THREE ESSAYS ON CORPORATE FINANCIAL DISCLOSURES

By YINAN YANG

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ABSTRACT OF THE DISSERTATION

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This dissertation consists of three papers. In the first paper we identify a new incentive for managers in determining management forecast (MF) characteristics stemming from the relative performance evaluation feature of CEO promotion tournaments. We document higher credibility of MF for firms with stronger tournament incentives (as proxied for by the CEO pay gap). We posit that the relative performance evaluation feature of CEO promotion tournaments creates mutual monitoring mechanism within the management team as well as the incentives for lower-ranked executives to provide high quality information to gain better evaluation results. We thereby extend previous MF literature that focuses mainly on equity-based incentives and reports mixed findings. Our results are robust to using different tournament measures, controlling for other known determinants of MF characteristics as well as manager skills, and corrections of endogeneity of all specifications.

In the second paper, we investigate the spill-over effect of customer fraud on non-fraudulent suppliers' investment decisions. We posit that suppliers utilize customers' information to infer future demand and economic prospects, and noisy information distorts and misguides the investment and productions decisions made by suppliers. The

overinvestment and misrepresented performance of customers signal a high demand and prosperous economic prospects for suppliers, resulting in overinvestment decisions by suppliers. We find that suppliers invest more during the fraud periods of customers. The degree of distortion is less severe when the supplier operates in concentrated industry and more severe when suppliers have higher sales volatility. In addition, we show that the overinvestments by suppliers are inefficient as associated future cash flows are significantly reduced. Our results are robust to different fraud samples, alternative research methodology, and controlling for other known determinants of investment decisions.

In the third paper, we investigate whether firms engaging in corporate fraud take advantages of strategic timing of earnings announcements (EA). We document that misreporting firms strategically time their EA in low attention periods (i.e. after trading hours) during violation years. In addition, we show that the timing strategy is followed by a longer detection period and more insider trading. We thereby extend previous corporate disclosure timing literature that mainly focuses on the content of reported news. We also extend the corporate fraud literature by showing a low-cost way in which firms can possibly “hide” the manipulated earnings. Our results are robust to different samples of fraud, different research methodology, different sample periods, and controlling for other known determinants of market attention.

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The basis for this research originally stemmed from my passion for a better understanding of firms' disclosure decisions. Managerial incentives matter in this process and the consequences of the disclosure choices not only affect the firm itself, but also non-financial stakeholders such as industry peers and suppliers

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I hope you enjoy your reading.

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CHAPTER 1: IMPACT OF TOURNAMENT INCENTIVES ON MANAGEMENT EARNINGS FORECASTS

1.1 Introduction

According to the tournament theory used in the business environment, best performers in the rank order tournament in a firm receive preference over others for promotion to the next higher rank ((Lazear and Rosen, 1981).[1] Some authors have, however, pointed out that the rank order tournaments are associated with negative consequences, which are referred to as dysfunctional consequences, and they include excessive risk taking (Knoeber and Thurman 1994; and Prendergast 1999), cheating (Cheng 2011), fraud (Haß, Müller, and Vergauwe 2015), and sabotage of competitors (Harbring and Irlenbusch 2011). Despite these potential negative consequences, firms are more impressed with the positive aspects of competitive tournaments and favor organizing rank order tournaments because they incentivize managers to work harder to win the tournament prize of promotion to the next higher level, which enhances their pay, and results in improving firms' overall performance (e.g. Kale, Reis, and Venkateswaran 2009).

Extending this line of research, we argue that hard work of participants in the rank-order tournament is also expected to have a significant influence on the quality of information, including future-oriented information contained in MEFs. In other words, we argue that

[1] The concept of firm-specific tournament has been expanded to the industry-wide competitive tournament where participants from different firms are motivated to compete for a CEO position in a particular firm with tournament prize, i.e. higher CEO salary in the industry (e.g. Coles, Li, and Wang 2013). Lately, it has also been extended to geographic level, where participants compete for the CEO position with the highest salary in a particular geographic region (e.g. Yin 2016)

the rank order tournament is likely to result in high quality information, which will enable CEOs, CFOs, or other managers at the higher levels, to issue MEFs that will also be of higher quality. Thus, we conjecture in this study that firms with rank order tournament incentives will issue MEFs that are of higher quality compared to MEFs issued by firms without tournament incentives, and we measure the MEF quality using the MEF attributes of accuracy and precision (e.g. Hirst Koonce, and Venkataraman. 2008).

Our expectation of the positive association between tournament incentives and MEF quality is based on the assumption that information provided by tournament participants, which will serve as an input to develop the MEFs, is expected to be of high quality compared to information used by firms without tournament incentives. The higher quality of information for firms with competitive tournament is supported based on the following arguments.

First, information provided by managers participating in the rank order tournament to the Disclosure Committee, consisting of top management and other managers (e.g. Brochet, Faurel, and McVay 2011), is expected to be of high quality because it will be used for the purposes of their own performance evaluation. (e.g. Keating 1997). Second, we expect the competitive tournament environment to result in strict internal monitoring to ensure that all participating managers follow the rules and regulations to ensure that information provided by them is not contaminated. The superior managers will ensure that tournament participating managers are providing unbiased information that will be used to evaluate them for promotion to the higher rank. If quality of this information is considered questionable because of massaging of information, such as, earnings manipulations, there will be heavy penalty, which may even include loss of tournament trophy (Dyck Morse, and Zingales 2010; Fauver and Fuerst 2006). Third, in addition to monitoring by superior managers, there may also be intra-group monitoring of each other because the participating members would be concerned about cheating by other members (Li 2014). Thus, it will motivate all participating members to keep a strict watch over each other's activities. Fourth, the quality of information is likely to be positively influenced by the participants' strong incentives to project their long horizon and it will avoid short-term focus that may convey negative signals on their capabilities (e.g. Acharya, Myers and Rajan 2011). Moreover, their focus on the long horizon will especially be desirable when they wish to be considered for promotion to the rank of CEO because a long-horizon approach is considered to be an important quality for CEOs to enhance firm value (Dechow and Sloan 1991).

Consistent with Hirst, et al (2008), we measure the quality of MEFs in terms of forecast accuracy and precision. We conduct analyses based on a sample of 28,337 observations. Consistent with the existing literature, we measure the tournament prize size as the natural logarithm of the pay gap between the CEO and other VPs (Kale et al. 2009). The results of our analyses show that there is a significantly positive association between tournament incentives and quality of MEFs (i.e. forecast accuracy and precision), confirming our expectation that firms with rank order tournament incentives issue MEFs that are of higher quality compared to the firms that do not have such incentives. We also find higher frequency of MEFs for firms with rank order tournament incentives, suggesting that these firms are more likely to update their forecasts and keep the market informed when changes are expected in future performance of the firm.

Next, we examine whether industry homogeneity and new CEO will affect the association between tournament incentives and MEF quality. First, it is argued that industry homogeneity opens opportunities for tournament participants to look for higher positions in other firms in the same industry group. We present that the availability of wider opportunities to the participants is likely to serve as a moderating factor because it will dampen participants' motivations to work hard to provide high quality information to superiors. Moreover, this situation will open up other avenues for firms to hire from outside the firm, which will send a negative signal to participants for promotion to the higher rank and thus participants' enthusiasm to work hard may also be dampened. Similarly, a new CEO in the firm will convey a negative signal to the tournament participants that promotion to the rank of CEO may not be available for quite some time and this will have a moderating effect on the association between tournament incentives and MEF quality. The results of empirical tests confirm the expectation of a moderating effect of industry homogeneity and new CEO on the positive association between tournament incentives and MEF quality.

We conduct several tests to confirm that our results are robust. First, we examine the impact of CEO ability and CEO fixed effects, and the results show that our results still hold and are not driven by these factors. Second, we examine the impact of corporate governance effectiveness on our findings. The results show that corporate governance also has an impact on MEF quality, but our results remain statistically unchanged when these factors are considered in our analyses. Third, we use alternative measures for tournament incentives, and our main findings remain unchanged. Finally, we examine whether there are any endogeneity concerns that would have an influence on our findings. We used the IV approach and we find that our results are not influenced by endogeneity concerns.

We conducted additional analyses to evaluate whether market participants and security analysts would recognize high quality of MEFs issued by firms with tournaments incentives. The results on the market reaction have confirmed that market participants reacted more positively to MEFs issued by firms with tournament incentives, suggesting that they recognized high quality of MEFs issued by these firms compared to MEFs issued by firms without tournaments. Similarly, the results based on the security analysts' reaction provided additional support to our expectation of high quality of MEFs issued by firms with tournament incentives.

Our paper makes several contributions to the MEF literature. First, to our knowledge, this is the first paper that emphasizes the important role of tournament incentives in enhancing MEF quality. The MEF quality has been examined from different perspectives in the literature, such as accuracy, precision, frequency, managerial motivation to disclose MEFs, security analysts' reaction forecasts, and investors' reaction to forecasts, etc. Our findings add to the existing findings that rank order tournaments in firms also have a significant influence on the disclosure policy of MEFs and they impact frequency, accuracy and precision of forecasts, and thus enhance the MEF quality. Second, our findings confirm that MEFs are the outcomes of efforts by several executives, who may contribute in different ways in developing quality MEFs. This finding implies that coordination among different executives, reflecting cumulative efforts of the management team associated with developing MEFs, is also an important factor to enhance the quality of MEFs. Our results show that properly coordinated efforts of several executives result in high quality of MEFs. Third, our findings add to the literature on the rank order tournaments in firms. The existing literature shows that tournaments serve as important tools to improve firm efficiency, deal with management compensation issues, motivate managers to put in their best effort to achieve company overall objectives, etc. Our findings add to these findings and show that the tournament objectives can also an important role in improving the quality of information and especially of future-oriented information contained in MEFs. In this paper, we especially highlight the role of tournament incentives in enhancing the quality of MEFs.

These findings provide useful information to investors, regulators, and researchers. While examining the quality of MEFs, investors can determine whether the firm has tournament incentives. The MEFs issued by firms with tournament incentives can be expected to have higher reliability and credibility. The regulators may use this information in developing regulations to ensure higher quality of disclosures made by firms to the outside users. This study should encourage researchers to conduct additional research into different issues related to the usefulness of MEFs and impact of MEFs on decisions by users of the financial information.

The reminder of the paper proceeds as follows. Section 2 develops the hypotheses based on prior literature. Section 3 on research methodology describes data, variable measurements and model specifications. Section 4 presents regression results, whereas sections 5, 6, and 7 discuss and contain results on robustness checks and additional tests. Conclusion is presented in Section 8.

1.2 Literature Review and Hypothesis Development

1.2.1 Literature Review

Our research review covers two streams of literature. First, we review the literature on voluntarily issued MEFs, including incentives for issuing MEFs. Second, we discuss the literature on the rank-order tournament incentives that have an impact on firm-specific performance, information generation process, and accounting disclosure policies.

Literature on Management Earnings Forecasts

Management earnings forecasts (MEFs) have been examined in the literature from different perspectives, such as motivation to issue MEFs, different attributes of MEFs (i.e. frequency, accuracy, precision of forecasts), market reaction to MEFs, etc. In general, managers voluntarily provide MEFs to achieve different objectives, such as self-serving goals, signal information to the market on upcoming earnings surprises (Kasznik and Lev 1995), reduce litigation risk (Skinner 1994), adjust investors' expectations (Waymire 1986; Cotter Tuna, and Wysocki 2006), develop reputation for providing transparent information (Graham, Harvey, and Rajgopal 2005), etc. On an overall basis, managers are likely to provide forecast information only when benefits outweigh costs.

Among different incentives, CEOs' are also motivated to issue MEFs that are influenced by the equity-based compensation and/or personal benefits.[2] It is argued that CEOs and other managers, who have superior information than outsiders, may use private information for personal benefits. For example, it has been presented in the literature that there is a link between the timing of MEFs and trading in the company stock (e.g. Penman 1982). Noe (1999) find that managers engage more in selling activity after issuing a price-increasing forecast and engage more in buying activity after issuing a price-decreasing forecast. Similarly, Cheng and Lo (2006) document that CEOs and other top managers strategically

[2] Examples include compensations based on stock option grants (Yermack 1997; Aboody and Kasznik 2000), and insider trading (Cheng and Lo 2006).

choose disclosure policy that they can use to make on their stock transactions. Aboody and Kasznik (2000) find that CEOs voluntarily time their disclosures around the stock option awards to maximize their stock option compensation. Thus, findings of these studies demonstrate that the issuance of MEFs may be influenced by personal benefits of top managers.

Recent studies have pointed out that incentives of non-CEO executives also influence the quality of information used in developing MEFs, thus influencing the quality of MEFs (Bamber, Jiang, and Wang 2010). The incentvies of non-CEO executives especially assume an important role when MEFs are the outcome of a teamwork consisting of CEO and other managers. A study by Kwak, Ro and Suk (2012) point out that many firms' disclosure decisions are made by a group of principal managers, in the form of a disclosure committee, and not just one single individual. Bertrand and Schoar (2003) also argue that a firm's policies are made as the outcomes of teamwork by its top executives. Recently, based on prior research on top management teams (TMTs), Wang (2015) provides evidence that top executives' functional diversity can influence management guidance. While the CEO behavior primarily responds to the performance-based incentives, non-CEO executives are expected to respond to both performance-based and tournament incentives (e.g., Baker, Jensen and Murphy 1988; Green and Stokey 1983). Consistent with these views, we present in this study that tournament incentives may play an important role in motivating non-CEO top managers to provide higher quality information in developing MEFs.

Recently, a study by Hirst, et al. (2008) has pointed out that not much attention has been paid in the literature to the MEFs' attributes such has frequency, accuracy, and precision of MEFs. They argue that these attributes are important to measure the quality of MEFs, and managers may also use these attributes to convey a message to investors that is consistent with their objectives. We expand this line of research and examine whether there is a link between MEF attributes and competitive tournament incentives.

Literature on Rank Order Tournament Incentives

Rosenbaum (1979) and Lazear and Rosen (1981) originally suggested that the relative performance evaluation scheme under certain circumstances[3] may be used to induce efforts from agents. In a traditional rank-order tournament, the best performer is promoted to the next level in hierarchy by passing over others. This provides incentives for tournament participants to perform well such that their chance of winning the promotion prize is maximized.

The existing findings on the rank-order tournament also document that tournament incentives improve corporate policies (e.g. Kini and Williams, 2012) and firm innovation (e.g. Jia, Tian, and Zhang 2016). Findings of these studies indicate that managerial compensation structure provides the basis for developing the rank-order tournament incentives, which incentivize subordinates to compete for a higher position, especially for the CEO position. The tournament incentives are measured by the difference in the CEO's pay and an average of key subordinates' pay (e.g. Kale et al. 2009; Kini and Williams 2012), whereas the key subordinates are referred to VPs in the literature. It is assumed that the pay difference is likely to encourage subordinates to work harder and give their best

[3] These circumstances include when monitoring is difficult or expensive, when agents are risk averse, and when the measurement costs of absolute performance are prohibitly high.

performance that enhances firm’s overall performance, which in turn would enhance firm value.

Some studies, on the other hand, have documented that the rank-order tournament is also likely to enhance firm risk (e.g. Kinni and Williams, 2012) because managers would be encouraged to undertake risky projects to achieve higher returns that may help them in winning the trophy. Kubick and Masli (2016) also find that firms with larger pay gap tend to adopt risky tax policies. In addition, managers may also engage in earnings management or even frauds to achieve higher targets that could help them increase the chance of promotion (Chen, Hui, You, and Zhang 2016; Haß et al. 2015). Furthermore, some recent studies document a decrease in the helping effort and more sabotage activities in firms with larger pay gaps (Chowdhury and Gurtler 2015; Dechenaux, Kovenock, and Sheremeta 2015).

We extend research on rank-order tournament and examine whether the quality of information generated by the tournament participating managers will enable superiors, i.e. CEOs, and/or CFOs to issue MEFs that will be of high quality, i.e. will have higher accuracy, and precision.

1.2.2 Hypotheses

Tournament Incentives and MEF Quality

The quality of MEF is considered important because it is one of the main sources of information for investors to develop their market expectations.[4] High quality of MEFs

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[4] It is well documented in the literature that investors find information provided in MEFs more useful for their investment decisions than forecast information obtained from other sources, such as security analysts’ forecasts, model forecasts based on historical data, etc. (e.g. Healy and Palepu 2001; Hutton et al., 2012).

enhances their value relevance and reduces information asymmetry, especially when they are reliable and credible (e.g. Jennings 1987; Mercer 2004). However, the Conference Board (2003) has estimated that only about 40% of investors view MEFs issued by firms as credible. Several researchers have explored what makes the MEFs more reliable and creditable. For example, Hirst, et al. (2008), who conducted an analysis to examine different aspects of MEFs, present that accuracy and precision of MEFs especially play an important role in enhancing their reliability and thus quality. We examine these attributes in relation to the rank order tournament with the objective to find out whether the tournament incentives in a firm would improve the MEF attributes.

Thus the main research question of interest to us is whether tournament incentives improve MEF accuracy and MEF precision. It is argued in the literature that tournament incentives motivate participating managers in the competitive tournaments to provide high quality information to superiors because it is used for evaluation of their capabilities, skills, and competence for promotion to a higher rank (Keating 1997). We extend this argument and present that high quality information provided by tournament participants will also improve the MEF quality, i.e. precision and accuracy of MEFs. If promotion trophy is for the CEO rank, the Board of Directors will use this information to evaluate which tournament participant has the capability to serve as CEO. Therefore, participants will make every effort to provide high quality information to the superiors, including board of directors, to improve the chances for winning the competitive tournament. This high quality detailed information would also enable the top management to improve the quality of disclosures and enable them to issue high quality MEFs.

The expectation of high quality of information from tournament participants is supported by the following arguments. First, tournament participants make every effort to provide high quality information because their evaluation will be based on this. If the forecast quality is low, it would raise doubts in the minds to evaluators with regard to the participants' capabilities, morale, and their seriousness. Second, superiors will be closely watching the tournament participants to ensure that there is no cheating in the process (e.g. Li 2014). Third, participating managers in the tournament will themselves be very cautious about the quality of information because there will be heavy penalty, including loss of trophy of promotion if the quality of information is considered questionable as a result of earnings manipulations, etc. Fourth, tournament participants will be watching each other to ensure that no one is cheating to gain some advantage. Fifth, Archaya et al. (2011) argues that VPs in general have longer investment horizons and if they are participants in the tournaments, tournament incentives will encourage them to generate information that is more suitable for long-term planning.

The arguments suggest that higher trophy will discourage participants to engage in myopic behavior. Thus, overall, we expect both accuracy and precision of MEFs to be positively associated with the level of trophy, and we develop the following hypotheses to test our expectation.

H1(a): There is a positive association between tournament incentives and MEF accuracy

H1(b): There is a positive association between tournament incentives and MEF precision.

The Moderating Effect of Homogeneity among Industry Groups and Appointment of New CEOs

Both homogeneity in industry groups and appointment of new CEOs are expected to reduce the perceived probability of promotion, especially to the rank CEO (e.g. Kales et al. 2009). Thus, we argue that the reduced probability of promotion will have a moderating impact on the association between the tournament incentives and MEF quality.

We argue that homogeneity among industry groups is likely to have a moderating effect on managerial motivation to work harder and provide high quality information because industry homogeneity, i.e. similarity in production technologies and also in products across firms (e.g. Parrino 1997, Chen et al., 2016), will broaden horizons for hiring by a firm and also broaden horizons for a job for the tournament participants. This argument suggests that if the potential for promotion also exists outside the firm and competition for promotion is stronger, participating managers' their enthusiasm may be dampened because promotion chances will be reduced. Consequently, participants' incentives to work harder in the firm and to provide high quality information will be moderated. Consequently, we expect the positive association between internal tournament incentives and MEF attributes to be less pronounced in homogeneous industries. We empirically test this on the following hypothesis:

H2(a): Industry homogeneity moderates the positive association between tournament incentives and MEF attributes of accuracy and precision.

The appointment of a new CEO could work as another moderating factor on the association between tournament incentives and MEF attributes. Appointment of a new CEO will reduce managers' motivation for harder work because promotion to the rank of CEO will not be available for quite some time. The appointment of a new CEO may in fact end the current promotion tournament and it will start again when there is an expected vacancy for this position (e.g. Kale et al., 2009).

The non-availability of the CEO position will negative affect tournament incentives, which means participants' motivation to compete will be lower. This will have a moderating effect on the association between tournament incentives and MEF quality. We develop the following hypothesis to test this expectation:

H2(b): The appointment of a new CEO moderates the positive association between tournament incentives and MEF attributes of accuracy and precision.

1.3 Methodology

1.3.1 Sample Selection

We obtain our compensation-based tournament sample from Compustat ExecuComp for the period from year 2002 to 2015. Following Kale, Reis, and Venkateswaran (2009), we define a CEO as the person who is identified as the chief executive officer of the firm in ExecuComp (data item CEOANN = CEO), and classify all other executives as subordinate managers/VPs.[5] [6] Following Kini and Williams (2012), we include the observation in our sample when there are with at least three VPs in addition to the CEO.[7] We exclude utilities and financial firms (Standard Industrial Classification (SIC) codes between 4900-4999 and 6000-6999, respectively) because firms in the regulated industries have different financial

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[5] We manually correct 104 observations for the CEO annual title in the Compustat ExecuComp. For firm-years with duplicates CEOs, we consider the one with the highest total compensation (data item TDC1) as the CEO and the remaining duplicates as VPs.

[6] Titles of subordinate managers include: chief operating officer, chief finance/accounting officer, chief marketing officer, VP, president, chairman, and so on so forth.

[7] Our results remain qualitatively unchanged when we restrict our sample to firm-years with at least one VP in addition to the CEO.

reporting incentives from those in other industries. We obtain management annual earnings forecasts from I/B/E/S Guidance during 2002 and 2015. To compare the consistency between the management forecasts and actual earnings per share, we also combine the forecast data with the actual reported earnings from I/B/E/S actual files. We collect firms' financial data and institutional shareholdings from Compustat and Thomson Reuters s34 Master File. We obtain data on firm and market returns from CRSP. The corporate board and governance data are collected from ISS (formerly RiskMetrics) database. We combine data from all sources together and drop observations with missing data of test variables. Our final sample consists of 28,337 observations for precision and accuracy analyses.

The time pattern of management forecasts over 2002 to 2015 is provided in Table 1. Though there is a small drop in 2009 and 2015 in the annual sample, there appears to be a steady increase in the number of forecasts over the sample period. This is consistent with prior studies that examined management forecasts. Majority of MEFs are expressed as range forecasts instead of point forecasts: on average, only about 9.7% of management forecasts are point forecasts.

[Insert Table 1 Here]

1.3.2 Tournament Incentive Measurements

We use two measures for tournament incentives, and the first measure is defined as the natural logarithm of the pay gap between the CEO and the next level of subordinate managers. Following Kale, Reis, and Venkateswaran (2009) and Kini, and Williams (2012), pay gap is defined as the difference between the CEO's total compensation package (ExecuComp variable TDC1) and the median subordinate managers' total compensation package. We label this variable as *Log(Gap)*.[8] This variable serves as a proxy for a firm's tournament incentive, which reflects the average increase in subordinate manager's salary if he/she wins the tournament trophy. The second measure of tournament incentive, *Log(Diff)*, is defined as the natural logarithm of the difference between the total CEO's compensation and the highest paid VP's compensation. It reckons the minimum salary increase for VPs if he's promoted to CEO and it conservatively estimates the tournament trophy. Next, we exclude former CEOs from our analyses if they are still with the firms' management team, and we drop their compensation when calculating both measures of tournament incentives.[9] After this correction, we get 1,095 firm-years with negative compensation gap; these observations are dropped from our sample for primary tests. The final tournament sample consists of 18,326 firm-year observations.

In Figure 1, we present the time-series distribution of both tournament measures from 2002 to 2015. The executive pay gap is relatively smooth before 2008 financial crisis and starts to surge after 2009. As salaries of CEOs get boosted, the pay gap increases, leading to increasing tournament incentives (see figure 1).[10]

[Insert Figure 1]

[8] The executive compensation data in ExecuComp is recorded in thousands. We further divide it by 1000 to make it in millions in order to make it comparable with firm size.
[9] This procedure corrects for the cases where the subordinate's compensation is greater than the CEO's compensation. Therefore, correct or potential upward bias for median subordinate's compensation. 1,338 observations are dropped.
[10] The rising executive pay gap triggers extensive attention on investigating cost and benefits of well-paid CEO compensation on corporate performance.

1.3.3 Model Specification

Regression Model to Test H1

We first test the association between tournament incentives and MEF quality. As discussed earlier, we use MEF accuracy and precision, two important attributes of MEF, as proxies for MEF quality. The following OLS regression model is used to test the association:

$$MEF\_Q_{i,t,m} = \beta_0 + \beta_1 Tournament\ Incentive_{i,t-1} + \beta Controls_{i,t} + \beta_k \sum Year + \beta_k \sum Industry + \varepsilon_{i,t} \qquad (1)$$

Where *i*= firm, *t*= year, and *m* = MEF attribute, i.e. *accuracy* or *precision.*

We follow Rogers and Stocken (2005) to measure the variables of *Accuracy* and *Precision* of MEF. *Precision* is defined as the difference between the forecast upper and lower bounds, deflated by the beginning stock price and multiplied by -1. *Precision* takes a value of 0 if a point forecast is given. We exclude qualitative and open-ended forecasts in our analysis since we cannot estimate the precision of these forecasts reliably. *Accuracy* is defined as the absolute difference between the forecast EPS and the actual reported EPS, deflated by the beginning stock price and multiplied by -1.[11] It measures the extent to which the actual earnings deviate from management earnings forecast.[12] We use lagged value of the executive pay gap to proxy tournament incentives to alleviate the possible endogeneity issues.

Following the existing literature, we use a set of control variables associated with voluntary disclosures decisions. We include firm size, defined as the natural logarithm of lagged total

[11] For a range forecast, we use the midpoint as the forecast value.
[12] We multiply both Accuracy and Precision with -1 to make them positive measures of MEF quality.

book assets (Lang and Lundholm 1996; Bhojraj, Libby, and Yang 2010). We control for institutional shareholdings because firms with higher institutional ownership are more likely to issue MEFs and they are likely to be more accurate and precise (Ajinkya et al. 2005). Prior literature has documented that firms with more volatile earnings are less (more) likely to issue (stop) forecasts and their forecasts are less likely to be precise nor accurate due to inherent uncertainty (Waymire 1986; Chen, Matsumoto, and Rajgopal 2011). We measure earnings volatility as the standard deviation of income before extraordinary items scaled by total assets over five years ending in year *t*. We include an indicator variable *Litigation* to control for litigation risk. *Litigation* equals to 1 for firms in following industries: Drugs (SIC codes 2833-2836), R&D services (8731-8734), Programming (7371-7379), Computers (3570-3577), and Electronics (2674-3600) (Skinner 1994; Kaznik and Lev 1995; Sengupta 2004). We do not have an expected sign for *Litigation* since the empirical results are mixed.[13] We control for firm performance by including *ROA*, and an indicator variable *Loss* for negative net income as firms with poor performance are less likely to provide high quality forecasts (Miller 2002). We include the market-to-book ratio *MTB* and *R&D* to control for growth and proprietary costs (Bamber and Cheon 1998). We include internal control effectiveness by using an indicator *Weak*, which takes the value of 1 if the firm disclosed a material internal control weakness during the sample period. Feng, Li, and Mcvay (2009) find that forecasts issued by firms with material internal control

[13] Skinner (1994) argued that the threat of lawsuits arising from large negative earnings surprises provide managers with incentives to pre-disclose the information in order to reduce litigation costs. In addition, Cheng and Lo (2006) showed that litigation risk is not preventing managers from voluntarily disclosing bad news and purchasing afterwards. On the other hand, litigation fears serve as an important obstacle to providing forward-looking information (AICPA1994; SEC 1994; Breeden 1995).

weaknesses are less accurate. Firms may provide more biased information when undergoing significant events or accessing capital markets. Thus, *M&A* and *Equity Issue* are included to control merger-related activities and equity offerings. We also control equity-based incentives for the executive management team, including shares of stocks as well as vested options owned by CEO and VPs (Malmendier and Tate 2005; Hribar and Yang 2016). We also control for the horizon of the forecast and the forecast news. *Horizon* is defined as the natural logarithm of days between the forecast period end date and the forecast announcement date. Longer the forecast horizon, lower the forecast accuracy and precision (Bamber and Cheon 1998). *News* is the difference between management forecast EPS and analyst consensus forecast (median) before management forecast, deflated by beginning stock price and multiplied by 100. Prior research shows that altering the market expectation is one of the most important factors that influence the quality of the forecast (Williams 1996). We include performance-matched discretionary accruals (*DA*) as a control variable as firms may engage in earnings management in order to meet their own forecasts (Dutta and Gigler, 2002). We also control for industry concentration, as firms in high-concentrated industries are more likely to issue pessimistic forecasts when it is difficult for potential competitors to detect misrepresentation in the forward looking information (Rogers and Stocken 2005). Finally, we control for tenure of the CEO and VPs because tenure is likely to be associated with both compensation structure and financial reporting incentives. We include year and industry fixed-effects in all regression models.

Development of Regression Test for H2

We refine regression model *(1)* by adding two interaction terms, i.e. *Tournament Incentive*Industry Homogeneity* and *Tournament Incentive*New CEO* in the equation:

$$MEF_{Q_{i,t,m}} = \beta_0 + \beta_1 Tournament\ Incentive_{i,t-1} + \beta_2(Tournament\ Incentive_{i,t-1} * Industry\ Homogeneity_{i,t}) + \beta_3 Industry\ Homogeneity_{i,t} + \beta Controls_{i,t} + \beta_k \sum Year + \beta_k \sum Industry + \varepsilon_{i,t} \quad (2)$$

$$MEF\_Q_{i,t,m} = \beta_0 + \beta_1 Tournament\ Incentive_{i,t-1} + \beta_2(Tournament\ Incentive_{i,t-1} * New\ CEO_{i,t}) + \beta_3 New\ CEO_{i,t} + \beta Controls_{i,t} + \beta_k \sum Year + \beta_k \sum Industry + \varepsilon_{i,t} \quad (3)$$

Where *i*= firm, *t*= year, and *m* = MEF attribute, i.e. *accuracy* or *precision.*

To identify *Industry Homogeneity*, we follow Parrino 1997. For each firm-year observation, we estimate partial correlation between firm and industry returns, controlling for market returns. We use 60 monthly returns until the end of the current fiscal year. Industry returns are defined as the average of all firms' monthly returns within the same two-digit SIC industry. For each industry-year, we calculate *Industry Homogeneity* as the mean of the partial correlation coefficients of all firms in that industry.

To identify the post-CEO turnover period, we first identify the year when the incumbent CEO left the company and the new CEO was appointed and denote it as year *t*. The indicator variable *New CEO* is defined to be 1 for year *t* and year *t+1* and 0 for other periods. To avoid frequent CEO turnover, we further exclude firm-years where the consecutive CEO turnover is less than three years.

1.4 Data Description and Empirical Results

1.4.1 Summary Statistics

In Table 2 we report summary statistics for our sample. There is no big difference in distribution of our two measures of tournament incentives i.e. *Log(Gap)* and *Log(Diff)*. The mean (median) value of the executive pay gap is 2.960(3.334) million. It is comparable to the statistics reported in Kale et al. (2009). The mean value of the forecast range is on average 0.366 percent of the share price. The mean value of forecast error is about 0.826, which indicates that the forecast in general deviates from the actual EPS around 0.826 percent of the share price. Distribution of control variables is in general consistent with the existing literature.

[Insert Table 2 Here]

1.4.2 Empirical Results

Association between MEF Quality and Tournament Incentives

First, we evaluate the association between MEF quality and tournament incentives based on regression model (1). We conduct two separate tests, one based on the precision dependent variable, and other based on the accuracy dependent variable. The results of these regression tests are contained in Table 3.

[Insert Table 3 Here]

The results in columns 1 and 2 on *Precision* show that coefficients of tournament incentives, measured by *Log(Gap)* (coefficient = 0.030) and *Log (Diff)* (coefficient = 0.017) are positive and statistically significant at the 0.01 level. Similarly, the results in columns in 3 and 4 on *Accuracy* show that coefficients of *Log(Gap)* (coefficient = 0.064) and *Log (Diff)* (coefficient = 0.042) are positive and statistically significant. The economic significance of precision shows that one standard deviation increase in *Log(Gap)* is associated with 8.525 percent increase in forecast precision. The coefficient 0.064 for accuracy indicates that one standard deviation increase in *Log(Gap)* is associated with 8.058 percent increase in forecast accuracy. These results confirm our hypotheses H1a and H1b that firms with tournament incentives are associated with higher MEF quality, as proxied by MEF precision and MEF accuracy.

The results on the control variables are overall consistent with prior literature. We find in our sample that MEF quality is positively associated with firm size, institutional ownership, growth opportunities, and firm performance, while forecast quality is negatively associated with earnings volatility, forecast horizons, and internal control weakness.

Additional Evidence supporting H1

Additionally, we investigate whether the MEF attribute frequency is also affected by tournament incentives. We conjecture that tournament incentives would provide strong motivation for managers to issue MEFs more often to keep investors and board of directors informed about expected changes in the future performance of the firm. We examined in this study whether there is difference in MEF frequency of firms with and without tournament incentives. We refine the regression model (1) by replacing the dependent variable with forecast frequency, where *MEF_Frequency* is defined as the number of MEFs issued by a firm during a year:

$$MEF\_Frequency_{i,t} = \beta_0 + \beta_1 Tournament\ Incentive_{t-1} + \beta Controls_{t-1} +$$
$$\beta_k \sum Year + \beta_k \sum Industry + +\varepsilon_{i,t} \quad (4)$$

The results (untabulated) show that coefficients of *Log(Gap)* (coefficient = 0.103) and *Log(Diff)* (coefficient = 0.101) are positive and statistically significant at 0.01 level. These results provide additional support to our H1and suggest that firms are more willing to provide MEFs when the forecast quality is higher.[14]

Moderating Effect of Industry Homogeneity and New CEO on the Association between Tournament Incentives and MEF Quality

We expect he association between tournament incentives and MEF quality to be moderated by certain factors, including industry homogeneity and new CEO. Higher industry homogeneity is associated with higher likelihood that the firm will hire an outsider as CEO and reduces the possibility of winning tournament inside the firm. Similarly, the appointment of new CEOs will reduce the possibility of getting promoted to CEO position. Thus, both factors will take away the strong incentive of tournament participants to work hard. We evaluate the moderating effect of these factors by including an interaction variable between tournament incentive measures and the moderating factor. The results are contained in Table 4.

[Insert Table 4 Here]

The results in the Panel A of Table 4 show that coefficient of the *Tournament Incentive* remains positive and statistically significant for both tournament measures, whereas the coefficient of *Industry Homogeneity* is negative and statistically significant. The coefficient of the interaction term (*Tournament Incentive*Industry Homogeneity*) is negative and statistically significant both for MEF precision and MEF accuracy (Column 1-4). The negative coefficient confirms that industry homogeneity has a moderating effect

[14] We also examine whether firms with tournament incentives are associated with more long-term MEFs. Archaya et al. (2011) argue that VPs focus more on long-term performance of the firm than CEOs. If VPs are actively involved in the formation and discussion of MEF, we expect them to provide more long-term forecasts. The results are consistent with our expectations. Both our tournament measures are positively associated with the frequency of long-term MEFs.

on the association between tournament incentives and MEF quality characteristics. This finding thus suggests that the impact of tournament incentives is moderated with high industry homogeneity, which may provide an opportunity to hire CEOs and other managers from outside the firm.

In Panel B, we examine the impact of the moderating factor on the association between MEF quality and tournament incentives, i.e. when the CEO in the firm is newly hired. The results show that coefficients of both tournament incentive measures are positive and statistically significant and the coefficient of *New CEO* is also positive. The coefficient of the interaction term (*Tournament Incentive* * *New CEO*) is negative and statistically significant for both proxies of higher quality of MEF, i.e. precision and accuracy. These findings confirm our expectation that the newly hired CEO has a moderating effect on the positive association of MEF quality and tournament incentive.

The above results support our hypotheses H2a and H2b that the association between MEF quality, proxied by accuracy and precision of MEF, is moderated when the tournament participants perceive the promotion probability to be slim.

1.5 Robustness Check Tests

It is possible that our findings are driven by CEO specific characteristics, some corporate governance mechanisms, and/or mismeasurement of tournament incentives. In the robustness tests, we control for the impact of CEO characteristics and certain aspects of corporate governance on MEF quality, and we use alternative proxies to address the measurement errors of tournament incentives.

1.5.1 CEO Ability, CEO Fixed Effect, and MEF Quality

Baik et al. 2009 show that CEO ability has a positive impact on the likelihood, frequency, and quality of MEF. In this section, we first examine whether our results are driven by CEOs' personal characteristic. We first evaluate the influence of CEO ability on MEF quality. We construct the *Ability* measure following Rajgopal et al. (2006) and Baik et al. (2011). We compute cumulative distribution function (CDF) of industry adjusted ROA for each CEO-firm-year by industry and take the mean of the CDF ranks of ROA for the first three years when a new CEO is appointed. We include it as a control variable in our regression model (1). The regression results are contained in Table 5, Panel A.

Similar to Baik et al. (2011), our results show that CEO ability (*Ability*) is positively associated with forecast quality, i.e. accuracy and precision. Additionally, our tournament incentive measures remain positive and statistically significant. These results support our main finding and indicate the positive association between tournament incentives and MEFs is not driven by CEO ability.

Bamber et al. (2010) argue that managers exert unique and significant influence on their firms' voluntary disclosure policies, which may be influenced by their style that is affected by many demographic characteristics and their personal background. To isolate the effect of CEO style, we include CEO fixed-effects in our regression models. The results are contained in Panel B of table 5. There are in total 2,361 unique CEOs for our sample period. The results show that the positive association between tournament incentives and MEF quality is robust even when CEO fixed effects is included in the regression.

[Insert Table 5 Here]

1.5.2 Corporate Governance and MEF Quality

It is well documented in the literature that effective corporate governance is associated with higher forecast quality (Eng and Mak 2003). Consistent with this line of reasoning, we present that effective corporate governance would encourage CEOs and other senior management to issue high quality MEFs. Therefore, it needs to be examined whether the positive association between tournament incentives and MEF quality is driven by corporate governance. We add three well-known corporate governance variables as control variables in our equation (1), including G-Index[15], CEO duality, and board independence. We follow Gompers et al. (2003) and use G Index, which is an inverse measure of shareholder rights, an indicator variable for *CEO Duality*, and a variable for Board independence. The CEO duality indicator is equal to 1 if the CEO is also the chairman of the board. The board independence is proxied by the percentage of independent outside directors on the board *(%IO Directors*). The results are provided in Table 6.

[Insert Table 6 Here]

The results show that the tournament incentives measures remain positive and statistically significant for all regression tests even after including additional control variables on corporate governance. Therefore, the results confirm our expectation that tournament incentives contribute to a better internal monitoring environment in additional to other corporate governance mechanisms. The results also show that MEFs quality is associated with stronger shareholder rights (lower G Index), positively associated with independent

[15] For G Index after 2007, we use their IRRC values in 2006 and assume these values will carry forward for the remaining sample periods.

board leadership, but board independence, proxied by the percentage of outside directors serving on the board, is negatively associated with MEF quality.

1.5.3 Alternative Tournament Incentive Proxy

The subordinate managers may be more concerned about the relative increase in their salaries rather than absolute tournament prize. One million pay differences will be less attractive for an executive who earns five million per year compared to manager who earns two million. Besides, the compensation packages of VPs and CEO are probably determined by common unobserved factors, which may correlate with issuance of MEFs. The use of relative proxy may mitigate this concern, as the effect of common factors will be canceled out. We use the logarithm of the ratio of the CEO compensation to the median VP's compensation minus 1, to capture the percentage increase in salary if the VP gets promoted. We re-estimate our models and the results (untabulated) remain unchanged.

Another concern may be that as opposed to other senior executives, CFOs may have more control over disclosures, including MEF disclosures (Chang, Chen, Liao, and Mishra 2006). We therefore test the effect of tournament incentives on CFOs. We construct the gap between CEO and CFO compensation to re-estimate our models. Our results remain qualitatively unchanged. In addition, the significant effect of pay gap between CEOs and CFOs confirms the role of tournament incentives for CFOs in making decision on MEFs.

1.5.4 Endogeneity Concerns

It could be argued that tournament incentives and MEF quality are endogenously determined. It is possible that tournament incentives induce high quality MEF, whereas high quality MEF results in better firm performance, which results in higher CEO compensation and tournament incentives. We use IV methodology to address the endogeneity concerns. Following previous literature, our two instruments are the executive pay gap lagged by two years and the industry median pay gap (Kale et al., 2009; Chen et al., 2016). The validity of these two instruments is supported on the ground that the lagged executive pay gap is less likely to be affected by voluntary disclosure decisions two years later and the industry median pay gap is not likely to affect the firm-level disclosure policy when industry fixed effects are included.

We present the second stage regression results in Table 7. The Shea R-square is 0.185 (0.144) (Column 1 and Column 2), which provides evidence that our instruments are relevant. The test results show that our main fidings still hold. Specifically, for the precisions regression, the coefficients of *Log(Gap)* and *Log (Diff)* are 0.039 and 0.025 respectively and are significantly significant at 0.01 level. Similarly, the coefficients of the accuracy regression for *Log (Gap)* and *Log (Diff)* are 0.094 and 0.090 respectively and are also statistically significant at 0.01 level. Thus, these results show that our main findings are not influenced by the endogeneity concerns.

[Insert Table 7 Here]

1.5.5 Economic Consequences

Market Reaction to MEFs issued by Firms with Tournament Incentives

Another way to assess whether MEFs issued by firms with tournament incentives are of higher quality is to evaluate market response to disclosure of MEFs. If market participants perceive that internal tournaments attest to the higher quality of MEFs, their response to MEFs issued by firms with tournaments incentvies will be stronger compared to MEFs issued by firms such incentives.

To test the market reaction to MEFs, we use cumulative abnormal returns (CARs) and abnormal trading volume around the disclosure date of MEFs as dependent variables and control for other factors that have an influence on investors' reaction. We use the following models to evaluate investors' reaction, where the interaction variable between *Tournament Incentive* and *News* will indicate whether investors take into consideration tournament incentives in responding to MEFs.

$$CAR_{i,[-1,1]} = \gamma_0 + \gamma_1 Tournament\ Incentive_{i,t-1} * News_{i,t} + \gamma_2 Tournament\ Incentive_{i,t-1} + \gamma_3 News_{i,t} + \gamma Controls_{i,t} + \gamma Controls_{i,t} * News_{i,t} + \gamma_k \sum Year + \gamma_k \sum Industry + \varepsilon_{i,t} \quad (5)$$

$$AbnVol_{i,[-1,1]} = \gamma_0 + \gamma_1 Tournament\ Incentive_{i,t-1} * |News_{i,t}| + \gamma_2 Tournament\ Incentive_{i,t-1} + \gamma_3 |News_{i,t}| + \gamma Controls_{i,t} + \gamma Controls_{i,t} * |News_{i,t}| + \gamma_k \sum Year + \gamma_k \sum Industry + \varepsilon_{i,t} \quad (6)$$

We measure CAR as abnormal returns adjusted by the size-decile-matched market return in [-1,1] window around the announcement date of MEFs. *AbnVol* is the average trading volume from three trading days around the management forecast announcement date, scaled by the median trading volume in prior 60 days. To reduce noises, we require the gap between any two consecutive announcement dates to be greater than 30 days, and we further delete forecasts announced within 30 days of annual earnings announcements. *News*, as defined early, is the difference between management forecast EPS and analyst consensus forecast (median) before management forecast, deflated by beginning stock price and multiplied by 100. If firms with tournament incentives are associated with more reliable forecasts, investors would be more responsive to those forecast news conditional on information content of forecasts. Thus, we expect the coefficient of interaction term *Tournament Incentive*News*, γ_1 to be significantly positive. Following Libby, Tan, and Hunton (2006), we control the form of the forecasts (*Point*) and the timeless of forecasts(*Timeliness*), since the market may rely more on point and timely forecasts. We also use several control firm characteristics that may impact the market reaction, including firm size, and earnings volatility (*EanVol*). All variables are interacted with *News* to disentangle different reactions to the magnitude of news. Industry and year fixed effects are also included.

The results are contained in Panel A of Table 8. In column 1-2, the coefficients of *Tournament Incentive* News* are positive and significant at 0.01 level for both tournament measures. These results support the argument that tournament incentives are associated with stronger investor reaction to information contained in forecasts because of investors' better perception of reliability of MEF quality when forecasts are issued by firms with tournament incentives. In Column 3 and 4, we replace *News* with its absolute value, since the dependent variable *Abn_Vol* should be associated with the information content in forecasts regardless of the sign of news. Again, we find that coefficients of the interaction term are significantly positive (0.082(0.051)) with a t-stat (3.16 (2.72)), respectively for accuracy and precision analyses, suggesting that investors are more likely to trade on information in forecasts issued by firms with tournament incentives.

[Insert Table 8 Here]

Analysts' Reactions to MEFs issued by Firms with Tournament Incentives

We also examine how analysts react to MEFs issued by firms with tournament incentives. We first examine the likelihood of analyst revising their forecasts in response to MEFs in general, and then we examine the speed of analysts' revisions following MEFs. [16] Overall, we expect a higher number of analyst revisions following MEFs issued by firms with tournament incentives in place since MEFs issued by these firms will be perceived by security analysts to be more reliable and credible. We also examine the speed of analyst revisions following the issuance of MEFs. It can be argued that analysts are likely to revise their forecasts in a timely manner if the information contained in MEFs is more valuable and accurate. Thus, we postulate that analysts take shorter time to revise their forecasts following MEFs issued by firms with tournament incentives.

Panel B in Table 8 reports the results for analyst revisions. We investigate two aspects of analyst reactions, i.e. fraction of analysts that revise their own forecasts and their speed of revisions. *Fraction* is defined as the ratio of analysts who revise forecasts within 90 days following the announcement dates of MEFs to the total number of analysts following the firm.[17] We refine regression model (6) by replacing the dependent variable with *Fraction* and we use absolute value of *News* to proxy for the difference in information content. As expected, Column 5 and 6 in Table 8 show that analysts are more likely to revise their forecasts following management forecasts issued by firms with tournament incentives (t=1.79 and 2.41 for *Log(Gap)* |News| and Log(Diff)*|News|*, respectively). Column 7 and 8 display the results for the speed of revisions. *Log(Days)* is defined as the natural

[16] We also do not examine the magnitude of revisions because we cannot determine the quality of analyst forecasts ex ante. We, however, recognize that there is link between the quality of analyst forecasts and revisions after issuance of MEFs. If analyst forecasts issued before MEFs are of high quality due to the good information environment for high tournament firms, the number of analysts revising their forecasts after the issuance of MEF will be significantly lower because their revision will not add any value in terms of quality of their forecasts. On the other hand, if preceding analyst forecasts are of poor quality, analysts will be motivated to revise their forecasts after issuance of MEFs to improve the quality of their forecasts.

[17] We define analyst following as the total number of analysts that issue at least one forecast for the firm during the year.

logarithm of the number of days between MEF date and analyst revision date immediately following the MEF. We find that analysts are inclined to revise faster for forecasts issued by firms with tournament incentive. The coefficient of *Tournament Incentive**|*News*| is negative and significant at 0.01 level.

To summarize the findings on investors' and analysts' perception of the reliability of MEF quality, our finding provide a strong support to our expectation that investors and analyst are more responsive to MEFs when tournament incentives are in place in the firm. These findings support our main hypotheses that MEF quality is high when forecasts are issued by firms with tournament incentives.

1.6 Conclusion

In this paper, we examine the relation between competitive rank order tournament incentives and MEF quality. We find that MEFs issued by firms with higher tournament incentives are of higher quality, proxied by MEF accuracy and MEF precisions, compared to MEFs issued by firms without competitive tournaments. Our test results on the third attribute of MEF quality (i.e. frequency) are also similar to our main results. The positive association between MEF quality and tournament incentives is moderated by industry homogeneity and appointment of new CEO in the firm. Our robustness tests show that findings are however robust because they are not driven by managerial ability, managerial style, or effectiveness of corporate governance, and they remain unchanged when alternative measures for tournament incentives are used.

Additionally, our tests on investors' and security analysts' response to MEFs support our expectation that they also perceive MEF quality to be high when MEFs are issued by firms with tournament incentives compared to the firms without tournament incentives.

Investors' response is stronger when firms with tournament incentives issue the forecasts. Similarly, security analysts respond to these MEFs by revising their forecasts and they revise their forecasts on a timely basis.

Our paper contributes to literature by highlighting the role of tournament incentives in contributing to MEF quality. Additionally, we show how subordinate contribute to higher quality of MEFs issued by CEOs or CFOs. Our paper also answers to the debates of the "overpaid" CEO compensation by unravelling the benefits of tournament incentives on disclosure quality.

CHAPTER 2: DO CORPORATE FRAUDS DISTORT SUPPLIERS' INVESTMENT DECISIONS?

2.1 Introduction

The real costs of corporate frauds on corporations engaging misconduct have been well-documented in the literature, such as the reduction in market trust (Giannetti and Wang, 2016), the penalty in labor market for CEOs (Karpoff, Lee and Martin, 2008) and the reduction in R&D or mistrust in patents. Specially, Kedia and Philippon (2007) show that misrepresentation in accounting will lead to the distortion of employment and capital in economy: the firms will hire more employees and invest more to pretend as "good firms". However, fraudulent information may also impact other clean firms. For example, Beatty, Liao and Yu (2013) show that the fraudulent financial reports foster the overinvestment among industry peers during the fraud period. Li (2016) expands such findings by showing the distortions occur in the broader definition of frauds (e.g., restatements) and in R&D, advertising and pricing policies as well.

Recently, researchers start to look at how the disclosure of fraudulent accounting will impact wealth fare of non-financial stakeholders, such as firms with supplier-customer economic ties. For instance, Kang and Tham (2012) show there's a negative spillover effect of earning restatements on supplier's market value and more dependent suppliers will be more likely to be cut off in post-restatement period. Files and Gurn (2014) argue that loan lenders will charge a higher spread as the response to restatements in supplier's industry. However, these studies focus on suppliers' reactions in the post period of customers' frauds and there is little understanding on how suppliers react to customer's misrepresentation during customers' cheating periods.

This paper attempts to fill up such research gap and investigate whether the customers' misrepresentation will lead to the distortion or inefficiency of suppliers' investment decisions. Thanks to the economic linkage between supply chain participants, suppliers make investment or other product market strategies based on the prospective of their customers (e.g., Subramani, 2004). For example, Lee, Padmanabhan and Whang (2017) document that the distorted order information can misguide upstream members (e.g., suppliers) in their inventory and production decisions. Consistent with the argument that the misrepresentation of financial performance leads to suboptimal investment decisions (Maurren and Stephen, 2008), it is reasonable to believe the misrepresented customers' information may distort suppliers' investment decisions. Additionally, in line with Kumar and Langer (2009), who shed lights on the association between frauds and overinvestment, we expect that if customers pretend to be better firms by engaging corporate frauds, it's very likely their suppliers will overinvest in capital and deteriorate their investment efficiency to keep up with customers' illusory prosperities. As a result, the sacrificed investment efficiency turns to be the real cost for suppliers.

In this paper, we adapt Li's (2016) broader definition of misrepresentation and utilize both litigation data (1996 - 2013) from the Securities Class Action Clearinghouse (SCAC) and restatement data (2002 - 2013) from Audit Analytics database (AA). After excluding financial and utility firms, our final litigation and restatement samples contain 1,502 and 2,129 fraudulent firms, respectively. In addition, we extract supply chain relationship information from COMPUSTAT segment data and use a combination of automatic and manual methods to identify customers.

With regard to the question that whether customers send out distorted positive demand signals to suppliers during their cheating periods, we first explicitly show that customers take real activities to cook their performance during the cheating periods, including hiring excessive employees, purchasing redundant assets, and boosting their sales. Then, to explore the main hypothesis, we find that affected suppliers[1] with cheating customers tend to have a higher level of capital expenditures during the cheating periods, comparing to unaffected suppliers without cheating customers.

Further, to examine the cross-sectional variations of distortion influences, we consider two factors that may moderate suppliers' informational reliance on their customers: the industry concentration and the sales volatility.

As argued in the study by Ali, klasa and Yeung (2014), industry leaders in a more concentrated industry take a large slice of market shares and thus they can provide more informative disclosure about future demand than firms in a less concentrated industry. In such manner, suppliers are able to acquire industry demand information and revise their investment strategies by observing industry leaders' behaviors and disclosures with relatively low costs. The emergence of this new information source attenuates the informational reliance on their customers. On the other hand, suppliers with less sales volatilities are more likely to be able to predict future performance based on historical

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[1] For a clear and concise demonstration, the affected suppliers refer to suppliers who engage with cheating customers and on the contrary, the unaffected suppliers represent suppliers who have no cheating customers.

information and consequently become less relied on customers' contemporaneous performance to make strategic decisions (e.g., Yu, Yan and Cheng, 2001, Chen and Lee, 2009). Together, our empirical results present that a higher industry concentration or a lower sales volatility can mitigate the level of suppliers' overinvestment when they were distorted by customers' rosy perspectives.

In additional analysis, to triangle our main findings, we first confirm that suppliers' distorted investments during the customers' cheating period are inefficient by examining the association between capital expenditures and future cash flows in the following two years. The results show that the existence of cheating customers indeed hurts the investment efficiency, reflected by the diminishing future cash flows. Next, we also report evidence that suppliers bogged down in a higher level of overinvestment during the cheating period, are likely to have more negative 3 (7) days market reactions when customers' frauds are made public, implying that the market is reluctant to believe that affected suppliers can easily get rid of the headaches of customers' distortions.

The results are robust to alternative empirical settings. Initially, our hypotheses are tested in a clean setting by ruling out any potential interference of industrial factors. To further address the issues arising from the pooled sample, we utilize the dynamic "Difference in Difference" (DID) model adapted from Kedia and Philippon (2009) to concrete our findings.

This paper adds to the accounting literature in the following three ways. In related studies, Beatty, Liao and Yu (2013) and Li (2016) show that the fraudulent financial reports foster the overinvestment among industry peers during the fraud periods. We expand such findings by illustrating that the influence of corporate frauds can be extended to a broader scope of victims. Specially, we document that corporate frauds incur the real economic costs to not only firms within the same industry but also to firms with supplier-customer economic ties. Second, consistent with prior literature (e.g., Baiman and Rajan, 2002; Choi and Krause, 2006; Patatoukas, 2012), we emphasize the importance of the credibility of information transferred over supply chain as well, showing that the inferior quality of customers' information erodes their suppliers' investment efficiency. Third, this paper has practical significance. To be specific, our findings reveal the nontrivial influence of principal customers in a certain supply chain network. The firms at the center of supply chain network may impair a large group of suppliers by distorting their future investment decisions. Therefore, we suggest regulators to raise attentions on the structure of supply chain and keep eyes on the suspicious behaviors of the "vital nodes" (principle customers) in the supply chain network.

The reminder of the paper proceeds as follows. Section 2 develops the hypotheses based on prior literature. Section 3 describes data, variable measurements and model specifications. Section 4 presents the results, Section 5 and Section 6 discusses additional tests and robustness checks. Section 7 concludes.

2.2 Literature Review and Hypothesis Development

2.2.1 Corporate Frauds and Investments

During the misrepresentation period, managers manipulate not only the financial numbers but also the resource allocation to paint a rosy view of economic prospects. Prior literature examines the effect of corporate frauds on the firm's investment decisions. Kedia and

Philippon (2009) show that firms engaged in frauds tend to overinvest in order to mimic good managers and conceal the low productivity. In line with this, Maurren and Stephen (2008) also show that misrepresentation of financial performance leads to suboptimal investment decisions. The theoretical model proposed by Kumar and Langberg (2009) also provides some insights on association between frauds and overinvestment. In their model, in order to pursue personal benefits from large incomplete commitments of investments, the manager is likely to misreport the productivity and overinvest in some states.

Along with the direct effect of frauds on investments, the spillover effect on non-fraudulent competitors is documented in the prior literature as well. Durnev and Claudine (2008) develop a simple model where firms use competitors' financial reports to gauge the unknown payoff of investments. They argue that restatements contain news about the investment projects of restating firm's competitors and find that competitors change their level of investments following restatement announcements. In related studies, Beatty, Liao and Yu (2013) show that the fraudulent financial reports foster the overinvestment by industry peers during fraud periods. Li (2016) documents that such distortions could occur in the broader definition of frauds and in R&D, advertising and pricing policies as well.

2.2.2 Supplier-Customer Relationship and Corporate Frauds

The relations with suppliers may shape the customers' decisions to opportunistically manage earnings. For example, Raman and Shahrur (2009) document that firms are more likely to manage accruals and consequently report higher earnings to encourage suppliers to invest in relationship specific assets. The disclosures of customers' frauds also impact the wealth fare of suppliers. Kang and Tham (2012) show that there's a negative spillover effect of earning restatement over supplier's market value and more dependent suppliers will be more likely to be cut off after restatements are announced. Files and Gurun (2014) argue that loan lenders will charge a higher spread as the response to restatements in supplier's industry. The fraudulent accounting induces reputational sanctions from the product market. Customers impose significant sanctions on detected cheating firms, leading to inferior operating performance of suppliers through increasing sell costs (Johnson, Xie and Yi, 2014). To avoid the relationship disruption and reputational damage, dependent suppliers being sued are more likely to reveal their good news and strategically withhold their bad news (Cen et al., 2014).

There's little understanding of how the misrepresentation will distort the investment decisions and real costs for non-financial stakeholders especially during the undetected customers' cheating periods. As suppliers utilize their customer's information to infer future demand and economic prospect, noisy information distorts and misguides their investment and production decisions (Lee, Padmanabhan and Whang 2017; Ha and Tong 2008). The manipulated charming performance of customers signals a potential high level of future demand and prosperous economic prospects for suppliers. In order to share the artificial prosperity, suppliers may overinvest to expand their production capacity to satisfy the illusory high demand and make overinvestment. Thus, we hypothesize that:

H1: Suppliers will invest more during the fraud periods of customers.

2.2.3 Informational Reliance and Suppliers' Overinvestment

Based on discussions above, we present the importance and potential effects of customers' information on suppliers' investment decisions during the cheating period. However, as we known, the demand signal from the customer side is not the unique information channel that suppliers can use to foresee the future demand. If suppliers have multiple choices of information sources, they may less rely on customers' information and consequently be less distorted by fictional charming prospects of their customers. Therefore, in this section, we specially identify two moderating effects that may affect suppliers' informational reliance on their customers: the industry concentration and the sales volatility.

First, it is costly for suppliers to aggregate customers' information and forecast future demand. However, industry leaders who own large market shares could have better understanding of industry dynamism and demand. They may be more capable of predicting future industry demand. As documented in Ali, Klasa, and Yeung (2014), in a concentrated industry, corporate disclosures may provide more reliable information about future industry demand than similar disclosures in a less concentrated industry. Therefore, suppliers are more likely to use the reliable information from observing industry leaders' behaviors or disclosures to revise their own strategies than simply rely on customers' information. The emergence of such additional information channel may dilute the value of customers' information and attenuate suppliers' informational reliance on their customers. Therefore, we expect the investment distortions of suppliers to be less severe in a highly concentrated industry.

H2(a): The distortion effects of fraudulent customers' information on suppliers' investment decisions will be less pronounced when suppliers are operating in a highly concentrated industry.

On the other hand, a stream of literature has documented the importance and benefits of information sharing in supply chain, especially when firms face greater demand uncertainty (Yu, Yan, and Cheng 2001, Chen and Lee 2009, Lee, Padmanabhan, and Whang 2017). When suppliers are operating in a volatile environment, it is hard to predict future demands solely based on historical firm information and thus the demand signals from customers become more essential to forecast future demands. Consequently, we expect the distortion effect to be more severe when suppliers rely more on their customers' information.

H2(b): The distortion effects of fraudulent customers' information on suppliers' investment decisions will be more pronounced when suppliers are operating in volatile environment.

2.3 Research Design

2.3.1 Data

We first proxy corporate frauds by class action lawsuits obtained from the Securities Class Action Clearinghouse (SCAC). The initial litigation sample is consisted of 2,055 lawsuits that can be matched to COMPUSTAT from 1996 to 2013. Then, we create restatement sample by focusing on firms with income-increasing restatements from 2002 to 2013 from the Audit Analytics database (AA). The initial restatement sample contains 2,846 restatements that are matched with COMPUSTAT.[2] We further exclude financial (SIC codes between 6000 and 6999) and utility firms (SIC codes between 4900 and 4999) for both samples. For firms that commit multiple frauds in our sample periods, we only keep

[2] We follow prior literature (e.g., Wang and Winton, 2010) and focus on *ex post* detected frauds.

the first case. Our final litigation and restatement sample contain 1,502 and 2,129 fraudulent firms, respectively.

We extract supply chain relationship from COMPUSTAT segment data. In accordance with the statement of Financial Accounting Standards (SFAS) No. 14 and No.131, public firms are required to disclose the identity of any customer that contributes at least 10% to the firm's revenues. However, only the names of principal customers or the abbreviations of the customer names are reported in the segment data. Next, we use a combination of automatic and manual methods to match customer names with company names appeared in the COMPUSTAT to obtain the GVKEY identifiers. We follow Fee and Thomas (2004) approach to conduct matching and use industry classification to verify matches. If still cannot find a match, we manually search S&P capital IQ to identify whether the customer is a corporate subsidiary. If so, the customer will be matched to its parent company.

In this paper, we define a firm as a dependent supplier if it reported at least one principal customer in the prior two years.[3] In order to identify fraudulent customers, we examine all disclosed customers in the past two years. We use the litigation and restatement data to identify the cheating periods of customers. In the litigation sample, we identify 391 unique cheating customers and 934 related dependent suppliers, resulting in 1,288 firm-years. Alternatively, in the restatement sample, we find 214 unique cheating customers and 435 unique related suppliers, resulting in 609 firm-years. Table 1 presents the summary of the time series trend of affected suppliers for both samples. As expected, the number of

[3] Following prior literature (Maurren and Stephen 2008), the principal customer is any disclosed customer which has at least 10% of its suppliers' total sales.

affected suppliers drastically drops after the implementation of Sarbane Oxley Act (2002).

[Insert Table 1 Here]

Finally, we obtain financial data from COMPUSTAT database. To attenuate the potential difference of firm characteristics between dependent suppliers and firms with no principal customers, we restrict our sample to firm-years where principal customers are disclosed in the prior two years. We also exclude all dependent suppliers engaged in fraudulent reporting for a clean research setting. There are 10,727 and 8,771 firm-years with non-missing financial information in the litigation sample and restatement sample, respectively.

2.3.2 Model Specifications

Test of H1: Investment Distortions of Affected Suppliers

When cheating customers signal prosperous prospects, we expect that the related suppliers will increase their investments in order to meet increased demand in the future. To test our hypothesis, we run the following OLS regression.

$$CAPEX_{i,t} = \beta_0 + \beta_1 Cheating\_Customer_{i,t} + \beta_2 Fundamental\_Controls_{i,t} + \varepsilon_{i,t} \quad (1)$$ [4]

The dependent variable CAPEX is the ratio of capital expenditure to lagged total asset. The main variable of interest Cheating_Customer is to capture the presence of a cheating principal customer. Cheating_Customer takes one if the customer is disclosed in either of the prior two years and the current year is part of its class period. We expect the coefficient of Cheating_Customer to be positive. Following Li (2016) and Beatty, Liao and Yu (2013), we include a set of fundamental factors to control for the specific characteristics of

[4] In the untabulated test, after controlling customers' fundamental controls, we still get significant and consistent empirical findings.

suppliers that influence their investment decisions. For instance, we control for firm size, Tobin's Q, and sales turnover, as firms with higher growth and investment opportunities tend to invest more. We also control for cash holdings, ROA, and external financing since extra cash or external financing facilitates investment, and firms' investment increases with profitable operations. We control for firms' financial leverage as previous literature document that financial frictions and ownership structure could be linked with corporate investments (Almelda and Campello 2007, Ozdagli 2012). Finally, we include industry and year fixed effects to the regression model for both samples.

Test of H2: The Moderating Effects of Suppliers' Informational Reliance on Customers

In this section, we investigate how suppliers' informational reliance on customers moderate the magnitude of suppliers' overinvestment during customers' cheating periods. Our expectation is that suppliers are less likely to use customers' information to infer future demand within a concentrated industry, but more likely to depend on customers' information when there's high uncertainty over sales. We construct the Herfindahl-Hirshman Index (HHI) to proxy for the industry concentration. HHI is defined as $\mathrm{HHI}_{i,t} = \sum_{i=1}^{n}(\Pi_i)^2$, where Π_i is the market share of company i within the same 2-digit SIC industry. Following Tong et al. (2008), we use the standard deviation of the natural logarithm of sales in the prior three years as the measure of volatility in the operating environment.

We refine the equation (1) by interacting both the HHI and sales volatility with our main variable of interest Cheating_Customer. We expect the coefficient of is

HHI*Cheating_Customer significantly negative, while the coefficient of Sales_Vol*Cheating_Customer is significantly positive.

$$CAPEX_{i,t} = \beta_0 + \beta_1 Cheating\_Customers_{i,t} + \beta_2 Cheating\_Customers_{i,t} * HHI_{i,t} + \beta_3 Fundamental\_Controls_{i,t} + \varepsilon_{i,t} \quad (2.1)$$

$$CAPEX_{it} = \beta_0 + \beta_1 Cheating\_Customers_{i,t} + \beta_2 Cheating\_Customers_{i,t} * Sales\_Vol_{i,t} + \beta_3 Fundamental\_Controls_{i,t} + \varepsilon_{i,t} \quad (2.2)$$

2.4 Results

2.4.1 Descriptive Statistics

Table 3 presents summary statistics for our entire sample. In accordance with Li (2016), we utilize both litigation (Panel A) and restatement (Panel B) in our empirical analyses. Detailed definitions of variables used in Table 3 are provided in Appendix A. We winsorize all financial variables at the 1st and 99th percentiles of their distributions to minimize the influence of outliers.

In panel A, the variable of our interest is the dummy variable "Cheating_Customer", which equals to 1 if the supplier has at least one cheating customer during the class period. It shows that 12% out of 10,727 observations are affected suppliers with cheating customers, implying that the existence of cheating customers in a supplier-customer relationship is not rare. Similarly, in Panel B, the main variable "Cheating_Customer" indicates that 6.9% out of 8,771 observations are affected suppliers with cheating customers in our restatement sample.

Other fundamental factors documented by prior literature that may impact corporate investment decisions have been included in our sample as well. In litigation sample, on average, the supplier has a logarithm of total assets value of 5.147, with a leverage ratio of 16.3%, a ROA of -10.5%, a cash holding of 19.5% and Tobin's Q of 2.101. Consistently, in restatement sample, an average supplier has a logarithm of total assets value of 5.648, with a leverage ratio 16.2%, a ROA of -8.9%, a cash holding of 19.6% and Tobin's Q of 2.042. Overall, the distributions of control variables are consistent in both litigation and restatement sample.

[Insert Table 3 Here]

2.4.2 Preliminary Results

Customers' Manipulations During Cheating Periods

Following prior literature (Kedia and Philippon 2007, Beatty et al., 2013, Li 2016), in our preliminary test, we investigate whether cheating customers are manipulating resource allocations to paint a rosy view of economic prospects during cheating periods. In line with Kedia and Philippon (2007), we compare cheating firms' capital expenditures, employee growth, property, plant, and equipment growth, growth in size, and sales growth in its market between cheating and clean periods for both our samples. As predicted, we find that cheating customers not only sugar up financial numbers, but also distort the overall resource allocations and investments in order to be viewed as "prosperous". For example, we observe that during cheating periods, the fraudulent customers on average overinvest by 0.4%, hire 3.3% more employees, experience 1.5% more growth in size, and 2.8% more growth in sales comparing to clean customers in the litigation sample. We also find similar results in the restatement sample.

[Insert Table 2 Here]

2.4.3 Main Results

Table 4 reports the regression results for our first hypothesis (H1) using the model of Equation (1). The dependent variable is suppliers' capital expenditures (CAPEX). The variable of interest is the dummy variable "Cheanting_Customer", which equals to 1 when suppliers have a cheating principle customer and 0 otherwise. The column (1) and (2) present the regression results for the litigation sample from 1996 to 2003. In column (1), we find a significantly positive association ($\beta_1 = 0.01$, t=3.51) between the existence of cheating customers and suppliers capital expenditures, implying that customers' misrepresentations distort their suppliers' to make overinvestment during the cheating period. In column (2), this result holds after controlling for factors known to explain firms' investment decisions. The significantly positive coefficient ($\beta_1 = 0.008$, t=2.68) suggests that affected suppliers tend to invest 11.4% more comparing to unaffected suppliers. The coefficients for control variables are significant and consistent with our expectations as well. Specially, during customers' cheating periods, suppliers who have higher cash holdings, sales, ROA and financing activities, but lower leverage are likely to be distorted to overinvest. Additionally, in accordance with Li (2016), we also conduct the same analysis utilizing the restatement sample, presented in column (3) and (4). Our results are robust and held. The coefficients of variable of interests are 0.01 (t=2.84) and 0.012 (t=3.08) in column (3) and (4) respectively. It indicates that affected suppliers are more likely to invest 21% more than unaffected suppliers during customers' cheating periods. Overall, the results in Table 4 suggest that customers' frauds have a spillover effect on suppliers' investment decisions and trigger suppliers to make overinvestment during the cheating period.

[Insert Table 4 Here]

2.4.4 Cross-sectional Tests

The second hypothesis aims to investigate the moderating effects of "information reliance" on the association between customers' misconduct and suppliers' overinvestment during customers' cheating periods. To explore H2, we estimate models in equation (2.1) and (2.2) and focus on the interaction term Cheating_Customer * HHI and the Cheating_Custmer * Sales_Vol.

Table 5 reports the regression results for H2. In column (1), consistent with our expectation, the coefficient of the interaction term Cheating_Customer*HHI is -0.11 (t=-2.48), suggesting that within a high concentrated industry, suppliers are less distorted by customers' misrepresentations to make overinvestment. Within a high concentrated industry, suppliers are able forecast future demands by extracting information from industry leaders' disclosures or observing leaders' behaviors with low cost, and thus suppliers' informational reliance on their customers is largely shrunk. On the other hand, in column (2), the coefficient of the interaction term Cheating_Customer * Sales_Vol is significantly positive (0.041, t=2.98), suggesting that suppliers with a high degree of sales uncertainty, are more distorted by customers' frauds. Suppliers with high sales volatilities are hard to predict their future performance solely based on historical data and thus rely more on their customers' information when making investment decisions. The results are still held in column (3) and (4) utilizing the restatement sample from 2002 to 2013. We find that the coefficient of the interaction term Cheating_Customer*HHI is -0.136 (t=-2.45) in column (3) and the coefficient of Cheating_Customer*Sales_Vol is 0.052 (t=2.09) in column (4). All specifications include the year and industry fixed effects to control for potential omitted variables.

[Insert Table 5 Here]

2.5 Additional Tests

2.5.1 The deteriorated investment decisions during the cheating period

To further triangle our main findings, we first confirm that suppliers' investment decisions during customers' cheating period are distorted and suboptimal, by examining how the existence of cheating customers impacts the association between capital expenditures and future two years' cash flows. We expect that the existence of cheating customers will mitigate the contribution of the investment to future operating performance.

To empirically test our argument, we only eliminate those firm-year observations when their following years fall in the post period of detected frauds. We control fundamental variables that could impact future cash flows, such as firm size, cash holdings, leverage, ROA, sales, financing and Tobin's Q. Specially, we utilize the following equation (3):

$$\mathrm{CFO}_{i,t+m} = \beta_0 + \beta_1 CAPEX_{i,t} * Cheating\_Customer_{i,t} + \beta_2 CAPEX_{i,t} + \beta_3 Cheating\_Customer_{i,t} + \beta_4 Fundamental\_Controls_{i,t} + \varepsilon_{i,t} \quad (3)$$

Where the dependent variable is future two years' cash flows CFO_{t+1} (m=1) and CFO_{t+2} (m=2) and the interaction term CAPEX*Cheating_Customer is our variable of interest. We expect a significant negative sign of the coefficient of the interaction term.

Table 6 reports the regression results by using both litigating sample and restatement sample.

[Insert Table 6 Here]

In the first two columns, we show that the coefficients of the interaction terms are significantly negative with both CFO_{t+1}(β_1 =-0.164, t=-2.50) and CFO_{t+2} (β_1 =-0.198, t=-2.22), supporting our expectation that during customers' cheating period, suppliers make suboptimal investment decisions and suffer from the inferior future operating performance in the following two years. The results presented in the column (3) and column (4) are still qualitatively consistent with our expectations, when we replace the litigation sample with the restatement sample.

2.5.2 The stock market reactions to the distortion on the date of the fraud disclosure

In this section, we aim to investigate whether the market will punish distorted suppliers after the disclosure of customers' frauds. If so, despite the investment inefficiency and the inferior operating cash flows during the cheating period, the negative stock market reaction from investors sets off a new wave of economic real costs to suppliers in the post period of detected frauds. To empirically test our expectations, we first select those suppliers who actually engage in overinvestment. Specially, during the cheating period, we use industry median of capital expenditures from unaffected suppliers as the benchmark level of investment and consequently the affected suppliers are classified as overinvestment suppliers if they have a higher level of capital expenditures than the benchmark in at least one year during the cheating period. Then, we use the disclosure dates of customers' misrepresentations as event dates to investigate market reactions to the suppliers' overinvestment at the end of cheating periods. Our treatment groups are affected suppliers engaged with overinvestments and control groups were unaffected suppliers. The regression model is conducted as following:

$$\mathrm{CAR}_{i,[-3,+3]}\ or\ \mathrm{CAR}_{i,[-1,+1]} = \beta_0 + \beta_1 High\_CAPEX\_Customer_{i,t} + \beta_2 Fundamental\_Controls_{i,t} + \varepsilon_{i,t} \quad (4)$$

Where the dependent variable are 3 days or 7 days cumulative abnormal returns (CAR) adjusted by the size portfolio, and the variable of interests is the dummy variable (High_CAPEX_Customer) indicating whether affected suppliers have ever overinvested during the cheating period.

The results can be found in Table 7. In the first two columns, the significantly negative coefficients (-0.013, t=-1.77 and -0.019, t=-2.16) of our variable of interests (High_CAPX_Customer) support our expectation that the market will punish the distorted suppliers' overinvestment decisions when their fraudulent major customers are caught and the negative market reaction is also a kind of real economic costs to suppliers. We find a qualitative consistent result after we replace our litigation sample with restatement sample. The results can be found in the last two columns.

Moreover, we further investigate that whether the level of overinvestment may trigger different magnitude of the negative market reaction for affected suppliers with cheating customers after the disclosure of customers' frauds. Specially, we still utilize the industry median of capital expenditures from unaffected suppliers as the benchmark and calculate the "abnormal investment level" for affected suppliers. Then, we take the average of the abnormal investment over the cheating period and classify those suppliers as highly overinvested suppliers if their average abnormal investment falls in the top half of the sample. Then we follow the same regression design by replacing the dummy variable from the one indicating whether suppliers engage in overinvestment with the one indicating whether suppliers have highly overinvested comparing to other affected suppliers. In this test, our treatment groups are highly overinvested suppliers and control groups were the rest of affected suppliers.

[Insert Table 7 Here]

In the untabulated table, we find that indeed, the more the suppliers engage in overinvestment, the more severe market reactions they receive after the frauds were made public, implying that investors are reluctant to believe suppliers can easily get rid of the headaches of customers' distortions. This finding concretes our argument that except the real costs during the cheating period, suppliers also need to pay off the costs from the stock market after the disclosure of customers' frauds.

2.6 Robustness Checks

Initially, our empirical results are tested in a cleaner setting. In prior related studies that investigate distortion effects among peer firms, the potential omitted industrial common economic factors and information learning between peers can drive the result. In their studies, they cannot disentangle these two effects. However, in our study, the "cross-industries" setting successfully rules out the interference of industrial common economic factors.

To alleviate the issues arising from the pooled matching of control groups (unaffected suppliers), we adapt the approach from Kedia and Philippon (2009) to compare dynamics of capital expenditures for affected suppliers around the cheating periods.

Firstly, we create a control group of unaffected suppliers that are matched in size, year and industry. Specially, for each affected suppliers, we choose all unaffected suppliers appear in two years before the beginning of customers' misconduct[5]. We then select unaffected suppliers which operate in the same industry, and that are in the same size quantile. To address survival bias, we also require the control group to survive through the entire customers' cheating periods. We adjust the variables of interest (capital expenditure) by subtracting the mean of this control group.

$$\widehat{\text{capex}}_{i,t} = \text{capex}_{i,t} - \overline{\text{capex}}_{c(i),t}$$

Where c(i) is the control group for firm i at year t.

We now turn to a formal empirical test to substantiate our evidence as follows:

$$\widehat{\text{capex}}_{i,t} = \beta_0 + \beta_1 During_{i,t} + \beta_2 After_{i,t} + \varepsilon_{i,t}$$

A positive estimated coefficient β_1 implies that the affected suppliers invested more than comparable unaffected suppliers during customers' cheating periods. Besides that, we also compare the coefficient over time to see if the dynamics of affected suppliers will significantly change after the disclosure of customers' frauds. After the disclosure of

[5] Different from Kedia and Philippon (2009), we create the control group in two years before the fraudulent period not in the beginning of our sample. Since fraudulent firms are likely to make preparation for misconduct in advance, it is reasonable to consider longer window to observe the dynamics of performance. However, our paper is to see spillover effects due to customers' frauds over supply chain. A shorter window is more proper, the firms selected in the control group are more similar to each other in fundamentals.

customers' frauds, the manipulated customers' prospects were corrected and suppliers' start to adjust the level of investments back to normal. Therefore, it is reasonable to expect that affected suppliers' capital expenditures will go down after the fraudulent periods. In this case, the null hypothesis is that $\beta_1 = \beta_2$.

[Insert Table 8]

The results are presented in table 8. The affected suppliers significantly (t=2.17) invest more during customers' fraudulent period in comparison to unaffected suppliers. Consist with our prediction, we find that the null hypothesis that β_1 is the same as β_2 can be rejected at less than 1% level, indicating that after the fraudulent periods, affected suppliers' capital expenditures go down, as we predicted.

2.7 Conclusion

The corporate frauds have attracted much attention from both financial and nonfinancial stakeholders. Prior literature well-document the real costs of corporate frauds on firms engaging misconducts (Kedia and Philippon 2009, KarpoffLee and Martin, Giannetti and Wang, 2014). Recently, researchers start to notice the spillover effects of fraudulent financial reporting on peer firms (Beatty, Liao and Yu, 2013) and broad the definition of fraudulent accounting (Li, 2016). In this paper, we expand their work and investigate the spillover effects of corporate frauds in the broader scope of victims. Specially, we document that corporate frauds incur the real economic costs to not only firms within the same industry but also to firms with supplier-customer economic ties.

We find that during customers' cheating periods, affected suppliers with cheating customers are more likely to be distorted to overinvest in comparison to unaffected suppliers. Further, in the cross sectional analysis, we test the moderating effects of suppliers' informational reliance on the positive association between the existence of cheating customers and suppliers' overinvestment. Additionally, we also provide evidence that after the disclosure of customers' frauds, suppliers engaged in overinvestment are going to experience the negative market reaction. Lastly, to triangle our main findings, we utilize a "difference in difference" (DID) approach to confirm that affected suppliers elevate the level of capital expenditures during customers' cheating periods and such high level of investments will go down after the disclosure of customers' frauds. Overall, our paper contributes to the current accounting literature by unraveling the real costs of corporate frauds over supply chains, emphasizing the importance of the credibility of information transferred over supply chain, and suggesting regulators to keep eyes on the customers at the center of the supply chain network.

CHAPTER 3: STRATEGIC EARNINGS ANNOUNCEMENTS TIMING AND FINANCIAL MISREPORTING

In the realm of corporate frauds, prior literature has provided evidence that companies strategically take activities to "hide" their misconduct and in consequence extend the detection duration due to the phobia of being punished by the market. For example, managers attempt to make overinvestment to disguise fraud by introducing valuation imprecisions and creating inference dispersions for outside information users (e.g. Wang 2004, Kedia and Phillipon 2009). Additionally, they may spend a fair amount of money in lobbying to lower the rate of being detected in frauds (Yu and Yu 2011). Moreover, managers are likely to increase the cost of extracting information from disclosures by strategically reducing the readability of financial reporting (Lo, Ramos and Rogo 2017). However, these studies neglect a low-cost strategy that may be beneficial for managers to camouflage their opportunistic behaviors: the timing strategy of Earnings Announcement (EA). In this paper, we are going to examine whether managers involved in accounting misreporting are inclined to strategically announce earnings news during the period of low market attention and further explore the underlying benefits of doing this.

The debate regarding the existence of strategic timing of EAs motivates our study. As argued in recent studies (e.g. Della Vigna and Pollet 2009; Melessa 2013; DeHaan et al. 2015; Michaely 2016), managers are aware of earnings news before the releasing date and take information advantage over investors to strategically decide the time of disclosure. Based on the "investor inattention hypothesis" (Hirshleifer et al. 2009), managers are apt to disclose bad news in low market attention time slots and benefit from reduced market responses. Prior literature devotes many pages to evaluate the proxy for the low market attention. For example, the pioneering “Firday” (e.g. DellaVigna and Pollet 2009), the specified “Friday evening”, the new insightful “after trading hours” and “busy announcement days” (e.g. DeHaan et al. 2015) and the unpredictable exogenous daily news pressure index (Israeli, Kasznik and Sridharan 2017). But these studies examine the existence of strategic announcing with respect to the content of news but overlooks the importance of the quality of the news. As well documented in the earnings management and corporate frauds literature, managers usually opportunistically manipulate the content of earnings in an upward direction to maximize their self-interests even paying additional costs (e.g. taxes): either inflate bad news to good news or shift the bad news from an extreme to an average extent (e.g. Burgstahler and Dichev 1997; Healy and Wahlen 1999; Erikson, Hanlon and Maydew 2004). In this way, the manipulated earnings result in a low quality and intentionally mislead investors’ expectations on firm value. At the meanwhile, for the fear of the market punishments after being required to restate or detected s (Palmrose, Richardson and Scholz 2004; Farber 2005; Ball 2009), managers strategically take real activities to conceal their misconduct. Following a similar logic, we expect managers engaged in misreporting may release their manipulated earnings strategically by picking up low market attention or high distraction time to lower the possibilities of being caught, such as after trading hours, Friday nights, or busy days with numerous news.

As we discussed above, for managers managing earnings, the primary benefit of strategic announcing is to lower the detection rate. In the era of information explosion, it seems impossible for managers to completely hide news from investors. Although the pricing impact through managing disclosure timing may be a flash in the pan, managers still prefer to drag down the rate of the discovery of opportunistic behaviors and bear with a gradual price drop in future to avoid a high crash and litigation risk (Donelson et al. 2012). Consistent with prior literature that find mangers successfully extend the detection period, we expect that the primary benefit of strategically managing EAs time is to lower the probability of being caught, resulting in a longer undetected period.

Moreover, insider trading may be an additional benefit to explain why cheating firms would like to announce manipulated earnings in low market attention time slots. In Michaely et al. (2016) study, they find that insiders benefit from trading in the direction of the content of the news soon after the EAs. However, it is not the case when the nature of the news is manipulated. Insiders take advantage of the information asymmetry over investors to trade based on the underlying quality of news rather than the reported content of news. Since firms are able to camouflage bad news to good news, In some cases, even the content of the news announced is good, insiders may still take a short position in shares because they can foresee that the faked good news may be discovered in future which increases their personal wealth risk. On the other hand, insiders may also buy shares during the cheating period to share the faked prosperity. Therefore, the direction of insider trading is unclear when the news is good. Contrastingly, if the disclosed news is bad, insiders are more likely to sell shares and benefit from market inattention and unawareness of manipulation.

To examine our proposed hypotheses above, we first identify financial manipulation by using accounting restatements from 2002 to 2015 from the Audit Analytics database. We only keep those income-increasing restatements to proxy the intentional upward manipulations (e.g. Archambeault, Dezoort and Hermanson 2010). To capture more severe accounting manipulation, we collect Accounting and Auditing Enforcement releases(AAER) data from 1999 to 2010, as our alternative sample. Specially, the SEC data are obtained from the University of Berkeley's Center for Financial Reporting and Measurement. After excluding financial firms and merging with the COMPUSTAT, we obtain 1,344 restatements and 308 SEC enforcements, respectively. Following prior literature (Bagnoli et al. 2005; Doyle and Magilke 2009; DeHaan et al. 2015; Michaely et al. 2016), we proxy limited attention period as the period after market closes (AMC) and the Friday, considering both time of the day and day of the week. To address the concern whether the annual EAs timing is as flexible as quarterly EAs timing, we compare the timing distribution of annual EAs to quarterly EAs and suggest that the changes of annual EAs timing are relatively common.

In the univariate analysis, we find that during the fraudulent period, misreporting firms make 4.61% more EAs than firms within the control group during the after trading hours in the restatement sample. We find a similar pattern in the AAER sample, whereas misreporting firms make 10.35% more EAs during the after trading hours than control firms. To attenuate the potential sample selection bias, we further restrict our sample to only misreporting firms and find that misreporting firms in fraudulent years tend to disclose more in after trading hours than that in non-fraudulent years. However, we are not able to find a similar result by using Friday as the proxy for low market attention period.

To bolster our univariate inferences, we perform cross-sectional regression analysis. Following prior literature, we control several firm specific variables. Although we focus on investigating the effect of the quality of the news, we control the content of the news proxied by the unexpected earnings surprise (*SUE*) as prior studies suggest. We find a significant positive association between the existence of fraudulent behaviors and the EAs announced in low market attention time slots, supporting our first hypothesis. Specifically, the decision to misreport is associated with 11.92% increase in the likelihood of after trading hours announcements in restatement sample, and 12.20% increase in AAER sample, respectively However, we fail to find a significant result if we replace our dependent variable from after trading hours to Friday, consistent with what is seen in the univariate analysis. The insignificant result for Friday suggest that intra-day timing strategy may impose a greater cost as investors may pay more attention to changes in announcement day and infer suspicious manipulations on earnings news. To further consolidate our result and mitigate sample selection bias, we conduct propensity score matching and consistently find that during the misreporting period firms are more likely to announce earnings in lower market attention period.

Next, we investigate the potential benefits of strategic announcing for firms engaged in financial misconduct. First, we restrict our sample to detected misconduct and examine whether disclosing EAs in low market attention time will reduce the detection rate and increase the length of undetected period. After controlling oversight detection intensity, industrial litigate risk and other firm fundamentals, we find a significant positive result, supporting our expectation that fraudulent firms with strategic announcements in low attention period are likely to enjoy a longer undetected period than other firms. Specifically, we find that taking the timing strategy during the violation periods generally delay the detection period by 161 days. In addition, we find some empirical evidence on whether strategic announcing help firms conceal insiders trading. As expected, we find more trades in the direction of surprise for only negative news announced in after trading hours by misreporting firms. This finding provides us an additional explanation why cheating firms prefer to strategically announce earnings during after trading hours.

This paper contributes to the current literature along several dimensions. First, we provide additional evidence on the existence and the effectiveness of the disclosure timing strategy. We suggest that managers involved in fraudulent activities are likely to announce manipulated earnings during a low market attention period: after trading hours period. Second, our paper contributes to the corporate fraud literature by emphasizing the importance of EAs timing. Specially, our paper is the first to suggest information users and regulators should pay attention to the earnings announced in the low attention period, since these announcements more likely to be associated with financial frauds. Furthermore, our findings also explain the prevalence of undetected financial misconduct as managers utilize investors inattention to evade detection. Third, instead of analyzing the managerial incentives based on the content of the news, our paper broads the scope of the research on strategic timing by utilizing the outcome-based measures (the restatement or the SEC enforcement) to examine the impact of the quality of news on the choice of strategical announcing.

The reminder of this paper is organized as follows. The section 2 summarizes the literature and develops hypotheses. The section 3 contains the research design and empirical results. The section 4 concludes.

3.2 Literature Review and Hypotheses Development

Our work is based on prior studies that investigate how the time of corporate announcements (EA) affects investors' expectations by examining the magnitude and timeliness of market responses. Since most firms are aware of earnings news before the dates of releasing, managers are able to strategically control the time of disclosure to attract or avoid excessive market attentions with a relatively low cost (deHaan, Shevlin and Thornock 2015; Johnson and So 2017). Thanks to the variation in market attentiveness, managers are likely to gain the benefits[6] from reducing (attracting) attentions to bad (good) news. The debate of the existence of the strategic announcing becomes an ad hoc topic in the area of accounting disclosures.

Specially, based on the proposed "Friday Effect" (Penman 1987; Damodaran 1989; and Bagnoli et al. 2006), a number of literature use the incidence of announcements on Friday as the proxy for the low market attention. For example, DellaVigna and Pollet (2009) present a reduced market response and a greater post-earnings-announcement-drift as the evidence for the limited investors' attention and argue that the low attention motivates managers to strategically disclose bad news on Fridays. However, this argument is challenged by another pool of research. Melessa (2013) contradicts this finding by attributing the reduced market response to the economic uncertainty. Additionally, Michaely, Rubin and Vedrashko (2016) conclude that the reduced market response to Friday announcement is due to the selection bias. Moreover, DeHaan et al. (2015) even claim that the investor attention is the same or even higher on Fridays. Finally, Doyle and Magilke (2009) find that the proposed "Friday Effect" is gone after controlling the frim fixed effect.

The debate regarding Friday announcements motivates researchers to find other proper

[6] The benefits may from a delayed (immediate) market response under a lazy (elaborate) market scrutiny, when firms are handing bad (good) news (Lim and Teoh 2010; Huberman and Regev 2001). In addition, although the timing strategy may only work in a short-term window, managers still prefer to have a gradual drop price to lower the crash risk and the litigation risk (Donelson et al. 2012).

identifications of low market attention. Hirshleifer et al. (2009) utilize the days with many EAs as the proxy for the low market attention and support that investors' limited attention cause market under-reactions. Further, DeHaan et al. (2015) provide evidence that after trading hours or on busy reporting days, managers are likely to take advantage of low market attention to public bad news. Moreover, Michaely et al. (2016) refine DeHaan et al. (2015)'s findings and show that investors are inattentive only on Friday evenings. In a recent study, Israeli, Kasznik and Sridharan (2017) utilize an unpredictable proxy (daily news pressure index: DNP) that exogenously captures the level of investors' distraction to further confirm the influence of investor attention on corporate announcements.

However, these studies only examine the existence of strategic announcing based on the content of the news (e.g. good or bad news), and neglect the importance of the quality of the news (e.g. fair or manipulated news). As documented in Michaely et al. (2016), firms that announce earnings within low market attention slots are less visible, implying that managers from those firms are more likely to strategically announce manipulated accounting information. Thus, it is necessary to make sure whether managers will strategically misreport earnings under a lazy market scrutiny to avoid the severe punishment from the market.

In fact, in the realm of corporate frauds, prior literature has provided plenty of evidence that companies strategically take activities to "hide" their misconduct. For example, managers attempt to make overinvestment to disguise frauds by introducing valuation imprecisions and creating inference dispersions for outside information users (e.g. Wang 2004, Kedia and Phillipon 2009). Additionally, they may spend a fair amount of money in lobbying to lower the rate of being detected (Yu and Yu 2011). Moreover, managers are likely to increase the cost of extracting information from disclosures by strategically reducing the readability of financial reporting (Lo, Ramos and Rogo 2017). Therefore, cheating firms may take the low cost timing strategy to camouflage misconduct well.

On the other hand, as pointed out in DeHaan et al. (2015), in the context of big data, with the rapid development of information technology, the idea that managers can "hide" manipulated earnings news is potentially not as feasible as old days. For example, the emergency of "trading robot" based on pre-programmed trading strategies may mitigate the investor inattention problem caused by earnings announcements at market low attention time. In addition, anecdotal evidence from press, interviews and surveys shows that a number of outside information users including investment bankers, analysts, fund managers are still working in after trading hours. Similar to the argument that investors may infer that Friday EAs contain bad news (DeHaan et al. 2015), it is possible that investors may pay additional attention on the EAs that published in the so-called low attention time slots. In sum, it is ambiguous to empirically identify whether firms engaged in financial misconduct strategically manage the timing of EAs. Based on above discussion, our first hypothesis states as follows (in alternative form):

H1: During the misreporting period, firms are (not) more likely to announce earnings in the lower market attention time slot.

As argued in prior studies, managers have incentives to limit public attention to bad news and to benefit from a delayed or reduced market response. Although managers are aware of the pricing impact exists in a short-term window, they still prefer to drag down the speed of the discovery of bad news, since a gradual price drop leads to a lower level of crash and litigation risk (Donelson et al. 2012). Instead of digging the benefits of strategical announcing based on the content of news, we focus on the benefits of doing so on the quality of news. To be specific, following the same logic, cheating firms are likely to take advantage of the timing strategy to hide their opportunistic manipulations on earnings and slow down the detection by the market at a low cost. Prior corporate frauds literature suggests that firms indeed take real activities (e.g. lobbying, making overinvestment, reducing report readability) and successfully extend the detection period. Thus, we expect the primary benefits of strategically managing EAs time is to lower the probability of being detected, as seen in a longer undetected period. We hypothesize our H2(a) h as follows:

H2 (a): The fraudulent firms with strategic announcing are likely to experience a longer undetected period than those firms which do not use opportunistic timing strategy to announce earnings.

In standard asset pricing model, the timing of the arrival of information has no impact on the market price (Ross 1989). However, considering the existence of information asymmetry, prior literature shows that the timing and the informativeness of disclosure have a great impact on investors' expectations (Coller and Yohn 1997; Lennox and Park 2006; Gong, Qu and Tarrant 2018). In this way, managers who strategically manage the timing of EAs may utilize the information asymmetry and benefit from insiders trading. In a related study, Michaely et al. (2016) argues that managers benefit from trading in the direction of the content of the news just after the EAs. In fact, firms are likely to opportunistically manipulate earnings information upward to maximize manager's self-interests (e.g. compensations and promotions), through either inflating bad news to good news or manipulating extreme bad news to average ones. Taking advantage of the information asymmetry, insiders make the investment based on the underlying quality of the news, while investors are trading based on the content of news. Since firms are able to camouflage bad news to good news, in some cases even the content of the news is good, insiders still take short positions in shares based on the underlying bad signal. On the other hand, insiders may buy shares during the cheating period to share the faked prosperity. Therefore, the direction of insider trading is unclear when the news is good. Contrastingly, if the content of news is bad, the underlying news is even worse. Insiders are more likely to sell shares and benefit from market inattention and ignorant of manipulation. The H2(b) is following

H2 (b): Insiders in firms engaged in financial frauds are more likely to gain the benefits from taking a short position in shares when firms strategically announce bad news in a low market attention time slot.

3.3 Research Design

3.3.1 Sample

We first proxy misreporting by restatement obtained from the Audit Analytics database. We identify 2,083 income-increasing restatements from 2002 to 2015[7]. To capture more severe accounting manipulation, we collect Accounting and Auditing Enforcement releases(AAER) data from 1999 to 2010, as our alternative sample. Specially, the SEC data are obtained from the University of Berkeley's Center for Financial Reporting and Measurement. We find 510 enforcement actions with non-missing CIK and violation

[7] We focus on income-increasing restatement since it better captures income increasing earnings management. In addition, there is no consensus requirement of the restatement sample, we also perform our test using alternative SEC enforcement restatements as well as accounting irregulations. Our results remain statistically unchanged.

period information.[8] We exclude financial firms and match both samples to Compustat for firm-level data. Our final misreporting samples contain 1,344 restatements and 308 SEC enforcements, respectively.

[Insert Table 1 Here]

3.3.2 Measures

Following deHaan et al. (2015) and Michaely et al. (2016), we define limited attention periods from two dimensions: time of the day, and day of the week. First, we divide time of the day into three parts: morning before trading hours (from 12:00 a.m. to 9:00 a.m.), trading hours (from 9:00 p.m. to 4:00 p.m.) and after trading hours or after the market closes (from 4:00 p.m. to midnight). Prior literature has documented that investors' attention is especially is lower after the market closes (AMC) compared to the morning hours (before trading hours) or during the trading hours (Bagnoli et al, 2005; Doyle and Magilke, 2009; dehaan et al. 2015; Michaely et al. 2016). Second, though prior research shows mixed evidence on investors' limited attention on Friday (DeHaan et al. 2015; Michaely et al. 2016), it is common for firms to disclose bad news on Friday. Michaely et al. 2016 further argues that only Friday evening is primarily the rational choice of managers to disclose bad news. Therefore, following Michaely et al. 2016, we use two variables to measure low attention periods, i.e. *AMC*, and *Friday*. [9] We obtain firms annual EA dates

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[8] We extend the sample beginning year to 1990 in order to obtain a large sample size.

[9] Different from DeHaan 2015, we do not consider day as a low attention period, which s with many competing earnings announcements as a predicted low attention period for firms. We believe how busy the day is actually depends on decisions of all the firms, which can't be determined or significantly affected by only one firm. Therefore, though investors' attention is low during busy days, firms are less likely to determine which day is busy or slow ex-ant to time their announcements.

and time from IBES Actual Files for the period from1990. To 2015. *AMC* equals to 1 when earnings are released after 4:00 p.m. to indicate for low attention periods and 0 otherwise. *Friday* equals to 1 if earnings are released on Friday and 0 otherwise. We further delete firm-year observations with earnings disclosed on Saturday or Sunday and include in our analyses the earnings that are disclosed on Monday through Friday.[10]

Prior literatures mainly use quarterly EAs in their empirical tests, and document that quarterly EA timings are of high variability with frequent switching by firms. Since our study focuses on annual EAs, one concern is that the annual EA timing may not be as flexible as quarterly EA timing, and frequent switching of EA timing by firms may draw attentions from the market participants. Therefore, we need to first verify whether annual EAs are similarly variable as quarterly EAs such that firms have the same flexibility in selecting annual earnings announcement dates and time. Following deHaan et al. (2015), we first identify EA timing along the time of day, then day of the week. Before trading hours are from 12:00 a.m. to 9:00 a.m., during trading hours are from 9:00 p.m. to 4:00 p.m., and after trading hours are from 4:00 p.m. to midnight.

[Insert Figure 1 and 2 Here]

As can be observed in Figure 1 and Figure 2, 26% of firms change their before/during/after trading hours timing and 60.5% of firms change their EA weekday. Over the entire sample period, 68.8% of our sample firms have at least one change in before/during/after hours timing and 46.2% firms have at least one Friday EA. These results are comparable to those reported in deHaan et al. (2015) and indicate that changes in EA timing also happen

[10] The analysis of earnings announcements shows that a very small number of firms disclose earnings forecasts on weekends and this elimination from the sample is not likely to affect our results.

frequently enough in annual EAs such that strategic changes likely do not draw the attention of market participants.

3.3.3 Tests of Hypothesis 1

Univariate Analysis

We test the first hypothesis and investigate whether firms are more likely to announce earnings in low attention periods when they misreport. Because misreporting firms have stronger incentives to hide themselves from the investors and reduce the risk of being detected by the market, we examine the EA timings throughout the entire violation period. During the violation period, misreporting firms make 51.57% earnings announcements during after trading hours, which is significantly higher than the 46.96% with respect to control firms (Table 2, Panel A). We find similar results when using the alternative SEC enforcement sample, whereas misreporting firms make 10.35%more earnings announcements during after trading hours than that of control firms (Table 2 Panel B). However, these differences in EA timings may be driven by firm-specific characteristics. To address this concern, we restrict our sample to just misreporting firms and assessing whether these firms make more earnings announcements in low attention periods during violation years than in non-violation years. We find that misreporting firms only make 46.31% (35.22%) earnings announcements during after trading hours in non-violation years, which is significantly lower when compared with the EA timings in violation years. However, we observe opposite results for Friday in both misreporting samples. Our results show that misreporting firms are less likely to disclose earnings in low attention periods compared with control firms, and in the SEC enforcement sample, we also find that misreporting firms disclose more earnings in low attention periods even during non-violation years. This result may indicate that Friday is probably not an “actual” low attention period and firms are realizing and incorporating this fact in selecting their timing strategies.

[Insert Table 2 Here]

Multivariate Analysis

To bolster the univariate inferences, we perform the following cross-sectional probit regression model in both our samples:

$$Inattention_{i,t} = \alpha_0 + \alpha_1 Misreporting_{i,t} + \alpha_2 Size_{i,t} + \alpha_3 BTM_{i,t} + \alpha_4 Lev_{i,t} + \alpha_5 Numest_{i,t} + \alpha_6 RepLag_{i,t} + \alpha_7 RepLag_{SQ_{i,t}} + \alpha_8 SUE_{i,t} + \alpha_9 InstOwn_{i,t} + Year + Industry + \varepsilon_{i,t} \quad (1)$$

The dependent variable *Inattention* is one of the two proxies for low attention period, i.e. *AMC* or *Friday*. *AMC* takes the value of one if the earnings announcement is made after 4:00 PM through midnight, and zero otherwise. *Friday* takes the value of one if the earnings announcement is made on Friday, and zero otherwise. Our main variable of interest is *Misreporting*, an indicator variable equal to one for years in which the firm is alleged to have misreported and all years until the end of the violation periods. We expect α_1 to be positive and statistically significant.

Following deHaan et al. (2015), we include several control variables that capture non-stationary firm characteristics that likely correlate with market attention: the natural log of total book assets (*Size*); growth opportunities (*BTM*); financial leverage (*Lev*); the number of analysts following the firm; the natural log of number of days between the fiscal year end and the EA date (*RepLag*); the reporting lag quadratic; and institutional ownership

(*InstOwn*). We also control for unexpected earnings surprise (*SUE*) since many studies have documented that bad (good) news is more (less) likely to be disclosed in after trading hours and Friday (Patell and Wolfson 1982; Bagnoli et al. 2005; Doyle and magilke 2009; Michaely et al. 2016). *SUE* is defined as the difference between the actual EPS and the consensus analyst forecast prior to the earnings announcement, deflated by the year end stock price. Industry and year fixed effects are added to the model and they control for stationary industry characteristics and common macroeconomic trends. We report the mean values of these variables in Table 3, separately for the misreporting and control samples.

[Insert Table 3 Here]

In Panel A and Panel B, we observe that firm characteristics are significantly different for misreporting and control samples. In table 4 we present the results of estimating Eq. (1). The coefficient of Misreporting is positive and significant at the 1% level in Column (1) and (2). The results are similar, though weak, in SEC enforcement sample. Consistent with H1, misreporting firms make more EAs during after trading hours in violation years. The decision to misreport is associated with 11.92% increase in the likelihood of after trading hours announcements in restatement sample, and 12.20% increase in SEC enforcement sample, respectively. We do not find significant results with respect to *Friday*. As discussed by Michaely et al. (2016), after correcting for selection bias, the “seemed like” market inattention disappears, raising a question of whether Friday is an actual low attention period. Therefore, we leave *Friday* in our base test while exclude it in all subsequent tests.

The coefficients of other control variables are in line with prior research. The negative and significant coefficient of *Size* suggest that larger firms are less likely to announce earnings when the market is closed. We also find positive effects of analyst following and institutional ownership on the probability of after trading hours EAs, which is consistent with the results reported by Doyle and Magilke (2009).

[Insert Table 4 Here]

Propensity Score Matching

The misreporting sample differs from the control sample on many dimensions (Table 3). Although we control for these firm characteristics in our empirical analysis, we also compare the firms in the misreporting sample with a propensity score matched sample of firms, such that the differences in firm characteristics are minimized, and the results are primarily driven by our variable of interest, i.e. the decision to misreport. In the first stage, we model misreporting as a function of firm characteristics included in Eq. (1) except the *Inattention* proxies, which are used as the dependent variables in the second stage. The first stage regression results are reported in Table 5.

[Insert Table 5 and 6 Here]

Based on the results of the first stage, we calculate propensity scores and identify one matched control firm, in the same industry and year, for each firm-year observation in the violation period in both misreporting samples. The treatment and propensity score matched control samples have very similar propensity scores. We provide the descriptive statistics of misreporting and propensity score matched samples in Table 6. In both misreporting samples, the treatment group and the propensity score matched control group are in general similar in firm characteristics except the EA timings. Specifically, in restatement sample.

misreporting firms make 51.78% EAs in after trading hours, which is significantly higher than the 45.97% for the control group. We find similar results in SEC enforcement sample in Panel B of Table 6.

We also perform the multivariate regression model specified in Eq. (1) using these samples. The results are displayed in Table 7. We continue to find a significantly positive association between *Misreporting* and *AMC* (p-value <0.001). The decision to misreport is associated with an 17.29% increase in after trading hours EAs in restatement sample, and 15.05% increase in SEC enforcement sample, respectively. Similarly, we still not find any significant results for *Friday*.

[Insert Table 7 Here]

3.3.4 Tests of Hypothesis 2

After trading hours EAs and detection period

One possible reason for misreporting firms to disclose earnings in after trading hours is to decrease the likelihood of being detected by the market, at least for a short period of time. Therefore, we restrict our sample to misreporting firms that are being detected and estimate the following regression model:

$$DetectionPeriod_i = \alpha_0 + \alpha_1 AMC\_Hide_i + \alpha_2 IndMisreporting_i + \alpha_3 MeanDetectSIC_i + \alpha_4 MeanDetectOther_i + \alpha_5 Size_i + \alpha_6 Lev_i + \alpha_7 Numest_i + \alpha_8 ROA_i + \alpha_9 Growth_i + \alpha_{10} InstOwn_i + \alpha_{11} AnnRet_i + \alpha_{12} RetVol_i + \alpha_{13} Turnover_i + Industry + \varepsilon_i \qquad (2)$$

The dependent variable *DetectionPeriod* is the natural log of the number of days between the starting date of the violation and the discovery date (filing date) of the misconduct.[11] Our main variable of interest is *AMC_Hide*, which is an indicator variable equals to one if the firm makes at least one EAs in after trading hours during violation years, and zero otherwise. This variable is intended to capture the strategic timing strategy taken by misreporting firms.[12] We predict the coefficient of *AMC_Hide* to be positive and significant.

We control several factors that might influence the time to detection. First, oversight by regulators, capital markets, and capital markets can be concentrated in a specific industry. For example, after the discovery of problems at Enron other firms in the same industry were also suspected of fraudulent practices and faced greater scrutiny. To capture the variation in the oversight, we estimate the average time to discovery of all misconducts, in a specific industry and all other industries that year (See Parsons, Sulaeman, and Titman (2015) for a similar measure). Specifically, *MeanDetectSIC* captures the prevailing oversight intensity for an industry and is defined as the mean value of *DetectionPeriod* for all misconducts in the same two-digit SIC industry in a year. MeanDerectOther captures prevailing oversight intensity for all other firms and is defined in a similar way except that only firms in other industries are included in the computation.

[11] If a firm commit multiple misconducts during the sample period, we keep all of them in our empirical tests. Our results still hold if we only keep the first misconduct of each firm.

[12] To the extent that *AMC_Hide* may not capture the strategic timing of misreporting firms, we also define *AMC_Hide* in an alternative way. It takes the value of one if the firm makes half of its EAs in after trading hours, and zero otherwise. We repeat the regressions using this variable definition and the results are similar.

We also control for other firm fundamentals that might influence the likelihood of detection in line with prior work by Yu and Yu (2011). We control for industry litigation risk since high industry litigation may increase an individual firm's litigation risk and reduce the time to detection (Khanna, Kim, and Lu (2015)). We define *IndMisreporting* as the number of restatements (lawsuits) in the two-digit SIC industry divided by the total number of firms in Compustat in that industry in a year. We control for analyst following and institutional ownership since they are important external monitor as documented in prior research (Chang, Dasgupta and Hilary (2008); Yu (2008)). We include *ROA*, sales growth (*Growth*), annual stock return (*AnnRet*), and stock return volatility (*RetVOl*), since prior research find that firm performance and growth opportunities are corelated with litigation risk (Johnson, Nelson, and Pritchard (2007)). We also include stock liquidity (*Turnover*), as it might be associated with greater investor harm and faster discovery. All variables are averaged over the entire violation period (See Appendix A for detailed variable definitions).

Table 8 displays the results of estimating Eq. (2) separately for an OLS model, a COX Proportional Hazard model, and a parametric Weibull hazard model, with industry fixed effects.

[Insert Table 8 Here]

In Column (1), the positive and significant coefficient of *AMC_Hide* in the OLS estimation implies that taking the timing strategy during the violation periods generally delay the detection period by161 days. We find similar results when using the COX Proportional Hazard model and a parametric Weibull hazard model, where the dependent variable is the hazard rate of being detected. As seen in Column (2) and (3), the negative and significant coefficient of *AMC_Hide* suggests that it is associated with lower hazard rate of being detected, implying that announcing earnings after the market is closed decreases the hazard of being detected by the market. We find weak but similar results when using the SEC enforcement sample.

The coefficients of our control variables are in line with prior research. As expected, *MeanDetectSIC* and *MeanDetectOther* are significant in general. Higher industry litigation intensity, disappointing firm performance, and higher analyst coverage are associated with shorter period of time to discovery.

After trading hours EAs and insider trading

Michaely et al. (2016) argue that managers can benefit from delayed market reaction through insider trading soon after the EAs, especially for bad news. Therefore, in this section, we empirically test whether misreporting firms are more likely to engage in insider purchasing or selling activities following EAs to gain personal benefits and take advantage of PEAD in violation years. We estimate the following cross-sectional regression model using a sample of both misreporting and control firms:

$$Value_{i,t} = \alpha_0 + \alpha_1 AMC_{i,t} + \alpha_2 Misreporting_{i,t} + \alpha_3 AMC_{i,t} * Misreporting_{i,t} + \alpha_4 SUE_{i,t} + \alpha_5 Size_{i,t} + \alpha_6 BTM_{i,t} + \alpha_7 Lev_{i,t} + \alpha_8 Numest_{i,t} + \alpha_9 RepLag_{i,t} + \alpha_{10} RepLag_{SQ_{i,t}} + \alpha_{11} InstOwn_{i,t} + \varepsilon_{i,t} \quad (3)$$

Where the dependent variable is the net dollar value of trades by insiders in a given firm during 90 days following an EA in a year. We normalize this variable by the total absolute value of transactions by the insiders in the firm during the entire sample period to control for the variations in insiders' wealth across firms. The variable of interest is the interaction of *AMC* and *Misreporting*. The control variables are the same as those in Eq. (1). We perform the regression model separately for positive and negative news based on *SUE* since insiders are trading in opposite directions regarding the news content. The results are displayed in Table 9.

[Insert Table 9 Here]

We find more trades in the direction of the surprise for only negative news announced in after trading hours by misreporting firms. The results provide further support for our main findings and explain why misreporting firms prefer announcing earnings news during evening.

Stock market reactions to the EA timing on the discovery of the misreporting

In this section, we investigate whether there are potential costs for misreporting firms of strategically timing EAs during periods of violation. Specifically, we test whether the stock market will punish misreporting firms with more EAs made in after trading hours after the disclosure of the misrepresentation. Is so, investors' negative reactions set off a wave of real economic costs for misreporting firms in the period after the misrepresentation is being detected. To empirically test this hypothesis, we restrict our sample to misreporting firms only and first identify the EA timings in violation years of these firms. Then we use the disclosure date of the misrepresentation as the event date to investigate the market reactions and estimate the following OLS regression model:

$$CAR_{i,[-1,1]}\ or\ CAR_{i,[-3,3]} = \alpha_0 + \alpha_1 AMC\_Hide_i + \alpha_2 Size_{i,t} + \alpha_3 BTM_{i,t} + \alpha_4 Lev_{i,t} + \alpha_5 Numest_{i,t} + \alpha_6 RepLag_{i,t} + \alpha_7 RepLag_{SQ_{i,t}} + \alpha_8 SUE_{i,t} + \alpha_9 InstOwn_{i,t} + Year + Industry + \varepsilon_{i,t} \qquad (4)$$

Where the dependent variable is either the 3-days or 7-days cumulative abnormal returns (CAR) adjusted by the size of the portfolio. The variable of interest is *AMC_Hide*, which is an indicator variable equals to one if the firm makes at least one EAs in after trading hours during violation years, and zero otherwise. We take the values of all other variables at the end of the fiscal year of the filing date. The results are displayed in Table 10.

[Insert Table 10 Here]

We only find negative and significant results for the restatement sample (coefficient = -0.0151, p-value = 0.011 in Column (1) and coefficient = -0.0014, p-value = 0.033 in Column (2), respectively), implying that the market will penalize misreporting firms for their timing strategy by reacting negatively on the disclosure date of the misrepresentations.

3.4 Conclusion

This paper provides additional evidence on the debate of the existence of strategic EAs and bridges the analysis of timing strategy to the research of opportunistic misreporting. We find that firms engaged with manipulated EAs tend to strategically disclose their earnings in the low market attention period. These firms take advantage of such announcing strategies to lower the rate of being detected and to benefit from insider trading. Specially, firms with strategic announcing are more likely to experience a longer undetected fraud period, and take a short position in shares soon after announcing bad news, benefiting from the lazy market scrutiny and the reduced market responses.

Instead of emphasizing the influence of the superficial content of news as prior studies did, our paper is the first to take opportunistic manipulations into consideration and investigate that how the underlying quality of news impacts the choice of EAs timing. In addition, we suggest both investors and regulators to keep eyes on the positive association between strategic timing and corporate frauds, adding contributions to the studies of corporate frauds.

APPENDICIES

Appendix A.

Variable	Definition
Tournament measures	
Log(Gap)	The natural logarithm of the difference between the CEO total compensation (ExecuComp data item TDC1) and the median of VPs' compensation.
Log(Diff)	The natural logarithm of the compensation (ExecuComp data item TDC1) gap between CEO and highest paid VP.
High Tournament	A dummy variable equal to 1 if executive pay gap is greater than the median, 0 otherwise.
Forecast quality characteristics	
Precision	The difference between the range forecast's upper and lower bounds, deflated by the beginning stock price and multiplied by -1. *Precision* is zero for point forecasts.
Accuracy	The absolute difference between the forecast EPS and the actual reported EPS, deflated by beginning stock price and multiplied by -1. If the forecast is a range forecast, the midpoint is treated as forecast value.
Market and analysts responsiveness	
CAR (-1,1)	The size-decile-adjusted market return for three days centered on the day of the issuance of the management earnings forecast.
AbnVol (-1,1)	The average trading volume from three trading days centering on the management forecast announcement date, scaled by the median trading volume in the prior 60 days.
Fraction	The ratio of the number of analysts revising their own forecasts within 90 days following the date of management forecast issuance to the total number of analysts issuing at least 1 forecast in the year ending 30 days before the date of management forecast issuance.
Log(Days)	The natural logarithm of the number of days between management forecast date and analyst revision date immediately following management earnings forecast.
Controls	
Log (AT)	The natural logarithm of lagged total assets (AT).
R&D	The research and development expense deflated by total assets.
Coverage	The number of estimates issued by analyst during 90 days prior to the fiscal year end.
Institutional Ownership	The percentage of shares held by institutional investors.
Earnings Volatility	The standard deviation of income before extraordinary items (IB) scaled by total assets over prior five years.
Litigation	An indicator variable equals to one if the firm belongs to Drugs (SIC codes 2833-2836), R&D services (8731-8734), Programming (7371-7379), Computers (3570-3577), Electronics (2674-3600), and zero

	otherwise.
ROA	Return on assets, defined as the income before extraordinary items scaled by beginning total assets.
Loss	An indicator variable equals to one if the firm reported loss in year t, and zero otherwise.
MTB	The market-to-book ratio, defined as the ratio of the market value of equity (CSHO*PRCC_F) to book value of equity (CEQ).
Weak	An indicator variable, which is equal to one if the firm discloses any material internal control weakness during the sample period (2002-2015), and zero otherwise.
M&A	An indicator variable which is equal to one if the firm's annual acquisition or merger-related costs (AQA) exceed 5 percent of net income (loss) during the year.
Equity Issue	An indicator variable that equals to one if the sum of new equity and debt issued during the year is greater than 0.05 of average asset, and zero otherwise.
ShrOwn CEO	Total shares owned by the CEO (SHROWN_EXCL_OPTS) deflated by outstanding shares.
ShrOwn VP	Total shares owned by subordinate managers deflated by outstanding shares.
Vest CEO	Total unexercised exercisable options owned by the CEO (OPT_UNEX_EXER_NUM), deflated by outstanding shares, multiplied by 10.
Vest VP	Total unexercised exercisable options owned by subordinate managers, deflated by outstanding shares, multiplied by 10.
CEO Tenure	The number of years the current CEO has stayed in the firm.
Median VP Tenure	The median value of the number of years subordinate managers have stayed in the firm.
Horizon	The natural logarithm of days between the forecast announcement date and the forecast period end date.
News	The difference between management forecast EPS and analyst consensus forecast (median) before management forecast, deflated by beginning stock price and multiplied by 100.
|*News*|	The absolute value of *News*.
DA	Kothari's performance-matched discretionary accruals.
Industry Concentration	Industry concentration ratio defined as the sum of revenue for the top five firms in its two-digit SIC industry, scaled by sum of revenue for all firms in the industry.
Industry Homogeneity	The mean of the partial correlation coefficients of all firms in the two-digit SIC industry. The partial correlation is estimated between firm and industry returns, controlling for market returns. We use the 60 monthly returns until the end of the current fiscal year. Industry returns are defined as the average of all firms' monthly returns within the same two-digit SIC industry.
New CEO	A dummy variable equal to 1 for year t and t+1 if the firm has a new CEO in year t, and 0 otherwise.
StdRet	The standard deviation of the firm's daily stock return in year *t*.
AF Dispersion	The standard deviation of analyst forecasts 90 days prior to the management forecast in year *t*.

Complex Geo	The sum of the squared sales of each geographic segment divided by the squared total sales of the firm and subtracted from 1.
Complex Cost	The correlation between revenues and net income before extraordinary items measured over the prior 3 years and multiplied by -1.
Point	An indicator variable equals to one if the management earnings forecast is a point forecast (Range_desc = 02/09/14)
Timeliness	The natural log of days between the earnings announcement dates and the forecast announcement dates.
Update	A dummy variable equal to 1 if the management updated a previous forecast, and 0 otherwise.
CEO Ability	The CEO ability measure followed Rajgopal et al. (2006). We compute the cumulative distributive function (CDF) of industry adjusted ROA for each CEO-firm-year by industry and take the mean of the CDF ranks of ROA for the first three years when a new CEO is appointed.
G Index	Gompers et al. 2003 corporate governance index. For each of the 24 provisions related to takeover defense and shareholder rights, 24 binary variables are used to indicate for the existence of each provision. G Index is defined as the sum of all binaries. For G Index after 2007, we use their IRRC values in 2006.
CEO Duality	An indicator variable that equals to one if the CEO is also the chairman of the board.
% IO Directors	The percentage of independent outside directors on the board.

Appendix B.

Variable Name	Definitions
Cheating_Customer	A dummy variable that equals to 1 if any of current customers were engaged in wrongdoing during year t. The customer is current if the customer is reported in the year t or year t-1.
CAPEX	The ratio of capital expenditure (COMPUSTAT “capx”) to lagged total assets (COMPUSTAT “at”).
Cash	The ratio of cash holdings (COMPUSTAT “ch”) to lagged total assets (COMPUSTAT “at”).
Leverage	Long-term debt (COMPUSTAT “dltt”) divided by total assets (COMPUSTAT “at”), measured at the beginning of the year.
ROA	Net income (COMPUSTAT “ni”) scaled by total assets (COMPUSTAT “at”).
Size	The natural logarithm of total assets (COMPUSTAT “at).
Sales	Total sales (COMPUSTAT “sales” scaled by lagged total assets.
Financing	Sum of equity issues (COMPUSTAT “sstk”) and debt issues (COMPUSTAT “dltis”) during the year scaled by total assets (COMPUSTAT “at”).
Q	Tobin’s Q, measured as the ratio of market value of assets (COMPUSTAT “prcc_f” * “csho” + “lt”) divided by book value of assets (COMPUSTAT “at”).
HHI	Industry concentration index. First calculate sales ratio by dividing sales of each firm (COMPUSTAT “sales”) to the total sales in the 2-digit SIC industry. Next, HHI is computed as the sum of the squares of the ratio for all firms in the same industry.
Sales_Vol	The standard deviation of natural log of Sales starting from year t-2 and ending at year t.
CFO	Net cash flow from operations (COMPUSTAT “oancf”), deflated by lagged total assets.
CAR	The 7-day or 11-day size-adjusted cumulative abnormal returns for suppliers surround the disclosure date of customers misreporting.
High_CAPEX_Customer	An indicator variable equals to 1 if the supplier’s average abnormal investment during customers’ scandal periods is higher than the median investment for all affect suppliers.
During	A dummy variable that equals to 1 during litigation/restatement period and 0 otherwise.
After	A dummy variable that equals to 1 for the three-year period starting from the first fiscal year following the litigation/restatement period.

$\widehat{\text{capex}}$	The difference between supplier's investment in treatment group and that in the control group.

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TABLES

Table 1.1 Descriptive Statistics for the Sample of Management Earnings Forecasts

	1	2	3	4
Year	Forecasts (#)	Forecasts (%)	Range Forecasts (#)	Point Forecasts (#)
2002	1,122	3.959	896	226
2003	1,651	5.826	1,396	255
2004	1,954	6.896	1,725	229
2005	1,882	6.641	1,713	169
2006	1,865	6.582	1,717	148
2007	2,081	7.344	1,899	182
2008	2,471	8.72	2,235	236
2009	1,983	6.998	1,819	164
2010	2,323	8.198	2,184	139
2011	2,276	8.032	2,134	142
2012	2,453	8.657	2,228	225
2013	2,351	8.297	2,121	230
2014	2,259	7.972	2,036	223
2015	1,666	5.879	1,487	179
Total	28,337	100	25,590	2,747

This Table reports the distribution of management earnings forecasts by year. The sample period is from 2002 to 2015. Column 1 reports the frequency of management earnings forecasts; Column 2 reports the percentage of management earnings forecasts; Column 3 and 4 report the types of management earnings forecasts by year. Forecast type is the type of forecast issued including point, and range forecasts.

Figure 1.1. The Time-series Distribution of Executive Pay Gap

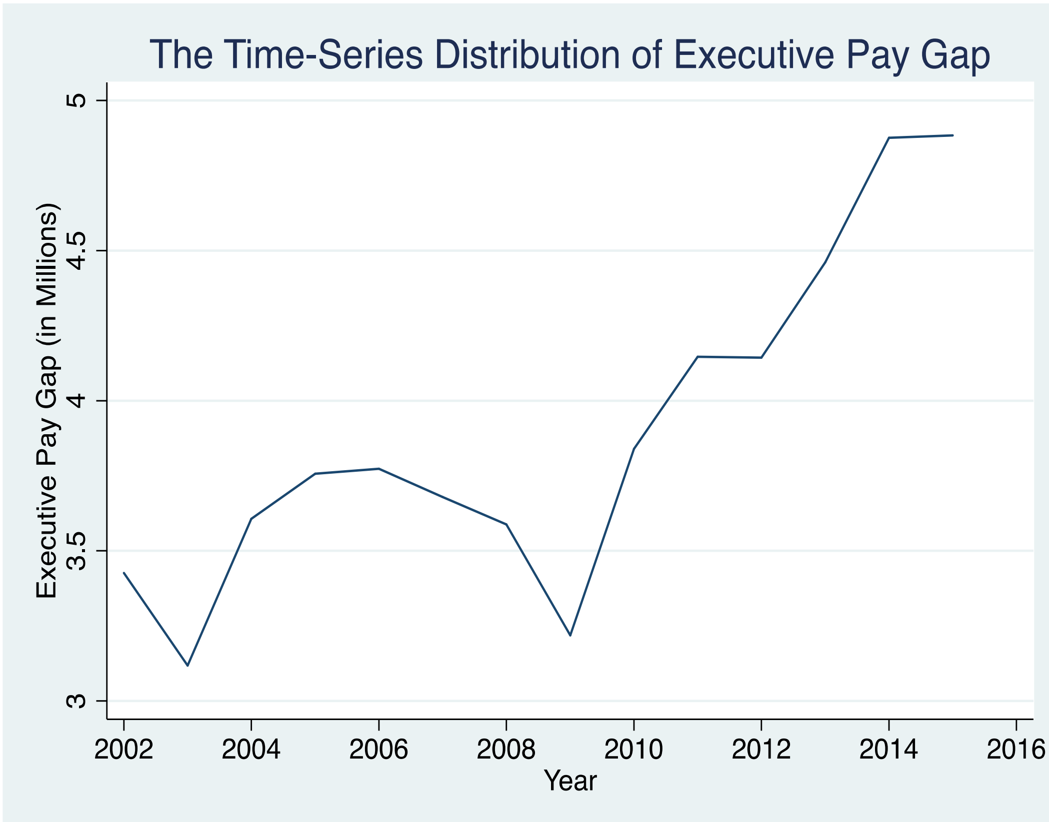

Table 1.2 Summary Statistics

Variables	N	Mean	25%	Median	75%	SD
Precision(%)	28,337	-0.366	-0.099	-0.218	-0.421	0.503
Accuracy(%)	28,337	-0.826	-0.094	-0.274	-0.740	1.837
Pay Gap(in millions)	28,337	2.960	1.652	3.334	5.943	1.040
Pay Diff(in millions)	28,337	2.065	1.055	2.520	4.764	1.254
InstOwn	28,337	0.790	0.698	0.803	0.900	2.228
Log(AT)	28,337	7.860	6.804	7.809	8.776	1.460
R&D	28,337	0.026	0.000	0.010	0.035	0.040
EarnVol	28,337	0.034	0.011	0.020	0.035	0.044
Litigation	28,337	0.192	0.000	0.000	0.000	0.394
MTB	28,337	3.625	1.803	2.727	4.047	4.508
Equity Issue	28,337	0.446	0.000	0.000	1.000	0.497
M&A	28,337	0.017	0.000	0.000	0.000	0.129
Weak	28,337	0.212	0.000	0.000	0.000	0.409
ROA	28,337	0.067	0.038	0.064	0.096	0.059
Loss	28,337	0.074	0.000	0.000	0.000	0.262
ShrOwn CEO	28,337	0.012	0.001	0.003	0.008	0.029
ShrOwn VP	28,337	0.008	0.001	0.002	0.006	0.019
Vest CEO	28,337	0.076	0.015	0.048	0.103	0.088
Vest VP	28,337	0.068	0.020	0.045	0.091	0.073
CEO Tenure	28,337	6.978	2.000	5.000	9.000	6.585
Median VP Tenure	28,337	3.779	2.000	3.000	5.000	2.637
Horizon	28,337	5.135	4.727	5.412	5.730	0.742
News	28,337	-0.0005	-0.001	-0.0001	0.001	0.005
DA	28,337	0.083	-0.176	-0.010	0.128	3.320
Conc	28,337	0.487	0.363	0.446	0.596	0.161

This table presents summary statistics for the dependent variables, tournament incentive and other control variables. Panel A reports summary statistics for the regression sample used to test the accuracy and precision of management earnings forecasts. The sample period is from 2002 to 2015. All variables are defined in Appendix A and winsorized at 1% and 99%.

Table 1.3 Association between MEF Quality and Tournament Incentives

	Precision		*Accuracy*	
	Log(Gap)	Log(Diff)	Log(Gap)	Log(Diff)
Tournament Incentive	0.030***	0.017***	0.064***	0.042***
	(7.72)	(6.52)	(4.69)	(4.46)
Institutional Ownership	0.227***	0.235***	0.632***	0.645***
	(9.59)	(9.95)	(6.36)	(6.49)
Log (AT)	0.009***	0.016***	0.054***	0.065***
	(3.07)	(5.82)	(4.37)	(5.71)
R&D	0.195**	0.216**	-0.756**	-0.721**
	(2.01)	(2.22)	(-2.19)	(-2.09)
Earnings Volatility	-1.145***	-1.133***	-2.968***	-2.949***
	(-12.42)	(-12.29)	(-9.44)	(-9.39)
Litigation	0.047***	0.044***	0.130***	0.126***
	(4.70)	(4.47)	(3.64)	(3.54)
MTB	0.006***	0.006***	0.017***	0.018***
	(9.15)	(9.36)	(8.22)	(8.34)
Equity Issue	-0.011**	-0.012**	-0.044**	-0.044**
	(-2.07)	(-2.19)	(-2.07)	(-2.11)
M&A	0.120***	0.117***	0.425***	0.420***
	(4.32)	(4.21)	(4.29)	(4.25)
Weak	-0.061***	-0.060***	-0.242***	-0.241***
	(-7.58)	(-7.52)	(-7.45)	(-7.44)
ROA	1.558***	1.572***	5.332***	5.349***
	(20.79)	(20.94)	(18.05)	(18.12)
Loss	-0.201***	-0.200***	-0.517***	-0.517***
	(-10.18)	(-10.15)	(-6.74)	(-6.73)
Horizon	-0.103***	-0.103***	-0.425***	-0.425***
	(-29.58)	(-29.56)	(-32.63)	(-32.64)
News	0.086***	0.086***	0.163***	0.163***
	(6.56)	(6.56)	(3.05)	(3.06)
DA	-0.002***	-0.002***	0.001	0.001
	(-3.12)	(-3.17)	(0.32)	(0.29)
Conc	-0.018	-0.011	0.535*	0.550*
	(-0.23)	(-0.14)	(1.72)	(1.77)
ShrOwn CEO	0.049	0.049	-0.364	-0.359
	(0.50)	(0.51)	(-0.85)	(-0.84)
ShrOwn VP	0.496***	0.506***	1.478**	1.515**

	(3.34)	(3.40)	(2.25)	(2.31)
Vest CEO	-0.193***	-0.183***	-0.663***	-0.650***
	(-4.71)	(-4.46)	(-4.18)	(-4.09)
Vest VP	0.018	0.025	0.292	0.305
	(0.36)	(0.48)	(1.34)	(1.40)
CEO Tenure	0.004***	0.004***	0.004**	0.005***
	(8.26)	(8.25)	(2.50)	(2.61)
Median VP Tenure	0.002**	0.002*	0.023***	0.023***
	(1.97)	(1.78)	(6.18)	(6.10)
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Obs	28,337	28,337	28,337	28,337
R Square	0.2857	0.2849	0.1859	0.1858

This table presents results from regressions of forecast precision and forecast accuracy on the executive pay gap. Column 1 and 2 display the OLS regression results for the forecast precision. Precision is the difference between the range forecast's upper and lower bounds, deflated by the beginning stock price and multiplied by -1. Precision is zero for point forecasts. Column 3 and 4 report the OLS regression results for the forecast accuracy. Accuracy is the absolute difference between the forecast EPS and the actual reported EPS, deflated by beginning stock price and multiplied by -1. If the forecast is a range forecast, the midpoint is treated as forecast value. Coefficients of both Precision and Accuracy are multiplied by 100. Log(Gap) is the natural logarithm of the difference between the CEO total compensation (ExecuComp data item TDC1) and the median of VPs compensation. Log(Diff) is the natural logarithm of the compensation gap between CEO and highest paid VP. All other variables are defined in Appendix A. Industry and year fixed effects are included. The t-statistics are reported in parentheses. ***, **, and * indicate 0.01, 0.05, and 0.10 significance levels, respectively.

Table 1.4 Moderating Effect of Industry Homogeneity and New CEO on the Association between Tournament Incentives and MEF Quality

Panel A. Industry Homogeneity

	Precision		*Accuracy*	
	Log(Gap)	Log(Diff)	Log(Gap)	Log(Diff)
Tournament Incentive	0.042***	0.033***	0.104***	0.067***
	(6.09)	(5.86)	(4.40)	(3.45)
Industry Homogeneity	-0.065***	-0.067***	-0.202***	-0.266***
	(-3.82)	(-4.67)	(-3.20)	(-4.91)
Tournament Incentive	-0.019**	-0.025***	-0.064*	-0.039
**Industry Homogeneity*	(-2.19)	(-3.36)	(-1.89)	(-1.43)
Controls	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Obs	28,337	28,337	28,337	28,337
R Square	0.2872	0.2866	0.1871	0.1870

Panel B. New CEO

	Precision		*Accuracy*	
	Log(Gap)	Log(Diff)	Log(Gap)	Log(Diff)
Tournament Incentive	0.028***	0.015***	0.085***	0.063***
	(6.54)	(5.33)	(6.10)	(6.24)
New CEO	0.035***	0.020*	0.224***	0.127***
	(2.68)	(1.94)	(5.47)	(3.86)
Tournament Incentive	-0.019**	-0.009	-0.149***	-0.092***
**New CEO*	(-2.43)	(-1.34)	(-5.81)	(-4.48)
Controls	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Obs	25,996	25,996	25,996	25,996
R Square	0.2983	0.2975	0.2056	0.2053

This table presents the regression results of the effect of perceived probability of promotion on the relation between the forecast characteristics and executive pay gap. Three settings are used where the perceived probability of promotion matters, including industry homogeneity, CEO turnover, and the state non-competition agreement enforcement. Results are presented in Panel A, Panel B, and Panel C, respectively. Precision is the difference between the range forecast's upper and lower bounds, deflated by the beginning stock price and multiplied by -1. Precision is zero for point forecasts. Accuracy is the absolute difference between the forecast EPS and the actual reported EPS, deflated by beginning stock price and multiplied by -1. If the forecast is a range forecast, the midpoint is treated as forecast value. Coefficients of both Precision and Accuracy are multiplied by 100. Log(Gap) is the natural logarithm of the difference between the CEO total compensation (ExecuComp data item TDC1) and the median of

VPs compensation. Log(Diff) is the natural logarithm of the compensation gap between CEO and highest paid VP. New CEO is a dummy variable equal to 1 for year t and t+1 if the firm has a new CEO in year t, and 0 otherwise. Industry Homogeneity is the mean of the partial correlation coefficients of all firms in the two-digit SIC industry. All other variables are defined in Appendix A. Industry and year fixed effects are included. The t-statistics are reported in parentheses. ***, **, and * indicate 0.01, 0.05, and 0.10 significance levels, respectively.

Table 1.5 Robustness Check: CEO Ability, CEO Characteristics and MEF Quality

Panel A: CEO Ability				
	Precision		*Accuracy*	
	Log(Gap)	Log(Diff)	Log(Gap)	Log(Diff)
Tournament Incentive	0.029***	0.016***	0.078***	0.051***
	(7.34)	(6.26)	(5.74)	(5.45)
Ability	0.117***	0.116***	0.431***	0.429***
	(7.27)	(7.21)	(6.63)	(6.59)
Controls	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Obs	27,355	27,355	27,355	27,355
R Square	0.282	0.281	0.197	0.197
Panel B: CEO Fixed Effects				
	Precision		*Accuracy*	
	Log(Gap)	Log(Diff)	Log(Gap)	Log(Diff)
Tournament Incentive	0.013***	0.008***	0.035**	0.024**
	(3.16)	(2.92)	(2.17)	(2.19)
Controls	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
CEO Fixed Effect	Yes	Yes	Yes	Yes
Obs	28,337	28,337	28,337	28,337
R Square	0.721	0.721	0.621	0.621

This table shows the regression results from robustness checks of CEO attributes. In Panel A we add the CEO ability variable as an additional control variable. In Panel B we report the main results by including CEO fixed effects. We compute the cumulative distributive function (CDF) of industry adjusted ROA for each CEO-firm-year by industry and CEO Ability is defined as the mean of the CDF rank of ROA for the first three years when a new CEO is appointed. Precision is the difference between the range forecast's upper and lower bounds, deflated by the beginning stock price and multiplied by -1. Precision is zero for point forecasts. Accuracy is the absolute difference between the forecast EPS and the actual reported EPS, deflated by beginning stock price and multiplied by -1. If the forecast is a range forecast, the midpoint is treated as forecast value. Coefficients of both Precision and Accuracy are multiplied by 100. Log(Gap) is the natural logarithm of the difference between the CEO total compensation (ExecuComp data item TDC1) and the median of VPs compensation. Log(Diff) is the natural logarithm of the compensation gap between CEO and highest paid VP. All other variables are defined in Appendix A. Industry and year fixed effects are included. The t-statistics are reported in parentheses. ***, **, and * indicate 0.01, 0.05, and 0.10 significance levels, respectively.

Table 1.6 Robustness Check: Corporate Governance

	Precision		*Accuracy*	
	Log(Gap)	Log(Diff)	Log(Gap)	Log(Diff)
Tournament Incentive	0.033***	0.018***	0.121***	0.067***
	(7.02)	(6.10)	(6.57)	(5.91)
G Index	-0.004**	-0.004**	-0.003	-0.002
	(-2.94)	(-2.78)	(-0.49)	(-0.35)
CEO Duality	-0.004	-0.003	-0.116***	-0.112***
	(-0.58)	(-0.44)	(-3.91)	(-3.79)
% IO Directors	-0.136***	-0.143***	-0.565***	-0.590***
	(-4.33)	(-4.53)	(-4.46)	(-4.62)
Controls	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Obs	18,588	18,588	18,558	18,588
R Square	0.352	0.351	0.210	0.209

This table shows regression results of management earnings forecasts characteristics on executive pay gaps by including additional corporate governance control variables. G Index is Gompers et al. 2003 corporate governance index. CEO Duality is a dummy variable equal to 1 if the CEO is also the chairman of the board. % IO Directors is the percentage of independent outside directors on the board. Precision is the difference between the range forecast's upper and lower bounds, deflated by the beginning stock price and multiplied by -1. Precision is zero for point forecasts. Accuracy is the absolute difference between the forecast EPS and the actual reported EPS, deflated by beginning stock price and multiplied by -1. If the forecast is a range forecast, the midpoint is treated as forecast value. Coefficients of both Precision and Accuracy are multiplied by 100. Log(Gap) is the natural logarithm of the difference between the CEO total compensation (ExecuComp data item TDC1) and the median of VPs compensation. Log(Diff) is the natural logarithm of the compensation gap between CEO and highest paid VP. All other variables are defined in Appendix A. Industry and year fixed effects are included. The t-statistics are reported in parentheses. ***, **, and * indicate 0.01, 0.05, and 0.10 significance levels, respectively.

Table 1.7 Endogeneity Concerns of Tournament Incentive

	Second Stage			
	Precision		*Accuracy*	
	Log(Gap)	Log(Diff)	Log(Gap)	Log(Diff)
Tournament Incentive	0.039***	0.025***	0.094***	0.090***
	(4.16)	(3.31)	(2.68)	(3.14)
Controls	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Obs	26,583	26,572	26,583	26,572
Centered R Square	0.283	0.283	0.187	0.186
Shea partial R Square	0.185	0.144	0.185	0.144
F-statistics	1344.60***	695.93***	1344.60***	695.93***
Anderson-Rubin Wald F-statistics	15.12***	8.98***	4.31**	5.54***
Hansen J	1.193	2.018	1.487	1.269

This table shows 2SLS regression results from the robustness check of endogeneity of our two pay gap measures Log(Gap) and Log(Diff). The two instruments implemented are the executive pay gap lagged by two years and lagged industry median pay gap, which is defined as the median executive pay gap for each two-digit SIC industry. Precision is the difference between the range forecast's upper and lower bounds, deflated by the beginning stock price and multiplied by -1. Precision is zero for point forecasts. Accuracy is the absolute difference between the forecast EPS and the actual reported EPS, deflated by beginning stock price and multiplied by -1. If the forecast is a range forecast, the midpoint is treated as forecast value. Coefficients of both Precision and Accuracy are multiplied by 100. Log(Gap) is the natural logarithm of the difference between the CEO total compensation (ExecuComp data item TDC1) and the median of VPs compensation. Log(Diff) is the natural logarithm of the compensation gap between CEO and highest paid VP. All other variables are defined in Appendix A. Industry and year fixed effects are included. The t-statistics are reported in parentheses. ***, **, and * indicate 0.01, 0.05, and 0.10 significance levels, respectively.

Table 1.8 Tournament Incentives and the Economic Consequences of Management Earnings Forecasts

	Panel A: Stock Market Reactions				Panel B: Analyst Revisions			
	CAR[-1,+1]		AbnVol[-1,+1]		Fraction		Log(days)	
	Log(Gap)	Log(Diff)	Log(Gap)	Log(Diff)	Log(Gap)	Log(Diff)	Log(Gap)	Log(Diff)
Tournament Incentive	0.0001	-0.0001	0.001	-0.004	0.003	-0.0004	0.031***	0.018**
	(0.21)	(-0.40)	(0.08)	(-0.54)	(1.29)	(-0.24)	(2.87)	(2.39)
*Tournament Incentive*News*	0.002**	0.002**	0.082***	0.051***	0.008*	0.007**	-0.043***	-0.036***
	(2.08)	(2.23)	(3.16)	(2.72)	(1.79)	(2.41)	(-2.65)	(-3.22)
News	0.129***	0.129***	1.446***	1.378***	0.314***	0.313***	0.045	0.030
	(8.29)	(8.37)	(4.65)	(4.51)	(5.77)	(5.90)	(0.21)	(0.15)
*Log(AT)*News*	-0.004***	-0.004***	-0.046**	-0.030	0.004	0.004	-0.032**	-0.033***
	(-4.23)	(-4.29)	(-2.27)	(-1.63)	(1.17)	(1.54)	(-2.47)	(-2.79)
*Point*News*	-0.011***	-0.011***	-0.042	-0.033	0.027**	0.028**	0.014	0.012
	(-3.30)	(-3.23)	(-0.56)	(-0.44)	(2.42)	(2.49)	(0.28)	(0.24)
*Timeliness*News*	-0.011***	-0.011***	-0.118**	-0.120**	-0.055***	-0.055***	0.020	0.020
	(-4.29)	(-4.34)	(-2.52)	(-2.56)	(-5.82)	(-5.82)	(0.56)	(0.56)
*EarnVol*News*	-0.050***	-0.050***	-1.623***	-1.626***	-0.227***	-0.236***	0.172	0.191
	(-3.06)	(-3.09)	(-4.24)	(-4.24)	(-3.60)	(-3.69)	(0.73)	(0.82)
*Update*News*	-0.0002	-0.0003	0.103**	0.102**	0.030**	0.031**	-0.235***	-0.235***
	(-0.06)	(-0.10)	(2.10)	(2.08)	(2.24)	(2.25)	(-4.04)	(-4.05)
Log(AT)	-0.001	-0.0005	-0.137***	-0.135***	-0.003*	-0.002	0.108***	0.114***
	(-1.59)	(-1.41)	(-17.99)	(-19.78)	(-1.93)	(-1.09)	(13.04)	(15.34)
Point	-0.001	-0.001	-0.034	-0.035	-0.033***	-0.033***	0.116***	0.118***
	(-0.69)	(-0.66)	(-1.27)	(-1.30)	(-5.75)	(-5.74)	(3.89)	(3.95)
EarnVol	0.020*	0.020*	0.650***	0.665***	0.024	0.031	0.158	0.173
	(1.83)	(1.86)	(3.07)	(3.15)	(0.58)	(0.74)	(0.75)	(0.83)
Timeliness	0.005***	0.005***	-0.048***	-0.048***	0.144***	0.144***	0.218***	0.218***
	(6.69)	(6.70)	(-2.95)	(-2.94)	(35.88)	(35.89)	(11.85)	(11.86)
Update	-0.005***	-0.005***	-0.291***	-0.291***	-0.030***	-0.030***	0.281***	0.282***
	(-4.47)	(-4.46)	(-12.79)	(-12.79)	(-3.06)	(-3.03)	(6.82)	(6.84)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	26,592	26,587	27,091	27,086	23,280	23,277	22,947	22,944
R Square	0.118	0.118	0.119	0.119	0.150	0.150	0.072	0.072

This table reports the economic consequences of management earnings forecasts issued by firms with tournament incentives. Colum 1 through 4 show the regression results for the stock market responsiveness to information in management earnings forecasts around the management earnings forecast date. Colum 5 through 8 show the regression results of analysts' reactions to management earnings forecasts. We measure CAR as the abnormal returns adjusted by the size-decile-matched market return in [-1,1] window around the day of the announcement of the management earnings forecast. AbnVol is the average trading volume from three trading days centering on the management forecast announcement date, scaled by the median trading volume in the prior 60 days. Fraction is defined as the ratio of the number of analysts revising their own forecasts within 90 days following the date of management forecast issuance to the total number of analysts issuing at least 1 forecast in the year ending 30 days before the date of management forecast issuance. Log(Days) is the natural logarithm of the number of days between management forecast date and analyst revision date. News is the difference between EPS in management earnings forecast and the analyst consensus forecast (median) before the management forecast, deflated by beginning stock price, and multiplied by 100. |News| is the absolute value of News, Log(Gap) is the natural logarithm of the difference between the CEO total compensation (ExecuComp data item TDC1) and the median of VPs compensation. Log(Diff) is the natural logarithm of the compensation gap between CEO and highest paid VP. All other variables are defined in Appendix A. Industry and year fixed effects are included. The t-statistics are reported in parentheses. ***, **, and * indicate 0.01, 0.05, and 0.10 significance levels, respectively.

Table 2.1 Time Series Pattern of Affected Suppliers with Cheating Customers

Year	Num. of affected suppliers	
	litigation sample	restatement sample
1996	59	-
1997	64	-
1998	100	-
1999	208	-
2000	252	-
2001	173	-
2002	149	124
2003	147	143
2004	164	177
2005	74	105
2006	63	75
2007	38	29
2008	30	27
2009	51	39
2010	53	43
2011	103	45
2012	78	41
2013	41	25
Num. of unique suppliers	934	435

This table presents the distributions of affected suppliers with cheating customers in both litigation and restatement sample. The litigation sample covers the period from 1996 to 2013 and the restatement sample covers the period from 2002 to 2013. A supplier is accounted as "affected" if it has a cheating customer during the current and/or the prior fiscal years.

Table 2.2 The Customers' Manipulations During Cheating Periods

Panel A. Litigation sample for the period of 1996-2013 (N=12,482)					
	CAPEX	*Employee Growth*	*PPE Growth*	*Assets Growth*	*Sales Growth*
Cheating Years	0.0138	0.0620	0.0914	0.0644	0.0629
Non-cheating Years	0.0094	0.0281	0.0305	0.0488	0.0349
Difference	0.0044***	0.0338***	0.0609***	0.0156**	0.0280***
t-statistics	(3.19)	(5.43)	(9.22)	(2.07)	(3.71)
Panel B. Restatement sample for the period of 2002-2013 (N=11,775)					
	CAPEX	*Employee Growth*	*PPE Growth*	*Assets Growth*	*Sales Growth*
Cheating Years	0.0098	0.0447	0.0435	0.0636	0.0438
Non-cheating Years	0.0061	0.0035	-0.0067	0.0115	-0.0031
Difference	0.0037***	0.0412***	0.0501***	0.0521***	0.0470***
t-statistics	(3.21)	(8.35)	(9.97)	(8.89)	(8.15)

This table presents the abnormal operating decisions of misreporting customers during cheating and non-cheating periods in litigation sample and restatement sample in Panel A and Panel B, respectively. Litigation sample covers the period from 1996 to2013. Restatement sample covers the period from 2002 to 2013. Cheating years are defined as the class periods in litigation and restatement samples and non-cheating years refer to periods with no misreporting. All variables are winsorized at 1 percent and 99 percent level *, **, and *** indicate significance at the <0.10, <0.05, and <0.01 levels, respectively based on t-tests.

Table 2.3 Descriptive Statistics

Panel A. litigation sample (1996-2013)						
Variable	Obs	Mean	Std. Dev.	Q1	Median	Q3
Cheating_Customer	10,727	0.120	0.325	0.000	0.000	0.000
CAPEX	10,727	0.070	0.101	0.016	0.035	0.075
Cash	10,727	0.195	0.299	0.028	0.098	0.239
Leverage	10,727	0.163	0.215	0.000	0.072	0.263
ROA	10,727	-0.105	0.404	-0.114	0.019	0.070
Size	10,727	5.147	2.066	3.732	5.073	6.586
Sales	10,727	1.197	0.942	0.549	1.007	1.545
Financing	10,727	0.190	0.330	0.005	0.040	0.237
Q	10,727	2.101	1.980	1.082	1.477	2.258
HHI	10,727	0.044	0.057	0.020	0.027	0.043
Sales_Vol	10,725	0.260	0.311	0.089	0.169	0.314
Panel B. restatement sample (2002-2013)						
Variable	Obs	Mean	Std. Dev.	Q1	Median	Q3
Cheating_Customer	8,771	0.069	0.254	0.000	0.000	0.000
CAPEX	8,771	0.057	0.089	0.014	0.029	0.060
Cash	8,771	0.196	0.266	0.039	0.119	0.250
Leverage	8,771	0.162	0.219	0.000	0.070	0.260
ROA	8,771	-0.089	0.363	-0.108	0.021	0.071
Size	8,771	5.648	2.155	4.204	5.615	7.171
Sales	8,771	1.100	0.875	0.519	0.910	1.431
Financing	8,771	0.172	0.307	0.005	0.033	0.207
Q	8,771	2.042	1.799	1.108	1.503	2.249
HHI	8,771	0.042	0.056	0.018	0.024	0.038
Sales_Vol	8,771	0.240	0.297	0.081	0.157	0.286

This table presents the descriptive statistics of all firm-years in litigation sample and restatement sample in Panel A and Panel B, respectively. Litigation sample covers the period from 1996 to 2013 and restatement sample is from 2002 to 2013. All variables are winsorized at the 1 percent and 99 percent level.

Table 2.4 The Effects of Customers' Misrepresentations on Suppliers Investment Decisions

	litigation sample (1996-2013)		restatement sample (2002-2013)	
CAPEX	Coef. (t-statistic)		Coef. (t-statistic)	
Cheating_Customer	0.010***	0.008***	0.010***	0.012***
	(3.51)	(2.68)	(2.84)	(3.08)
Cash		0.033***		0.004
		(5.85)		(0.86)
Leverage		-0.015***		-0.013**
		(-2.64)		(-2.24)
ROA		0.019***		0.019***
		(5.51)		(4.90)
Size		0.006***		0.003***
		(7.22)		(3.95)
Sales		0.009***		0.006***
		(5.11)		(3.02)
Financing		0.047***		0.036***
		(8.68)		(6.54)
Q		0.002***		0.001**
		(3.54)		(2.11)
Intercept	0.095***	0.040***	0.048***	0.027*
	(8.07)	(2.66)	(4.01)	(1.67)
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
R square	0.295	0.361	0.354	0.383
Obs	12,147	10,727	9,759	8,771

This table reports the parameters estimated from the following regression for all suppliers in both litigation sample and restatement sample:

$$\text{CAPEX}_{it} = \beta_0 + \beta_1 Cheating\_Customer_{i,t} + \beta_2 Fundamental\_Controls_{i,t} + \varepsilon_{i,t} \quad (1)$$

All variables are winsorized at the 1 percent and 99 percent level. Industry and year fixed-effects are included. The standard errors are clustered by firms. *, **, and *** indicate significance at the <0.10, <0.05, and <0.01 levels, respectively, based on one-tailed tests if the signs are predicted, and two-tales tests otherwise.

Table 2.5 The Effects of Industry Concentration and Sales Uncertainty on Suppliers' Decisions in Response to Customers' Misconduct

	litigation sample (1996-2013)		restatement sample (2002-2013)	
	HHI	Sales_Vol	HHI	Sales_Vol
CAPEX	Coef. (t-statistic)		Coef. (t-statistic)	
Cheating_Customer*HHI	-0.110**		-0.136**	
	(-2.48)		(-2.45)	
Cheating_Customer*Sales_Vol		0.041***		0.052**
		(2.98)		(2.09)
HHI	0.075		-0.034	
	(1.52)		(-0.93)	
Sales_Vol		0.024***		0.014***
		(4.38)		(2.61)
Cheating_Customer	0.013***	-0.003	0.017***	-0.002
	(3.38)	(-0.83)	(3.24)	(-0.27)
Cash	0.033***	0.028***	0.004	0.002
	(5.84)	(4.88)	(0.84)	(0.33)
Leverage	-0.015***	-0.014**	-0.013**	-0.013**
	(-2.63)	(-2.49)	(-2.24)	(-2.15)
ROA	0.019***	0.022***	0.019***	0.021***
	(5.52)	(6.38)	(4.89)	(5.36)
Size	0.006***	0.006***	0.003***	0.003***
	(7.24)	(7.45)	(3.91)	(4.12)
Sales	0.009***	0.010***	0.006***	0.006***
	(5.11)	(5.41)	(3.03)	(3.33)
Financing	0.047***	0.044***	0.036***	0.035***
	(8.69)	(8.47)	(6.53)	(6.36)
Q	0.002***	0.002***	0.001**	0.001*
	(3.55)	(3.19)	(2.10)	(1.72)
Intercept	0.027	0.039***	0.038*	0.024
	(1.48)	(2.68)	(1.88)	(1.47)
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
R square	0.361	0.368	0.384	0.387
Obs	10,727	10,725	8,771	8,771

This table reports the parameters estimated from the following regressions for all suppliers in both litigation sample and restatement sample:

CAPEX$_{i,t} = \beta_0 + \beta_1 Cheating_Customer_{i,t} * HHI_{i,t} + \beta_2 Cheating_Customer_{i,t} + \beta_3 HHI_{i,t} + \beta_4 Fundamental_Controls_{i,t} + \varepsilon_{i,t}$ (2.1)

CAPEX$_{i,t} = \beta_0 + \beta_1 CheatingCustomer_{i,t} * Sales_Vol_{i,t} + \beta_2 Cheating_Customer_{i,t} + \beta_3 Sales_Vol_{i,t} + \beta_4 Fundamental_Controls_{i,t} + \varepsilon_{i,t}$ (2.2)

All variables are winsorized at the 1 percent and 99 percent level. Industry and year fixed-effects are included. The standard errors are clustered by firms. *, **, and *** indicate significance at the <0.10, <0.05, and <0.01 levels, respectively, based on one-tailed tests if the signs are predicted, and two-tales tests otherwise.

Table 2.6 The Association between Current Investments and Future Cash Flows

	litigation sample (1996-2013)		restatement sample (2002-2013)	
	CFOt+1	CFOt+2	CFOt+1	CFOt+2
CFOt+i	Coef. (t-statistic)		Coef. (t-statistic)	
CAPEX*Cheating_Customer	-0.164**	-0.198**	-0.044	-0.071
	(-2.50)	(-2.22)	(-0.62)	(-0.80)
CAPEX	0.153***	0.122***	0.191***	0.167***
	(4.93)	(3.62)	(5.90)	(4.83)
Cheating_Customer	0.008	0.023	-0.002	0.012
	(0.87)	(1.60)	(-0.16)	(0.76)
Cash	-0.061***	-0.074***	-0.063***	-0.080***
	(-5.60)	(-5.51)	(-4.63)	(-5.17)
Leverage	0.019	-0.0002	0.018	0.0005
	(1.09)	(-0.001)	(0.96)	(0.02)
ROA	0.334***	0.257***	0.367***	0.285***
	(18.79)	(13.90)	(17.16)	(13.65)
Size	0.020***	0.023***	0.016***	0.019***
	(9.38)	(9.57)	(8.57)	(9.24)
Sales	0.017***	0.017***	0.022***	0.026***
	(4.48)	(4.14)	(4.56)	(5.54)
Financing	-0.087***	-0.077***	-0.072***	-0.056***
	(-6.90)	(-5.87)	(-5.65)	(-4.02)
Q	-0.005*	-0.0003	-0.005	0.0001
	(-1.81)	(-0.10)	(-1.43)	(0.02)
Intercept	-0.045	-0.103**	-0.008	-0.083
	(-0.99)	(-2.16)	(-0.14)	(-1.39)
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
R square	0.544	0.433	0.561	0.462
Obs	7,377	6,309	6,918	6,192

This table presents the parameters estimated from the following regression for all suppliers in both litigation sample and restatement sample during customers' scandal periods:

$$\mathrm{CFO}_{i,t+m} = \beta_0 + \beta_1 CAPEX_{i,t} * Cheating\_Customer_{i,t} + \beta_2 CAPEX_{i,t} + \beta_3 Cheating\_Customer_{i,t} + \beta_4 Fundamental\_Controls_{i,t} + \varepsilon_{i,t}$$

Where m=1,2;

All variables are winsorized at the 1 percent and 99 percent level. Industry and year fixed-effects are included. The standard errors are clustered by firms. *, **, and *** indicate significance at the <0.10, <0.05, and <0.01 levels, respectively, based on one-tailed tests if the signs are predicted, and two-tales tests otherwise.

Table 2.7 The Market Reactions to Suppliers' Investment Decisions After The Disclosure of Customers' Frauds

	litigation sample (1996-2013)		restatement sample (2002-2013)	
	CAR(-3,3)	CAR(-5,5)	CAR(-3,3)	CAR(-5,5)
	Coef. (t-statistic)		Coef. (t-statistic)	
High_CAPX_Customer	-0.013*	-0.019**	-0.016**	-0.016
	(-1.77)	(-2.16)	(-2.20)	(-1.60)
Cash	-0.019	-0.038*	0.030***	0.010
	(-0.80)	(-1.67)	(2.71)	(0.64)
Leverage	-0.021	-0.015	0.020	0.031
	(-1.49)	(-0.83)	(1.00)	(1.23)
ROA	0.010	0.018	-0.033**	0.018
	(0.88)	(1.02)	(-2.03)	(0.82)
Size	0.005**	0.005*	-0.001	-0.004
	(1.98)	(1.85)	(-0.56)	(-1.32)
Sales	0.006	0.007	0.002	-0.002
	(1.06)	(1.14)	(0.38)	(-0.40)
Financing	-0.0004	-0.005	-0.064***	-0.038
	(-0.03)	(-0.31)	(-2.82)	(-1.26)
Q	0.003	0.005**	-0.001	-0.002
	(1.56)	(2.00)	(-0.45)	(-0.55)
Intercept	-0.028	-0.025	0.009	0.015
	(-1.62)	(-1.34)	(0.65)	(0.71)
R square	0.022	0.039	0.083	0.034
Obs	696	696	228	228

This table presents the parameters estimated from the following regression for all suppliers in both litigation sample and restatement sample:

$$\mathrm{CAR}_{i,[-3,+3]}\ or\ \mathrm{CAR}_{i,[-5,+5]} = \beta_0 + \beta_1 High\_CAPEX\_Customer + \beta_2 Fundamental\_Controls_{i,t} + \varepsilon_{i,t}$$

All variables are winsorized at the 1 percent and 99 percent level. The standard errors are clustered by firms. *, **, and *** indicate significance at the <0.10, <0.05, and <0.01 levels, respectively, based on one-tailed tests if the signs are predicted, and two-tales tests otherwise.

Table 2.8 The Robustness Check: Difference-in-Difference Approach

		litigation sample (1996-2013)	restatement sample (2002-2013)
Capital expenditure	Pred.	Coef. (t-statistic)	Coef. (t-statistic)
During	+	0.004**	0.005**
		(2.17)	(2.26)
After	-	-0.004***	0.002
		(-2.60)	(0.72)
R square		0.003	0.004
Obs		7,049	3,763
During=After (F-statistic)		20.11***	3.12*

This table presents the parameters estimated from the following DID regression for all suppliers in both litigation sample and restatement sample:

$$\widehat{\text{capx}}_{i,t} = \beta_0 + \beta_1 During_{i,t} + \beta_2 After_{i,t} + \varepsilon_{i,t}$$

All variables are winsorized at the 1 percent and 99 percent level. *, **, and *** indicate significance at the <0.10, <0.05, and <0.01 levels, respectively.

Figure 3.1 Transition Matrix of Before/During/After Trading Hours Announcement Times

	Previous Year			
Current Year	Before (%)	During (%)	AMC (%)	Total
Percent before hours	44.6%	3.8%	4.6%	53.0%
Percent during hours	4.2%	4.9%	3.3%	12.4%
Percent after hours	7.0%	3.1%	24.6%	34.7%
Total	55.8%	11.8%	32.5%	100.0%
Sum of shaded green = % that change in any given year				26.0%
Percent of firms with >=1 change in before/during/AMC timing				68.8%

This figure presents the year-over-year transitions matrix of EA during the day from 1990 to 2015. Before trading hours are from 12:00 AM to 9:00 AM; During trading hours are from 9:00 AM to 4:00 PM; and after trading hours are from 4:00 PM to midnight.

Figure 3.2 Transition of Matrix of Announcement Weekdays

	Previous Year					
Current Year	Monday	Tuesday	Wednesday	Thursday	Friday	Total
Monday	4.6%	2.8%	2.5%	2.6%	1.8%	14.3%
Tuesday	3.4%	8.9%	4.3%	4.3%	2.0%	22.9%
Wednesday	2.6%	5.0%	9.5%	4.7%	1.9%	23.7%
Thursday	2.5%	4.6%	5.5%	12.9%	2.3%	27.8%
Friday	1.5%	1.9%	1.9%	2.4%	3.6%	11.3%
Total	14.6%	23.2%	23.7%	26.9%	11.6%	100.0%
Sum of shaded green = percent that change in any given year						60.5%
Percent of firms with >=1 Friday announcement						46.2%

This figure presents the year-over-year transitions matrix of EA by weekday from 1990 to 2015. Saturday and Sunday EAs are excluded from the sample.

Table 3.1 Sample Description

Sample characteristic	**Restatements (2002-2015)**	**SEC Enforcements (1990-2010)**
Original events	1,344	308
Unique firms	1,130	304
Firm-years in violation period	3,548	834

The restatement sample consists of all firms that have income-increasing restatements from 2002 to 2015. The SEC enforcement sample consists of all firms subject to accounting and auditing SEC enforcement actions from 1990 to 2010. Both samples are required to be matched with Compustat to have necessary data of firm fundamentals. For purposes of our analyses, the violation period covers the years the firm misreported.

Table 3.2 Univariate Test

Panel A. Restatements (2002-2015)			
	Mean		***N***
	AMC	**Friday**	
Misreporting firms – violation years (1)	51.57%	6.45%	3,056
Misreporting firms – other years (2)	46.31%	6.40%	6,324
Control firms – all years (3)	46.96%	7.15%	36,260
Significance test: (1) versus (2)	<0.001***	0.469	
Significance test: (1) versus (3)	<0.001***	0.073*	

Panel B. SEC Enforcements (1990-2010)			
	Mean		***N***
	AMC	**Friday**	
Misreporting firms – violation years (1)	42.49%	7.12%	772
Misreporting firms – other years (2)	35.22%	10.06%	2,256
Control firms – all years (3)	32.14%	10.64%	69,534
Significance test: (1) versus (2)	<0.001***	<0.001***	
Significance test: (1) versus (3)	<0.001***	<0.001***	

This table presents the EA timing for misreporting firms relative to control firms that have not had any misrepresentation event during our sample period. The restatement sample consists of all firms that have income-increasing restatements from 2002 to 2015. The SEC enforcement sample consists of all firms subject to accounting and auditing SEC enforcement actions from 1990 to 2010. "Misreporting firms – violation years" represents years in which the firm misreported. "Misreporting firms – other years" represents non-violation years of the misreporting firm. "Control firms – all years" represents all years of control firms. We report the mean value of *AMC* and *Friday*, which are indicators for EA made after 4:00 PM and on Friday, respectively.

Table 3.3 Descriptive Statistics

Panel A. Restatements Pooled Sample (2002-2015)			
	Misreporting	**Control**	**Difference (t-statistic)**
AMC	0.5157	0.4759	0.0398*** (4.25)
Friday	0.0645	0.0704	-0.0059 (-1.24)
Size	6.6041	6.6796	-0.0755** (-2.00)
BTM	0.5615	0.5355	0.0260*** (2.61)
Lev	0.2050	0.2201	-0.0150*** (-3.75)
Numest	7.2857	7.1217	0.1639* (1.35)
RepLag	3.8702	3.8459	0.0243*** (3.23)
SUE	-0.0367	-0.0350	-0.0017 (-0.28)
InstOwn	0.6032	0.5003	0.1029*** (16.01)
Obs	3,056	42,584	Total 45,640
Panel B. SEC Enforcement Pooled Sample (1990-2010)			
	Misreporting	**Control**	**Difference (t-statistic)**
AMC	0.4249	0.3224	0.1025*** (6.06)
Friday	0.0712	0.1063	-0.0350***(-3.15)
Size	6.7249	5.9990	0.7258*** (10.08)
BTM	0.4985	0.5486	-0.0500*** (-2.64)
Lev	0.2174	0.2223	-0.0049 (-0.64)
Numest	9.4080	6.2698	3.1382*** (13.96)
RepLag	3.6842	3.7958	-0.1116*** (-6.42)
SUE	-0.0059	-0.0691	0.0633*** (3.68)
InstOwn	0.5282	0.3697	0.1585*** (13.18)
Obs	772	71,790	Total 72,562

This table reports firm characteristics for the misreporting sample and control sample that have not had any misrepresentation event during our sample period. The restatement sample consists of all firms that have income-increasing restatements from 2002 to 2015. The SEC enforcement sample consists of all firms subject to accounting and auditing SEC enforcement actions from 1990 to 2010. All variables are defined in Appendix A. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. Two sided p-values are based on the t-statistic for differences in means.

Table 3.4 EA Timings During Periods of Misreporting

	Restatements (2002-2015)				SEC Enforcements (1990-2010)			
	AMC		*Friday*		*AMC*		*Friday*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Misreporting	0.1034***	0.1192***	0.018	-0.0410	0.1260*	0.1220*	-0.1125	-0.0322
	(2.98)	(3.14)	(0.49)	(-0.89)	(1.81)	(1.81)	(-1.47)	(-0.41)
Size		-0.1507***		0.0569***		-0.1088***		0.0161**
		(-16.93)		(5.83)		(-15.20)		(2.50)
BTM		0.0187		0.0568***		-0.0215		0.0866***
		(0.96)		(2.75)		(-1.44)		(6.06)
Lev		0.0357		0.0027		-0.1552***		0.1199***
		(0.56)		(0.04)		(-3.26)		(2.86)
Numest		0.0139***		-0.0120***		0.0206***		-0.0096***
		(5.49)		(-3.84)		(9.60)		(-4.74)
RepLag		-0.3376		-0.7866***		0.0109		0.0744
		(-1.26)		(-3.25)		(0.10)		(0.66)
RepLag_SQ		0.0248		0.1336***		-0.0226*		0.0064
		(0.76)		(4.64)		(-1.65)		(0.47)
SUE		-0.0218		-0.0684***		-0.0281**		-0.0709***
		(-1.05)		(-2.67)		(-2.21)		(-5.92)
InstOwn		0.2342***		-0.2270***		0.1909***		-0.3342***
		(5.46)		(-4.98)		(5.15)		(-8.98)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	54,396	45,640	54,396	45,539	72,562	72,562	72,559	72,559
Pseudo R2	0.038	0.068	0.019	0.045	0.145	0.158	0.061	0.080

This table reports probit regression over the misreporting firms and control firms in which the dependent variable is either *AMC* or *Friday*. *AMC* is an indicator for earnings announcements made after 4:00 PM; *Friday* is an indicator for earnings announcements made on Friday. Misreporting is an indicator variable equal to one for years in which the firm is alleged to have misreported. The restatement sample consists of all firms that have income-increasing restatements from 2002 to 2015. The SEC enforcement sample consists of all firms subject to accounting and auditing SEC enforcement actions from 1990 to 2010. All other variables are defined in Appendix A. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. p-values are two-sided. Standard errors are clustered by firm.

Table 3.5 Propensity Score Matching – First Stage

	Restatements (2002-2015)	**SEC Enforcements (1990-2010)**
Size	0.0226*	0.0491***
	(1.75)	(2.65)
BTM	0.0579**	-0.0076
	(2.03)	(-0.19)
Lev	-0.0455	0.0849
	(-0.50)	(0.65)
Numest	0.0015	0.0185***
	(0.43)	(4.07)
RepLag	-1.3501***	0.0517
	(-5.71)	(0.19)
RepLag_SQ	0.2218***	0.0195
	(7.73)	(0.62)
SUE	0.0032	0.2557***
	(0.09)	(3.83)
InstOwn	0.4964***	0.5785***
	(8.20)	(4.93)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Obs	45,622	69,309
Pseudo R2	0.0998	0.1290

This table reports the results of the first stage of propensity score matching in which the dependent variable *Misreporting*, is an indicator variable equal to one for years in which the firm is alleged to have misreported. The restatement sample consists of all firms that have income-increasing restatements from 2002 to 2015. The SEC enforcement sample consists of all firms subject to accounting and auditing SEC enforcement actions from 1990 to 2010. All other variables are defined in Appendix A. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. p-values are two-sided. Standard errors are clustered by firm.

Table 3.6 Descriptive Statistics

Panel A. Restatements PSM Sample (2002-2015)			
	Misreporting	**Control**	**Difference (t-statistic)**
AMC	0.5178	0.4597	0.0582*** (4.29)
Friday	0.0649	0.0662	-0.0012 (-0.17)
Size	6.6085	6.5291	0.0794* (1.64)
BTM	0.5642	0.5629	0.0013 (0.09)
Lev	0.2095	0.2080	0.0016 (0.28)
Numest	7.1645	6.9928	0.1717 (1.00)
RepLag	3.8681	3.8679	0.0002 (0.02)
SUE	-0.0391	-0.0416	0.0025 (0.32)
InstOwn	0.5969	0.5834	0.0135*(1.56)
Obs	2,632	2,801	Total 5,433
Panel B. SEC Enforcement PSM Sample (1990-2010)			
	Misreporting	**Control**	**Difference (t-statistic)**
AMC	0.4347	0.3912	0.0435** (1.90)
Friday	0.0674	0.0630	0.0045 (0.39)
Size	6.7716	6.7339	0.0378 (0.40)
BTM	0.5361	0.5003	0.0358* (1.40)
Lev	0.2271	0.2275	-0.0004 (-0.04)
Numest	9.0953	9.3094	-0.2141 (-0.62)
RepLag	3.7554	3.7216	0.0338* (1.35)
SUE	-0.0599	-0.0541	-0.0057 (-0.31)
InstOwn	0.5372	0.5285	0.0086 (0.59)
Obs	934	905	Total 1,839

This table reports firm characteristics for the misreporting sample and propensity score matched control sample that have not had any misrepresentation event during our sample period. The restatement sample consists of all firms that have income-increasing restatements from 2002 to 2015. The SEC enforcement sample consists of all firms subject to accounting and auditing SEC enforcement actions from 1990 to 2010. All variables are defined in Appendix A. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. Two sided p-values are based on the t-statistic for differences in means.

Table 3.7 EA Timings During Periods of Misreporting – Propensity Score Matching

	Restatements (2002-2015)				SEC Enforcements (1990-2010)			
	AMC		*Friday*		*AMC*		*Friday*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Misreporting	0.1611***	0.1729***	-0.0032	-0.0015	0.1213*	0.1505**	0.084	0.0934
	(3.47)	(3.72)	(-0.05)	(-0.26)	(1.71)	(1.98)	(0.92)	(1.00)
Size		-0.1710***		0.0657***		-0.1831***		0.0932***
		(-8.72)		(2.72)		(-5.71)		(2.64)
BTM		-0.0320		0.1431**		-0.0276		0.1084
		(-0.70)		(2.48)		(-0.39)		(1.27)
Lev		-0.0354		0.2149		-0.1531		-0.2336
		(-0.27)		(1.37)		(-0.71)		(-0.91)
Numest		0.0210***		-0.0100		0.0390***		-0.0192**
		(4.26)		(-1.43)		(5.33)		(-2.01)
RepLag		-0.5693		-0.3121		-1.2153**		-1.1829*
		(-1.25)		(-0.54)		(-2.09)		(-1.75)
RepLag_SQ		0.0449		0.0864		0.1287*		0.1719**
		(0.83)		(1.33)		(1.83)		(2.17)
SUE		-0.0146		-0.0412		-0.0625		-0.0703
		(-0.56)		(-0.45)		(-0.82)		(-0.87)
InstOwn		0.2022**		-0.2937***		0.2173		-0.6347***
		(2.36)		(-2.99)		(1.44)		(-3.43)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	5,433	5,433	5,355	5,355	1,839	1,839	1,881	1,881
Pseudo R2	0.070	0.093	0.061	0.096	0.139	0.177	0.112	0.156

This table reports probit regression over the misreporting firms and propensity score matched control firms in which the dependent variable is either *AMC* or *Friday*. *AMC* is an indicator for earnings announcements made after 4:00 PM; *Friday* is an indicator for earnings announcements made on Friday. *Misreporting* is an indicator variable equal to one for years in which the firm is alleged to have misreported. The restatement sample consists of all firms that have income-increasing restatements from 2002 to 2015. The SEC enforcement sample consists of all firms subject to accounting and auditing SEC enforcement actions from 1990 to 2010. All other variables are defined in Appendix A. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. p-values are two-sided. Standard errors are clustered by firm.

Table 3.8 Days to Detection with EAs Made in After Trading Hours

	Restatements (2002-2015)			SEC Enforcements (1990-2010)		
	OLS	***COX***	***Weibull***	***OLS***	***COX***	***Weibull***
	(1)	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***
AMC_Hide	0.0981***	-0.2389***	-0.2676***	0.0363	-0.2317*	-0.2574*
	(3.65)	(-3.87)	(-3.90)	(0.94)	(-1.67)	(-1.82)
IndMisreporting	-0.1465	0.0439	0.2668	-3.1714***	11.4886***	14.4552***
	(1.38)	(0.19)	(0.99)	(-3.94)	(5.26)	(6.38)
MeanDetectSIC	0.0124	-0.0493***	-0.0637***	0.0137*	-0.0534*	-0.0541*
	(1.61)	(-2.72)	(-3.54)	(1.69)	(-1.90)	(-1.97)
MeanDetectOther	0.4769***	-1.1678***	-1.6151***	0.0794	-0.2375***	-0.2249**
	(4.15)	(-4.75)	(-5.69)	(1.25)	(-2.63)	(-2.56)
Size	0.0184*	-0.0030	0.0127	-0.0266	0.1060*	0.1232**
	(1.72)	(-0.13)	(0.51)	(-1.43)	(1.81)	(2.18)
Lev	0.0094	-0.1165	-0.0808	0.2987**	-1.1821***	-1.1592**
	(0.12)	(-0.18)	(-0.44)	(2.35)	(-2.67)	(-2.52)
Numest	-0.0108***	0.0191**	0.0219***	-0.0105*	0.0391**	0.0429***
	(-3.11)	(2.52)	(2.65)	(-1.87)	(2.46)	(2.65)
ROA	0.1131	-0.3353	-0.3449	0.2623*	-1.9102***	-1.7070***
	(1.21)	(-1.26)	(-1.22)	(1.84)	(-4.15)	(-4.07)
Growth	-0.1073**	0.4227***	0.4223***	0.0962**	-0.3508**	-0.3443**
	(-2.55)	(3.31)	(3.52)	(2.03)	(-2.15)	(-2.17)
InstOwn	0.0439	-0.1449	-0.2257*	0.0542	-0.2369	-0.3062
	(0.86)	(-1.29)	(-1.86)	(0.68)	(-0.87)	(-1.11)
AnnRet	0.0180	-0.0050	0.0072	-0.0287	0.3361*	0.2889
	(0.44)	(-0.05)	(0.06)	(-0.62)	(1.88)	(1.59)
RetVol	-1.5116	5.1511*	6.2959**	-6.0752***	23.8489***	22.2794***
	(-1.19)	(1.67)	(2.00)	(-3.19)	(3.94)	(3.76)
Turnover	-0.0002	0.0146	0.0158	-0.0139	0.0582	0.0376
	(-0.03)	(0.67)	(0.67)	(-0.94)	(1.00)	(0.65)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1,313	1,313	1,313	308	308	308
R-squared	0.149			0.423		

This table reports the regression results for the detection period of misreporting firms over the EA timing in violation years. The dependent variable *DetectionPeriod* is the natural log of number of days from the beginning of the violation to the end of it. *AMC_Hide* is an indicator variable equals to one if the firm makes at least one EAs in after trading hours during violation years. Column (1) and (4) report an OLS estimation. Columns (2) and (5) report the results of a COX Hazard estimation. Column (3) and (6) report the results of a parametric Weibull hazard estimation. The restatement sample consists of all firms that have income-increasing restatements from 2002 to 2015. The SEC enforcement sample consists of all firms subject to accounting and auditing SEC enforcement actions from 1990 to 2010. All other variables are defined in Appendix A and are averaged in the violation years. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. p-values are two-sided. Standard errors are clustered by firm.

Table 3.9 Insider Trading with EAs Made in After Trading Hours

	Restatements (2002-2015)		SEC Enforcements (1990-2010)	
	Positive	***Negative***	***Positive***	***Negative***
	(1)	***(2)***	***(3)***	***(4)***
AMC	-0.0002	0.0066	0.0038	-0.0004
	(-0.04)	(1.03)	(0.99)	(-0.09)
Misreporting	0.0280**	0.0192	-0.0090	0.0124
	(2.46)	(1.59)	(-0.45)	(0.69)
*AMC*Misreporting*	-0.0073	-0.0412**	-0.0322	-0.0399*
	(-0.52)	(-2.42)	(-1.15)	(-1.67)
SUE	0.1150	0.0084	0.2232***	-0.0111
	(1.35)	(0.34)	(3.05)	(-1.01)
Size	-0.0369***	-0.0146**	-0.0291***	-0.0110***
	(-7.29)	(-2.35)	(-8.23)	(-3.02)
BTM	0.1484***	0.0851***	0.1336***	0.0745***
	(18.37)	(10.61)	(23.19)	(15.70)
Lev	0.0909***	0.1007***	0.1279***	0.1038***
	(4.76)	(4.90)	(9.25)	(7.42)
Numest	0.0021***	0.0012*	0.0023***	0.0019***
	(3.95)	(1.90)	(5.50)	(4.14)
RepLag	-0.1533	-0.3505**	0.0686	0.0028
	(-1.06)	(-2.26)	(1.15)	(0.05)
RepLag_SQ	0.0175	0.0482**	-0.0061	0.0038
	(0.89)	(2.36)	(-0.76)	(0.49)
InstOwn	0.0639***	0.0128	0.0171	0.0216*
	(4.34)	(0.75)	(1.53)	(1.93)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs	14,830	11,035	22,075	19,100
R-squared	0.0184	0.0280	0.0179	0.0228
		Chi2		*Chi2*
H0: AMC*Misreporting (1) =AMC*Misreporting (2)		2.46*		0.63

This table reports the results for insider trading following EAs separately for positive and negative news. We divide news based on *SUE*, which is standardized unexpected earnings, calculated as actual annual EPS per IBES less the most recent analyst forecast consensus per IBES, deflated by year-end stock price per Compustat. The dependent variable *Value* is the net dollar value of trades by insiders in a given firm during 90 days following an EA in a year. *AMC* is an indicator for earnings announcements made after 4:00 PM. *Misreporting* is an indicator variable equal to one for years in which the firm is alleged to have misreported. The restatement sample consists of all firms that have income-increasing restatements from 2002 to 2015. The SEC enforcement sample consists of all firms subject to accounting and auditing SEC enforcement actions from 1990 to 2010. All other variables are defined in Appendix A. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. p-values are two-sided. Standard errors are clustered by firm.

Table 3.10 The Market Reactions Following the Disclosure of Misreporting

	Restatements (2002-2015)		SEC Enforcements (1990-2010)	
	CAR [-1,1]	***CAR [-3,3]***	***CAR [-1,1]***	***CAR [-3,3]***
	(1)	***(2)***	***(3)***	***(4)***
After_Hide	-0.0151**	-0.0014**	0.0037	-0.0131
	(-2.55)	(-2.13)	(0.31)	(-0.74)
Size	0.0058**	0.0060**	0.0047	0.0060
	(2.28)	(2.14)	(0.76)	(0.85)
BTM	-0.0218***	-0.0323***	-0.0232	-0.0040
	(-3.12)	(-4.03)	(-1.33)	(-0.16)
Lev	-0.0446***	-0.0506***	-0.0296	-0.0221
	(-2.69)	(-2.69)	(-0.80)	(-0.55)
Numest	-0.0011*	-0.0016**	-0.0013	-0.0001
	(-1.68)	(-2.02)	(-0.95)	(-0.05)
RepLag	-0.0101	-0.0001	0.0929	0.0837
	(-0.37)	(0.05)	(0.81)	(0.48)
RepLag_SQ	-0.0009	-0.0028	-0.0119	-0.0097
	(-0.27)	(-0.57)	(-0.90)	(-0.48)
SUE	0.0296***	0.0301***	0.0025	0.0437
	(3.42)	(2.91)	(0.08)	(1.47)
InstOwn	-0.0026	0.0061	0.0349	0.0548
	(-0.24)	(0.47)	(1.46)	(1.39)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs	1,023	1,023	144	144
R Squared	0.181	0.176	0.439	0.635

This table reports the results for CAR surrounding the discovery date (filing date) of the misreport. The dependent variable *CAR* is the 3-day (7-day) size-adjusted abnormal returns surround the filing date of the restatement or lawsuit. *After_Hide* is an indicator variable equals to one if the firm makes at least one EAs in after trading hours during violation years, and zero otherwise. The restatement sample consists of all firms that have income-increasing restatements from 2002 to 2015. The SEC enforcement sample consists of all firms subject to accounting and auditing SEC enforcement actions from 1990 to 2010. All other variables are defined in Appendix A. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. p-values are two-sided. Standard errors are clustered by firm.