.11%
2016	2,308	95.14%	118	4.86%	2,426	4.89%
2017	2,242	95.04%	117	4.96%	2,359	4.76%
2018	1,875	94.98%	99	5.02%	1,974	3.98%
Total	48,027	96.84%	1,568	3.16%	49,595	100.00%

Panel B: CEO Gender Distribution by Industry

	Male		Female		Total	
	N	Percent	N	Percent	N	Percent
1 Consumer Nondurables	2,727	95.48%	129	4.52%	2,856	5.76%
2 Consumer Durables	1,321	98.00%	27	2.00%	1,348	2.72%
3 Manufacturing	5,674	97.34%	155	2.66%	5,829	11.75%
4 Energy	2,518	99.57%	11	0.43%	2,529	5.10%
5 Chemistry	1,451	96.93%	46	3.07%	1,497	3.02%
6 Business Equipment	11,025	97.76%	253	2.24%	11,278	22.74%
7 Transmission	1,391	94.50%	81	5.50%	1,472	2.97%
8 Utilities	1,753	95.32%	86	4.68%	1,839	3.71%
9 Wholesale, Retail	5,315	95.05%	277	4.95%	5,592	11.28%
10 Healthcare	6,923	96.02%	287	3.98%	7,210	14.54%
11 Finance	1,711	97.27%	48	2.73%	1,759	3.55%
12 Others	6,218	97.37%	168	2.63%	6,386	12.88%
Total	48,027	96.84%	1,568	3.16%	49,595	100.00%

Panel C: Summary Statistics and Univariate Comparisons by CEO Gender

	Male CEOs			Female CEOs			Mean difference	
	N	Mean	STD	N	Mean	STD	Difference	T-statistics
MF	48,027	0.307	0.461	1,568	0.353	0.478	-0.046***	-3.862
NEGCHG	48,027	0.431	0.495	1,568	0.432	0.495	-0.001	-0.051
MFE	13,391	0.751	2.453	497	0.686	2.136	0.065	0.581
GAP_MF	13,391	0.238	0.191	497	0.208	0.171	0.030***	3.473
FOLLOW	13,391	13.073	8.171	497	13.654	7.973	-0.581	-1.558
ROA	13,391	0.046	0.091	497	0.055	0.086	-0.009**	-2.101
LOSS	13,391	0.131	0.338	497	0.125	0.331	0.007	0.429
VOLATILITY	13,391	0.099	0.055	497	0.098	0.056	0.002	0.639
ABSCHG	13,391	0.052	0.145	497	0.057	0.165	-0.005	-0.792
DISTRESS	13,391	-3.200	1.146	497	-3.347	1.199	0.148***	2.815
MB	13,391	3.469	4.623	497	3.964	5.572	-0.495**	-2.325
SIZE	13,391	7.518	1.671	497	7.643	1.913	-0.125	-1.631
BIG	13,391	0.933	0.250	497	0.962	0.192	-0.029**	-2.547
INST_OWN	13,391	0.600	0.386	497	0.514	0.432	0.086***	4.880
AEM	13,391	0.003	0.057	497	-0.006	0.058	0.009***	3.513
ABSAEM	13,391	0.041	0.040	497	0.042	0.040	-0.001	-0.684
REM	13,391	0.008	0.079	497	0.019	0.070	-0.011***	-3.102
ABSREM	13,391	0.058	0.062	497	0.053	0.060	0.005*	1.670

Table 1.3: Correlation Matrix

This table reports the correlations between the variables used to test H2 and H3. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	MFE	FCEO	GAP_MF	FOLLOW	ROA	LOSS	VOLATILITY	NEGCHG
MFE	1.00							
FCEO	-0.00	1.00						
GAP_MF	0.27***	-0.03**	1.00					
FOLLOW	-0.13***	0.01	-0.05***	1.00				
ROA	-0.35***	0.02*	-0.16***	0.13***	1.00			
LOSS	0.33***	-0.01	0.16***	-0.08***	-0.66***	1.00		
VOLATILITY	0.31***	-0.01	0.20***	-0.19***	-0.34***	0.36***	1.00	
NEGCHG	0.11***	-0.00	0.09***	-0.03**	-0.28***	0.26***	0.11***	1.00
ABSCHG	0.40***	0.01	0.12***	-0.08***	-0.53***	0.44***	0.39***	0.14***
DISTRESS	0.14***	-0.02**	0.01	-0.00	-0.46***	0.25***	0.01	0.13***
MB	-0.09***	0.03*	-0.04***	0.15***	0.17***	-0.05***	-0.09***	-0.08***
SIZE	-0.16***	0.02	-0.15***	0.59***	0.11***	-0.20***	-0.44***	-0.03*
BIG	-0.06***	0.02*	0.01	0.15***	0.01	-0.04***	-0.10***	-0.02
INST_OWN	-0.13***	-0.05***	-0.05***	0.00	0.03***	-0.03***	-0.06***	-0.02*
AEM	0.00	-0.03***	-0.02	-0.00	0.07***	-0.10***	-0.06***	-0.01*
REM	-0.11***	0.03**	-0.01	-0.05***	0.30***	-0.14***	0.03*	-0.07***

Table 1.3: Correlation Matrix (cont.)

	ABSCHG	DISTRESS	MB	SIZE	BIG	INST_OWN	AEM	REM
ABSCHG	1.00							
DISTRESS	0.29***	1.00						
MB	-0.12***	-0.05***	1.00					
SIZE	-0.09***	0.28***	0.00	1.00				
BIG	-0.03***	0.10***	0.04***	0.25***	1.00			
INST_OWN	-0.07***	0.03*	0.06***	0.01	0.01*	1.00		
AEM	0.04***	0.17***	-0.03***	0.12***	-0.00	-0.00	1.00	
REM	-0.08***	-0.23***	0.11***	-0.25***	-0.09***	0.01	-0.41***	1.00

Table 1.4 : Earnings Forecast Issuance by CEO Gender

This table presents the linear probability model (LPM) regression results of Model (1). The dependent variable is *MF*, an indicator variable equal to 1 if a company provides annual earnings forecasts, and to 0 otherwise. The independent variable of interest is the CEO's gender, *FCEO*. Both firm and year fixed effects are included. Variable definitions are shown in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. t-statistics are reported in parentheses, and ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	MF
FCEO	**0.046***** **(3.667)**
ROA	-0.004 (-0.288)
LOSS	-0.060*** (-12.704)
NEGCHG	0.013*** (4.318)
VOLATILITY	-0.093*** (-4.196)
DISTRESS	-0.002 (-1.066)
MB	0.001** (2.081)
FOLLOW	0.006*** (10.447)
SIZE	0.044*** (11.915)
BIG	0.038*** (5.749)
INST_OWN	0.025** (2.529)
Intercept	-0.046* (-1.953)
Firm FE	YES
Year FE	YES
Adj. R-sq.	0.598
N	49,595

Table 1.5 : Earnings Forecast Accuracy by CEO Gender

This table presents the OLS regression results of Model (2). The dependent variable is the management forecast error, *MFE*. The independent variable of interest is the CEO's gender, *FCEO*. In Columns (1) and (2), we control for CEO ability using *ADJROA* and *DEASCORE*, respectively. *ADJROA* is the average ranked industry-adjusted ROA for the previous (up to) three years for the same CEO. *DEASCORE* is the firm operating efficiency score, estimated using data envelopment analysis. Both firm and year fixed effects are included. Variable definitions are shown in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. t-statistics are reported in parentheses, and ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	MFE	MFE
FCEO	**-0.304****	**-0.298****
	(-2.140)	**(-2.102)**
ROA		-1.488**
		(-2.209)
ADJROA	-0.004***	
	(-3.239)	
DEASCORE		-0.729**
		(-2.217)
LOSS	0.810***	0.761***
	(7.739)	(6.797)
ABSCHG	1.958***	1.790***
	(6.931)	(6.018)
VOLATILITY	4.103***	4.281***
	(4.556)	(4.713)
DISTRESS	0.121***	0.055*
	(3.050)	(1.651)
MB	-0.008*	-0.007
	(-1.700)	(-1.581)
FOLLOW	-0.016***	-0.018***
	(-3.214)	(-3.626)
SIZE	-0.117**	-0.102*
	(-2.079)	(-1.908)
BIG	0.076	0.079
	(0.393)	(0.410)
GAP_MF	2.343***	2.342***
	(15.940)	(15.772)
ABSAEM	0.697	0.694
	(1.128)	(1.111)

ABSREM	0.664	0.610
	(1.295)	(1.178)
INST_OWN	-0.316**	-0.287**
	(-2.193)	(-2.000)
Intercept	1.318**	1.563***
	(2.533)	(2.763)
Firm FE	YES	YES
Year FE	YES	YES
Pseudo R-sq.	0.533	0.535
N	13,888	13,854

Table 1.6 : Analyst Following and CEO Gender

This table presents the OLS regression results of Models (3), (4), and (5) in Columns 1, 2, and 3, respectively. The dependent variable is *LEAD_FOLLOW*, the number of analysts following the stock in the following year. *MF* is an indicator variable equal to 1 if a company issues an annual earnings forecast, and to 0 otherwise. *LOW_MFE* (*HIGH_MFE*) is an indicator variable equal to 1 if a company provides an earnings forecast and the earnings forecast error is below (above) the sample median, and to 0 otherwise. Both firm and year fixed effects are included. Variable definitions are shown in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. t-statistics are reported in parentheses, and ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	LEAD_FOLLOW	LEAD_FOLLOW	LEAD_FOLLOW
FCEO	**-0.225****	**-0.277****	**-0.298****
	(-2.224)	**(-2.139)**	**(-2.327)**
MF		**0.048**	
		(1.167)	
FCEO × MF		**0.112**	
		(0.609)	
LOW_MFE			**0.200*****
			(3.787)
HIGH_MFE			**-0.064**
			(-1.379)
FCEO × LOW_MFE			**0.432****
			(2.043)
FCEO × HIGH_MFE			**-0.161**
			(-0.697)
TRADE_VOL	0.059***	0.059***	0.060***
	(8.265)	(8.291)	(8.433)
ROA	0.206	0.207	0.209
	(1.518)	(1.521)	(1.538)
LOSS	-0.278***	-0.275***	-0.271***
	(-7.719)	(-7.629)	(-7.528)
ABSCHG	-0.714***	-0.714***	-0.714***
	(-15.688)	(-15.691)	(-15.679)
VOLATILITY	0.224	0.228	0.238
	(1.154)	(1.177)	(1.229)
DISTRESS	-0.100***	-0.100***	-0.099***
	(-5.293)	(-5.282)	(-5.208)
MB	0.049***	0.049***	0.049***
	(14.709)	(14.701)	(14.663)
FOLLOW	0.702***	0.702***	0.701***

	(115.504)	(115.193)	(115.191)
SIZE	0.507***	0.504***	0.508***
	(14.518)	(14.459)	(14.540)
BIG	0.051	0.048	0.049
	(1.072)	(1.027)	(1.046)
INST_OWN	0.250***	0.249***	0.244***
	(3.735)	(3.721)	(3.665)
Intercept	-1.001***	-0.996***	-1.019***
	(-4.530)	(-4.508)	(-4.611)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Adj. R-Sq.	0.942	0.942	0.942
N	46,314	46,314	46,314
F-test:			
FCEO + FCEO x LOW_MFE			0.57
			(0.452)

Table 1.7 : Earnings Forecast Frequency and Forecast Horizon

This table presents the OLS regression results of Model (1), where the dependent variable *MF* is replaced with *Frequency*, the number of forecasts provided, which includes revisions to the forecast. Panel A reports a univariate comparison of the values of *Frequency* between male and female CEOs for the larger sample used to test H1 and the smaller sample used to test H2. Panel B reports the multivariate results. Column 3 reports multivariate results on the relations between *GAP_MF*, the number of calendar days from the issuance of the management forecast to the end of the fiscal year, divided by 365 (days). Both firm and year fixed effects are included. Variable definitions are shown in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. t-statistics are reported in parentheses, and ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Panel A: Summary Statistics and Univariate Comparisons by CEO Gender

	Male CEOs			Female CEOs			Mean Difference	
	N	Mean	STD	N	Mean	STD	Difference	T-statistics
Frequency (H1 sample)	48,027	1.437	2.579	1,568	1.776	3.014	-0.338***	-5.081
Frequency (H2 sample)	13,391	4.676	2.618	497	4.936	3.162	-0.260**	-2.158

Panel B: Multivariate Regression – Earnings Forecast Frequency

	Frequency	Frequency	GAP_MF
	H1 Sample	H2 Sample	
FCEO	**0.259*****	**0.352***	**-0.023****
	(2.992)	**(1.871)**	**(-2.296)**
ROA	-0.148**	1.014***	-0.174***
	(-2.063)	(3.314)	(-5.164)
LOSS	-0.331***	-0.291***	0.051***
	(-14.029)	(-3.643)	(6.751)
NEGCHG	0.041**	0.048	0.011***
	(2.467)	(1.155)	(3.625)
VOLATILITY	-0.326***	-0.026	0.115**
	(-3.211)	(-0.059)	(2.357)
DISTRESS	-0.017	0.006	-0.004
	(-1.568)	(0.174)	(-1.292)
MB	0.004**	0.003	-0.000
	(2.182)	(0.580)	(-0.674)
FOLLOW	0.027***	0.021***	0.001
	(9.041)	(3.209)	(1.059)
SIZE	0.307***	0.513***	-0.005

	(14.999)	(7.992)	(-0.993)
BIG	0.303***	0.133	0.011
	(10.112)	(1.001)	(0.748)
INST_OWN	0.111**	0.113	-0.013
	(2.063)	(0.963)	(-1.276)
Intercept	-0.982***	0.336	0.239***
	(-7.707)	(0.652)	(5.679)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Adj. R-sq.	0.614	0.410	0.310
N	49,595	13,888	13,888

Table 1.8 : Additional Evidence on Female CEO Efforts

This table presents univariate and multivariate results of the 10-K filing and CEO gender. Panel A provides a comparison of various 10-K dimensions between male and female CEOs. Panel B presents the OLS regression results of the relations between *FILESIZE*, the natural logarithm of the 10-K file size (Column 1), *WORD*, natural logarithm of the number of words (Column 2), *EXHIBIT*, number of exhibits (Column 3), and *UNIQUE*, the natural logarithm of the number of unique words (Column 4), and CEO gender. Panel C presents the OLS regression results of the relations between *GUNNING_FOG*, the Gunning-Fog index (Column 1), *SMOG_FOG*, SMOG-Fog index (Column 2), and *AVG_LENGTH*, the average number of words in a sentence (Column 3), and CEO gender. Both firm and year fixed effects are included. Variable definitions are shown in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. t-statistics are reported in parentheses, and ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Panel A: Univariate Comparison of Properties of 10-K Filing – Male vs. Female CEO

	Male CEOs			Female CEOs			Mean Difference	
	N	Mean	STD	N	Mean	STD	Difference	T-statistics
FILESIZE	41,972	12.723	0.533	1,337	12.756	0.539	-0.033**	-2.217
WORD	41,972	10.674	0.554	1,337	10.713	0.560	-0.039**	-2.505
EXHIBIT	41,972	10.414	5.525	1,337	11.497	5.938	-1.083***	-7.041
UNIQUE	41,972	7.992	0.242	1,337	8.019	0.242	-0.027***	-3.983
AVG_LENGTH	41,972	25.947	3.770	1,337	26.292	3.434	-0.345***	-3.304
GUNNING_FOG	41,972	19.354	1.581	1,337	19.573	1.408	-0.219***	-5.000
SMOG_FOG	41,972	18.455	1.900	1,337	18.681	1.653	-0.226***	-4.295

Panel B: Multivariate Regression – 10-K Filing Dimensions

	FILESIZE	WORD	EXHIBIT	UNIQUE
FCEO	**0.042****	**0.046****	**0.447*****	**0.020****
	(2.308)	**(2.398)**	**(2.647)**	**(2.075)**
ROA	-0.054**	-0.064***	-0.350*	-0.038***
	(-2.563)	(-2.898)	(-1.870)	(-3.659)
LOSS	0.047***	0.050***	0.239***	0.019***
	(7.833)	(7.985)	(4.217)	(6.843)
NEGCHG	0.001	0.001	0.053	0.001
	(0.197)	(0.144)	(1.436)	(0.710)
VOLATILITY	0.199***	0.227***	0.632**	0.106***
	(6.514)	(7.117)	(2.188)	(7.900)
DISTRESS	0.018***	0.017***	0.032	0.004***
	(5.795)	(5.178)	(1.243)	(2.807)
MB	-0.000	-0.000	-0.007*	-0.000
	(-0.560)	(-0.474)	(-1.885)	(-0.212)
FOLLOW	-0.004***	-0.005***	-0.014**	-0.002***
	(-6.656)	(-6.993)	(-2.344)	(-6.270)
SIZE	0.124***	0.125***	0.581***	0.055***
	(24.343)	(23.657)	(12.250)	(23.159)
BIG	-0.002	-0.005	-0.203**	-0.001
	(-0.209)	(-0.462)	(-2.427)	(-0.204)
INST_OWN	-0.027**	-0.033**	-0.124	-0.014**
	(-2.104)	(-2.482)	(-1.054)	(-2.387)
Intercept	11.997***	9.936***	7.010***	7.655***
	(354.896)	(280.835)	(23.300)	(470.594)
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Adj. R-sq.	0.561	0.554	0.628	0.559
N	43,309	43,309	43,309	43,309

Panel C: Fog Index and Average Sentence Length by CEO Gender

	GUNNING_FOG	SMOG_FOG	AVG_LENGTH
FCEO	**0.045**	**0.053**	**0.157**
	(0.879)	**(0.794)**	**(1.158)**
ROA	0.112*	0.211**	0.445**
	(1.712)	(2.511)	(2.473)
LOSS	0.072***	0.073***	0.177***
	(3.662)	(2.883)	(3.248)
NEGCHG	0.020	0.027	0.052
	(1.507)	(1.551)	(1.481)

VOLATILITY	-0.053	-0.237*	-0.257
	(-0.549)	(-1.917)	(-0.944)
DISTRESS	0.043***	0.060***	0.133***
	(4.518)	(4.872)	(5.078)
MB	-0.003*	-0.005**	-0.008**
	(-1.893)	(-2.386)	(-2.013)
FOLLOW	-0.009***	-0.011***	-0.026***
	(-4.257)	(-4.075)	(-4.570)
SIZE	0.144***	0.192***	0.316***
	(8.179)	(8.474)	(6.928)
BIG	-0.055*	-0.063*	-0.182**
	(-1.928)	(-1.747)	(-2.343)
INST_OWN	0.075*	0.096*	0.135
	(1.769)	(1.722)	(1.171)
Intercept	18.640***	17.529***	24.635***
	(160.366)	(118.135)	(81.692)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Adj. R-sq.	0.422	0.325	0.271
N	43,309	43,309	43,309

Table 1.9 : Analyst Earnings Forecast Errors and Forecast Dispersion and Management Forecast Errors

This table presents the OLS regression results of Model (6) in Columns (1) and (2), respectively. The dependent variable in Column (1) is *AFE*, the absolute average forecast errors of the analysts, divided by the stock price and multiplied by 100. The dependent variable in Column (2) is *AF_DISP*, the standard deviation of analyst forecasts, divided by the stock price (analyst earnings forecast dispersion). The independent variable of interest is the interaction of the management forecast error with CEO gender, *FCEO x MFE*. In Columns (3) and (4), we report the results for the expanded Model (6), which adds *FIRST*, an indicator variable equal to 1 for the first year a company is covered by analysts (no analyst follows the company in the previous three years), and to 0 otherwise, and its interaction term with *FCEO* and *MFE*. Our variable of interest in Columns (3) and (4) is *FCEO x MFE* x *FIRST*. Firm and year fixed effects are included in both models. Variable definitions are shown in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. t-statistics are reported in parentheses, and ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	AFE	AF_DISP	AFE	AF_DISP
FCEO	**0.063**	**-0.017**	**0.043**	**-0.008**
	(1.030)	**(-0.267)**	**(0.657)**	**(-0.128)**
MFE	**0.323*****	**0.172*****	**0.320*****	**0.180*****
	(20.472)	**(11.826)**	**(21.375)**	**(12.947)**
FCEO x MFE	**0.161*****	**0.115***	**0.149*****	**0.109****
	(3.817)	**(1.889)**	**(4.031)**	**(2.059)**
FIRST			0.036	-0.093**
			(0.723)	(-2.159)
FCEO x FIRST			0.296	0.090
			(1.004)	(0.323)
MFE x FIRST			-0.021	0.064**
			(-0.506)	(2.116)
FCEO x MFE x FIRST			**-0.390*****	**-0.339*****
			(-4.519)	**(-2.650)**
ROA	0.060	0.191	0.019	0.289
	(0.205)	(0.609)	(0.066)	(0.984)
LOSS	0.096**	0.279***	0.097**	0.295***
	(2.127)	(5.474)	(2.177)	(5.987)
ABSCHG	0.488***	0.764***	0.509***	0.682***
	(3.072)	(4.707)	(3.408)	(4.482)
VOLATILITY	0.469	2.042***	0.416	1.987***
	(1.436)	(6.388)	(1.344)	(6.529)

DISTRESS	0.027**	0.034**	0.030**	0.040**
	(1.983)	(2.314)	(2.070)	(2.536)
MB	-0.001	-0.003	-0.001	-0.003
	(-0.794)	(-1.440)	(-0.757)	(-1.524)
FOLLOW	-0.009***	0.001	-0.009***	-0.000
	(-4.110)	(0.429)	(-4.339)	(-0.172)
SIZE	-0.022	0.034	-0.019	0.015
	(-1.032)	(1.264)	(-0.871)	(0.593)
BIG	0.032	-0.062	-0.000	-0.110
	(0.404)	(-0.788)	(-0.002)	(-1.423)
ABSAEM	0.267	0.067	0.159	-0.151
	(1.060)	(0.242)	(0.652)	(-0.560)
ABSREM	-0.150	-0.002	-0.145	0.016
	(-0.730)	(-0.008)	(-0.759)	(0.070)
GAP_AF	0.477***	0.709***	0.509***	0.719***
	(5.388)	(8.269)	(5.810)	(8.809)
INST_OWN	-0.011	-0.077	-0.056	-0.127**
	(-0.231)	(-1.405)	(-1.171)	(-2.285)
LAFE	0.007			
	(0.337)			
LAF_DISP		0.032		
		(1.323)		
Intercept	0.360*	-0.164	0.415**	0.113
	(1.832)	(-0.689)	(2.040)	(0.504)
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Adj. R-Sq.	0.694	0.603	0.682	0.605
N	12,896	12,618	13,888	13,662

Table 1.10 : Difference-in-Difference Research Design

This table presents the results related to the difference-in-difference tests. Panel A reports the number of CEO transitions and related observations from male-to-female CEOs, and from male-to-male CEOs separately. Panel B presents the results of the difference-in-difference regression models for H1 and H2. The independent variable of interest is the interaction of the indicator variable for male-to-female CEO transitions, with an indicator variable for the post-CEO transition, *F_TRANS x POST*. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. Significance at the 10 percent, 5 percent, and 1 percent levels is indicated by *, **, and ***, respectively.

Panel A: Transition Matrix

Hypothesis	Transition Type	Transitions	Observations
H1	From male CEO to female CEO	105	770
	From male CEO to male CEO	1,654	12,206
H2	From male CEO to female CEO	43	296
	From male CEO to male CEO	578	3,660

Panel B: Difference-in-Difference Results

	MF	MFE
F_TRANS X POST	**0.053*** **	**-0.287* **
	(2.627)	**(-1.694)**
ROA	-0.033	0.329
	(-1.022)	(0.227)
LOSS	-0.052***	0.683***
	(-5.446)	(3.308)
NEGCHG	0.004	
	(0.761)	
ABSCHG		2.354***
		(4.151)
VOLATILITY	-0.115**	3.960*
	(-2.280)	(1.821)
DISTRESS	-0.013***	0.021
	(-2.920)	(0.319)
MB	0.001	0.002
	(1.140)	(0.264)
FOLLOW	0.006***	-0.032***
	(4.837)	(-3.552)
SIZE	0.064***	-0.285**
	(7.212)	(-2.100)

BIG	0.047***	0.314
	(2.961)	(0.440)
GAP_MF		2.001***
		(7.603)
ABSAEM		0.191
		(0.164)
ABSREM		1.604*
		(1.753)
INST_OWN	-0.020	-0.099
	(-0.925)	(-0.420)
TENURE	0.002*	-0.013
	(1.812)	(-1.397)
Intercept	-0.184***	2.067
	(-2.908)	(1.533)
Firm FE	YES	YES
Year FE	YES	YES
Adj. R-Sq.	0.669	0.444
N	12,976	3,953

Table 1.11 : PSM and Entropy-Balancing Approaches

This table presents the results of the balanced samples generated by propensity score matching (PSM) and entropy balancing. Panel A reports the regression results of Models (1) and (2) with the matched samples. The results of the matched sample based on PSM are reported in Columns (1) and (2), and the results of the balanced sample generated by entropy balancing are reported in Columns (3) and (4). Both firm and year fixed effects are included. Panels B and C present the results of the balancing tests of the sample matched on propensity scores. Variable definitions are shown in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. t-statistics are reported in parentheses, and ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Panel A: Results with Matched Sample

	PSM		Entropy Balancing	
	MF	MFE	MF	MFE
FCEO	**0.032***	**-0.901***	**0.049*****	**-0.521***
	(1.659)	**(-1.840)**	**(3.860)**	**(-1.710)**
ROA	0.010	-2.646	0.010	-2.894
	(0.248)	(-0.939)	(0.317)	(-1.425)
LOSS	-0.079***	0.387	-0.074***	0.511*
	(-5.078)	(1.089)	(-6.127)	(1.883)
NEGCHG	0.016*		0.015**	
	(1.715)		(2.116)	
ABSCHG		1.984***		1.978***
		(2.801)		(3.430)
VOLATILITY	-0.095	2.472	-0.086	3.218
	(-1.351)	(0.571)	(-1.595)	(1.123)
DISTRESS	0.003	0.031	0.000	0.003
	(0.459)	(0.206)	(0.075)	(0.023)
MB	-0.001	0.006	-0.001	0.002
	(-0.885)	(0.520)	(-1.116)	(0.256)
FOLLOW	0.008***	-0.001	0.008***	-0.005
	(4.284)	(-0.090)	(5.484)	(-0.409)
SIZE	0.037***	-0.111	0.037***	-0.068
	(3.087)	(-0.489)	(4.028)	(-0.480)
BIG	-0.010	-0.184	-0.002	-0.254
	(-0.581)	(-0.524)	(-0.170)	(-0.842)
INST_OWN	-0.007	-0.254	0.009	-0.242
	(-0.229)	(-0.781)	(0.373)	(-1.104)
ABSAEM		1.967*		1.901**
		(1.769)		(2.249)
ABSREM		-0.116		-0.220

		(-0.090)		(-0.232)
GAP_MF		2.131***		2.288***
		(5.643)		(8.381)
Intercept	0.060	1.589	0.028	0.998
	(0.796)	(0.929)	(0.509)	(0.916)
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Adj. R-Sq.	0.658	0.438	0.683	0.545
N	13,119	3,831	49,595	13,888

Panel B: Balancing test of PSM H1 Sample

	Mean					t-test	
Variable	N	Female CEO	N	Male CEO	% Bias	t	p>t
ROA	1,561	-0.048	11,558	-0.045	-0.900	-0.260	0.797
LOSS	1,561	0.340	11,558	0.330	2.100	0.580	0.564
NEGCHG	1,561	0.431	11,558	0.431	0.000	0.010	0.995
VOLATILITY	1,561	0.132	11,558	0.131	2.100	0.580	0.561
DISTRESS	1,561	-2.966	11,558	-2.985	1.100	0.300	0.765
MB	1,561	3.394	11,558	3.395	0.000	-0.010	0.996
FOLLOW	1,561	9.327	11,558	9.416	-1.000	-0.280	0.776
SIZE	1,561	6.401	11,558	6.441	-2.000	-0.540	0.592
BIG	1,561	0.810	11,558	0.812	-0.400	-0.110	0.912
INST_OWN	1,561	0.464	11,558	0.469	-1.500	-0.420	0.677

Panel C: Balancing test of PSM H2 Sample

	Mean					t-test	
Variable	N	Female CEO	N	Male CEO	% Bias	t	p>t
ROA	488	0.055	3,343	0.056	-0.800	-0.120	0.903
LOSS	488	0.119	3,343	0.116	0.800	0.120	0.905
ABSCHG	488	0.073	3,343	0.070	1.100	0.170	0.867
VOLATILITY	488	0.097	3,343	0.096	1.500	0.220	0.822
DISTRESS	488	-3.353	3,343	-3.352	-0.100	-0.020	0.985
MB	488	4.019	3,343	3.695	6.200	0.920	0.356
FOLLOW	488	13.779	3,343	13.945	-2.000	-0.310	0.758
SIZE	488	7.661	3,343	7.757	-5.400	-0.830	0.409
BIG	488	0.965	3,343	0.970	-2.400	-0.370	0.708
ABSAEM	488	0.042	3,343	0.041	3.300	0.490	0.624
ABSREM	488	0.053	3,343	0.051	3.500	0.530	0.594
INST_OWN	488	0.512	3,343	0.501	2.600	0.400	0.688

Table 1.12 : Beating Management Earnings Forecast by CEO Gender

This table presents the OLS regression results of the likelihood of the actual earnings exceeding the manager's forecasted earnings by CEO gender. The dependent variable is *BEAT*, an indicator variable equal to 1 if the actual earnings exceed the manager's earnings forecast, and to 0 otherwise. Both firm and year fixed effects are included. Variable definitions are shown in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. t-statistics are reported in parentheses, and ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	BEAT
FCEO	**-0.036**
	(-1.002)
ROA	0.303***
	(3.948)
LOSS	-0.050***
	(-2.841)
ABSCHG	0.031
	(1.405)
VOLATILITY	-0.014
	(-0.126)
DISTRESS	-0.010
	(-1.269)
MB	0.005***
	(4.023)
FOLLOW	-0.006***
	(-4.287)
SIZE	-0.022
	(-1.622)
BIG	-0.030
	(-0.874)
GAP_MF	-0.215***
	(-8.339)
ABSAEM	-0.030
	(-0.238)
ABSREM	0.304***
	(2.972)
INST_OWN	-0.067**
	(-2.361)
Intercept	0.738***
	(6.593)
Firm FE	YES
Year FE	YES
Adj. R-Sq.	0. 135

N	13,888

Table 1.13 : Firm performance in the Year prior to CEO Change by CEO Gender

This table presents a comparative data on firm performance in the years prior to male-to-female CEO transitions and male-to-male CEO transitions. Variable definitions are shown in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	Male CEOs			Female CEOs			Mean difference	
	N	Mean	STD	N	Mean	STD	Difference	T-statistics
AVG_ROA	1,654	-0.011	0.194	105	0.013	0.134	-0.024	-1.241
ROA_Y3	1,342	-0.001	0.204	86	0.021	0.158	-0.022	-0.977
ROA_Y2	1,525	0.001	0.200	97	0.019	0.159	-0.018	-0.885
ROA_Y1	1,654	-0.015	0.209	105	0.008	0.152	-0.023	-1.101
AVG_AR	1,654	0.087	0.349	105	0.054	0.311	0.032	0.928
AR_Y3	1,342	0.160	0.636	86	0.122	0.638	0.038	0.541
AR_Y2	1,525	0.098	0.510	97	0.213	0.606	-0.115**	-2.127
AR_Y1	1,654	0.011	0.443	105	0.017	0.470	-0.006	-0.139
LOSS	1,654	0.288	0.453	105	0.257	0.439	0.031	0.674
VOLATILITY	1,654	0.123	0.081	105	0.109	0.065	0.014*	1.770
DISTRESS	1,654	-2.991	1.545	105	-3.168	1.373	0.177	1.143
MB	1,654	2.844	4.482	105	3.523	6.339	-0.679	-1.463
SIZE	1,654	6.766	1.997	105	7.255	1.980	-0.488**	-2.430

Chapter 2
Female CFOs' Earnings Forecasts, Street Earnings Management, and Stock Price Crash

Abstract

This study focuses on the conservatism of earnings forecasts by female CFOs and its consequences. I hypothesize that female CFOs provide less optimistic earnings forecasts and that, as a result, they have less need to adjust their street earnings upward to meet the earnings benchmarks related to forecasts. Consequently, this should lead to a lower risk of stock price crash for companies led by female CFOs than by male CEOs. The empirical tests support these conjectures. This study highlights the positive effect female CFOs play in lowering information risk. Furthermore, the study enriches the very limited literature on gender difference in management forecasts and non-GAAP earnings management.

2.1 Introduction

Since Hambrick and Mason (1984) developed the upper echelons theory, a large volume of studies has investigated how manager-specific characteristics affect organizational outcomes (e.g., Bantel and Jackson, 1989; Barker and Mueller, 2002; Bertrand and Schoar, 2003). These studies suggest that the individual characteristics of top executives help shape their perceptions and interpretations of various situations and that this has a substantial impact on the performance of their companies. For example, Bamber, Jiang and Wang (2010) find that managers with financial and legal backgrounds, managers born before World War II, and managers with military experience tend to be more conservative in their companies' voluntary disclosures. Since financial planning and reporting are the primary responsibilities of chief financial officers (CFOs), accounting research on the individual characteristics of CFOs examines the influence of CFOs on financial reporting, especially after the passage of the Sarbanes-Oxley Act (SOX). [26] For instance, Ham, Lang, Seybert, and Wang (2017) find that CFO narcissism is associated with lower financial reporting quality. Condie, Obermire, Seidel, and Wilkins (2021) find that CFOs with significant prior audit experience report less aggressively than their counterparts.

Among a variety of individual characteristics, the gender of top executives is an important trait that has a significant influence on corporate performance. Studies investigating female top executives generally suggest that they tend to be less aggressive, less overconfident, and more risk averse in decision-making (e.g., Huang and Kisgen, 2013; Faccio, Marchica and Mura, 2016). The literature on financial disclosure also finds that female CFOs and CEOs are more conservative with regard to financial reporting and are less likely to engage in financial statement irregularities (e.g., Francis, Hasan, Park and Wu, 2015; Ho, Li, Tam and Zhang, 2015; Gupta, Mortal, Chakrabarty, Guo, and Turban, 2020). However, the effect of top executive gender, especially of the CFO on corporate voluntary disclosure is mostly unexplored. Management earnings forecast is an important type of voluntary financial disclosure and is subject to management discretion and judgement. Given the important role management earnings forecasts play in conveying

[26] SOX requires the CFO to certify the accuracy and completeness of their companies' financial reports.

voluntary information to financial statement users, in this study, I examine the conservatism of earnings forecasts by female CFOs[27] and the possible consequences of this gender differences on earnings management of street earnings and on stock price crash risk.

My first hypothesis predicts that female CFOs issue less optimistic earnings forecasts than their male counterparts. According to Brochet, Faurel, and McVay (2011), CFOs influence the formation and discussion of management forecasts. As discussed above, female CFOs tend to be more conservative and cautious. Since female CFOs use more conservative accounting (Francis et al., 2015), they are less likely to delay the disclosure of bad news, and as a result, I expect them to be more cautious when considering their company's prospects. In addition, social forces may shape the properties of earnings forecasts of female CFOs. Female executives are under-represented in top management. Although female top executives have showed a distinguishable ability to break through the glass ceiling, they still have a higher risk of being fired (Gupta, Mortal, Silveri, Sun and Turban, 2020). Since female CFOs suffer from a higher risk of being punished for management failures, they may adapt a more conservative attitude in their earnings forecasts to hedge the risk related to the potential inequality between female and male CFOs. Following these arguments, I expect the earnings forecasts of female CFOs to be less upward biased.

To investigate the possible consequences of gender difference in earnings forecasts, I first examine the actions CFOs take to meet their earnings forecasts. Management earnings forecasts affect analysts' forecasts and investors' expectations, and the failure to meet these forecasts is a bad signal to the market because it implies that the firm is unable to deliver the expected earnings. Firms that miss forecasts are likely to be penalized by investors and to face negative stock price reaction. To avoid these negative consequences, companies whose GAAP earnings fall short may adjust their streets earnings upward (Black, Christensen, Taylor Joo, and Schmardebeck, 2017). Commonly known as pro-

[27] Various parties are involved in the process of predicting a company's future performance. However, prior studies provide evidence that CFO plays a major role in preparing the forecasts (Brochet, Faurel, and McVay, 2011; Li and Zeng, 2019). For simplicity of exposition, I use terms such as "earnings forecast by female CFOs" to refer to the forecasts disclosed by the companies with female CFOs.

forma earnings, street earnings are a measure of non-GAAP earnings that excludes non-recurring items. Prior studies have found that stock markets tend to focus more on street earnings than GAAP earnings (Bradshaw and Sloan, 2002). The adjustments to street earnings do not affect the earnings reported under GAAP, and in contrast to discretionary accruals, they do not reverse in following periods. Thus, excluding negative items from street earnings is an effective, low-cost way for management to manage earnings. During the past several decades, companies have been increasingly inflating street earnings by guiding analysts to exclude a variety of expenses, some of them recurring, to meet analysts' and investors' expectations (Bradshaw and Sloan, 2002; Christensen, Merkley, Tucker, and Venkataraman, 2011). Since I expect female CFOs to provide less optimistic forecasts in order to meet their forecasts, female CFOs will not have to exclude as many negative items as male CFOs. I therefore predict that street earnings of female CFOs have less expenses exclusions.

The second consequence I examine is the risk of stock price crash. Companies' optimistic projections will lead to inflated investor expectations of future profitability, and make their equity overvalued. Once companies are unable to meet market projections, to avoid market punishment managers are likely to venture into earnings management. However, earnings management is unsustainable and can only temporarily help withholding bad news and will eventually lead to a stock price crash (Jensen, 2005). As discussed above, male CFOs may be more optimistic in companies' prospects and more likely to engage in managing street earnings. Therefore, even though they may do more to prevent a stock price crash in the current year, I maintain that they are likely to have a higher risk of facing a stock price crash in the following year.

In this study, I use OLS regression models to test my hypotheses. In all the regressions, I control for year and industry fixed effects and cluster standard errors at firm and year levels. In the empirical part of my study, I first find that earnings forecasts of female CFOs tend to be lower than those of male CFOs, and correspondingly, the actual earnings of female CFOs are more likely to exceed their forecasted earnings. Also, I find that the earnings forecasts of female CFOs are more accurate. Companies with female CFOs tend to have lower forecast errors. These results are consistent with earnings forecasts of female CFOs being less upward biased and more accurate and are consistent with my first hypothesis. With regard to the consequences of the gender difference in management earnings forecasts, I find that female CFOs make fewer upward adjustments to street earnings and that companies with female CFOs have a lower risk of stock price crashes during the following year. These results are consistent with H2 and H3.

In the additional test, I examine whether there is a gender difference in management earnings forecast precision. Since female CFOs tend to be more cautious, they may disclose forecasts in more general types, so that their forecasts can be easily met or beaten. Therefore, I compare the types of earnings forecasts disclosed by female and male CFOs. With the sample including only the last forecasts disclosed before the fiscal year end, I do not find any difference in the precision of earnings forecasts disclosed by female and male CFOs. However, after expanding the sample to include all the forecasts disclosed during the year, I find that female CFOs tend to issue more general, less precise forecasts than male CFOs.

My study makes three contributions to the literature. First, although gender issues have been extensively studied, the impact that gender differences among top executives have on voluntary financial disclosure has been rarely explored. My examination of management earnings forecasts reveals that female CFOs tend to issue less optimistic and more accurate forecasts.

Second, I provide an in-depth analysis of the positive consequences of earnings forecasts by female CFOs. I find that female CFOs exclude less negative items in deriving street earnings, which lowers the likelihood of overvaluation of the company's equity. This in turns, results in a lower risk of stock price crash during the following year. By establishing a link between CFO gender and more conservative and accurate earnings forecasts, I extend the study of Li and Zeng (2019), who also document a lower stock price crash risk of companies with female CFOs.

Finally, this study also contributes to the literature on the impact of female CFOs on earnings management. Recent studies examine the relationship between female CFOs and the manipulation within GAAP earnings, while this study explores the effects of female

CFOs on street (non-GAAP) earnings management and shows that female CFOs are less likely to manage their street earnings upward.

The remainder of the paper proceeds as follows. I present the related literature and develop the hypotheses in section 2. In section 3, the research design, the sample formation, and the descriptive statistics are provided. Section 4 reports the main empirical results. The results of the robustness tests are presented in Section 5. The final section summarizes and concludes this study.

2.2 Related Literature and Hypothesis Development

Because managers have access to information that is not available to the public, their earnings forecasts communicate private information, and thus, reduce information asymmetry and shape shareholder expectations of prospects. Companies can manage analysts' and investors' expectations by providing forecasts. Optimistic forecasts projected by management can build investor confidence and boost companies' valuations. However, optimistic forecasts carry the risk of not being able to meet them. A failure to deliver the expected earnings can induce stakeholder doubt about the manager's ability to correctly estimate future performance and even their ability to control the business (Graham, Harvey, and Rajgopal, 2005). CFOs who are responsible for financial disclosure have to make a tradeoff between the benefits and the risks of providing optimistic forecasts. In this study, I start by examining whether female CFOs make less optimistic earnings forecasts than male CFOs do.

Gender differences in personal traits have been extensively documented in the fields of sociology and psychology. Researchers in these fields find that men and women think and behave differently when making decisions, and that they have different levels of tolerance for risk-taking. Women tend to be less aggressive and more cautious and risk averse. Byrnes, Miller, and Schafer (1999) conduct a meta-analysis of 150 studies examining gender difference in risk taking and conclude that women are generally more risk averse than men. Coates, Gurnell, and Sarnyai (2010) attribute the difference in risk-taking to the gender physiological difference that women hormones levels are less reactive to risks than those of men. Women are also less overconfident. Lundeberg, Fox, Punćcohaŕ (1994) find that men show more confidence when facing uncertainty. O'Laughlin and Brubaker (1998) report the results of a cognitive experiment which shows that even though men and women can perform equally well, women are less confident in their answers. Barber and Odean (2001) also find that compared with female investors, male investors trade more excessively because of their overconfidence.

Upper echelons theory (Hambrick and Mason, 1984) maintains that managerial background characteristics in top-level management affect organizational outcomes. Previous studies have provided a great deal of evidence that financial decisions are affected by the gender of top managers. Huang and Kisgen (2013) find that firms with male executives undertake acquisitions and issue debt more frequently, and that the returns of their announcement of acquisitions are lower than those of firms with female executives. Firms with female executives also make less risky investments (Sunden and Surette, 1998; Bernasek & Shwiff, 2001). Furthermore, the gender of top executives has been shown to affect corporate financial reporting. A large body of studies documents that female CFOs are less likely to engage in earnings management and that firms with female CFOs have higher quality of accruals (e.g., Barua, Davidson, Rama, and Thiruvadi, 2010; Peni and Vähämaa, 2010). More importantly, Francis et al. (2015) find that female CFOs are more accounting conservative.

A more conservative mindset of the CFO should lead a company to adopt more conservative financial reporting practices. This should include a tendency to recognize bad news faster, and to be more cautious with regard to future prospects. Since women are more conservative and risk averse than men, I expect earnings forecasts of female CFOs to be more conservative than those of male CFOs.

Another reason to expect female CFOs to issue more conservative earnings forecasts is because of the elevated career risks they face. Gupta et al. (2020) find that female CFOs are more likely than male CFOs to be blamed for bad performance and consequently to be fired. This fact should further encourage female CFOs to forecast less optimistic earnings forecasts, such that they are not blamed for negative earnings surprises when the reported earnings come short of the forecasted earnings.

Therefore, my first prediction is that female CFOs will provide less optimistic earnings forecasts than male CFOs.

***H1**: The earnings forecasts of Female CFOs are less optimistic than those of male CFOs.*

Management forecasts provide essential input to financial analysts in preparing their own forecasts. Management forecasts also shape investor expectations (Hassell, Jennings, and Lasser, 1988). Companies who miss the analysts' forecasts are penalized by the stock market, and their CFOs are seen as less competent by the executive labor market (Graham et al., 2005). Thus, companies take a variety of actions to avoid missing the forecasts. Matsumoto (2002) finds that companies often manage their earnings upward using abnormal accruals and also guide the analysts downwards to avoid negative earnings surprises. In addition to the two mechanisms identified by Matsumoto (2002), Bradshaw and Sloan (2002) show that managers also inflate their street earnings by excluding charges from the GAAP earnings to reach the numbers forecasted by analysts[28]. Because the more optimistic forecasts of male CFOs can lead to higher forecasts from analysts, male CFOs may need to take more actions to converge the actual earnings with the analysts' expectations. As extensively discussed in prior studies, female CFOs engage less in earnings management than their male counterparts do (e.g., Barua et al., 2010; Peni and Vähämaa, 2010). However, whether female CFOs make fewer adjustments to street earnings is still unknown.

According to Bradshaw and Sloan (2002), managers, financial analysts and investors are more focus on earnings from "continued operations" basis than on GAAP earnings when assessing firm performance. Also known as "street earning", these earnings exclude a variety of items required under GAAP, such as non-recurring charges and other non-operating items. Since investors view street earnings as more value relevant, stock market returns are more associated with street earnings than with GAAP earnings. During the past few decades, a growing divergence has developed between street earnings and GAAP earnings. In order to meet earnings benchmarks and avoid markets' punishment, managers

[28] Analysts' forecasts also exclude non-operating and non-recurring items, and therefore, correspond to street earnings instead of GAAP earnings.

report higher street earnings by excluding more and more expenses (Bradshaw and Sloan, 2002). In other words, street earnings adjustment is an effective, low-cost approach, which enables firms whose GAAP earnings fall short of their earnings benchmarks to avoid the negative consequences of this failure.

Because less optimistic management forecasts lead to lower analysts' forecasts, female CFOs who provide less aggressive forecasts will face less challenges in meeting those forecasts. Therefore, I expect female CFOs to exclude fewer negative items in deriving the street earnings.

H2: *Female CFOs exclude fewer negative items from street earnings than male CFOs do.*

My last hypothesis explores the effects of the gender difference in management earnings forecasts on corporate stock market performance. More specifically, I investigate the association between CFO gender and the likelihood that the company will experience a stock price crash.

As discussed above, missing management and analyst forecasts has very serious negative consequences, and managers are likely to take various actions to meet these short-term targets. However, these actions improve the appearance of the company's financial position but harm its long-term value. As emphasized by Jensen (2005), earnings manipulation to meet short-term objectives is nearly impossible to stop because managers have a tendency to keep pushing the problem forward. This leads to overvalued corporate equities on the stock market. When the overvalued companies fail to deliver the earnings expected by the market, they experience a dramatic drop in their stock price, an event known as a stock price crash.

When female CFOs provide lower forecasts, they have less difficulty than their male counterparts to meet or beat management and analyst forecasts. Male CFOs who face greater pressure to meet these short-term targets are more likely to engage in both GAAP earnings and street earnings management and to withhold bad news in order to improve corporate short-term performance. However, these actions lead to the overvaluation of their equity, to the sacrifice of the long-term value of firms, and to an increase in their risk of future stock price crashes. Therefore, companies with female CFOs should have lower stock price crash risk. Thus, my last hypothesis is as follows:

H3: *Firms with female CFOs have a lower stock price crash risk than firms with male CFOs.*

2.3 Research Design, Sample Selection, and Sample Description

2.3.1 Research Design

To test whether female CFOs issue less optimistic earnings forecasts than male CFOs do (H1), I regress the forecasted earnings per share (EPS) and the likelihood of actual earnings meeting or beating forecasts on CFO gender and other control variables.

$$\begin{aligned} FORECAST = {} & \beta_0 + \beta_1\, FCFO + \beta_2\, LAG\_EPS + \beta_3\, LAG\_PRICE + \beta_4\, CHANGE \\ & + \beta_5\, VOLATILITY + \beta_6\, DISTRESS + \beta_7\, LITIRISK + \beta_8\, MB + \beta_9\, SIZE \\ & + \beta_{10}\, FOLLOW + \beta_{11}\, HORIZON + \beta_{12}\, INST\_OWN + \beta_{13}\, COMP\_AGE \\ & + \beta_{14}\, SEGMENT + Industry\ fixed\ effect + Year\ fixed\ effect + \varepsilon \qquad (1) \end{aligned}$$

$$\begin{aligned} MEET = {} & \beta_0 + \beta_1\, FCFO + \beta_2\, LAG\_EPS + \beta_3\, LAG\_PRICE + \beta_4\, CHANGE \\ & + \beta_5\, VOLATILITY + \beta_6\, DISTRESS + \beta_7\, LITIRISK + \beta_8\, MB + \beta_9\, SIZE \\ & + \beta_{10}\, FOLLOW + \beta_{11}\, HORIZON + \beta_{12}\, INST\_OWN + \beta_{13}\, COMP\_AGE \\ & + \beta_{14}\, SEGMENT + Industry\ fixed\ effect + Year\ fixed\ effect + \varepsilon \qquad (2) \end{aligned}$$

The dependent variable in model (1), *FORECAST*, is the EPS value provided in the last management forecast disclosed before the fiscal year end. Earnings forecasts can be classified into qualitative forecasts and quantitative forecasts, which include point, range, and open-ended forecasts (Ajinkya, Bhojraj, and Sengupta, 2005). In this study, I focus on quantitative earnings forecasts and use the predicted annual earnings per share given in these forecasts as the dependent variable for this model. For the range forecasts, I examine the lower bound of the ranges because I focus on the conservatism of forecasts in this study, and additionally, analysts place more weight on the lower bounds (Tang, Zarowin, and Zhang, 2015).

The dependent variable in model (2), *MEET*, is an indicator variable equal to 1 when a company's actual GAAP earnings meet or beat the last management forecast issued before the fiscal year end, and to 0 if not. Following Bradshaw and Sloan (2002), I use diluted GAAP earnings per share before extraordinary items from *Compustat* as the measure for companies' actual earnings. With a binary dependent variable, I estimate model (2) using linear probability model, and I also run a logit model as a robustness check and obtain similar results.

The independent variable in model (1) and (2) is CFO gender, *FCFO*, which is equal to 1 for female and to 0 for male. As I expect the forecasts of female CFOs to be less optimistic, their forecasts are more likely to be met and beaten by actual earnings. A negative coefficient of *FCFO* in model (1) and a positive coefficient in model (2) will be consistent with H1a.

I include various control variables that are identified in the prior literature as influencing management earnings forecasts. The annual earnings per share of the last year, LAG_EPS, and the stock price at the end of the last year, LAG_PRICE, are included because managers of companies having great financial performance in previous years are more likely to have optimistic attitudes when forecasting corporate prospects. I include the change in annual earnings per share, CHANGE, to control for a company's profitability in the current year. I also control the following firm-level characteristics in my regression models: monthly stock return volatility, *VOLATILITY*; financial distress, *DISTRESS*, measured using Zmijewski's *Z*-Score; litigation risk, *LITIRISK*, which is an indicator variable equal to 1 if the company belongs to the high-litigation risk industries identified by Francis, Philbrick, and Schipper (1994); market to book ratio, *MB*; firm size, *SIZE*, measured as the natural logarithm of firm total assets; and the percentage of institutional ownership, *INST_OWN*. In addition, I include company age, *COMP_AGE*, and the total number of operating and geographical segments, *SEGMENT*, to control for corporate operational complexity because companies whose operations are more complex have greater difficulties in making accurate forecasts. Since managers issuing forecasts at an earlier time face higher earnings uncertainty (Baginski and Hassell, 1997), I control for *HORIZON*, which is defined as the number of days between managers issuing the last earnings forecasts and the end of fiscal year. The number of analysts following, *FOLLOW*, may also affect managers' behaviors in earnings forecasts and is also controlled in my regression models. A list of all variable definitions is provided in the Appendix.

To deal with outliers, I run influence diagnostics and exclude observations with Cook's Distance larger than 4/n (where n is the sample size). According to Leone, Minutti-Meza, and Wasley (2019), this method outperforms winsorization and truncation when dealing with observations with extreme values. I also include here and in all the other models industry[29] and year fixed effect, and I cluster standard errors at the firm and year levels.

To test H2 that female CFOs are less likely to engage in street earnings management than male CFOs, I run the following OLS regressions:

$$\begin{aligned} ADJUST = {} & \beta_0 + \beta_1\, FCFO + \beta_2\, LAG\_EPS + \beta_3\, LAG\_PRICE + \beta_4\, CHANGE \\ & + \beta_5\, VOLATILITY + \beta_6\, DISTRESS + \beta_7\, LITIRISK + \beta_8\, MB + \beta_9\, SIZE \\ & + \beta_{10}\, FOLLOW + \beta_{11}\, HORIZON + \beta_{12}\, INST\_OWN + \beta_{13}\, COMP\_AGE \\ & + \beta_{14}\, SEGMENT + Industry\ fixed\ effect + Year\ fixed\ effect + \varepsilon \end{aligned} \tag{4}$$

Following Bradshaw and Sloan (2002), street earnings adjustment, *ADJUST*, is defined as street earnings per share reported by *I/B/E/S* minus GAAP earnings per share excluding extraordinary items from *Compustat*. GAAP has restricted requirements regarding whether an event can be qualified as an extraordinary item, especially before the concept of extraordinary items was eliminated in 2015. However, managers can exclude extraordinary or non-operational items from street earnings in a more aggressive way. I use GAAP earnings excluding extraordinary items to reduce the noise caused by real infrequent and unusual events and to measure the street earnings adjustment that managers make intentionally. Since female CFOs are predicted to exclude fewer negative special

[29] Industry is classified based on Fama-French 48 industry (Fama and French, 1997).

items from street earnings than male CFOs do, I expect the coefficient of *FCFO* in model (4) to be negative.

Additionally, I investigate whether the more aggressive street earnings management of male CFOs offsets the impact of CFO gender on the likelihood of meeting or beating management earnings forecasts between male and female CFOs. I run the following linear probability model:

$$\begin{aligned} STMEET = {} & \beta_0 + \beta_1\, FCFO + \beta_2\, LAG\_EPS + \beta_3\, LAG\_PRICE + \beta_4\, VOLATILITY \\ & + \beta_5\, CHANGE + \beta_6\, DISTRESS + \beta_7\, LITIRISK + \beta_8\, MB + \beta_9\, SIZE \\ & + \beta_{10}\, FOLLOW + \beta_{11}\, HORIZON + \beta_{12}\, INST\_OWN + \beta_{13}\, COMP\_AGE \\ & + \beta_{14}\, SEGMENT + Industry\ fixed\ effect + Year\ fixed\ effect + \varepsilon \qquad (5) \end{aligned}$$

Similar to *MEET*, *STMEET* is an indicator variable, representing the likelihood of street earnings to meet or beat management forecasts. As predicted in H1a, female CFOs tend to issue less optimistic earnings forecasts that are more likely to be met and beaten by actual earnings. However, I also expect that compared with female CFOs, male CFOs engage in more aggressive street earnings management in order to meet earnings forecasts. Therefore, it is highly likely that CFO gender is not significantly associated with *STMEET* under these counteracting impacts.

To examine whether CFO gender is associated with stock price crash risk, I construct three measures of stock price crash risk following the previous literature (e.g., Hutton, Marcus, and Tehranian, 2009; Kim, Li, and Zhang, 2011). To construct the measures of stock price crash risk, I first estimate firm-specific residual weekly returns from the following extended market index regression model:

$$r_{j,t} = \alpha_j + \beta_{1,j}\, r_{m,t-2} + \beta_{2,j}\, r_{m,t-1} + \beta_{3,j}\, r_{m,t} + \beta_{4,j}\, r_{m,t+1} + \beta_{5,j}\, r_{m,t+1} + \varepsilon_{j,t} \qquad (6)$$

where $r_{j,t}$ is the return of stock j in week t, and $r_{m,t}$ is the return of the CRSP value-weighted market index in week t. In this extended model, the market return of two lead and lag weeks are included to correct for non-synchronous trading (Dimson, 1979). I then define the firm-specific weekly return as the natural log of one plus the residual return estimated from equation (6), that is, $W_{j,t} = ln\left(1 + \varepsilon_{j,t}\right)$.

My first measure of crash likelihood is *CRASH*, an indicator variable equal to 1 if the firm experiences one or more firm-specific crash weeks during the fiscal year, and to 0 otherwise. Crash weeks are defined as weeks during which the firm experiences firm-specific weekly returns 3.2 standard deviations (0.1% frequency in the normal distribution) below the mean firm-specific weekly returns over the fiscal year.

My second measure of crash likelihood is *DUVOL*, the natural logarithm of the standard deviation of the firm-specific weekly return in the down weeks to the standard deviation of the firm-specific weekly return in the up weeks. I compute DUVOL as follows:

$$DUVOL_{j,T} = ln\left\{\frac{(n_{u,j,T}-1)\sum_{t=1}^{n_{d,j,T}} W_{j,t}^2}{(n_{d,j,T}-1)\sum_{t=1}^{n_{u,j,T}} W_{j,t}^2}\right\} \qquad (7)$$

Where I define the up(down) weeks as the weeks during which the firm-specific weekly returns are above (below) its annual mean. $n_{u,j,T}(n_{d,j,T})$ is the number of up (down) weeks for stock *j* in fiscal year *T*.

My third measure of stock price crash risk is *NCSKEW*, the negative coefficient of skewness of firm-specific weekly returns, measured as the negative of the third moment of firm-specific weekly returns for each firm in a fiscal year divided by the standard deviation of firm-specific weekly returns raised to the third power. I calculate *NCSKEW* as follows:

$$NCSKEW_{j,T} = -\frac{n_{j,T}(n_{j,T}-1)^{\frac{3}{2}}\sum_{t=1}^{n_{j,T}} W_{j,t}^3}{(n_{j,T}-1)(n_{j,T}-2)(\sum_{t=1}^{n_{j,T}} W_{j,t}^3)^{\frac{3}{2}}} \qquad (8)$$

To test H3, I estimate the following OLS regression models to examine the association between my measures of crash risk in year $T+1$ and CFO gender in year T :

$$
\begin{aligned}
CRASH\ RISK_{T+1} = {} & \beta_0 + \beta_1\ FCFO_T + \beta_2\ RET_T + \beta_3\ SIGMA_T + \beta_4\ ROA_T \\
& + \beta_5\ DISTRESS_T + \beta_6\ LITIRISK_T + \beta_7\ LEV_T + \beta_8\ MB_T + \beta_9\ SIZE_T \\
& + Industry\ fixed\ effect + Year\ fixed\ effect + \varepsilon \qquad (9)
\end{aligned}
$$

To be consistent with other models above, I use linear probability regression model when the dependent variable is *CRASH* and use OLS regressions when the dependent variable is *DUVOL* and *NCSKEW*. Since higher values of my crash risk measures represent higher stock price crash risk, negative coefficients of these measures will be consistent with my hypothesis.

A list of all variable definitions is also provided in the Appendix.

2.3.2 Sample Selection and Description

My sample period is from 2001 to 2018. To be included in my initial sample, firm-year observations are required to have CFO gender information from ExecuComp, foundational accounting data from Compustat, stock market performance from CRSP, and analyst-related information from IBES Academic. In my initial sample, there are 26,537 firm-year observations having all the fundamental information needed. To test H1 and H2, I exclude firm-year observations without management earnings forecasts from IBES guidance and observations missing data for control variables. The sample that I use to test H1 and H2 contains 8,462 firm-year observations from 1,428 unique US-based firms. To measure the stock price crash risk, I require observations to have stock price data for more than 26 weeks and the stock price at the year end cannot be lower than $1. Observations with non-positive book values and non-positive total assets are also excluded. After all these steps, I have 7,240 firm-year observations with available data to estimate stock price crash risk in H3. Table 1 summarizes the sample construction process.

[insert Table 2-1 here]

In Panel A of Table 2, I present the sample distribution by year. My sample used to test H1 and H2 contains 704 firm-year observations with female CFOs and these observations account for 8.32 percent of the total sample. In contrast to the substantial increase in the number of female CEOs over the past decade, the percentage of female CFOs is relatively stable. Within the sample period from 2001 to 2018, the percentage of female CFOs is lowest during the financial crisis in 2008 and 2009 and reaches the peak in 2015 and 2016.

In Panel B of Table 2, I present the sample distribution by Fama-French's 12 industries. The percentage of female CFOs is relatively high in wholesale and retail industry and relatively low in Finance, Consumer durables, and Chemistry industries.

In Panel C of Table 2, I present the summary statistics for my main variables and the univariate comparison results between male and female CFOs. In general, male CFOs have higher *FORECAST* and lower *MEET* than female CFOs. The average *BIAS* is positive, showing that the forecasted earnings are generally higher than the actual earnings reported under GAAP. Male CFOs also tend to have a higher *BIAS*. These significant univariate results provide preliminary evidence that female CFOs are less optimistic when issuing earnings forecasts. The average *ADJUST* of male CFOs is also significantly higher than that of female CFOs. Furthermore, the average *ADJUST* is positive, indicating that in general street earnings are higher than GAAP earnings before extraordinary items. These results are consistent with my second hypothesis that male CFOs tend to make more upward street earnings adjustments. The univariate comparison result of STMEET between male and female CFOs is not significant, which is consistent with my prediction that the more aggressive street earnings management of male CFOs may offset the impact of CFO gender on the likelihood of meeting or beating management forecasts.

In addition, I also find that female CFOs are associated with lower stock return volatility, lower financial distress, fewer analysts following them, and they are likely to be hired by smaller, younger companies from high litigation risk industries, with higher percentage of institutional ownership, and with fewer segments.

[insert Table 2-2 here]

I also check the correlations for my main variables in the sample that I use to test H1 and H2 (untabulated). In general, the correlations between FCFO and dependent variables are consistent with the univariate comparison results. The correlations between independent variable and control variables are relatively small. Nonetheless, I check the variance inflation factor (VIF) of each variable tested in each model and the VIF results suggest that multicollinearity should not be of a concern in this study.

2.4 Results

Table 3 presents regression results for the effect of CFO gender on management forecasts optimism. In the Column (1), the coefficient of FCFO is negative and statistically significant, indicating that the earnings forecasts of female CFOs are lower than the forecasts of male CFOs. In the Column (2), I also find a significant positive impact of female CFO on the likelihood of meeting or beating earnings forecasts, which suggests that firms with female CFOs are more likely to meet or beat their management forecasts than firms with male CFOs. These findings are consistent with my hypothesis that female CFOs are less optimistic when issuing earning forecasts.

With respect to the control variables, firms with better financial performance in the last year and this year tend to issue higher earnings forecasts and those forecasts are also more likely to be met or beaten by the actual earnings. Firms with greater stock return volatility, financial distress, and litigation risk tend to be over-optimistic in forecasting as their forecasted earnings are higher but less likely to be met or beaten by actual earnings. Larger firms, firms with more institutional ownerships are also more likely to be over-optimistic. The forecasts issued at an earlier time during the year are generally higher and less likely to be met or beaten by actual earnings than the forecasts issued closer to the year-end, which is consistent with the earnings forecast walkdown (Richardson, Teoh, and Wysocki, 2004; Bradshaw, Lee, Peterson, 2016).

[insert Table 2-3 here]

Table 4 presents the regression results regarding the association between CFO gender and street earnings management. The result in Column (1) shows that female CFOs are associated with lower *ADJUST*. Since univariate results show that street earnings are generally higher than GAAP earnings before extraordinary items, I can conclude that female CFOs make less upward adjustment to street earnings. In other words, female CFOs exclude fewer negative special items from street earnings than male CFOs do. I then investigate whether male CFOs eliminate the difference in the likelihood of meeting or beating management forecasts by excluding negative items from street earnings more aggressively. In the Column (2), FCFO is not significantly associated with STMEET, which suggests that there is no significant difference between male and female CFOs indicated by the likelihood of street earnings meeting or beating management forecasts. Since street earnings are more strongly correlated with stock return than GAAP earnings are, these results support my prediction that male CFOs make more upward adjustments to street earnings in order to avoid the negative consequences of missing their optimistic forecasts.

More profitable firms have less need to adjust their street earnings upward. However, firms with higher stock price, stock price volatility, financial distress, litigation risk exclude more negative items from their street earnings. Firms with larger size and more institutional ownerships are also more likely to manage their street earnings upward. Collectively, the firms that issue more optimistic forecasts are more likely to inflate their street earnings.

[insert Table 2-4 here]

The results of model (9) on the relationship between CFO gender and stock price crash risk are reported in Table 5. In column (1), (2), and (3), I present how female CFOs are associated with the three different measures of crash risk I construct, *CRASH*, *DUVOL*, and *NCSKEW*. I find that the coefficients of these three measures are all significantly negative, indicating that firms with female CFOs have a lower stock price crash risk than firms with male CFOs. These findings are consistent with my third hypothesis.

[insert Table 2-5 here]

2.5 Supplementary Analysis and Robustness Checks

As I find that female CFOs are more conservative in forecasting earnings, I further examine whether female CFOs disclose more general forecasts which are easier for their actual earnings to meet or beat. Quantitative earnings forecasts are mainly in three types: (1) open-ended forecast, which only give a predicted upper bound or lower boundary (e.g., "the annual earnings per share is expected to be higher than 1"); (2) range forecast, which provides a range of the predicted earnings (e.g., "the annual earnings per share is expected to be higher than 1, but lower than 2"); (3) point forecast, which provides a precise value as the forecasted earnings (e.g., "I expect the annual earnings per share to be 1.5"). Open-ended forecasts are most general and can be easily met by actual earnings, while point forecast are most precise. Therefore, I construct a measure for forecast precision, *F_TYPE*, which equals to 1 if the forecast is open-ended, to 2 if the forecast is given in a range, and to 3 if the forecast is a precise point. A higher value of *F_TYPE* represents a greater forecast precision.

In column (1) of Table 7, I present the results of regressing forecast precision on CFO gender with the sample used to test H1 and H2. The results show that there is no significant difference in the precision of the last forecasts disclosed by female and male CFOs in a fiscal year. Then, I run the regression with the model expanded with all the forecasts for annual EPS disclosed during the year, and the results are reported in column (2) of Table 7. With the expanded sample, I find that female CFOs are associated with a lower precision of the forecasts, indicating that female CFOs tend to provide more general forecasts. This is probably because female CFOs are more conservative in forecasting annual EPS when they have limited information to predict companies' annual performance.

[insert Table 2-6 here]

2.6 Conclusion

A great number of studies show that female executives tend to be more conservative in companies' disclosure. Following this stream of studies, in this paper, I examine whether the gender of CFOs has significant impacts on the earnings forecasts disclosed, and further investigate whether this gender difference affects companies' street earnings management and risk of stock price crash. More specifically, I examine the difference in earnings forecasts by focusing on one important property of earnings forecasts: optimistic bias. Because of female CFOs' conservative mindset and the high career risk they face, I expect female CFOs provide less optimistic and more accurate earnings forecasts. To avoid the penalty of missing their earnings forecasts, managers take a variety of actions to inflate their earnings, which includes street earnings adjustment. As female CFOs may have less challenges to meet their earnings benchmarks, I expect female CFOs have less need to manage their street earnings and are less likely to engage in street earnings management. The actions managers take to improve the appearance of the company's financial positions will harm the company's long-term value and cause their equity overvalued, eventually leading to stock price crash. Therefore, I also examine whether the gender of CFO is associated with the company's stock price crash risk.

Using OLS regression models that control for year and industry fixed effects and cluster standard errors at firm and year levels, I find empirical evidence that supports all my hypotheses. I find that, in general, management earnings forecasts are optimistically biased, but female CFOs tend to provide less optimistic forecasts which are therefore closer to actual earnings. I further find that the street earnings adjustment by female CFOs are less than those of male CFOs and female CFOs have a lower risk of having stock price crash in the following year. In the additional analysis, I expand my sample from including only the last forecasts during the year to including all the forecasts, and I find that female CFOs tend to use more general, less precise way to disclose their forecasts. This result is consistent with my argument that female CFOs tend to be more conservative in voluntary financial disclosure.

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Table 2.1: Sample construction

This table describes the sample selection process for the tests of Hypotheses 1, 2, and 3.

	N
Firm-year observations with CFO gender information	45,675
Less: Observations missing accounting data from Compustat	-10,953
Less: Observations missing stock price data from CRSP	-5,384
Less: Observations missing information from IBES Analytics	-2,801
Firm-year observations with fundamental information	26,537
Less: Observations without management forecast	-15,202
Less: Observations missing data for other control variables	-2,873
Number of observations for H1 and H2	8,462
Less: Observations missing data for stock price crash risk in the following year	-1,222
Number of observations for H3	7,240

Table 2.2 : Sample Distribution and Descriptive Statistics

This table presents a comparison between the subsamples of companies with female CFOs and male CFOs. Panel A presents the distribution of subsamples by year, and Panel B presents the distribution by Fama-French's 12 industries. Panel C provides descriptive statistics and univariate comparisons of the variables used in the analysis between female and male CFOs. Variable definitions are provided in the Appendix 2-1. All continuous variables are winsorized at the top and bottom 1 percent. Significance at the 10 percent, 5 percent, and 1 percent levels is indicated by *, **, and ***, respectively.

Panel A: CFO Gender Distribution by Year

	Male		Female		Total	
	Number	Percent	Number	Percent	Number	Percent
2001	234	92.13%	20	7.87%	254	3.00%
2002	273	92.54%	22	7.46%	295	3.49%
2003	286	91.67%	26	8.33%	312	3.69%
2004	343	92.45%	28	7.55%	371	4.38%
2005	314	90.75%	32	9.25%	346	4.09%
2006	502	90.45%	53	9.55%	555	6.56%
2007	558	92.85%	43	7.15%	601	7.10%
2008	550	93.54%	38	6.46%	588	6.95%
2009	462	93.33%	33	6.67%	495	5.85%
2010	479	92.65%	38	7.35%	517	6.11%
2011	486	92.75%	38	7.25%	524	6.19%
2012	501	91.26%	48	8.74%	549	6.49%
2013	501	91.09%	49	8.91%	550	6.50%
2014	511	90.44%	54	9.56%	565	6.68%
2015	472	89.90%	53	10.10%	525	6.20%
2016	437	89.73%	50	10.27%	487	5.76%
2017	431	90.17%	47	9.83%	478	5.65%
2018	418	92.89%	32	7.11%	450	5.32%
Total	7,758	91.68%	704	8.32%	8,462	100.00%

Panel B: CEO Gender Distribution by Industry

	Male		Female		Total	
	N	Percent	N	Percent	N	Percent
1 Consumer Nondurables	516	94.16%	32	5.84%	548	6.48%
2 Consumer Durables	250	96.90%	8	3.10%	258	3.05%
3 Manufacturing	1,036	94.44%	61	5.56%	1,097	12.96%
4 Energy	93	92.08%	8	7.92%	101	1.19%
5 Chemistry	301	95.25%	15	4.75%	316	3.73%
6 Business Equipment	1,716	90.03%	190	9.97%	1,906	22.52%
7 Transmission	92	89.32%	11	10.68%	103	1.22%
8 Utilities	695	92.18%	59	7.82%	754	8.91%
9 Wholesale, retail	751	86.72%	115	13.28%	866	10.23%
10 Healthcare	1,124	92.82%	87	7.18%	1,211	14.31%
11 Finance	275	97.17%	8	2.83%	283	3.34%
12 Others	909	89.21%	110	10.79%	1,019	12.04%
Total	7,758	91.68%	704	8.32%	8,462	100.00%

Panel C: Summary Statistics and Univariate Comparisons by CEO Gender

	Male CFOs			Female CFOs			Mean difference	
	N	Mean	STD	N	Mean	STD	Difference	T-statistics
FORECAST	7,758	2.218	2.164	704	1.955	1.586	0.257***	3.075
MEET	7,758	0.433	0.496	704	0.489	0.500	-0.056***	-2.852
STMEET	7,758	0.807	0.395	704	0.808	0.394	-0.002	-0.110
BIAS	7,758	0.393	1.767	704	0.246	2.312	0.148**	2.061
MFE	7,758	0.842	1.603	704	0.758	2.198	0.085	1.295
ADJUST	7,758	0.383	1.702	704	0.249	2.282	0.134*	1.936
LAG_EPS	7,758	1.785	2.002	704	1.667	1.700	0.118	1.519
LAG_PRICE	7,758	41.339	31.590	704	42.726	30.606	-1.387	-1.119
CHANGES	7,758	0.088	1.657	704	0.165	1.466	-0.076	-1.181
VOLATILITY	7,758	0.094	0.050	704	0.090	0.049	0.004**	2.220
DISTRESS	7,758	-3.148	1.104	704	-3.398	1.105	0.250***	5.762
LITIRISK	7,758	0.306	0.461	704	0.369	0.483	-0.063***	-3.47
MB	7,758	3.749	5.445	704	4.005	6.367	-0.257	-1.179
SIZE	7,758	7.780	1.689	704	7.477	1.598	0.304***	4.590
FOLLOW	7,758	13.776	7.973	704	12.973	7.872	0.803**	2.563
HORIZON	7,758	0.224	0.177	704	0.213	0.163	0.011	1.568
INST_OWN	7,758	0.808	0.201	704	0.836	0.179	-0.028***	-3.546
COMP_AGE	7,758	29.499	19.968	704	25.658	18.493	3.842***	4.917
SEGMENT	7,758	16.519	10.284	704	15.283	11.678	1.237***	3.019
CRASH	6,636	0.272	0.445	604	0.248	0.432	0.023	1.238
DUVOL	6,636	0.076	0.484	604	0.053	0.520	0.022	1.073
NCSKEW	6,636	0.244	1.262	604	0.186	1.406	0.059	1.082
RET	6,636	-0.108	0.295	604	-0.100	0.244	-0.007	-0.577
SIGMA	6,636	0.041	0.024	604	0.039	0.021	0.002	1.480
ROA	6,636	0.051	0.083	604	0.062	0.082	-0.011***	-3.076
LEV	6,636	0.237	0.168	604	0.197	0.165	0.040***	5.642

Table 2.3 : CFO Gender and Forecast Optimism

This table presents the OLS regression results of Model (1) and linear probability model (LPM) regression results of Model (2) in Columns 1 and 2 respectively. In Column 1, the dependent variable is forecasted annual earnings per share, *FORECAST*. In Column 2, the dependent variable is *MEET*, an indicator variable equal to 1 if a company's actual earnings meet or beat the forecasted earnings, and to 0 otherwise. The independent variable of interest is the CFO gender, *FCFO*. Both industry and year fixed effects are included. Variable definitions are shown in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. t-statistics are reported in parentheses, and ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	(1) *FORECAST*	(2) *MEET*
FCFO	**-0.130*****	**0.057****
	(-2.910)	**(2.143)**
LAG_EPS	0.436***	0.080***
	(16.033)	(12.514)
LAG_PRICE	0.025***	-0.002***
	(15.301)	(-5.187)
CHANGE	0.288***	0.089***
	(13.137)	(14.421)
VOLATILITY	2.084***	-0.444***
	(8.185)	(-3.348)
DISTRESS	0.118***	-0.052***
	(7.264)	(-6.209)
LITIRISK	-0.007	-0.105**
	(-0.093)	(-2.501)
MB	-0.000	0.000*
	(-0.946)	(1.912)
SIZE	0.180***	-0.042***
	(8.509)	(-4.764)
FOLLOW	-0.011***	-0.001
	(-3.834)	(-1.023)
HORIZON	0.117*	-0.163***
	(1.974)	(-3.518)
INST_OWN	0.197**	-0.091**
	(2.593)	(-2.413)
COMP_AGE	0.004***	-0.001*
	(3.151)	(-2.066)
SEGMENT	-0.001	-0.001
	(-0.658)	(-1.109)
Intercept	-1.005***	0.787***

	(-5.305)	(9.187)
Industry & year fixed effect	YES	YES
Adj. R2	0.868	0.256
N	8,033	8,261

Table 2.4 : CFO Gender and Street Earnings Management

This table presents the OLS regression results of Model (4) and linear probability model (LPM) regression results of Model (5) in Columns 1 and 2 respectively. In Column 1, the dependent variable is street earnings adjustment, *ADJUST*, which is defined as street earnings per share reported by *I/B/E/S* minus GAAP earnings per share excluding extraordinary items from *Compustat.* In Column 2, the dependent variable is ST*MEET*, an indicator variable equal to 1 if a company's street earnings meet or beat the forecasted earnings, and to 0 otherwise. The independent variable of interest is the CFO gender, *FCFO*. Both industry and year fixed effects are included. Variable definitions are shown in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. t-statistics are reported in parentheses, and ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	(1) *ADJUST*	(2) *STMEET*
FCFO	**-0.128****	**0.023**
	(-2.868)	**(1.737)**
LAG_EPS	-0.520***	0.011***
	(-17.885)	(4.635)
LAG_PRICE	0.024***	-0.000
	(13.044)	(-1.648)
CHANGE	-0.650***	0.026***
	(-24.735)	(8.292)
VOLATILITY	1.823***	-0.632***
	(6.755)	(-4.064)
DISTRESS	0.097***	-0.011*
	(5.500)	(-2.033)
LITIRISK	0.004	0.050**
	(0.049)	(2.486)
MB	-0.000	-0.000
	(-0.667)	(-0.603)
SIZE	0.186***	0.006
	(8.714)	(1.257)
FOLLOW	-0.011***	0.002**
	(-3.943)	(2.431)
HORIZON	-0.149**	-0.713***
	(-2.317)	(-18.960)
INST_OWN	0.213**	0.000
	(2.776)	(0.017)
COMP_AGE	0.003**	-0.000
	(2.812)	(-0.708)
SEGMENT	-0.002	-0.000
	(-1.010)	(-0.717)

Intercept	-1.032***	0.941***
	(-5.172)	(25.556)
Industry & year fixed effect	YES	YES
Adj. R2	0.665	0.223
N	8,043	7,914

Table 2.5 : CFO Gender and Stock Price Crash

This table presents the OLS regression results of Model (9). In Column 1, the dependent variable is my first measure of crash likelihood, *CRASH* $_{T+1}$, an indicator variable equal to 1 if the firm experiences one or more firm-specific crash weeks during the fiscal year T+1, and to 0 otherwise. In Column 2, the dependent variable is my second measure of crash likelihood, *DUVOL* $_{T+1}$, the natural logarithm of the standard deviation of the firm-specific weekly return in the down weeks to the standard deviation of the firm-specific weekly return in the up weeks for year T+1. In Column 3, the dependent variable is my third measure of crash likelihood, *NCSKEW* $_{T+1}$, the negative coefficient of skewness of firm-specific weekly returns for year T+1. The independent variable of interest is the CFO gender for year T, *FCFO* $_{T}$. Both industry and year fixed effects are included. Variable definitions are shown in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. t-statistics are reported in parentheses, and ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	(1) CRASH $_{T+1}$	(2) DUVOL $_{T+1}$	(3) NCSKEW $_{T+1}$
FCFO $_{T}$	**-0.056*****	**-0.059****	**-0.136*****
	(-2.985)	**(-2.883)**	**(-3.016)**
RET $_{T}$	0.095**	0.150***	0.344***
	(2.775)	(3.773)	(4.088)
SIGMA $_{T}$	0.714	0.888*	2.009*
	(1.687)	(1.940)	(2.107)
ROA $_{T}$	7.732	10.259**	21.532**
	(1.527)	(2.683)	(2.311)
DISTRESS $_{T}$	1.674	2.205**	4.647**
	(1.491)	(2.594)	(2.248)
LITIRISK $_{T}$	-0.004	-0.009	-0.028
	(-0.434)	(-0.528)	(-0.936)
LEV $_{T}$	-9.540	-12.616**	-26.480**
	(-1.499)	(-2.609)	(-2.251)
MB $_{T}$	0.000	0.000	0.000
	(0.810)	(1.341)	(1.319)
SIZE $_{T}$	-0.007*	0.005	0.002
	(-1.937)	(1.215)	(0.242)
Intercept $_{T}$	7.531	9.535**	20.143**
	(1.552)	(2.588)	(2.249)
Industry & year fixed effect	YES	YES	YES
Adj. R2	0.027	0.041	0.029
N	6,890	6,890	6,890

Table 2.6 : CFO Gender and Forecast Type

This table presents the OLS regression results of the additional tests. The dependent variable is the management earnings forecast precision, *F_TYPE*, which equals to 1 for open-ended forecasts, to 2 for range forecasts, and to 3 for point forecasts. The independent variable of interest is the CFO gender, *FCFO*. Column 1 shows the results of the sample including only the last management forecasts disclosed before the fiscal year end. Column 2 shows the results of the sample including all the management forecasts disclosed during the year. Both industry and year fixed effects are included. Variable definitions are shown in the Appendix. All continuous variables are winsorized at the top and bottom 1 percent. t-statistics are reported in parentheses, and ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

	(1) *F_TYPE*	(2) *F_TYPE*
FCFO	**-0.017**	**-0.028*****
	(-1.409)	**(-3.334)**
LAG_EPS	0.008**	-0.000
	(2.863)	(-0.165)
LAG_PRICE	-0.001***	-0.000*
	(-5.027)	(-1.913)
CHANGE	0.004**	0.001
	(2.456)	(0.427)
VOLATILITY	-0.099	-0.036
	(-0.994)	(-0.897)
DISTRESS	-0.000	-0.003
	(-0.047)	(-0.617)
LITIRISK	0.057**	0.013
	(2.566)	(1.050)
MB	-0.000	0.000
	(-0.708)	(0.321)
SIZE	0.008	0.006
	(1.300)	(1.542)
FOLLOW	0.003**	0.002**
	(2.880)	(2.779)
HORIZON	-0.054*	-0.010
	(-1.988)	(-0.818)
INST_OWN	0.030	0.013
	(0.994)	(0.437)
COMP_AGE	-0.000	-0.001**
	(-1.025)	(-2.120)
SEGMENT	-0.001	-0.000
	(-1.196)	(-0.467)
Intercept	2.013***	1.989***
	(38.565)	(62.708)

Industry & year fixed effect	YES	YES
Adj. R2	0.049	0.049
N	7,738	37,234

Chapter 3
Do Critical Audit Matters Indicate Poor Accruals Quality?

Abstract

The requirement to report critical audit matters (CAMs) is the most significant change to auditor reports in more than 70 years. Yet, it remains unknown what investors can learn from CAMs. In this study, we investigate the relation between CAMs and accruals quality using a sample of large accelerated filers in the U.S. whose auditors started reporting CAMs after June 30, 2019. We find that companies with more CAMs are generally associated with poorer accruals quality. We also find that the negative association between the number of CAMs and accruals quality is mitigated in companies with a high-quality audit committee. Further analysis shows that revenue-related CAMs and fair value estimation-related CAMs are the primary drivers of poor accruals quality. Our results are robust to various measures of accruals quality and the inclusion of innate firm characteristics that affect accruals quality. Our findings provide insights on the informativeness of CAM reporting, as we show that CAMs provide investors with useful information about companies' accruals quality. Our evidence has implications for the PCAOB, audit firms, investors, and other related parties.

3.1 Introduction

The content in audit reports has significantly increased in the past decade, as auditors are currently required to provide information related to audit risk as part of their audit reports. Known as Key Audit Matters (KAMs) according to international audit standards, and as Critical Audit Matters (CAMs) under U.S. audit standards, the matters disclosed in the newly extended auditor report identify the areas that require additional auditor effort to assess the reported amounts. As such, the report may reveal areas of information risk to financial statement users. This significant enhancement to the auditor report is mainly driven by three factors: (1) decreased public confidence in the capital markets following the scandals at the beginning of the 21st century and the 2007-2008 financial crisis, (2) an information gap between the needs of users of financial reporting and the information provided in the auditor report, and (3) a growing need for better indicators of corporate compliance with accounting standards (Vanstraelen, Schelleman, Meuwissen, and Hofmann 2012; Cordoş and Fülöp 2015; Bédard, Coram, Espahbodi, and Mock 2016; Minutti-Meza 2021). Under the newly expanded audit report, auditors have an increased responsibility to communicate significant audit-related matters to the users of financial reports. Regulators aspire, through this mandate, to decrease the information asymmetry between auditors and users, and to make the auditor report more relevant to users (PCAOB 2017; FRC 2020).

While the expanded audit report is intended to facilitate communication between auditors and financial reporting users, there exists a debate among regulators and scholars over whether CAMs/KAMs and other disclosures in the expanded audit report provide useful information to users. Regulators believe that additional auditor disclosure enhances the informativeness of the audit report and increase transparency regarding their efforts. However, some scholars argue that users may not benefit from the extended audit report because they have already acquired the information from other channels of corporate disclosure, thereby preempting the informativeness of this report (Gutierrez, Minutti-Meza, Tatum, and Vulcheva 2018; Lennox, Schmidt, and Thompson 2022).

Academic evidence on the informativeness of CAM reporting to investors and other stakeholders is rather inconclusive. In line with the report being informative, Klevak, Livnat, Pei, and Suslava (2020) find a more negative market reaction to companies with a greater number of CAMs mentioned in the auditor report. Likewise, Burke, Hoitash, Hoitash, and Xiao (2021) also find a negative market reaction to unexpected CAM disclosures. However, a larger number of studies do not find incremental information content provided to investors in the expanded report (e.g., Gutierrez et al. 2018; Liao, Minutti-Meza, Zhang, and Zou 2019; Liao, Sharma, Yang, and Zhao 2021; Lennox et al. 2022). Thus, these researchers call into question the usefulness of expanding audit reports with additional information.

In the context of this debate, we examine the CAMs disclosed by large accelerated filers in the U.S. in the fiscal year 2019, but we take a different approach. Instead of examining the market reaction to CAM disclosure, we investigate whether there is an association between the number and the content of CAMs and accruals quality, an important aspect of financial reporting quality. A positive association, if found, will attest to the information content of CAM disclosure by the auditor.

Financial reporting quality is important because accounting intends to convey valuable information to decision makers. Accruals quality is a key aspect of accounting quality. Accruals adjust for temporary timing differences in cash flows and enable earnings to better reflect the economic reality and predict future cash flows (e.g., Dechow 1994; Dechow, Kothari, and Watts 1998; Kim and Kross 2005). However, the superior predictive ability of earnings over cash flows can be diminished by low accruals quality. Unintentional estimation errors and/or intentional manipulation impair the quality of accruals and reduce the relevance of accounting earnings for decision making. Francis, LaFond, Olsson, and Schipper (2005) show that investors price accruals quality and consider low-quality accruals as an information risk factor, which leads to higher costs of debt and equity. Thus, in this study, we focus on the quality of accruals and investigate whether CAM disclosure reflects accruals quality.

Our first hypothesis is that the number of CAMs and accruals quality are negatively associated. We see two reasons for this predicted association. First, CAMs are related to items with high managerial discretion. Earnings management behavior (for other than signaling purposes) leads to poor accruals quality. Managers who choose to engage in accrual-based earnings management are likely to apply discretion over those accounts related to CAMs. Second, in addition to intentional manipulations, unintentional estimation errors are also more likely to occur in the areas related to CAMs because those areas are complex and require a high degree of judgment. Therefore, we expect companies with more CAMs to have lower accruals quality.

Our sample consists of large accelerated filers in the U.S. who have been required to disclose CAMs since June 2019. Using data from the years 2011-2019, we estimate companies' accruals quality before the adoption of CAM disclosure, and we generate three different measures of accruals quality. For our first two measures, we use the standard deviation and the average absolute values of residuals from the Dechow and Dichev (2002) model, as modified by McNichols (2002). For our third measure, we use discretional accruals from the Kothari, Leoni, and Wasley (2005) model. We regress the accruals quality measures on the number of CAMs and company characteristics known to affect accounting quality. With all three measures, we find consistent results that a greater number of CAMs is associated with lower accruals quality, which supports our prediction.

We further examine the association of specific CAM topics with accruals quality. We read the CAM reports for each company in our sample and identify six main CAM categories as being related to: expenses, revenues, tax, mergers and acquisitions, the fair value of financial assets and liabilities, and others.[30] We then regress our measures of accruals quality on the number of CAMs in each category. Results show that CAMs related to revenues and fair value estimation are strongly associated with accruals quality, while the other CAM topics are not. These results suggest that CAMs related to revenues and fair value estimation can be used by financial statement users as indicators of low accounting quality.

[30] We discuss the categorization process in detail in the "Research Design" section.

Our second hypothesis is that audit committee effectiveness moderates the relationship between accruals quality and CAM disclosure. According to auditing standard AS 3101, CAMs are critical matters that should be communicated with the audit committee. An effective audit committee is likely to encourage auditors to communicate CAMs, thus leading to more elaborate CAM disclosures. At the same time, the audit committee oversees the corporate financial reporting process and the system of internal controls. Effective audit committee monitoring should restrain managers from using this judgment to manipulate earnings. Thus, even though CAM items may be associated with a high degree of judgment, with effective monitoring from the audit committee, these CAMs should restrain intentional earnings management. We therefore expect the negative association between the number of CAMs and accruals quality to be mitigated in companies with an effective audit committee. We use the proportion of financial experts on the audit committee as a proxy for audit committee effectiveness and examine its interaction effect. Consistent with our second hypothesis, we find the association between the number of CAMs and accruals quality to be moderated by the level of financial expertise of the audit committee.

Because we consider the disclosure of revenue-related CAMs to be a signal of low accruals quality, in a supplementary analysis, we further investigate whether the number of revenue-related CAMs is positively associated with the magnitude of revenue manipulation. Using premature revenue recognition, the most common form of revenue management, as a proxy for revenue manipulation, we find that the magnitude of premature revenue recognition is positively associated with the number of revenue-related CAMs but not with the total number of CAMs. These results demonstrate that while the number of CAMs is a good indicator of accruals quality, CAMs only related to revenues signal the risk of revenue manipulation. In a robustness check, we use four alternative measures for accruals quality: (1) the average absolute value of discretionary accruals estimated from the Jones model, (2) restatements, (3) earnings persistence, and (4) earnings prediction ability. The results using these measures are consistent with our main results and further support our findings of a negative association between the number of CAMs and accruals quality.

This study makes several contributions to the field. First and foremost, our study contributes to the ongoing debate over CAM reporting informativeness and usefulness. We demonstrate that a higher number of CAMs indicate lower accruals quality. This is important because earnings quality is unobservable and not easy to estimate. Because CAM disclosure reveals information about accruals and earnings quality, financial statement users can use the number of CAMs reported to form their perceptions of earnings quality.

Second, this study contributes to our understanding of the informativeness of specific CAM topics. We show that beyond the usefulness of the overall CAM disclosure, specific CAM topics matter with respect to accruals quality. Revenue and fair-value-related CAMs are more strongly associated with low accruals quality than other types of CAMs. Furthermore, we demonstrate that the disclosure of revenue-related CAMs can be an effective signal of revenue manipulation behavior. By examining the specific CAMs, we respond to the call by Minutti-Meza (2021) to extend the literature by "determining whether common KAM and CAM topics have unique effects on complex aspects of financial reporting (e.g., revenue recognition, impairments, and deferred taxes)."

Overall, our study demonstrates that even though the information contained in CAMs may have already been revealed by corporate past performance or existing disclosures, CAM reporting effectively and efficiently communicates information risk, which is important for stakeholders' decision-making.

The remainder of the paper is organized as follows. We provide background information and review the literature in section 2. In section 3, we develop our hypotheses. In section 4, we describe the research design, sample formation, and provide the descriptive statistics. Section 5 reports the main empirical results. The results of the supplementary analyses and robustness tests are presented in section 6. The final section summarizes and concludes this study.

3.2 Background and Literature Review

3.2.1 Background

The requirement that financial statements be accompanied by an audit report dates back to the year 1900 in the U.K. and the year 1934 in the U.S. Since then, and until recently, there have been only minor changes to the audit report, which for the most part uses standardized paragraphs to describe the audit scope and opinion. However, public confidence in global capital markets and in the credibility of audited financial statements has eroded in light of the high-profile scandals of the early 2000s and the financial crisis of 2008. In addition, knowledgeable financial statement users have argued that there is a gap between the information they want to receive from the auditor and the information available in the audit report (e.g., Vanstraelen et al. 2012; Minutti-Meza 2021).

In response to the demand by financial statement users for more thorough information from the external auditor, regulators have responded by introducing expanded audit reports. The expanded audit report was first adopted by the Financial Reporting Council (FRC) in the U.K. in 2012. It became effective in September 2013 for U.K. companies with a premium listing of equity shares on the London Stock Exchange (LSE) Main Market, and in June 2017 for companies listed on the LSE Alternative Investment Market and Public Interest Entities. The FRC's ISA700 requires that in addition to audit opinions, the auditor must report (1) the risks of material misstatement, (2) the application of materiality, and (3) the scope of the audit.

The International Auditing and Assurance Standards Board (IAASB) followed suit by revising audit standard ISA700 and issuing audit standard ISA701 in 2015, which require the discussion of Key Audit Matters (KAM) in expanded audit reports. The definition of KAM is "those matters that, in the auditor's professional judgment, were of most significance in the audit of the financial statements of the current period. Key audit matters are selected from matters communicated with those charged with governance" (ISA 701, paragraph 8). To converge with IAASB standards, the FRC (U.K.) revised its standards and added the requirements regarding KAMs in 2016.

Although the expanded audit report has been mandated in most European countries and many countries all around the world since 2016, it was not until 2019 that auditors in the U.S. were required to provide an expanded audit report. In 2017, the SEC approved audit standard AS 3101 of the Public Company Accounting Oversight Board (PCAOB), which became effective for large accelerated filers in June 2019 and for all other filers in December 2020. AS 3101 requires auditors to disclose CAMs as well as information on auditor tenure. AS 3101 defines a CAM as "any matter arising from the audit of the financial statements that was communicated or required to be communicated to the audit committee and that (a) relates to accounts or disclosures that are material to the financial statements; and (b) involved especially challenging, subjective, or complex auditor judgment." Although CAMs also identify high-risk areas with high estimation uncertainty, there are substantial differences in the number, types, and details of KAMs/CAMs disclosed under different regulation environments (Minutti-Meza 2021). Nevertheless, publicly traded companies in many jurisdictions are currently required to report CAMs/KAMs in their audit reports.[31]

3.2.2 Literature Review

Determinants of KAMs/CAMs Disclosure

Lennox et al. (2022) find that the number of KAMs is positively associated with company complexity (based on the number of subsidiaries) and company risk (those in financial distress and with financial reporting issues). Using the number of business segments as a proxy for complexity, Pinto and Morais (2019) also find it to be positively associated with KAMs. Further, they find KAMs to be associated with more precise accounting standards. Sierra-García, Gambetta, García-Benau, and Orta-Pérez (2019) find that the clients of Deloitte, EY, and KPMG are usually less complex and regulated than those of PwC; therefore, they are associated with fewer KAMs. The authors further find that audit fees, structural client characteristics, the types of business transactions, and industry membership also influence the number and types of KAMs reported.

Information Effect of KAMs/CAMs

[31] For a comprehensive overview of the development of the expanded report and a comparison between KAM and CAM, please refer to sections 2 and 3 in Minutti-Meza (2021).

Some researchers attempt to infer the information content of KAM/CAM disclosure using the stock price reaction. For the most part, they fail to detect a significant market reaction to KAM/CAM disclosure. Bédard et al. (2016) report no evidence of a significant market reaction in France. Both Gutierrez et al. (2018) and Lennox et al. (2022) find no market reaction in the U.K. Lennox et al. (2022) attempt to understand the lack of a market reaction and note that it is not that this information is irrelevant, but rather that investors have already obtained the information prior to the audit report via earnings announcements, conference calls, or the previous year's annual report. Liao et al. (2019) examine the staggered adoption of KAM and fail to find a significant market reaction to it in Hong Kong and Mainland China. In a recent U.S. study, Burke et al. (2021) do not find a significant market reaction to CAM disclosure, but in cross-sectional analyses, they find a negative abnormal reaction to unexpected CAM disclosures. Klevak et al. (2020) examine the initial CAM reports in the U.S. and find that CAM conveys relevant information about firm uncertainty. Specifically, the authors find that a higher number of CAMs, a greater number of required auditing procedures, and wordier and more extensive CAM discussions are associated with negative stock returns, higher stock price volatility, negative analyst earnings revisions, and increased analyst forecast dispersion. Boolaky and Quick (2016) find that banks do not perceive KAM disclosure as useful for the credit approval process.

Reid, Carcello, Li, Neal, and Francis (2019) find decreased absolute abnormal accruals and a lower propensity to meet/beat analyst forecasts and increased earnings response coefficients in financial reporting in the U.K. in the post-CAM regime. Bens, Chang, and Huang (2019) also observe a decrease in the information asymmetry and an improvement in the financial reporting quality in the U.K. following the adoption of the extended auditor report. Using staggered adoption by share class in China, Goh, Li, and Wang (2020) show an improvement in the financial reporting environment in the post-extended auditor report period, as earnings response coefficients and abnormal trading volumes are higher, and stock price synchronicity is lower. Overall, these studies suggest a positive effect of the new CAM reporting regime on financial reporting quality.

In two experimental studies with nonprofessional investors, Dennis, Griffin, and Zehms (2019) and Rapley, Robertson, and Smith (2021) document a negative market reaction to CAM disclosure, indicating that the disclosure is perceived as a forewarning of high misstatement risk and uncertainty (Velte and Issa 2019; Kachelmeier, Rimkus, Schmidt, and Valentine 2020). Consistent with the findings of Dennis et al. (2019) and Rapley et al. (2021), Christensen, Glover, and Wolfe (2014) predict and find that nonprofessional investors have less confidence and are less willing to invest in firms with CAM disclosures.

Relations to Auditor

Results regarding the effect of CAM disclosures on audit quality are rather mixed. Gutierrez et al. (2018) find no association between KAM disclosures and audit quality, whereas Reid et al. (2019) report improved audit quality in the post-KAM period. Neither of these studies detect a significant change in audit fees following the KAM regulation, implying that the incremental costs associated with expanding the audit report are insignificant relative to total audit costs (Gutierrez et al. 2018; Reid et al. 2019). In the U.S., Burke et al. (2021) similarly do not find significant changes in audit quality or audit fees following the CAM regulation, while Pinto and Morais (2019) find a positive association between audit fees and the number of KAMs disclosed.

Relations to Management

When a CAM is disclosed, managers receive more challenges from audit committee members about their accounting estimates (Kang 2019) and issue more comprehensive disclosures about complex accounting estimates (Fuller, Joe, and Luippold 2021). In addition, using an experiment, Gold, Heilmann, Pott, and Rematzki (2020) show that managers expect more scrutiny following the KAM disclosure and respond by improving the financial reporting quality.[32]

[32] In an experimental setting, Bentley, Lambert, and Wang (2021) find that managers at firms that disclose CAMs may change their real operating activities to avoid CAM disclosures that reveal confidential and proprietary information.

Our paper is mostly related to the line of research on the information value of CAMs by showing that the number of CAMs (in particular, the CAMs related to revenues and fair value estimation) is indicative of accruals quality. Our results are related to the experimental finding of Elliott, Fanning, and Peecher (2020) that investors consider the extended auditor report as an effective means to communicate information about financial reporting quality. We provide empirical evidence that auditor reporting on CAMs is indeed correlated with accruals quality.[33]

3.3 Hypotheses

Accruals quality is a key indicator of financial reporting quality because accruals affect how well current earnings represent fundamental performance and predict future cash flows (Dechow and Dichev 2002; Dechow and Schrand 2004: Francis et al. 2005; Doyle Ge, and McVay 2007). Intentional manipulation of accruals and unintentional estimation errors can both lead to poor accruals quality. Managers often use discretionary accruals to manage earnings, diminishing the ability of accruals to predict future cash flows (e.g., Jones 1991; Dechow, Ge, and Schrand 2010). Dechow and Dichev (2002) argue that accrual estimation errors also reduce the predictive ability of accruals and lead to decreased accruals quality. Doyle et al. (2007) further find that internal control weaknesses, which have the potential to allow both intentional management and unintentional errors, are negatively associated with accruals quality. In general, evidence from prior studies indicates that accruals quality is lower when there is a high likelihood of earnings management or a high level of difficulty in estimating accruals accurately.

AS 3101 defines a critical audit matter (CAM) as any matter that is material to financial statements and involves "challenging, subjective or complex auditor judgment" (PCAOB 2017). Accordingly, CAMs are often related to accounting areas that require high degrees of management estimation and judgment. These items are more prone to intentional manipulation due to their high degree of subjectivity, which gives the manager more room

[33] A concurrent paper by Sulcaj (2020) shows that increased litigation risk motivates auditors to disclose a higher number of CAMs to preempt shareholders' lawsuits, and that the number of CAMs map into financial reporting quality. Our paper is different than Sulcaj (2020), as we also examine the CAM topics most related to accruals quality and the mitigating effect of an effective audit committee.

for accrual manipulation in those areas. These items are also prone to unintentional accrual estimation errors because they are related to future cash realization, which has an inherently higher degree of uncertainty. Thus, these amounts are more difficult to predict accurately. We therefore expect accrual estimation errors (intentional and unintentional) to be associated with CAMs. As an example of the link between CAMs and both estimation uncertainty and subjectivity, Kimberly-Clark's auditor, Deloitte, reported one CAM in its expanded report for the fiscal year 2019 related to the estimation of future customer claims under a trade promotional program. This estimation not only involved a high level of managerial uncertainty and subjectivity, but also required extensive auditor effort and judgment. Thus, this CAM may be associated with either intentional or unintentional estimation errors related to the net revenue accounts.

However, there are also reasons as to why we may not observe a negative association between the number of CAMs and accruals quality. First, although CAMs are related to complex and subjective accounting amounts, auditors usually expend more effort when auditing the areas identified as CAMs. In the CAM report, auditors describe in detail the procedures and strategies they employed to address each CAM, such as testing the effectiveness of the internal controls related to the CAM areas, using a specialist auditor to perform specific tests, exerting additional effort to evaluate managerial assumptions, and so forth. If the additional auditor efforts succeed in reducing the potential estimation risks related to the CAM, then the number of CAMs reported should not be associated with poor accruals quality. Second, the main goal of CAM reporting is to enhance the transparency of the audit report rather than convey negative information (PCAOB 2017). As stated by Lisa Smith, managing director of quality and professional practice at Deloitte, "The existence of a CAM does not mean there is something wrong with the audit. That just happens to be an area of the audit that the auditor found especially challenging or complex or subjective" (Smith, Zietsman, Mahoney, and Ray 2020). CAMs are also not intended to predict potential future problems. If a CAM is merely a disclosure of audit effort, it should not serve as an indicator for poor accruals quality.

Overall, however, we do not expect these counter forces to dominate, as the subjectivity and inherent complexity related to CAMs may still lead to accrual estimation errors, and as a result, to poor accruals quality. Thus, we state our first hypothesis in an alternative form as follows:

H1: The number of CAMs is negatively associated with accruals quality.

The responsibility of audit committees is to oversee the financial reporting process and the work of external auditors (Ashraf, Choudary, and Jaggi 2020). While in general we expect the reporting of a higher number of CAMs to be negatively associated with accruals quality, effective monitoring from an audit committee can mitigate managerial opportunism and help produce high-quality accruals. Evidence from prior studies shows that having a financial expert on the audit committee increases the committee's effectiveness, such as mitigating earnings management (Carcello, Hollingsworth, and Neal 2006; Zhang, Zhou, and Zhou 2007; Badolato, Donelson, and Ege 2014). Effective monitoring may also motivate managers to exert more effort over items that are difficult to estimate, resulting in more accurate estimates. Therefore, we expect an effective audit committee to mitigate the negative association between CAMs and accruals quality. This leads to our second hypothesis:

H2: The negative association between the number of CAMs and accruals quality is mitigated in companies with effective audit committees.

3.4 Research Design, Sample Selection, and Description

3.4.1 Research Design

To investigate the relationship between CAMs and accruals quality, we employ three different proxies for accruals quality. The first two measures are based on the Dechow and Dichev (2002) model, as modified by McNichols (2002), which considers past, present, and future cash flows as well as the explanatory variables from the Jones (1991) model. As discussed in McNichols (2002) and Doyle et al. (2007), this model not only captures management's intentional errors, but also nonintentional measurement errors. Thus, compared with other measures of earnings management, this measure is more suitable for estimating a company's overall accruals quality. The model is as follows:

$$\Delta WC_t = \beta_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1} + \beta_4 \Delta Sales_t + \beta_5 PPE_t + \varepsilon_t \qquad (1)$$

where ΔWC is the change in working capital accounts from the previous to the current year, as disclosed in the cash flow statement. *CFO* is the cash flow from operations. $\Delta Sales$ is the change in sales from the previous to the current year, and *PPE* is the property, plant, and equipment levels. All variables except β_0 are scaled by average total assets.

Following Francis et al. (2005) and Doyle et al. (2007), we estimate the above regression by industry and year, based on the 48 Fama and French (1997) industry classifications. If any industry-year pair has fewer than 15 observations, these observations are dropped from the sample. All variables in Model (1) are winsorized at the 1st and 99th percentiles each year to exclude the effects of extreme values. Appendix I provides a description of all the variables. We measure accruals quality for the years 2012-2018[34], before the adoption of CAM disclosures.

Our first measure of accruals quality, *SD_AQ*, is the company's standard deviation of the yearly residuals calculated from Model (1) during the period 2012-2018. Our second measure of accruals quality, *Avg_AQ*, is the company's average yearly absolute residual calculated from Model (1) over the period 2012-2018. For both measures, we require each company to have data for at least four out of the seven years. Higher values for *SD_AQ* and *Avg_AQ* suggest a weaker association between accruals and cash flows and lower accruals quality.

While our first two measures of accruals quality consider only working capital accruals, our third measure considers both working capital and long-term accruals. For that, we use the Kothari et al. (2005) model as follows:

$$TAC_t = \beta_0 + \beta_1 (1/Total\_Assets_{t-1}) + \beta_2 \Delta Sales_t + \beta_3 PPE_t + \beta_4 ROA_t + \varepsilon_t \qquad (2)$$

The dependent variable, *TAC*, is total accruals, measured as the difference between income before extraordinary items and cash flow from operations. *ROA* is the net income

[34] Because the model requires a one-year lag and one-year lead data, we use data for the years 2011-2019.

in the current year. *ΔSales* and *PPE* are the same, as described above. All the variables in Model (2) are scaled by lagged total assets. We once again require a minimum of 15 observations per industry and year and winsorize the variables at the 1st and 99th percentiles by year. *DA* is the average absolute value of the error term over the period 2012-2018, and we once again require each company to have at least four years of data.

To test our first hypothesis that a higher number of CAMs indicates lower accruals quality, we run the following regression:

$$\begin{aligned} AQ = {} & \beta_0 + \beta_1 CAM\_N + \beta_2 Loss\_Proportion + \beta_3 Sales\_Volatility \\ & + \beta_4 CFO\_Volatility + \beta_5 Total\_Assets + \beta_6 Operating\_Cycle + \beta_7 Age \\ & + \beta_8 Segment + \beta_9 Complexity + \beta_{10} High\_Growth + \beta_{11} Restructuring\_Charge \\ & + \beta_{12} ICW + \varepsilon_t \end{aligned} \tag{3}$$

The dependent variable in Model (3) is accruals quality, for which we apply the three aforementioned measures, *SD_AQ*, *Avg_AQ*, and *DA*. The independent variable of interest is *CAM_N*, the number of CAMs, as included in the auditor report for the year 2019. As higher values for our accruals quality measures mean lower accruals quality, a positive and significant coefficient of *CAM_N* will be consistent with our first hypothesis of a negative association between the number of CAMs and accruals quality.

With regard to the timing of measuring accruals quality, we use a similar approach to that of Doyle et al. (2007). We assume that financial reporting issues have existed for several years before auditors started reporting on CAMs. For this reason, we calculate accruals quality over the period 2012-2018. An alternative approach would be to measure accruals quality for the same period in which CAMs are reported. However, the disadvantage of this approach is that the impending CAM reporting may affect the management's use of discretion over accruals or the auditor's audit of accruals. This in turn, may affect the accruals quality and distort the ongoing relations between CAM reporting and accruals quality, especially in the first year of implementing the new reporting format. The calculation of accruals quality up to 2018 prevents this problem. Nonetheless, the relations we document between accruals quality and CAM continue to hold if we extend the period over which we calculate accruals quality to 2012-2019, or if we use the accruals of 2019.

In Model (3) we control for the firm characteristics shown in prior studies to affect accruals quality. *Loss_Proportion* is the proportion of loss years in the period 2012-2018. Because more volatile operations make it more difficult to estimate future cash flows, companies with more volatile operations will experience lower accruals quality (Dechow and Dichev 2002). Thus, we include in the model *Sales_Volatility*, the standard deviation of sales, and *CFO_Volatility*, the standard deviation of cash flow from operations, both scaled by average total assets. We also control for firm size (*Total_Assets)*, operating cycle (*Operating_Cycle)*, and firm age *(Age)*. To control for operation complexity, we include the sum of operating and geographical segments *(Segment)* and the proportion of foreign income *(Complexity)*. We also include *High_Growth*, an indicator variable that is equal to 1 if industry-adjusted sales growth is in the top quintile, and *Restructuring_Charge,* the sum of restructuring charges in 2018 and 2019, scaled by market capitalization (Doyle et al. 2007). Finally, because Doyle et al. (2007) find that poor accruals quality is associated with weak internal controls, we add the indicator variable *ICW,* which is set to 1 if the company disclosed a material weakness in the internal controls under Sections 302 or 404 of the Sarbanes-Oxley Act, and to 0 otherwise.[35]

As CAMs are related to a variety of auditing issues, we further explore the relationship between accruals quality and the topics of CAMs. After reading a large sample of CAMs, we find that they are mainly related to 15 topics. We further consolidate these topics into six main categories. CAMs related to impairment, estimated liabilities, depreciation, capitalized costs and compensation are categorized as *CAM_Expenses*. CAMs related to revenues and accounts receivable are categorized into *CAM_Revenues*. CAMs related to business combinations are categorized into *CAM_M&A*. The next two categories are CAMs related to taxes, *CAM_Tax*, and the fair value of financial assets and liabilities, *CAM_FV*. All the remaining topics are categorized as *CAM_Others*. Appendix II provides

[35] Following prior studies (e.g., Reichelt and Wang 2010; Minutti-Meza 2013), we do not control for industry fixed effects in our model, as our measures of accruals quality are estimated by industry.

detailed topic definitions. Then, we examine how the number of CAMs in each category is associated with our measures of accruals quality, using the following model:

$$AQ = \beta_0 + \beta_1 CAM\_Expenses + \beta_2 CAM\_Revenues + \beta_3 CAM\_M\&A + \beta_4 CAM\_Tax + \beta_5 CAM\_FV + \beta_6 CAM\_Others + \beta_7 Loss\_Proportion + \beta_8 Sales\_Volatility + \beta_9 CFO\_Volatility + \beta_{10} Total\_Assets + \beta_{11} Operating\_Cycle + \beta_{12} Age + \beta_{13} Segment + \beta_{14} Complexity + \beta_{15} High\_Growth + \beta_{16} Restructuring\_Charge + \beta_{17} ICW + \varepsilon_t \quad (4)$$

where *CAM_Expenses*, *CAM_Revenues*, *CAM_M&A*, CAM_*Tax*, *CAM_FV*, and *CAM_Others* represent the number of CAMs in each of these categories, as defined above. All other variables are defined in Model (3).

Our second hypothesis is that the effectiveness of the audit committee will moderate the negative association between the number of CAMs and accruals quality. To test this hypothesis, we use the following model:

$$AQ = \beta_0 + \beta_1 CAM\_N + \beta_2 Fin\_Expert + \beta_3 CAM\_N \times Fin\_Expert + \beta_4 Loss\_Proportion + \beta_5 Sales\_Volatility + \beta_6 CFO\_Volatility + \beta_7 Total\_Assets + \beta_8 Operating\_Cycle + \beta_9 Age + \beta_{10} Segment + \beta_{11} Complexity + \beta_{12} High\_Growth + \beta_{13} Restructuring\_Charge + \beta_{14} ICW + \varepsilon_t \quad (5)$$

We use *Fin_Expert*, the proportion of financial experts on the audit committee in 2019, as a proxy for the effectiveness of the audit committee. In Model (5), our variable of interest is the interaction variable *CAM_N × Fin_Expert*. A negative coefficient of the interaction variable will indicate that a more effective audit committee mitigates the negative relationship between the number of CAMs and accruals quality. All the other variables are defined in Model (3).

3.4.2 Sample Selection and Description

AS 3101, *The Auditor's Report on an Audit of Financial Statements When the Auditor Expresses an Unqualified Opinion*, requires the auditors of large accelerated filers (whose fiscal year ends on or after June 30, 2019) to communicate critical audit matters in a separate section. Thus, our sample consists of large accelerated filers in the U.S., and our sample period is the fiscal year 2019, the first year these companies started reporting on CAMs. We first use Python to identify the companies communicating CAMs in their auditor report in the fiscal year 2019; the 1,985 companies identified constitute our initial sample. Then, we manually collect the number and the content of CAMs from their 10-K filings and classify these CAMs into different topics to ensure data accuracy. An example of a CAM disclosure and its classification is provided in Appendix III.

All the companies in our sample are required to have available data for at least one measure of accruals quality and all the control variables. We obtain the financial data from Compustat Fundamentals Annual, segment information from Compustat Segments, firm age from CRSP, and information on the effectiveness of the internal controls from Audit Analytics. As described in the Research Design section, we drop the industry and year pairs with fewer than 15 observations. To calculate *SD_AQ*, the standard deviation of the residuals from Model (1), companies must have data for at least four out of seven years, from 2012-2018. A total of 109 companies missing data for any of the three measures of accruals quality are deleted, and 214 companies missing data for the control variables are also removed. Our final sample comprises 1,662 companies. Panel A of Table 1 summarizes the sample composition.

[Insert Table 3-1 here]

Panel B of Table 1 presents the sample distribution based on the number of CAMs. Most of the companies from our sample report either one or two CAMs (50.5 percent and 36.9 percent, respectively). Only two companies (0.12 percent) in our sample report as many as five CAMs, and nine companies (0.54 percent) do not report any CAM.

Panel C of Table 1 presents the distribution of the CAM categories and topics. CAMs related to expenses make up the largest category, with 43.8 percent of the CAMs. This is followed by CAMs related to revenues (22.2 percent), taxes (10.2 percent), mergers and acquisitions (9.4 percent), and fair value estimates (7.3 percent). CAMs in all the other areas account for 8.2 percent. Within the topics, CAMs related to impairments (26.1 percent) and revenues (17.9 percent) are the most common. CAMs related to estimated liabilities (12.2 percent), tax (10.3 percent), business combinations (9.4 percent), and the fair value of financial assets and liabilities (7.3 percent) also account for more than 5 percent of CAMs.

Table 2 presents the descriptive statistics for the variables we use in Model (3). On average, the likelihood that a company reports a loss is 19.3 percent. The average standard deviation of sales and cash flow from operations are 0.141 and 0.041, respectively. The average natural logarithm of total assets and the operating cycle are 8.429 and 4.619, respectively. Company age has an average of 25.8 years, and the sum of geographic and business segments is 5.5. Foreign income is approximately 1.4 percent of total assets, and 19 percent of the companies are high growth.[36] The average restructuring charges are 0.9 percent of market capitalization, and 5.5 percent of the companies report weakness in their internal controls.

[Insert Table 3-2 here]

Table 3 provides the Pearson correlations for the variables we use in Model (3). As expected, the accruals quality measures are positively correlated with each other. The correlations between our independent variables and other control variables are small, and the untabulated variance inflation factors (VIF) of each of the variables are all below 1.5, which suggests that multicollinearity is not a concern.

[Insert Table 3-3 here]

3.5 Results

3.5.1 Accruals Quality and the Number of CAMs

[36] This is slightly lower than a quintile because some companies missing other control variables are eliminated.

Table 4 reports the multivariate results on the association between accruals quality and the number of CAMs reported (Model 3). Columns 1, 2, and 3 present the regression results using *SD_AQ*, *Avg_AQ*, and *DA*, respectively, as proxies for accruals quality. In all three columns, the coefficients on *CAM_N* are positive and significant at the 0.05 level, indicating that firms with a higher number of CAMs are more likely to have a higher standard deviation of discretionary accruals (*SD_AQ)* and higher discretionary accruals (*Avg_AQ* and *DA*). These results are consistent with the prediction of our first hypothesis that accruals quality is negatively associated with the number of CAMs. With respect to the control variables, accruals quality is negatively associated with the likelihood of reporting a loss (*Loss_Proportion*), cash flow volatility (*CFO_Volatility*), and internal control weakness (*ICW*), and is positively associated with company size (*Total_Assets*), age (*Age*), and the number of segments (*Segment*).

[Insert Table 3-4 here]

3.5.2 Accruals Quality and CAM Categories

The results on the association between accruals quality and the various CAM categories (Model 4) are reported in Table 5. As before, in Columns 1, 2, and 3, the dependent variable is *SD_AQ*, *Avg_AQ*, and *DA*, respectively. We find that the coefficients on *CAM_Revenues* and *CAM_FV* are both positive and statistically significant, indicating that the number of CAMs related to revenues and fair value estimations are positively associated with the accruals quality measures, and hence, are negatively associated with accruals quality. These findings suggest that financial reporting related to revenues and fair value estimation involves a greater level of managerial discretion and is difficult to audit, resulting in lower accruals quality. The coefficients on the control variables are similar to those reported in Table 4.

[Insert Table 3-5 here]

3.5.3 The Effect of Financial Expertise of the Audit Committee

Next, we examine Hypothesis 2 in terms of whether the negative association between the number of CAMs and accruals quality is mitigated by an effective audit committee, proxied by the proportion of financial experts serving on the committee (*Fin_Expert*). Results of Model (5) are presented in Table 6. Columns 1, 2, and 3 show the regression results with the three accruals quality measures, *SD_AQ*, *Avg_AQ*, and *DA*, respectively. We find that the coefficients on *CAM_N* in all three columns remain positive and significant at the 0.05 level, confirming the negative association between the number of CAMs and accruals quality measures (Hypothesis 1). Furthermore, in support of Hypothesis 2 the coefficients on the interaction term *CAM_N* × *Fin_Expert* in all columns are significantly negative. This result suggests that financial expertise on the audit committee mitigates the negative association between the number of CAMs and accruals quality. In other words, financial expertise on the audit committee increases the committee's effectiveness in monitoring financial reporting, leading to improved accruals quality. The coefficients of the control variables are generally similar to those reported in Tables 4 and 5.

[Insert Table 3-6 here]

3.6 Supplementary Analysis and Robustness Checks

3.6.1 Premature Revenue Recognition

According to Table 5, the number of CAMs related to revenues have a significant association with accruals quality. To further investigate whether a higher number of revenue-related CAMs indicates more revenue manipulation, we examine the association between premature revenue recognition and the number of revenue-related CAMs. To manage revenues upward, companies may recognize revenue prematurely into the current period. Premature revenue recognition is the most common form of revenue management (Feroz, Park, and Pastena 1991; Stubben 2010). We use the measure of premature revenue recognition developed by Stubben (2010) to proxy for revenue management. This measure is estimated from the following regression:

$$\begin{aligned} \Delta AR_t = {} & \beta_0 + \beta_1\, \Delta Sales_t + \beta_2\, \Delta Sales_t \times Total\_Assets_t + \beta_3\, \Delta Sales_t \times Age_t \\ & + \beta_4\, \Delta Sales_t \times Age\_SQ_t + \beta_5\, \Delta Sales_t \times GRR\_P_t + \beta_6\, \Delta Sales_t \times GRR\_N_t \\ & + \beta_7\, \Delta Sales_t \times GRM_t + \beta_8\, \Delta Sales_t \times GRM\_SQ_t + \varepsilon_t \end{aligned} \tag{6}$$

where *ΔAR* is the annual change in accounts receivable, and *ΔSales* is the annual change in sales, both scaled by average total assets. *GRR_P* and *GRR_N* are the industry-median-adjusted sales growth rate when positive and negative, respectively. *GRM* is the industry-median-adjusted gross margin. *Age_SQ* and *GRM_SQ* are the squared firm age and industry-median-adjusted gross margin, respectively, which are included to allow for nonlinear relations. *ΔSales*, *Total_Assets*, and *Age* are described above. As with Models (1) and (2), we estimate this model by year and industry and drop any industry-year pair with fewer than 15 observations. All the variables in Model (6) are winsorized at the 1^{st} and 99^{th} percentiles.

Given that premature revenue recognition results in overstated accounts receivable, companies with accelerating revenues are expected to have abnormally high accounts receivable in the current year. Thus, the residual from Model (6) captures the unexpected accounts receivable and represents management discretion. Our two measures of revenue management over the period 2012-2018 are *Avg_Premature* and *SD_Premature*, the average absolute value and the standard deviation of the residuals calculated from Model (6).

Because of our finding that revenue-related CAMs are associated with low accruals quality (Table 5), we predict a positive relationship between our measures of revenue management and the number of revenue-related CAMs. Consistent with this prediction, the results in Columns 1 and 2 of Table 7 show that the coefficients of *CAM_Revenues* are significantly positive at the 0.01 level. These results imply that the number of revenue-related CAMs is an effective signal for revenue management.

[Insert Table 3-7 here]

3.6.2 Alternative Measures for Accruals Quality

To ensure the robustness of our results, we use four additional measures of accruals quality. The first measure, *DA_Jones*, is the average absolute value of discretionary accruals estimated from the Jones (1991) model.[37] As reported in the first column of Table 8, the coefficient of *DA_Jones* is positive and significant at the 0.01 level, which is consistent with our main results.

Companies reporting restatements tend to have lower earnings quality (Jones, Krishnan, and Melendrez 2008). Thus, our second alternative accruals quality measure is the indicator variable, *Hist_Restate*, which equals 1 if the company has restated its financial statements at least once during the period 2012-2018, and 0 otherwise. Based on our first hypothesis, companies with a higher number of CAMs will have lower accruals quality, and accordingly, should be more likely to restate their financial statements. The second column of Table 8 shows that the coefficient of *Hist_Restate* is positive and significant at the 0.10 level.

The third and fourth alternative measures are the earnings persistence and earnings prediction of future cash flows. Following Dechow and Dichev (2002) and Doyle et al. (2007), we estimate the earnings persistence for each company using the following model:

$$Earn_{t+1} = \beta_0 + \beta_1 Earn_t + \varepsilon_t \qquad (7)$$

where $Earn_t$ is the earnings before long-term accruals, calculated as the cash flow from operations (CFO_t) plus the change in working capital (ΔWC_t). The firm-specific coefficient β_1 is the earnings persistence parameter, *Persistence*. Similarly, earnings prediction, which reflects the ability of earnings to predict next year's cash flow, is estimated from a model regressing the cash flow from the operations of year t+1 on the *Earn* of year t, as follows:

$$CFO_{t+1} = \beta_0 + \beta_1 Earn_t + \varepsilon_t \qquad (8)$$

The coefficient of *Earn* in Model (8) is the variable *Prediction.* Because companies with lower accruals quality have poorer earnings persistence and poorer earnings prediction ability (Dechow and Dichev 2002; Richardson, Sloan, Soliman, and Tuna 2005), we

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[37] The modified Jones model from Kothari et al. (2005) that we use to estimate our third main measure for accruals quality (*AQ*) is the Jones (1991) model augmented with ROA.

expect the number of CAMs to have negative relationships with *Persistence* and *Prediction*. The results reported in Columns 3 and 4 of Table 8 are consistent with our expectations, showing that the number of CAMs is significantly negatively associated with *Persistence* and *Prediction* at the 0.01 and 0.05 levels, respectively.

Conclusively, the results of the four alternative measures we use to check the robustness of our results all corroborate our first hypothesis.

[Insert Table 3-8 here]

3.7 Conclusion

In an attempt to gain a deeper understanding of the informativeness of CAM disclosure in expanded audit reports, we examine the association between the number and the content of CAMs and accruals quality. Accruals quality is an important measure of financial reporting quality, which is essential for the decision-making of financial-statement users. As CAMs identify the high-risk areas that are likely to involve more management judgment, we predict that companies with a higher number of CAMs will have lower quality accruals. We further predict that this association will be more salient in companies whose audit committees tend to be less effective.

For a sample of large accelerated filers in the U.S. who started reporting on CAMs on or after June 2019, we measure accruals quality based on data in the six years prior to the first year of their CAM reporting. We then investigate the association between their accruals quality and the number and the content of CAMs reported in the fiscal year 2019. We find that companies with a higher number of CAMs are more likely to have lower quality accruals. We then consider the various CAM categories and find that the numbers of CAMs related to revenues and fair value estimation are significantly associated with accruals quality. Thus, a higher number of CAMs, especially those related to revenues and fair value estimation, are effective signals of poor accruals quality.

We further examine whether the negative association between the number of CAMs and accruals quality is mitigated in companies with effective audit committees. CAMs identify the high-risk areas that are more likely to be subject to management manipulation or unintentional estimation errors, which may lead to poor accruals quality. However, an effective audit committee can ensure that these estimations are done more diligently to reduce potential errors and can restrain managerial opportunistic behavior; thus, an effective audit committee is likely to play a positive role in improving accruals quality. Consistent with our prediction, we find that the negative association between CAMs and accruals quality is mitigated when a company has higher financial expertise on the audit committee, which is a corporate governance mechanism shown to increase monitoring effectiveness (Xie, Davidson, and DaDalt 2003; Bédard, Chtourou, and Courteau 2004).

In additional analyses, we examine the association between the revenue-related CAMs and premature revenue recognition, which is the most common type of revenue manipulation behavior. We find that companies with more revenue-related CAMs tend to engage in more revenue manipulation. As a robustness check for our first hypothesis, we employ four alternative measures of accruals quality and continue to find consistent results.

This study contributes to the literature by showing that both the number and the categories of CAMs reported convey useful information regarding the risks in financial reporting. We demonstrate that the number of CAMs can be used as an instrument to assess accruals quality by investors and other users, given that companies with a greater number of CAMs tend to have lower accruals quality. We further find that lower accruals quality is more closely associated with CAMs related to revenues and fair value estimation than with CAMs in other categories. This finding shows that the CAMs in these two categories are more likely to reveal information risk. Our study contributes to an understanding of CAM informativeness and usefulness by demonstrating that even though CAMs may not provide incremental information to investors for valuation, they draw attention to information risk and provide a signal of potential problems.

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Table 3.1 : Sample Selection and Distribution

Panel A: Sample Selection

Identified firms with critical audit matter in 2019	1,985
Less: Firms with unavailable data to calculate accruals quality	-109
Less: Firms with unavailable data for control variables	-214
Final sample used in multivariate regressions	1,662

Panel B: CAM-Number Distribution

Number of CAM	Frequency	Percent	Total number
0	9	0.54%	0
1	839	50.48%	839
2	613	36.88%	1226
3	172	10.35%	516
4	27	1.62%	108
5	2	0.12%	10
Total	1,662	100%	2699

Panel C: CAM Topic Distribution

Topic	Freq.	Percent	Category	Freq.	Percent
Impairment	705	26.12%			
Estimated liabilities	328	12.15%			
Depreciation	65	2.41%	CAM_Expenses	1181	43.76%
Expense capitalization	42	1.56%			
Compensation	41	1.52%			
Revenue	482	17.86%	CAM_Revenues	572	21.19%
Account receivable	90	3.33%			
Business combination	253	9.37%	CAM_M&A	253	9.37%
Tax	276	10.23%	CAM_Tax	276	10.23%
Fair value	196	7.26%	CAM_FV	196	7.26%
Lease	89	3.30%			
Regulation	55	2.04%			
Convertible debt	25	0.93%	CAM_Others	221	8.20%
Consolidation	17	0.63%			
Others	35	1.30%			

This table presents the sample selection process and the CAM distribution. Panel A presents our sample selection process. Panel B presents the CAM distribution by the number of CAMs in each report, and Panel C presents the CAM distribution by topic and category.

Table 3.2 : Descriptive Statistics

	N	Mean	STD	Q1	Median	Q3
SD_AQ	1,491	0.023	0.018	0.011	0.017	0.028
Avg_AQ	1,543	0.023	0.021	0.011	0.017	0.027
DA	1,543	0.045	0.038	0.021	0.033	0.055
CAM_N	1,662	1.624	0.751	1	1	2
Loss_Proportion	1,662	0.193	0.294	0.000	0.000	0.286
Sales_Volatility	1,662	0.141	0.159	0.044	0.094	0.181
CFO_Volatility	1,662	0.041	0.045	0.016	0.028	0.049
Total_Assets	1,662	8.429	1.550	7.366	8.277	9.385
Operating_Cycle	1,662	4.619	1.077	4.064	4.594	5.068
Age	1,662	25.780	21.182	9.000	22.000	34.000
Segment	1,662	5.456	3.463	3.000	5.000	7.000
Complexity	1,662	0.014	0.048	0.000	0.000	0.023
High_Growth	1,662	0.190	0.393	0.000	0.000	0.000
Restructuring_Charge	1,662	0.009	0.043	0.000	0.000	0.005
ICW	1,662	0.055	0.229	0.000	0.000	0.000

This table provides descriptive statistics of the variables used to test Hypothesis 1. Variable definitions are provided in Appendix II.

Table 3.3 : Correlation Matrix

Variables	1	2	3	4	5	6	7
1. CAM_N	1.00						
2. SD_AQ	-0.06^{**}	1.00					
3. Avg_AQ	-0.03	0.76^{***}	1.00				
4. DA	-0.07^{**}	0.64^{***}	0.63^{***}	1.00			
5. Loss_Proportion	-0.00	0.44^{***}	0.35^{***}	0.44^{***}	1.00		
6. Sales_Volatility	-0.03	0.15^{***}	0.14^{***}	0.10^{***}	0.07^{***}	1.00	
7. CFO_Volatility	-0.15^{***}	0.55^{***}	0.43^{***}	0.56^{***}	0.41^{***}	0.25^{***}	1.00
8. Total_Assets	0.25^{***}	-0.37^{***}	-0.30^{***}	-0.33^{***}	-0.34^{***}	-0.20^{***}	-0.36^{***}
9. Operating_Cycle	0.04	0.01	-0.03	0.01	0.01	-0.18^{***}	0.00
10. Age	0.08^{***}	-0.23^{***}	-0.24^{***}	-0.28^{***}	-0.29^{***}	-0.12^{***}	-0.20^{***}
11. Segment	0.13^{***}	-0.21^{***}	-0.21^{***}	-0.26^{***}	-0.19^{***}	-0.05^{**}	-0.21^{***}
12. Complexity	-0.01	-0.09^{***}	-0.11^{***}	-0.14^{***}	-0.27^{***}	-0.01	-0.07^{***}
13. High_Growth	0.05^{**}	0.13^{***}	0.09^{***}	0.14^{***}	0.16^{***}	0.04	0.09^{***}
14. Restructuring_Charge	0.06^{**}	-0.01	-0.00	-0.02	0.05^{**}	0.03	-0.03
15. ICW	0.06^{***}	0.07^{**}	0.06^{***}	0.01	0.01	-0.00	-0.01

Variables	8	9	10	11	12	13	14	15
8. Total_Assets	1.00							
9. Operating_Cycle	0.10^{***}	1.00						
10. Age	0.32^{***}	0.07^{***}	1.00					
11. Segment	0.23^{***}	0.15^{***}	0.26^{***}	1.00				
12. Complexity	0.12^{***}	0.03	0.12^{***}	0.26^{***}	1.00			
13. High_Growth	-0.09^{***}	-0.00	-0.13^{***}	-0.12^{***}	-0.05^{**}	1.00		
14. Restructuring_Charge	0.04	0.01	0.03	0.13^{***}	-0.06^{**}	-0.05^{*}	1.00	
15. ICW	-0.06^{**}	0.01	-0.05^{**}	0.04	-0.03	0.03	0.08^{***}	1.00

Mean VIF=1.19

This table reports the correlation matrix for the variables used to test Hypothesis 1. Variable definitions are provided in Appendix II. ***, **, * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 3.4 : Accruals quality and the Number of CAMs

	(1) SD_AQ	(2) Avg_AQ	(3) DA
CAM_N	0.001**	0.002**	0.002**
	(2.049)	(2.484)	(2.255)
Loss_Proportion	0.012***	0.010***	0.021***
	(8.397)	(5.508)	(7.034)
Sales_Volatility	-0.001	0.003	-0.011**
	(-0.309)	(0.980)	(-2.222)
CFO_Volatility	0.169***	0.139***	0.382***
	(16.805)	(11.447)	(19.420)
Total_Assets	-0.002***	-0.001***	-0.002***
	(-6.272)	(-4.168)	(-3.710)
Operating_Cycle	0.001	-0.000	0.001
	(1.394)	(-0.159)	(1.337)
Age	-0.000	-0.000***	-0.000***
	(-1.304)	(-3.619)	(-4.595)
Segment	-0.000**	-0.000***	-0.001***
	(-2.125)	(-3.208)	(-4.212)
Complexity	0.010	-0.001	-0.014
	(1.198)	(-0.092)	(-0.865)
High_Growth	0.002	0.001	0.004**
	(1.597)	(0.733)	(2.061)
Restructuring_Charge	0.000	0.002	-0.002
	(0.043)	(0.166)	(-0.135)
ICW	0.004**	0.005***	0.002
	(2.479)	(2.741)	(0.496)
Intercept	0.026***	0.029***	0.045***
	(8.517)	(8.037)	(7.565)
Adj R^2 / Pseudo R^2	0.383	0.253	0.405
N	1,491	1,543	1,543

This table presents the OLS regression results of Model (3). The dependent variable is accruals quality, which is measured by *SD_AQ*, *Avg_AQ*, and *DA* in Columns 1, 2, and 3, respectively. The independent variable of interest is the number of CAMs disclosed, *CAM_N*. Variable definitions are shown in Appendix II. t-statistics are reported in parentheses, and *** , **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 3.5 : Accruals Quality and the Topics of CAM

	(1) SD_AQ	(2) Avg_AQ	(3) DA
CAM_Expenses	-0.000	-0.001	-0.001
	(-0.357)	(-0.640)	(-0.964)
CAM_Revenues	0.004***	0.005***	0.005***
	(4.236)	(5.214)	(3.204)
CAM_M&A	0.000	0.001	0.003*
	(0.319)	(0.988)	(1.657)
CAM_Tax	0.002*	0.002	0.003
	(1.871)	(1.514)	(1.350)
CAM_FV	0.002	0.005***	0.014***
	(1.383)	(2.996)	(5.212)
CAM_Others	0.001	0.001	-0.000
	(0.893)	(0.500)	(-0.088)
Loss_Proportion	0.012***	0.010***	0.022***
	(8.405)	(5.488)	(7.395)
Sales_Volatility	-0.000	0.005	-0.007
	(-0.013)	(1.559)	(-1.541)
CFO_Volatility	0.164***	0.132***	0.368***
	(16.230)	(10.863)	(18.755)
Total_Assets	-0.002***	-0.001***	-0.002***
	(-5.966)	(-3.909)	(-3.773)
Operating_Cycle	0.000	-0.000	0.000
	(0.820)	(-0.967)	(0.463)
Age	-0.000	-0.000***	-0.000***
	(-0.870)	(-2.904)	(-3.899)
Segment	-0.000**	-0.000***	-0.001***
	(-1.989)	(-2.905)	(-3.978)
Complexity	0.008	-0.002	-0.013
	(1.024)	(-0.156)	(-0.822)
High_Growth	0.002	0.001	0.003*
	(1.548)	(0.539)	(1.646)
Restructuring_Charge	0.002	-0.001	0.001
	(1.269)	(-0.474)	(0.281)
ICW	0.004**	0.006***	0.002
	(2.508)	(2.835)	(0.737)
Intercept	0.026***	0.030***	0.048***
	(8.529)	(8.171)	(8.086)
Adj R^2 / Pseudo R^2	0.399	0. 270	0.412
N	1,491	1,543	1,543

This table presents the OLS regression results of Model (4). The dependent variable is accruals quality, which is measured by *SD_AQ*, *Avg_AQ*, and *DA* in Columns 1, 2, and 3, respectively. The independent variable of interest is the number of CAMs in each category, *CAM_Expenses*, *CAM_Revenues*, *CAM_M&A*, *CAM_Tax*, *CAM_FV*, and *CAM_Others*. Variable definitions are shown in Appendix II. t-statistics are reported in parentheses, and *** , **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 3.6 : The Effect of Financial Expertise of the Audit Committee

	(1) SD_AQ	(2) Avg_AQ	(3) DA
CAM_N	0.003**	0.004**	0.007***
	(2.316)	(2.433)	(2.724)
Fin_Expert	0.005	0.004	0.009
	(1.549)	(1.137)	(1.427)
CAM_N×Fin_Expert	-0.003*	-0.004*	-0.008**
	(-1.757)	(-1.776)	(-2.144)
Loss_Proportion	0.013***	0.010***	0.022***
	(8.500)	(5.636)	(7.227)
Sales_Volatility	-0.000	0.003	-0.009*
	(-0.134)	(0.900)	(-1.792)
CFO_Volatility	0.174***	0.145***	0.377***
	(16.456)	(11.679)	(18.004)
Total_Assets	-0.002***	-0.001***	-0.002***
	(-6.031)	(-3.595)	(-3.160)
Operating_Cycle	0.001	-0.000	0.001
	(1.376)	(-0.393)	(1.312)
Age	-0.000	-0.000***	-0.000***
	(-1.435)	(-3.695)	(-4.207)
Segment	-0.000*	-0.000***	-0.001***
	(-1.756)	(-3.052)	(-4.069)
Complexity	0.004	-0.004	-0.019
	(0.404)	(-0.373)	(-0.980)
High_Growth	0.002*	0.002	0.004**
	(1.657)	(1.382)	(2.224)
Restructuring_Charge	-0.010	-0.005	-0.050**
	(-0.872)	(-0.403)	(-2.181)
ICW	0.005***	0.005**	0.002
	(2.631)	(2.516)	(0.703)
Intercept	0.022***	0.026***	0.037***
	(6.129)	(6.016)	(5.194)
Adj R^2 / Pseudo R^2	0.392	0.270	0.397
N	1,386	1,432	1,432

This table presents the OLS regression results of Model (5). The dependent variable is accruals quality, which is measured by *SD_AQ*, *Avg_AQ*, and *DA* in Columns 1, 2, and 3, respectively. *Fin_Expert* is the proportion of financial experts on the audit committee. The variable of interest in the model is the interaction term between the number of CAMs and the proportion of financial experts, *CAM_N×Fin_Expert*. Variable definitions are shown in Appendix II. t-statistics are reported in parentheses, and *** , **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 3.7 : Premature Revenue Recognition and the CAMs Related to Revenues

	(1) Avg_ Premature	(2) SD_ Premature
CAM_Revenues	0.004***	0.003***
	(6.772)	(5.049)
Loss_Proportion	0.003**	0.004***
	(2.367)	(3.347)
Sales_Volatility	0.013***	0.014***
	(6.987)	(6.742)
CFO_Volatility	0.021***	0.043***
	(3.061)	(5.207)
Total_Assets	-0.001***	-0.002***
	(-7.002)	(-7.530)
Operating_Cycle	0.001***	0.001***
	(3.417)	(4.379)
Age	-0.000**	-0.000
	(-2.387)	(-0.925)
Segment	0.000	0.000*
	(0.595)	(1.751)
Complexity	-0.014**	-0.024***
	(-2.380)	(-3.352)
High_Growth	0.002**	-0.000
	(2.336)	(-0.315)
Restructuring_Charge	0.001	0.001
	(0.671)	(0.924)
ICW	0.001	0.001
	(0.783)	(0.771)
Intercept	0.016***	0.017***
	(7.532)	(6.703)
Adj R^2 / Pseudo R^2	0.181	0.192
N	1,657	1,650

This table presents the OLS regression results of the association between companies' revenue management and the number of CAMs related to revenues. The dependent variable is revenue management, which is measured by *Avg_Premature* and *SD_Premature* in Columns 1 and 2, respectively. The independent variable of interest is the number of CAMs related to revenues, *CAM_Revenues*. Variable definitions are shown in Appendix II. t-statistics are reported in parentheses, and *** , **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 3.8 : Other Proxies of Accruals Quality and the Number of CAMs

	(1) DA_Jones	(2) Hist_Restate	(3) Persistence	(4) Prediction
CAM_N	0.003***	0.028*	-0.056***	-0.051**
	(2.611)	(1.747)	(-2.737)	(-2.228)
Loss_Proportion	0.038***	0.067	0.026	0.031
	(10.809)	(1.449)	(0.453)	(0.476)
Sales_Volatility	0.000	0.194**	-0.169*	-0.145
	(0.075)	(2.531)	(-1.731)	(-1.330)
CFO_Volatility	0.389***	-0.442	0.632*	0.413
	(16.403)	(-1.499)	(1.668)	(0.978)
Total_Assets	-0.003***	0.000	0.032***	0.021*
	(-4.039)	(0.027)	(2.890)	(1.700)
Operating_Cycle	0.000	0.031***	-0.057***	-0.052***
	(0.271)	(2.801)	(-4.063)	(-3.354)
Age	-0.000***	-0.001	-0.002***	-0.002**
	(-5.022)	(-1.135)	(-2.948)	(-2.171)
Segment	-0.001***	0.004	-0.009*	-0.005
	(-2.967)	(1.191)	(-1.874)	(-0.938)
Complexity	-0.059***	0.262	0.473	0.098
	(-3.048)	(1.016)	(1.459)	(0.271)
High_Growth	0.006***	-0.061**	0.078**	0.092**
	(2.641)	(-2.028)	(2.020)	(2.136)
Restructuring_Charge	-0.018	0.207	-0.595*	-0.583
	(-0.864)	(0.765)	(-1.761)	(-1.549)
ICW	0.008**	0.243***	-0.237***	-0.223***
	(2.055)	(4.781)	(-3.391)	(-2.850)
Intercept	0.054***	0.108	0.624***	0.663***
	(7.560)	(1.222)	(5.536)	(5.283)
Adj R^2 / Pseudo R^2	0.427	0.025	0.040	0.022
N	1,543	1,662	1,578	1,576

This table presents the regression results of Model (3), where the measures for the dependent variable, accruals quality, are replaced with four alternative measures. The alternative measures are *DA_Jones*, *Hist_Restate*, *Persistence*, and *Prediction* in Columns 1, 2, 3, and 4, respectively. The independent variable of interest is the number of CAMs disclosed, *CAM_N*. Variable definitions are shown in Appendix II. t-statistics are reported in parentheses, and *** , **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Conclusion

In this thesis, I examined whether the gender of top managements affects companies' voluntary disclosure and whether critical audit matters disclosed in auditing reports indicate companies' accruals quality. I find that companies with female CEOs are more likely to provide earnings forecasts and their forecasts are more accurate and that companies with female CFOs tend to provide more conservative forecasts. In the third essay examining critical audit matters, I find that the number of critical audit matters are negatively associated with the companies' accrual quality and this association is mitigated in the companies with effective audit committees.

According to the previous literature, CEOs play a crucial role in deciding firm-level forecasting policy, while CFOs participate in the preparation and discussion of guidance (Brochet, Faurel, and McVay, 2011). Since CEOs and CFOs influence companies' forecasting behavior in different mechanisms, I respectively investigate how the gender of CEOs and CFOs affect companies' earnings forecasts in the first and second essays.

In the first essay, we (my coauthors and I) find that female CEOs are more likely to provide earnings forecasts and their forecasts are relatively more accurate than those of male CEOs. The bias against women is prevalent in top management, and female CEOs may face prejudice because of their gender. Female CEOs are subjected to greater media scrutiny and have higher pressure to demonstrate their ability and establish their reputation. Baik, Farber, and Lee (2011) argue that CEOs may use earnings forecasts to reveal their ability and that high-ability CEOs provide forecasts more frequently and provide more accurate forecasts. Accordingly, we expect female CEOs are associated with higher forecast frequency and forecast accuracy. We further examine whether the gender of CEOs has an influence on the number of financial analysts following. We find that in general, analysts prefer to follow the companies with male CEOs. However, female CEOs' provision of more accurate forecasts helps eliminate this gap.

In the second essay, I investigate whether female CFOs provide more conservative forecasts. Since females are more risk averse and more likely to be punished for management failures, female CFOs may provide less optimistic forecasts which will lead to a lower risk of missing the expectation of stakeholders. I further examine the possible consequences of this gender difference in management forecasting. As female CFOs provide lower forecasts, it is easier for the actual earnings of female CFOs to meet or beat their own forecasts than those of male CFOs. Therefore, female CFOs have less need to adjust their street earnings upward. Managers' engagement in earnings forecasts will lead to overvalued equity and stock price crash, and as a result, I expect companies with female CFOs have lower stock price crash risk. The empirical results support all these hypotheses.

In the third essay, we examine whether critical audit matters are associated with companies' accruals quality. We find that the higher number of CAMs are associated with lower accruals quality, and this association is mitigated in companies with a high-quality audit committee. We also investigate the relationship between CAMs topics and accruals quality and find that revenue-related CAMs and fair value estimation -related CAMs are the primary drivers of poor accruals quality.

Appendix

Appendix 1-1: Variable Definitions for Chapter 1

Variable Name	Definition
Main Variables	
FCEO	An indicator variable equal to 1 when the CEO is a female, and to 0 when the CEO is a male.
MF	An indicator variable equal to 1 when the company issues annual earnings forecasts, and to 0 otherwise.
MFE	Management earnings forecast error, measured as the absolute difference between the management earnings forecast per share and the actual earnings per share (street earnings), divided by the stock price and multiplied by 100.
FOLLOW	The number of analysts following the company.
LEAD_FOLLOW	The number of analysts following the company in the subsequent year.
LOW_MFE	An indicator variable equal to 1 if the company provides a management forecast and the MFE is below the sample median, and to 0 otherwise.
HIGH_MFE	An indicator variable equal to 1 if the company provides a management forecast and the MFE is above the sample median, and to 0 otherwise.
Other Variables	
ROA	Return on assets, measured as net income divided by total assets.
ADJROA	Average ranked industry-adjusted ROA for the previous (up to) three years for the same CEO.
DEASCORE	Firm efficiency of generating output (sales) with various inputs (cost of goods sold, acquired assets, R&D expenditures, goodwill, SG&A expenditures, operating leases, and other intangible assets), calculated using data envelopment analysis.
LOSS	An indicator variable equal to 1 if the firm's current earnings are negative, and to 0 otherwise.
VOLATILITY	Stock return volatility, measured as the standard deviation of the company's monthly stock returns in the previous 12 months.
NEGCHG	An indicator variable equal to 1 when current earnings are smaller than the previous year's earnings, and to 0 otherwise.
ABSCHG	The absolute value of the difference between the current and previous annual earnings per share, divided by the stock price.
DISTRESS	Financial distress, measured using Zmijewski's (1984) Z-Score.

MB	The ratio of the market value per share to the book value per share.
SIZE	Natural logarithm of total assets.
BIG	An indicator variable equal to 1 if the company is audited by a Big N firm, and to 0 otherwise.
INST_OWN	The percentage of institutional ownership.
GAP_MF	The number of calendar days from the issuance of the management forecast to the end of the fiscal year, divided by 365 (days).
GAP_AF	The average number of calendar days between analyst forecasts and the end of the fiscal year, divided by 365 (days).
ABSAEM	The absolute value of performance-adjusted discretionary accruals, estimated using Kothari et al.'s (2005) model.
ABSREM	The absolute value of the abnormal cash flow from operations, measured using Roychowdhury's (2006) model.
FREQUENCY	The number of annual management earnings forecasts disclosed in one year, including forecast revisions.
FILESIZE	The natural logarithm of the total number of characters in the 10-K filing without tables or exhibits.
WORD	The natural logarithm of the number of words in the 10-K filing.
EXHIBIT	The number of exhibits in the 10-K filing.
UNIQUE	The natural logarithm of the number of unique words in the 10-K filing.
AVG_LENGTH	Average number of words per sentences, defined as the number of words divided by the number of sentences in the 10-K filing.
GUNNING_FOG	A measure for the readability developed by Gunning (1952), calculated as 0.4 x (average length of sentences + percentage of complex words).
SMOG_FOG	A measure for the readability developed by Mc Laughlin (1969). This index estimates the years of education a person needs to comprehend the 10-K report.
AFE	Analyst forecast error, measured as the difference between the analyst consensus earnings forecast per share and the actual earnings per share reported (street earnings), divided by the stock price and multiplied by 100.
AF_DISP	The standard deviation of analyst earnings forecasts per share, divided by the stock price.
LAFE	Average analyst forecast error in the previous year, divided by the stock price and multiplied by 100.
LAF_DISP	Analyst forecast dispersion in the previous year.
FIRST	An indicator variable equal to 1 for the first year a company is covered by analysts (no analyst follows the company in the previous three years), and to 0 otherwise.

TRADE_VOL	Annual trading volume, measured as the sum of the daily trading volume during that year (in units of hundred million shares).
F_TRANS	An indicator variable equal to 1 for observations in the treatment sample of male-to-female CEO transitions, and to 0 for observations in the control sample of male-to-male CEO transitions.
POST	An indicator variable equal to 1 for observations after the CEO transition, and to 0 otherwise.
TENURE	The number of years the CEO has occupied that post.
BEAT	An indicator variable equal to 1 if actual earnings exceed the manager's forecast, and to 0 otherwise.
AVG_ROA	The average return on assets (ROA) in the 3 years prior to the CEO transition.
ROA_Y1	Return on assets (ROA) in the year prior to the CEO transition.
ROA_Y2	Return on assets (ROA) in the second year prior to the CEO transition.
ROA_Y3	Return on assets (ROA) in the third year prior to the CEO transition.
AVG_AR	The average market-adjusted abnormal return (AR) in the 3 years prior to the CEO transition.
AR_Y1	Market-adjusted abnormal return in the year prior to the CEO transition.
AR_Y2	Market-adjusted abnormal return in the second year prior to the CEO transition.
AR_Y3	Market-adjusted abnormal return in the third year prior to the CEO transition.
FCFO	An indicator variable equal to 1 when the CFO is female, and to 0 when the CFO is male.

Appendix 2-1: Variable Definition for Chapter 2

Variable Name	Definition
Main Variables	
FCFO	An indicator variable equal to 1 when the CFO is a female, and to 0 when the CFO is a male.
FORECAST	The guidance value given in the last management earnings forecasts before the fiscal year end. For a range forecast, this variable is equal to the lower bound of the range.
MEET	An indicator variable equal to 1 when the company's realized annual earnings per share before extraordinary items (GAAP earnings) meet or beat the management earnings forecasts, and to 0 otherwise.
BIAS	Management forecast of annual earnings per share minus realized earnings per share before extraordinary items (GAAP earnings). If BIAS>0, the earnings forecast is positively biased.
MFE	The absolute value of BIAS. A higher value of MFE represents lower earnings forecast accuracy.
ADJUST	The actual earnings per share from I/B/E/S (street earnings) minus the realized earnings per share from Compustat (GAAP earnings). If ADJUST>0, more negative items are excluded from the street earnings than positive items are.
STMEET	An indicator variable equal to 1 when the actual earnings per share from I/B/E/S (street earnings) meet or beat the management earnings forecasts, and to 0 otherwise.
CRASH	An indicator variable equal to 1 if the firm experiences one or more firm-specific crash weeks during the fiscal year, and to 0 otherwise. Crash weeks are defined as weeks during which the firm experiences firm-specific weekly returns 3.2 standard deviations (0.1% in the normal distribution) below the mean firm-specific weekly returns over the fiscal year.
DUVOL	Natural logarithm of the standard deviation of the firm-specific weekly return in the down weeks to the standard deviation of the firm-specific weekly return in the up weeks.
NCSKEW	Negative coefficient of skewness of firm-specific weekly returns, measured as the negative of the third moment of firm-specific weekly returns for each firm in a fiscal year divided by the standard deviation of firm-specific weekly returns raised to the third power.

Other Variables	
LAG_EPS	Realized earnings per share before extraordinary items (GAAP earnings) of the previous year.
LAG_PRICE	Stock price at the end of last fiscal year.
VOLATILITY	Stock return volatility, measured as the standard deviation of the company's monthly stock returns in the previous 12 months.
CHANGE	Annual earnings per share of the current year minus the annual earnings per share of the previous year. A positive CHANGE represents an increase in earnings.
DISTRESS	Financial distress, measured by Zmijewski's (1984) Score.
LITIRISK	Corporate litigation risk, an indicator variable equal to 1 for firms in the high-litigation industries identified in Francis, Philbrick, and Schipper (1994), and to 0 otherwise.
MB	Market to book ratio.
SIZE	Natural logarithm of total assets.
FOLLOW	The total number of analysts following during the year.
HORIZON	The number of calendar days between the issuance of the last management earnings forecast and the end of fiscal years, divided by 365 (days).
INST_OWN	Percentage of the common stock held by institutions.
COMP_AGE	The number of years that the company is included in COMPUSTAT.
SEGMENT	The total number of operational and geographical segments.
RET	The mean of firm-specific weekly returns over the fiscal year, times 100
SIGMA	The standard deviation of firm-specific weekly returns over the fiscal year.
ROA	Return on assets, measured as net income divided by total assets.
LEV	Leverage, measured as total debt divided by total assets.
F_TYPE	Earnings forecast precision, equals to 1 for open-ended forecasts, to 2 for range forecasts, and to 3 for point forecasts.

Appendix 3-1: Variable Definitions for Chapter 3

Variable Name	Definition
Dependent variables	
SD_AQ	The standard deviation of the yearly residuals over the period 2012-2018, calculated from Model (1). We require each company to have at least four years of data.
Avg_AQ	The average yearly absolute residual over the period 2012-2018, calculated from Model (1). We require each company to have at least four years of data.
DA	The average yearly absolute value of discretionary accruals over the period 2012-2018, calculated from Model (2). We require each company to have at least four years of data.
DA_Jones	The average yearly absolute discretionary accruals over the period 2012-2018, calculated from the Jones model.
Hist_Restate	An indicator variable equal to 1 if the company restated its financial statements at least once during the period 2012-2018, and to 0 otherwise.
Persistence	The coefficient of the firm-specific regressions of the next year’s earnings (earnings before long-term accruals) on the current year’s earnings (Model 7).
Prediction	The coefficient of the firm-specific regression of the next year’s cash flow from operations on the current year’s earnings (earnings before long-term accruals) (Model 8).
Avg_ Premature	The average absolute yearly discretionary revenues over the period 2012-2018, calculated using Model (6).
SD_ Premature	The standard deviation of the yearly residuals over the period 2012-2018, calculated from Model (6).
Independent variables	
CAM_N	The number of critical audit matters disclosed in the 10-K form for the fiscal year 2019.
CAM_Expenses	The number of critical audit matters related to expenses (see Appendix II).
CAM_Revenues	The number of critical audit matters related to revenue recognition (see Appendix II).
CAM_M&A	The number of critical audit matters related to merger and acquisition activities (see Appendix II).

CAM_Tax	The number of critical audit matters related to tax (see Appendix II).
CAM_FV	The number of critical audit matters related to the evaluation of firms' financial assets/liability (see Appendix II).
CAM_Others	The number of critical audit matters not belonging to the above five categories (see Appendix II).
Fin_Expert	The proportion of financial experts (as defined by SEC rules) on the audit committee in 2019.
Control variables	
Loss_Proportion	The proportion of years with negative income before extraordinary items during the years 2012-2018.
Sales_Volatility	The standard deviation of sales scaled by average total assets over the years 2012-2018.
CFO_Volatility	The standard deviation of the cash flow from operations scaled by average total assets over the years 2012-2018.
Total_Assets	Natural logarithm of total assets in 2019.
Operating_Cycle	Natural logarithm of the operating cycle in 2019, calculated as: 365/(Sales/Average Accounts Receivable)+365/(Cost of Goods Sold/Average Inventory).
Age	The number of years the company has been appearing on CRSP as of 2019.
Segment	The sum of the company's operating and geographic segments in 2019.
Complexity	Foreign pretax income scaled by total assets in 2019.
High_Growth	An indicator variable that is equal to 1 if the company's industry-adjusted sales growth from 2018 to 2019 falls into the top quintile, and to 0 otherwise.
Restructuring_Charge	The sum of restructuring charges in 2018 and 2019, divided by the market capitalization in 2019.
ICW	Internal control weaknesses. An indicator variable that is equal to 1 if the company's disclosure controls (SOX 302) or internal controls (SOX 404) are ineffective, as reported by Audit Analytics, and to 0 otherwise.
Variables used to estimate the dependent variables	
ΔWC	The annual change in working capital accounts from the previous year.

CFO	Cash flow from operations.
∆Sales	The annual change in sales from the previous year.
PPE	Property, plant, and equipment.
TAC	Total accruals, measured as the difference between income before extraordinary items and the cash flow from operations.
ROA	Return on assets, measured as net income divided by lagged total assets.
∆AR	The annual change in accounts receivable from the previous year.
GRR_P	Industry-median-adjusted sales growth rate if positive (equal to 0 if negative), calculated as the ratio of current to prior-year sales less the median yearly industry growth rate.
GRR_N	Industry-median-adjusted sales growth rate if negative (equal to 0 if positive), calculated as the ratio of current to prior-year sales less the median yearly industry growth rate.
GRM	Industry-median-adjusted gross margin, calculated as the gross margin less the median industry gross margin.
GRM_SQ	The squared industry-median-adjusted gross margin.
Age_SQ	The squared firm age.
Earn	Earnings before long-term accruals, calculated as the cash flow from operations (*CFO*) plus the change in working capital (*∆WC*).

Appendix 3-2: CAM Category Classification

	Topic	Definition	Category
1	Impairment	Valuation of the carrying value of tangible or intangible assets.	
2	Estimated liabilities	Estimated liability, including contingent liabilities and warranty liability.	
3	Depreciation	Depreciation/amortization/depletion of tangible or intangible assets.	CAM_Expenses
4	Expense capitalization	Capitalized expenses/costs	
5	Compensation	Compensation/pension/other employee benefits	
6	Revenues	Revenue recognition	CAM_Revenues
7	Accounts receivable	Accounts receivable/loans receivable/ credit losses/Allowance for credit losses	
8	Business combination	Merger & acquisition/discontinued operation	CAM_M&A
9	Tax	Income taxes/deferred tax assets/ unrecognized tax benefits/other tax-related issues	CAM_Tax
10	Fair value	Valuation of the fair value of financial assets/liabilities	CAM_FV
11	Lease	Issues related to leases, including the adoption of the new lease accounting standard.	
12	Regulation	Risk related to compliance with laws and regulations.	
13	Convertible debt	Convertible debt.	CAM_Others
14	Consolidation	Business consolidation.	
15	Others	Others (e.g., disclosure, audit procedures).	

Appendix 3-3: CAM Example

Inventory Valuation

Description of the Matter

On December 28, 2019, the Company’s net inventory balance was $982 million. As discussed in Note 2 of the consolidated financial statements, the Company adjusts the inventory carrying value to the lower of the actual cost or the estimated net realizable value after completing ongoing reviews of on-hand inventory quantities in excess of forecasted demand, by considering recent historical activity as well as anticipated or forecasted demand.

Auditing management’s inventory carrying value adjustments involved significant judgment because the estimates are based on a number of factors affected by the market, industry, and competitive conditions outside the Company's control. In particular, in estimating inventory carrying value adjustments, management developed assumptions such as forecasts of future sales quantities and selling prices, which are sensitive to the competitiveness of product offerings, customer requirements, and product lifecycles. These significant assumptions are forward-looking and could be affected by future economic and market conditions.

CAM number

1

CAM topic

Impairment

CAM category

CAM_Expenses