The Spillover Effect of Fraudulent Financial Reporting on Peer Firms' Investments

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1 Introduction

How accounting information affects investment is a fundamentally important question. A growing literature examines how a firm's accounting quality and stock market mispricing affect its *own* investment. However, there is little systematic evidence on how a firm's accounting information affects *other* firms' real investment behavior (Leuz and Wysocki, 2008).

Within an industry one firm's disclosures can have a spillover effect on other firms' investments. Gigler (1994) models the tension between ex post disclosure of favorable information to the capital market, thereby lowering financing costs, and to the product market, resulting in increased competitor output. In addition, Bushman and Smith (2001) argue that "managers can identify promising new investment opportunities on the basis of the high profit margins reported by other firms," and, therefore, distortion of the investment opportunity signal by fraudulent accounting may lead to sub-optimal investments by industry peers. Consistent with this possibility, Kumar and Langberg (2010) develop a rational expectations model where peer firms increase investments as an equilibrium response to the industry leader's inflated productivity report.

Anecdotal evidence also supports these arguments. Sidak (2003) shows that WorldCom's falsified FCC internet traffic reports and overstated earnings encouraged widespread overinvestment in network capacity by industry rivals. Brenner (2003) reports that annual investments in telecommunication infrastructure more than doubled between 1996 and 2000, resulting in a glut of fiber-optic cable capacity with utilization rates at only 2.5-3%.

Based on the theoretical literature on the effects of *ex post* disclosure on competitors' investment decisions as well as the anecdotes supporting these predictions, we hypothesize that peer firms will invest more during the scandal period than during the pre-scandal period in response to the industry leader's overstated earnings. This analysis of the investment spillover effect of fraudulent accounting may however be confounded by omitted factors that affect both industry investment and fraud, or by the possibility of reverse causality that industry investment booms may result in underperforming firms' accounting fraud. For example, Povel et al. (2007) model the fraud dynamic and demonstrate that fraud is related to the business cycle, although not monotonically. On a related note, Wang and Winton (2010) find that while firms' fraud propensity is insensitive to industry investment booms in concentrated industries, firms in competitive industries have a pro-cyclical propensity to commit frauds.

To test our hypothesis, we examine the effect of accounting frauds on industry peers' investments during the scandal period. We focus on frauds conducted by high-profile industry leaders (Fortune 500 firms accused of an accounting fraud in SEC Accounting and Auditing Enforcement Releases) because their financial reports are highly visible and more likely to be used to evaluate market conditions and investment opportunities. Using a difference-in-differences design where peer firms share the fraud firm's 3-digit SIC code and control firms share the fraud firm's 2-digit SIC code, we find significantly greater capital expenditures by the peer relative to the control firms during the fraud period compared to the three-preceding-year control period.[1]

We conduct several additional tests to mitigate reverse causality or omitted variables concerns. First, we examine the lead-lag relation between fraud and investment. Our finding that fraud precedes increases in peers' investments, combined with our failure to find peer investment increases prior to the fraud, supports the hypothesis that the increases in peers' investments result from fraud rather than the reverse. Next, we investigate whether the spillover effect differs between competitive and concentrated industries, and between high and low growth industries. If industry booms cause both frauds and increased peer investments, then we should observe stronger results in higher growth and in more competitive industries (Wang and Winton, 2010). The observed lack of significant differences in the relation between fraud and peer investment in high versus low growth or in competitive versus concentrated industries further mitigates the concern that changes in investments cause frauds.[2]

After documenting that the industry leader's accounting fraud affects peer investment only during the scandal period, we then consider cross-sectional variations in the extent of the spillover effect. Kumar and Langberg (2010) theorize that the spillover effect should increase with the magnitude of falsified productivity. They also argue that

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[1] We confirm the fraud period using subsequent earnings restatements. We use the terms "fraud period" and "scandal period" interchangeably. They both denote the period that the scandal firm engaged in fraudulent financial reporting, before the actual detection of the fraud.

[2] In addition to addressing this primary goal, these tests also help address concerns about changes in peer investments leading to fraud *detection* because Wang and Winton (2010) also use ex post detected frauds to test Povel et al.'s (2007) predictions about an increase in fraud propensity during investment booms in competitive vs. concentrated industries. Their evidence is consistent with ex post detected frauds being an order preserving proxy for unobservable fraud propensity.

that in industries with higher investor sentiment, lower cost of capital and higher private benefits of control, an inflated lead firm report is more likely to trigger a run-up in conditional market expectations divergent from the true industry productivity along the equilibrium path. Based on these arguments, we hypothesize that the spillover effect on peers' investment will be positively associated with the magnitude of the scandal firm's earnings overstatement and will be stronger in industries with higher investor sentiment, lower cost of capital and higher private benefits of control.

We further examine whether the spillover effect may be partially fueled by propagation of industry-wide information contained in analysts' recommendations. Cotter and Young (2007) find that analysts are not able to distinguish true frauds from fictitious frauds. Akhigbe et al. (2006) argue that because analysts' recommendations reflect overall industry prospects, industry rivals often experience valuation effects in the same direction as the revised firm. If analysts help transmit distorted industry investment signals, then we expect the unexplained overlap in analysts' coverage of scandal firms and peer firms will strengthen the spillover effect of distorted signals on peers' investment decisions.[3] In addition, we directly examine whether equity analysts' recommendations are more favorable for peer firms during the scandal period.

Finally, we argue that peer firms' investments during the fraud period resulting from distorted signals by industry leaders should produce a weaker association between future cash flows and investments compared to investments in previous periods.

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[3] We use a model to remove the economic similarity between the scandal firms and peer/control firms. The residual is denoted as the "unexplained" overlap. More details are provided in the following sections.

We find that peer firms' investments are positively associated with the magnitude of the scandal firm's earnings overstatements during the scandal period, after controlling for the scandal firm's contemporaneous investment and the co-movement of peer and scandal firms' growth opportunities. In addition, we find that peer firms' investments are greater in industries where the investor sentiment is high, the industry cost of capital is low and managers' private benefits of control are large.

In addition to using 3-digit vs. 2-digit SIC codes to identify peer and control firms, we use peer firms' secondary segments as an alternative control group. One advantage of this identification strategy is that we use the firm as its own control thereby circumventing the concern that firms with the same 2-digit SIC codes may have different growth opportunities or other firm characteristics from the peer firms. We find that the spillover effect on peers' investments continues to hold using this alternative identification of the control group.

We further find that the above investment findings hold only for firms with high unexplained overlap in analyst coverage between scandal and peer firms, suggesting that analysts transmit the distorted investment opportunity signal. In addition, corroborating this interpretation, we find that equity analysts' recommendations are more favorable during the scandal period for peer firms and that this finding only exists for firms with high unexplained overlap in analyst coverage with scandal firms. Finally, we find a lower correlation between peer firms' future performance and investments made in the scandal period. This phenomenon persists for at least three years after the investment. This result suggests that scandal period investments are likely to be sub-optimal.

In supplemental analyses, we find that peer firms' insiders purchase more shares during the scandal period, suggesting that peer firms' executives were misled by the inflated scandal firm financial performance. Further, we find the spillover effect of leaders' restated earnings on peer investment to be similar to that of overstated earnings. This provides additional support that peer management does not see through fraudulent reporting by industry leaders. Finally, we find that our documented spillover effect on peers' investments only hold for scandals related to revenue recognition.[4]

Our paper makes several contributions. We address a deficiency identified by Leuz and Wysocki (2008) who argue that the spillover effect of fraudulent financial reporting on real investment behavior remains under-explored. Our findings suggest that a leading firm's distorted accounting information plays an important role in peer firms' investment prior to the announcement of misreporting. We contribute to the fraud dynamics literature by analyzing the lead-lag and contemporaneous associations between accounting fraud and peer firm investment and by examining how the association differs based on industry competition and growth. These analyses complement Durnev and Mangen's (2009) finding that competitors' investments are lower in the year after other firms in the industry announce restatements by shedding further light on the causality between fraud and peer firm investment. In addition, our study extends their findings by considering analysts' role in transmitting the distorted investment opportunity signal.

Furthermore, we contribute to the literature documenting consequences of financial statement misreporting. Francis (2001) calls for research on "the adverse effects of bad accounting." Sadka (2006) also argues that the existing literature understates the

[4] This finding is consistent with prior theory papers, e.g., Darrough and Stoughton (1990) and Gigler (1994).

economic consequences of accounting fraud. We respond to their call for research by providing systematic evidence that accounting frauds distort industry competitors' investment decisions and result in investments that generate lower future cash flows.

The rest of the paper is organized as follows. Section 2 provides background information. We develop our hypotheses in Section 3. We describe our research design and sample in Section 4. We present our results in Section 5 and conclude in Section 6.

2 Background

2.1 Anecdotal evidence

On June 26, 2002, the SEC filed a complaint charging WorldCom, a major telecommunications firm, with "a massive accounting fraud totaling more than $3.8 billion."[5] WorldCom later admitted that from 1999 through the first quarter of 2002, the company materially overstated its reported earnings by about $9 billion in the fraud.[6]

In a WorldCom case study, Sidak (2003) concludes that "WorldCom's false internet traffic reports and accounting fraud encouraged overinvestment in long-distance capacity and Internet backbone capacity" by competitors. Worldcom's overstated earnings distorted the economic gains of acquiring new customers causing other firms to overinvest. AT&T Labs reported in 2001 that rival telecommunications providers made investment decisions relying on WorldCom's fraudulent reports. The Eastern Management Group also argued that a substantial fraction of the $90 billion invested by other carriers in the industry was misallocated because of WorldCom's faulty projections.

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[5] Source: SEC Litigation Release No. 17588 and Accounting and Auditing Release No. 1585.
[6] Source: SEC Litigation Release No. 17829 and Accounting and Auditing Release No. 1658.

Charles Noski, AT&T's vice chairman prior to the WorldCom scandal, said that "we were constantly dissecting all of the public information about WorldCom/MCI and we would scratch our heads and try to figure out how they were doing it all." He also mentioned discussions with AT&T's COO offering $2-$4 billion for upgrading of systems.

2.2 Related research

2.2.1 Accounting information and firms' own investment behavior

Prior literature has examined the direct effect of a firm's accounting quality on its own investment efficiency. Several studies including Biddle and Hilary (2006), Biddle et al. (2009) and Beatty et al. (2010) examine how differences in accounting quality in the absence of misstatements affect firms' investments. Kedia and Philippon (2009) build a model where bad managers fraudulently boost reported accounting performance while mimicking good managers' investment decisions to maintain consistency between reported performance and investments. In equilibrium, fraud firms invest too much. Similarly, Sadka's (2006) model predicts that fraud firms' output decisions should be consistent with their reported performance. He points to real actions taken by WorldCom to mimic efficiency in their financial reports, including increasing market share and attracting customers via a price war.[7]

Kumar and Langberg (2009) extend this literature by developing a rational expectations equilibrium model where fraud and overinvestment jointly occur. In their model, agency conflicts arise because privately informed managers derive personal

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[7] His model further predicts negative externalities arising from the effect of fraud firm's financial reports on competing firms' output decisions. However, he does not provide a large sample test of this prediction.

benefits from larger investments, and shareholders cannot credibly pre-commit to *ex-post* inefficient investment policies that would induce manager truth-telling because such policies are not renegotiation-proof in an active takeover market. They show that the optimal renegotiation-proof contract induces misreporting by insiders, which results in overinvestment in some states by rational investors.

2.2.2 Ex ante versus ex post disclosure

Christensen and Feltham (2003) summarize models of the potential effects of product market competition on disclosure policy. They discuss papers both from the industrial organization literature and the accounting literature that consider two types of disclosure, those that are ex ante and those that are ex post.

They discuss that in the ex ante disclosure equilibria, firms are assumed to make an ex-ante commitment to a credible disclosure policy that will be implemented irrespective of the manager's ex-post incentives. They note that in the ex-ante rational expectations equilibrium, incumbents' attempts to manipulate entrants' inferences will be fruitless. They summarize that a firm's *ex ante* disclosure policy will depend on the type of competition, Bertrand versus Cournot, and the type of information, firm-specific versus industry-wide. Under Cournot competition, reporting good news about firm-specific information or bad news about industry-wide information will induce the competitor to reduce his production, but the incentive reverses for Bertrand competition.

The predictions for *ex post* disclosure, such as an accounting fraud, differ from those for *ex ante* disclosure. In the absence of tension in the *ex post* setting, full disclosure is the equilibrium choice regardless of the information type. Christensen and Feltham (2003) state that:

> *Partial disclosure policies can only be sustained as equilibria in the ex-post setting when the ex-ante optimal policy is no disclosure … a compelling reason for equilibrium partial disclosure policies in the ex post setting is that there can be a tension between disclosure to product market competitors and disclosure to the capital market. If a firm must raise new equity to finance operations, ex post, it would like to disclose that it has low productions costs or that product market conditions are favorable.*

This tension is modeled by Darrough and Stoughton (1990) who discuss these countervailing incentives by modeling "an incumbent with favorable information [that] wishes to communicate the information to the financial market to raise its valuation, but otherwise does not want to make this known to the potential entrant." An examination of this tension as it pertains to financial fraud is provided by Gigler (1994). In his model

> *a firm with private information about the demand for its product makes a direct public disclosure to both a competitor and the capital market. The firm would like to convince the capital market that the demand for its product is high, thereby increasing the value of the firm's stock. But the firm would also like to convince its competitor that demand is low, decreasing the competitor's output and thereby increasing the informed firm's profit. The primary insight of this paper is that, while any disclosure made privately to either the capital market or the competitor cannot be credible, trading off the benefits of overstating demand to the capital market against those of understating demand to the product market can make the firm's equilibrium public disclosures believable and informative to both groups…A key assumption of this model is that firms wish to mislead the capital market.*

Because in this paper we study the spillover effects of fraudulent reporting, it is more appropriate to apply the ex-post disclosure literature. That is, although overstating demand creates higher valuation of their securities, it may also invite more entrants and competition in the product markets.

In appendix A we provide benchmark evidence in support of the effects of disclosure on peer firms' investment incentives in the non-scandal periods. Based on the arguments made by Darrough and Stoughton (1990) and Gigler (1994), when an industry leader has an increase in reported revenue, competing firms should increase their investments if this disclosure represents an ex post rather than an ex ante disclosure. In contrast, if a large increase in revenue of an industry leader is disclosed as a result of an ex ante disclosure policy and this increase in revenue reflects firm-specific information under Cournot competition or industry-specific information under Bertrand competition, then according to Christensen and Feltham (2003) this would instead provide a signal for competitors to reduce investments and possibly exit the industry.

We use Fortune 100 firms as industry leaders. We determine shock years by first identifying the year with the highest lead firm revenue growth in excess of the median peer firm's revenue growth for that year. Within the distribution of highest lead firm excess revenue growth years we select those above the median as being shock years. Based on this process we obtain 34 shock periods for our lead firms. We identify peer and control groups in the same fashion as our main analysis, i.e., 3-digit vs. 2-digit SIC codes. We find that peer firms' capital expenditures are higher during the shock period than control firms' capital expenditures and that peer firms' capital expenditures increase with industry leaders' earnings growth in the shock periods. This baseline model validates the assumption we have in the paper that peer firms' investments are affected by leading firms' reported earnings.

2.2.3 Accounting information and spillover effects

Gleason et al. (2008) find that accounting restatements that adversely affect restating firms' shareholder wealth also induce share price declines among non-restating industry peers. Their contagion results are consistent with the notion that accounting restatements cause investors to reassess the financial statement information previously released by non-restating firms. This study provides initial evidence of the contagion effect of restatements, but does not investigate the real effects caused by accounting restatements.

Kumar and Langberg (2010) argue that a spillover effect of fraudulent reporting that distorts industry-wide investment can occur even in a rational and frictionless capital market. In their model, outsiders' posterior beliefs on industry growth potential and their investment responses depend on the incumbent firm's information disclosure. Privately informed managers of these leading firms have a strong incentive to manipulate outsiders' beliefs by inflating their reported performance to attract larger investment flows. Therefore, along the perfect Bayesian equilibrium investment path, inflated performance reports by the incumbent firm could lead to a run-up in the market expectation of industry productivity that diverges from the true state, resulting in over-investments by competitors entering the industry to exploit the new investment opportunities.

Durnev and Mangen (2009) investigate whether the announcement of an accounting restatement is associated with a systematic change in peers' investments. They find that peer firms significantly lower their investment growth in the year after a competitor's restatement announcement, and the reduction in investment is greater the more negative the competitor's abnormal return at the restatement announcement. In their model, a restatement announcement serves as an exogenous shock that reveals new information, which is different from Kumar and Langberg's (2010) perspective. They infer that peer firms learn from the new information and modify their investment strategies accordingly.[8]

2.2.4 The effect of investment on the incidence of fraud

Povel et al. (2007) model a firm's fraud decision based on investor's prior beliefs about the state of the economy and the cost of monitoring the firm. They predict a non-monotonic relationship between optimistic priors and the incidence of fraud. Specifically, they predict that when priors are low, even if a firm's public information is positive, there is enough uncertainty for investors to monitor firms carefully so there is little incentive for fraud. When priors are fairly optimistic, investors do not monitor a firm with positive public information carefully because the report confirms their view that the firm is very likely to be good, but they do monitor firms with negative public information, so the incentive for fraud is high. However, when priors are so optimistic that investors do not even monitor firms with negative public information, the incentives for fraud are once again low.

Wang and Winton (2010) test Povel's (2007) model by examining how the association between investment booms and fraud propensity differs in competitive versus concentrated industries. Using industry level data, they observe a large increase in the fraud propensity during investment booms in competitive industries, with the peak in fraud propensity occurring in the year after the maximum investment boom. In contrast, in concentrated industries they observe a constant fraud rate across the years without a

[8] Karaoglu et al. (2006) also examine spillover effects of fraud on peer firms' earning management.

clear relation with investment booms. In firm-specific regressions, they find that fraud propensity is negatively related to investment booms, but that this negative relation disappears in competitive industries. Taken together, their results suggest that fraud propensity is more positively associated with investment booms in competitive industries than concentrated industries, although the likelihood of frauds does *not* increase with investment booms on average.

2.2.5 Analysts' role in the spillover effect

Cotter and Young (2007) find that analysts are not able to distinguish true frauds from fictitious frauds and that even for large frauds analysts are not significantly more likely to show downward revisions in recommendations prior to the public disclosure of fraud. Their findings suggest that, as information intermediaries, analysts do not have a superior ability to see through frauds; instead, it is possible that they may help transmit the distorted signals. On a related note, Jensen (2005) argues that when equity is overvalued, analysts pressure managers for higher growth to justify the valuation, leading managers to make greater capital investments than they would otherwise make. Finally, Akhigbe, Madura, and Newman (2006) argue that because analysts' recommendations reflect overall industry prospects, industry rivals are likely to experience valuation effects in the same direction as the revised firm.

3 Hypothesis Development

3.1 Association between fraud and peer firm investment

We hypothesize that a high-profile firm's fraudulent financial reporting can have real effects on the investments of other firms in their industry. Competitors may rely on the high-profile firm's financial reports to mitigate uncertainty of the product market and distinguish between promising and inauspicious investment projects. Therefore, when a high-profile firm materially inflates its reported financial performance, the overstated investment prospects will encourage competitors to make more investments than they would absent the misleading information. These arguments lead us to hypothesize:

H1a: *Investment by peers will be greater in the scandal period compared to investment in the pre-scandal period.*

Based on Kumar and Langberg (2010), we argue that the magnitude of the investment by peer firms should be positively associated with the amount of excess profits reported by the industry leaders. Therefore, we hypothesize:

H1b: *The amount of the peer firms' investment during the scandal period is positively associated with the magnitude of the earnings overstatement by the scandal firms.*

Kumar and Langberg (2010) also contend that the strategic information manipulation by one firm are more likely to generate a dynamic externality on industry-wide investment distortion "when the cost of capital is low or when the agency costs [of private control benefits] are high or when investors have optimistic *a priori* assessment of the growth potential of the innovation." Under these conditions, inflated reports by the incumbent firm are more likely to cause a run-up in outsiders' posterior beliefs that diverge from the true industry productivity. More optimistic market expectation in turn dampens the information content of subsequent signals and prevents peers from uncovering the true productivity, thereby increasing peer firms' reliance on the lead firm's profit reports in making investment decisions. Therefore, we predict that the spillover effect of fraudulent earnings on peer firms' investment efficiency will be stronger when these three conditions are met. We thus hypothesize:

H1c: *The amount of the peers' investment during scandal periods is greater when the cost of capital is low, managers' private benefit of control is high, and investor sentiment is high in the industry.*

Based on Jensen's (2005) argument, pressure from analysts for higher growth to justify overvalued equity leads managers to make greater capital investments. We argue that analysts may therefore play an information transmission role that facilitates the real spillover effect. For each of these hypotheses, we also consider the possibility that the magnitude of the effect will depend on the extent to which the analysts' coverage of the scandal firm overlaps with that of the industry peer firms. That is, we expect that when more peer firms are covered by the same analysts that cover the scandal firm, the investment spillover effects should be stronger.

3.2 Industry effects of analyst recommendations

Based on the findings in Cotter and Young (2007) that analysts are not able to distinguish true frauds from fictitious frauds and in Akhigbe, Madura, and Newman (2006) that analysts' recommendations reflect overall industry prospects, we expect analysts may help transmit the distorted fraud signals. We hypothesize:

H2: *Equity Analyst's recommendations for peers will be more favorable in the scandal period compared to recommendations in the pre-scandal period.*

3.3 Efficiency of peer firms' investment

Fraudulent financial reporting sends out misleading information about the demand and profitability of the product markets. To the extent that peer firms made their investment decisions based on the falsified information during the scandal period, the investments are likely to be inefficient and should have a weaker association with future performance compared to previous investments. This leads us to hypothesize:

H3: *The association between peers' investments and future performance is weaker during the scandal period compared to the pre-scandal period.*

4 Research Design

To identify fraudulent reporting firms, we adopt a strategy similar to Karaoglu et al. (2006) by focusing on accounting frauds of a group of high-profile firms.[9] We define these high-profile scandal firms as those that were accused of accounting fraud by the SEC from 1999 to 2009, and were in the Fortune 500. These scandal firms are more likely to be leading firms in their industries due to their size and visibility. For each industry classified using 3-digit SIC codes, if we identified more than one high-profile scandal firm, we only include the first firm that commit a fraud in the sample period.[10] We also exclude financial institutions (SIC code 6000-6999) because financial institutions' investment behaviors are different from other industries.

To identify the scandal period, we start with the periods stated in SEC Accounting and Auditing Enforcement Releases. Then we verify, using historical 10K filings, that the scandal firm in fact restated reported earnings during the period after the fraud is detected. We identify 35 scandal firms representing 35 different industries. We provide descriptive statistics about the magnitude of the frauds in Panel A of Table 1. Similar to previous studies, revenue recognition related frauds are the predominant type of fraud, making up 40% of our sample. The mean restatement amount in earnings in our sample is slightly over $423 million for revenue recognition related frauds and $282 million for other

[9] We follow prior literature (e.g. Wang and Winton 2010) and focus on ex post detected frauds. Our results may not generalize to un-detected frauds..

[10] We exclude the remaining scandal firms from "peer firms" and "the control group" defined below.

frauds and represents nearly 16% of the average pre-scandal period revenues for revenue recognition related frauds and 7.6% for other frauds.

We define peer (or competing) firms as firms with the same 3-digit SIC code as the scandal firms.[11] Our sample includes 2,305 peer firms distributed among 35 industries. To investigate how the scandal firm's fraudulent reporting affects peer firms' investments during the scandal period vis-à-vis the pre-scandal period, we employ a difference-in-differences approach to control for industry and time effects, where the pre-scandal period is defined as the three years before the onset of the scandal period. We use firms that have the same 2-digit SIC code as the scandal firm (excluding peer firms) as the control group.[12] We assume that firms with the same 2-digit SIC codes share similar overall growth opportunities but non-peer firms are less likely to rely on scandal firms' financial reports for their investment decisions than peer firms.[13] We understand that this approach is not perfect, so we employ a second identification strategy by using peer firm's segments that operate in other industries as a control for the segments in the same industry as the fraud firm.

The observations in our models are clustered in the time periods surrounding the 35 frauds in our sample, with an average of nearly 100 firms per scandal year. To address the resulting lack of independence, we cluster the standard errors in our models by time.

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[11] We use the terms competing firms (competitors) and peer firms interchangeably.

[12] As a robustness check, we also assign firms with the same 2-digit SIC code as the scandal firm to be peer firms and assign those with the same one-digit SIC code as the scandal firm (excluding peer firms) as control firms. Our results continue to hold.

[13] We compare the firm size and market-to-book ratios between peer firms and control firms in the pre-scandal periods. To make these two groups of firms comparable, we delete the top 2% control firms in firm size and top 2% control firms in market-to-book ratios. After this procedure, our control sample and peer firms have comparable firm size and market-to-book ratios that proxy for growth opportunities.

In addition, firms in the sample could appear during each of the 3 pre-scandal period years as well as in each scandal period year. To control for time-series correlation, we also check the sensitivity of our results to clustering by both year and firm. We find that two-way clustering does not change the results.[14]

To provide additional support for our hypothesized relation between the fraud firms' overstated earnings and peers' incentives to invest, we examine peer firms' exit and entry into the industry, defined using the 3-digit SIC codes, during the scandal period. The results of these analyses are reported in Panel B of Table 1. Consistent with an incentive for peers to increase their investments during the scandal period, we find a significant decline in the ratio of firms exiting the industry to the number of firms in the industry, and a significant increase in the ratio of firms entering the industry to the number of firms in the industry. Consistent with the results reported in Appendix A, these results suggest that competitors have incentives to increase investment as a result of the fraud.

4.1 Investment model

To test our hypotheses that peer firms increase their investment in the periods when the leading firm committed a fraud, we run the following OLS regression.[15]

$$\begin{aligned}\mathbf{CAPEX} = \boldsymbol{\beta_0} &+ \boldsymbol{\beta_1}\mathbf{*PEER} + \boldsymbol{\beta_2}\mathbf{*SCAN} + \boldsymbol{\beta_3}\mathbf{*RESTATE\ (or\ I\_FACTOR)} \\ &+ \boldsymbol{\beta_4}\mathbf{*PEER*SCAN} + \boldsymbol{\beta_5}\mathbf{*PEER*SCAN*RESTATE\ (or} \\ &\mathbf{PEER*SCAN*I\_FACTOR)} + \boldsymbol{\beta_6}\mathbf{*SIZE} + \boldsymbol{\beta_7}\mathbf{*MTB} + \boldsymbol{\beta_8}\mathbf{*LEV} \\ &+ \boldsymbol{\beta_9}\mathbf{*CFO} + \boldsymbol{\beta_{10}}\mathbf{*RATING} + \boldsymbol{\beta_{11}}\mathbf{*SG} + \boldsymbol{\beta_{12}}\mathbf{*CAPEX\_S} + \boldsymbol{\beta_{13}}\mathbf{*COMOVE} + \\ &\boldsymbol{\varepsilon} \qquad \mathbf{(1)}\end{aligned}$$

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[14] In fact, two-way clustering increases t-values of our variables of interest in most regressions.

[15] We measure investment using only capital expenditures due to limited R&D data availability across all fraud industries and at the segment level. However, using available R&D data in our measure of investment does not change our results.

Variable Definitions:

CAPEX: the ratio of capital expenditure (COMPUSTAT "capx") to lagged properties, plants and equipment (COMPUSTAT "ppent").
PEER: an indicator variable equal to one for firms in the same 3-digit SIC codes as the fraudulent firms, and zero for control firms that have the same 2-digit SIC codes as the fraudulent firms (but different 3-digit SIC codes).
SCAN: an indicator variable equal to one for years during which fraudulent firms committed frauds (unless explicitly defined otherwise), and zero for 3 years prior to the scandal period.
RESTATE: tercile rankings of the ratio of fraudulent firms' total restatement to the average revenues of the pre-scandal period.
I_FACTOR: an indicator variable for firms in the industries (defined by 3-digit SIC codes) that have investor sentiments higher than the median of all industries, earnings-to-price ratio (measured at the median of the industry) lower than the median of all industries and higher counts of M&A activities than the annual median.
SIZE: the natural log of lagged total assets (COMPUSTAT "at").
MTB: lagged ratio of market value of total assets (COMPUSTAT "at" – "ceq" + "prcc_f" * "csho") to book value of total assets (COMPUSTAT "at").
LEV: long term debt (COMPUSTAT "dltt") divided by total assets (COMPUSTAT "at"), measured at the beginning of the year.
CFO: cash flow from operations (COMPUSTAT "oancf") divided by lagged total assets (COMPUSTAT "at").
RATING: an indicator variable for firms with S&P credit ratings.
SG: change in revenues (COMPUSTAT "revt") divided by lagged total assets (COMPUSTAT "at").
CAPEX_S: fraudulent firms' CAPEX.
COMOVE: tercile rankings of the co-movement of change in market-to-book ratios between the fraudulent firms and sample or control firms in the pre-scandal period (at the 3-digit SIC code level). The co-movement is measured as β in the regression $\Delta MTB = \alpha + \beta \Delta MTB\_S + \varepsilon$, where ΔMTB is defined as annual change in MTB and ΔMTB_S represents fraudulent firms' change in MTB.

Our baseline model to test H1a excludes the variables designed to capture cross-sectional variation in the extent of the spillover effect (i.e., 3-way interaction term as well as the RESTATE or I_FACTOR variable) from model (1). Based on H1a, we expect the coefficient on **PEER*SCAN** to be positive. If the increased investment arises from the fraudulent signals rather than the propensity to commit fraud increasing with the investment booms, then we expect the increased investment should not precede the fraud, the increased investment in the fraud periods should not be greater in competitive versus concentrated industries based on Wang and Winton (2010), and the increased investment should not be greater for high growth versus low growth industries, where peer industry sales growth, measured at the inception of the fraud, captures an industry boom.[16]

Specifically, to provide further support for H1a we examine: whether the increase in peer firms' investment in the year prior to the inception of the scandal period differs from their investment in the three prior years, whether the increase in peer firms' investment during the scandal period differs in competitive versus concentrated industries, and whether the increase in peer firms' investment during the scandal period differs in high growth versus low growth industries. When **SCAN** is set equal to one in the one-period prior to fraud inception, we do not expect to find a significant coefficient on **PEER*SCAN.** Similarly, once **SCAN** is set equal to one in the years after fraud inception**,** if increased peer firm investment reflects a reaction to the fraud rather than frauds following investment booms, then the coefficient on **PEER*SCAN** for firms in competitive industries should not exceed that for firms in concentrated industries and the coefficient on **PEER*SCAN** for firms in high growth industries should not exceed that for firms in low growth industries.

To test H1b, we collect the restatement data and use the total restatement in earnings during the scandal period (scaled by the average sales in the pre-scandal period), we then use the tercile ranking of this variable (i.e., **RESTATE**) as our proxy to test

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[16] We also partition the sample using peer firms' change in sales growth from the year before the fraud inception to the beginning year of the fraud period. The results are similar.

whether peer firms' investment is affected by leading firms' misstatements. Based on H1b we expect a positive coefficient on **PEER*SCAN*RESTATE**.

To test H1c, we use investor sentiment measured as Baker and Wurgler (2006) to proxy for investors' expectations of industry productivity. That is, for each year and industry at the 3-digit SIC code level, we take the first principal component of the following variables using factor analysis: *IPO_count*, *IPO_ret, Turnover,* and *MTB_diff*. We measure *IPO_count* as the total number of IPOs, *IPO_ret* as the average first-day returns of IPOs, *Turnover* as the average ratio of share volume to the number of shares outstanding, and *MTB_diff* as the difference of the market-to-book ratios between divided payers and non-payers.[17] We measure the industry cost of capital by calculating the median earnings-to-price ratio for each year and industry at the 3-digit SIC code level. Finally, to capture the private benefits of control, we count the number of merger and acquisitions for the industry-year, assuming that management can accrue more private benefits of control by empire building.

To capture the overall effect of the three Kumar and Langberg (2010) variables, we construct a composite variable **I_FACTOR,** measured as an indicator variable for firms in the industries (defined by 3-digit SIC codes) that have investor sentiments higher than the annual median of all industries, earnings-to-price ratio (measured at the median of the industry-year) lower than the annual median of all industries and higher counts of

[17] We do not include in the main analysis the ratio of total equity issues over the sum of equity and public debt issues, as we will lose 4 industries. However, including this variable to calculate investor sentiment does not change the main results.

M&A activities than the annual median.[18] Based on H1c, we expect **PEER*SCAN*I_FACTOR** to have a positive coefficient.[19]

To ensure that we are not merely capturing mimicking behavior we also control for the scandal firm's investment (**CAPEX_S**). Following prior literature (e.g., Biddle and Hilary, 2006; Biddle et al., 2009; and Beatty et al., 2010), we also control for firm size, market-to-book ratio, whether the firm is rated by the S&P, leverage, sales growth and operating cash flows.[20] We expect that capital expenditures increase with sales growth and market-to-book ratios, as investment tends to be higher when the firm has more growth opportunities. Finally, to ensure that we are not just capturing the similarity of growth opportunities between the peer firms and the scandal firms, we control for the co-movement in growth opportunities (proxied by MTB) between the scandal firms and either peer firms or control firms measured in the pre-scandal periods.

4.2 Analyst coverage effects

We test the effects of analyst coverage by estimating model (1) for sub-samples based on the overlap in analyst coverage. We classify industries based on the extent to which peer and control firms are covered by the same analysts as the scandal firms. We understand that firms with more economic similarity are more likely to be covered by the same analysts, and therefore we adopt the following procedure to remove this component from the ratio of overlapped analysts. First, we run the following regression: *Overlap* =

[18] I_FACTOR might also capture industry booms. To mitigate this concern, we examine the trend of the components of I_FACTOR over time and find that these components are quite constant before the inception of the fraud period and then increase (or decrease for cost of capital) after the inception of the fraud period as predicted by Kumar and Langberg (2010) if these factors fuel frauds. This pattern is not consistent with the reverse causality.

[19] Alternatively, we can also investigate the effect of each I_Factor variable individually. We conduct such analyses as robustness checks, and the flavour of the results is the same as the main test.

[20] We control for whether the firm is rated to control firms' access to the public debt market.

$\alpha + \beta_1{*}Comove\_return + \beta_2{*}SIZE\_m + \beta_3{*}MTB\_m + \beta_4{*}LEV\_m + \beta_5{*}SG\_m + \varepsilon$ for each industry-year, where *Overlap* is measured as the ratio of the number of peer/control firms that have at least one analyst also covering the scandal firm to the total number of peer/control firms that have any analyst coverage at the 3-digit SIC code level, *Comove_return* is the R-squared of the regression of peer/control firms' daily returns on scandal firms' returns, measured annually, and *SIZE_m* (*MTB_m, LEV_m, and SG_m*) is measured as the industry median SIZE (MTB, LEV and SG). Industries that have higher regression residual than the median are defined as "High Overlap"; otherwise, "Low Overlap".[21] We expect the H1a, b, and c results to be stronger in the "High Overlap" sub-sample.[22]

We estimate the following ordered probit model on analyst recommendations to test hypothesis 2.

$$\begin{aligned}\textbf{Recom} = {} & \beta_0 + \beta_1{*}\textbf{PEER} + \beta_2{*}\textbf{SCAN} + \beta_3{*}\textbf{PEER*SCAN} + \beta_4{*}\textbf{SIZE} + \beta_5{*}\textbf{MTB} \\ & + \beta_6{*}\textbf{LEV} + \beta_7{*}\textbf{CFO} + \beta_8{*}\textbf{RATING} + \beta_9{*}\textbf{SG} + \beta_{10}{*}\textbf{CAPEX\_S} \\ & + \beta_{10}{*}\textbf{COMOVE} + \varepsilon \end{aligned} \qquad \textbf{(2)}$$

Variable Definitions:

Recom (Dependent Variable): the median value of all analysts' recommendations during a year. 1 represents strong buy and 5 represents strong sell.

All other variables are as defined above.

We expect the coefficient on **PEER*SCAN** to be negative based on H2; that is, if analysts cannot see through the fraudulent reporting, they may overestimate the overall

[21] In the regression, we find that the coefficient on *Comove_return* is consistently significantly positive, suggesting that the ratio of overlapped analysts do capture economic similarity. The R-squared of this model ranges from 0.17 to 0.40 in various years.

[22] As a robustness check, we also put the predicted value of *Overlap* from this prediction model in the investment regression as a control variable, and all results continue to hold.

industry prospects and thereby provide better recommendations. We further test the effects of analyst coverage by estimating model (2) for sub-samples based on the overlap in analyst coverage in the same way as for model (1). We expect the recommendations spillover effect to be stronger when the overlap between peer and scandal firms is higher.

4.3 The association of current investment with future performance

To test whether the investment made during the scandal period is suboptimal compared to the pre-scandal period, we run the following panel data regression.

$$\begin{aligned}\mathbf{CFO_{t+i}} = {} & \boldsymbol{\beta_0 + \beta_1{*}PEER + \beta_2{*}SCAN + \beta_3{*}PEER{*}SCAN + \beta_4{*}CAPEX} \\ & \boldsymbol{+ \beta_5{*}CAPEX{*}PEER + \beta_6{*}CAPEX{*}SCAN + \beta_7{*}CAPEX{*}PEER{*}SCAN} \\ & \boldsymbol{+ \beta_8{*}SIZE + \beta_9{*}MTB + \beta_{10}{*}LEV + \beta_{11}{*}RATING + \varepsilon} \qquad \mathbf{i=1,2,3} \qquad \mathbf{(3)}\end{aligned}$$

Variable Definitions:

CFO_{t+i}: one-year (or two, three-year) ahead CFO, where CFO is defined as cash flow from operations (COMPUSTAT “oancf”) divided by lagged total assets (COMPUSTAT “at”).

All other variables are as defined above.

Based on H3, we predict the coefficient on **CAPEX*PEER*SCAN** to be negative. That is, we expect that capital expenditures made in the scandal period will generate lower cash flows compared to those made in the pre-scandal period.

5 Results

5.1 Univariate results

We compare the descriptive statistics between the peer firms and the control group in Table 2. We find that there is no significant difference between our control group firms and peer firms in SIZE, MTB and SG in the pre-scandal period, suggesting that they are comparable in terms of asset-in-place and investment opportunities. However, peer firms have significantly higher capital expenditures than the control group even in the three-year period before the scandal period. However, the difference becomes insignificant in the multivariate analysis that follows this section. In the scandal period, we find that peer firms' capital expenditures are higher than the control group, consistent with our hypotheses. However, we also observe that peer firms and control group are significantly different in other firm characteristics and so it is important that we control for these variables in the regressions.

We show the Pearson correlation coefficients in Table 3. The correlations suggest that firms in the industry where the leading firms overstated their earnings more tend to have larger capital expenditures.

5.2 Multivariate results

In Panel A of Table 4, we report the results of the investment models where we set the dummy variable $SCAN_t$ equal to 1 for the period that is one year prior to, the year of, the first year following, and the second year following fraud inception respectively. In addition, we examine the one year following the end of the fraud period. In models (3) and (4), we find results consistent with H1a that peer firms make more investments in the first or second years following the fraud inception than in the pre-scandal period. The economic magnitude of this incremental investment is similar across these two models and is large: compared to peer firms' capital expenditure level in the pre-scandal period, there is an approximately 20% (i.e., 0.054/0.286 and 0.06/0.278 [23]) increase in investment. Interestingly, the coefficient on $SCAN_t$, which captures the effect of the scandal period on our control firms' investments, is insignificant. In addition, the coefficient on PEER,

[23] The denominator is the sum of the intercept and the coefficient on PEER, representing the investment level for the peer firms in the pre-scandal period.

which captures the difference in capital expenditures between the peer firms and the control group during the pre-scandal period, is not significant. This suggests that the control firms are serving the desired role in our difference-in-differences design.

In contrast, the coefficient on PEER*SCAN$_t$ is insignificant in models (1) and (2), suggesting that firms are reacting to the fraudulent reports after they are issued, and that the increase in investment is a response to the fraud rather than higher capital expenditures of the peer firms providing an incentive for leading firms to commit fraud. Finally, in model (5), the coefficient on **PEER*SCAN** is not significant suggesting that the investment after the fraud period reverts to the pre-fraud period levels.

In Panel B of Table 4, we examine whether our results differ for competitive versus concentrated industries and for high versus low sales growth firms, based on Wang and Winton's (2010) argument that fraud in competitive industries is more likely to be driven by investment booms. We find no significant difference in the coefficient on PEER*SCAN for firms in competitive versus concentrated industries or in high versus low growth firms. Both panels of Table 4 seem to suggest that our results are not merely driven by reverse causality or by omitted factors affecting both industry investment boom and fraud propensity, but are more consistent with our spillover hypothesis.

The results of our tests of H1b and H1c are reported in Table 5. The first three models are conducted at the firm level using firms that share 2-digit SIC codes with the scandal firms as control firms. The second set of three models is conducted at the segment level, using the segments of the same peer firm that operate in other industries as controls. Specifically, in our segment level analysis, PEER=1 for the segment of the peer firm that share 3-digit SIC codes with the scandal firms, and PEER=0 for other segments of the peer firm.

Consistent with the results reported in Table 4, the first model in Table 5 shows that on average capital expenditures are greater during the scandal period for peer firms compared to control firms. In model (2), consistent with H1b, we find that peer firm's capital investment is increasing in the amount that leading firms overstate their earnings during the fraudulent period. This spillover effect is economically significant. Moving from the bottom tercile to the top tercile in scandal firms' misstatement, peers firms' investment increases by 0.088, representing a 32% increase in the investment from the pre-scandal period. In model (3), we find that the increase in peers' capital expenditures is greater when the industry has a higher investor sentiment, a lower cost of capital and larger private benefits of control (i.e., the coefficient on **PEER*SCAN*I_FACTOR** is positive). This result is consistent with both H1c and Kumar and Langberg (2010). Again, this effect is significant economically: firms in the high I_FACTOR industries on average invest more than low I_FACTOR industries by 0.085, representing 33% of the investment in the pre-scandal period. The results of our segment level analysis and of our firm level analysis are quite similar. The similarity of the results provides comfort that our control firms based on 2-digit SIC codes are performing in the desired way.

Other than the main variables of interest, our control variables also load as predicted. For example, capital expenditures increase with growth opportunities. We also find that peer/control firms' investments increase with scandal firms' investments, suggesting that firms also directly mimic industry leaders' investment behavior besides the information spillover effect that we document. Finally, we also find that capital expenditures increase with the co-movement in MTB between peer/control firms and scandal firms, suggesting that peer/control firms' investment is more likely when their growth opportunities are co-moving with scandal firms.

Table 6 reports the results of repeating our investment tests for a sub-sample of firms in industries with a high degree of unexplained overlap in analyst coverage with the scandal firm versus those with a low degree of unexplained overlap. We find that the results that peer firms' investments are greater in the scandal period, are increasing in the amount of the scandal firm's earnings overstatement during the fraudulent period, and are greater when the industry has a higher investor sentiment, a lower cost of capital and larger private benefits of control, are primarily concentrated in the high-overlap sub-sample, but not in the low-overlap subsample. These results support our hypothesis that information intermediaries play an important role in transmitting information from scandal firms to peer firms.

In Table 7 we directly examine whether analysts' recommendations help transmit the distorted fraud signals. For our overall sample we find more favorable recommendations during the scandal period for peer firms. Further, we only find this result for our high unexplained overlap sample, but not for the low unexplained overlap sample. These findings again suggest that the spillover effect on peer investments may be facilitated by analysts' information intermediary roles.

In Table 8 Model 1, we find that capital investments made by peer firms in the pre-scandal period have a positive correlation with future cash flows for at least three years after the investment is made. Consistent with H3, the coefficients on CAPEX*PEER*SCAN are significantly negative and greater in absolute magnitude than those on CAPEX*PEER in all models, consistent with the positive correlation being offset for investments made by peer firms in the scandal period, supporting the notion that the investment made by peer firms during the scandal period are likely sub-optimal.

One competing explanation for the observed weaker association between peer investment and future cash flows is that *after* a fraud is *detected*, contracting parties may impose reputational penalties on all firms in the fraud industry, resulting in declining future performance for peers. To disentangle this competing hypotheses, we investigate the investment-cash flow relation before vs. after the fraud is detected. Specifically, we allow CAPEX*PEER*SCAN to vary with whether the cash flow is observed after the scandal period since frauds are detected after the scandal period. While our hypothesis predicts no difference between the investment-cash flow relation for cash flows before and after fraud detection, the reputational penalty story predicts a more negative investment-cash flow relation for cash flows observed after fraud detection than for those before fraud detection. In Model 2 of Table 8, we find results consistent with our hypothesis but inconsistent with this alternative explanation.

5.3 Supplemental analysis and robustness checks

5.3.1 Peer managers' information

We argue that managers of peer firms engage in sub-optimal investments during the scandal period because they are misled by the rosy prospects portrayed in the scandal firm's financial reports. In support of this argument, Mandel (2002) argues that "when Enron Corp. reported revenue growth of 70% annually from 1997 to 2000, and operating profit growth of 35% a year, that drew other electric and gas utility companies into energy trading. *The fact that Enron achieved much of its gains by moving debt off the* *books and using other accounting tricks was not obvious at the time*." As a result, managers of peer firms will be optimistic about their investment returns and choose to increase their insider holdings during the scandal period to benefit from the expected stock price jumps.

To test this prediction, we investigate peer firms' insider trading behavior. We follow Piotroski and Roulstone (2005) by measuring the insider purchase ratio as shares purchased over the sum of shares purchased and shares sold. The insider trading data is collected from Thomson Financial that collects from SEC filings (forms 3, 4 and 5). In Table 9, we show results consistent with our prediction: insiders in peer firms tend to purchase more shares in the scandal periods compared to pre-scandal periods.

5.3.2. Different types of scandals/restatements

In this section we investigate whether the spillover effect on peer investments depends on the types of accounting frauds: revenue recognition versus others. Based on Gigler (1994) that management has incentives to provide private information about the *demand for its product* to the capital market that inevitably induces competitors to increase investments, we investigate whether our results are driven by frauds involving revenue recognition issues to proxy for market demand. In Table 10, we find that peer investments increase in the scandal periods only when the restatements are related to revenue recognition. Similarly, we find that the effects of the magnitude of restatements and macro-variables on the increase in peer investments are only significant for revenue recognition driven frauds.

5.3.3. Robustness checks

While not tabulated, we also investigate the effect of each macro variable composing I_FACTOR separately and find that the tenor of the results for each variable (i.e., investor sentiment, industry cost of equity, and private benefits of control) is the same as using our composite measure. We also allow COMOVE to interact with PEER, SCAN and PEER*SCAN and the main results continue to hold. Further, we also partition cash flow analysis by industry growth, and we do not find that our results are driven by the high growth industries.

To examine whether peers respond differentially to the fraudulent earnings compared to the restated earnings of the fraud firms, we compare the coefficients on overstated earnings and original earnings in the investment regression. If the coefficients do not differ, then this suggests that peer firms cannot see through the frauds and therefore behave as if the falsified earnings are true earnings. We find that (untabulated) the coefficient on PEER*SCAN interacted with restatement do not differ statistically or economically from that on PEER*SCAN interacted with the originally reported earnings. In addition, we also find that when we put both variables in the same regression, the interaction of PEER*SCAN with overstated earnings is positive rather than negative but is insignificant. This indicates that peer firms do not discount the overstated earnings when making capital expenditures, suggesting that peer firms do not seem to distinguish fraudulent versus restated earnings of the leading firms.

Finally, we also investigate whether the peer firms' equity issuance is affected by industry leaders' fraudulent reporting. Based on our previous findings that analysts' recommendations tend to be more favorable in the scandal periods, it would be consistent to find that peer firms also increase equity issuance to fuel the increased investments. We find (untabulated) that peers' equity increases in the scandal periods, and the increase in equity issuance is more pronounced when the restatement is large and when the I_FACTOR is high.

6 Conclusions

We examine whether a firm's accounting quality has real effects on peer firms' investments. This real spillover effect remains largely unexplored in the prior literature (Leuz and Wysocki, 2008). Focusing on accounting frauds conducted by a group of high-profile firms that are more visible and more likely to be used as benchmarks, we find peer firms' investments are greater during the scandal period using difference-in-differences estimation. This association does not appear to be driven by an increase in fraud during investment booms. We also find that the peer firms' investments are positively associated with scandal firms' earnings overstatement, and are greater when their industry has higher investor sentiment, a lower cost of capital and higher private benefits of control. Furthermore, we find that the investment findings hold only for firms when there is high unexplained overlap in analyst coverage between scandal and peer firms, suggesting that equity analysts transmit the distorted signal. We provide additional support for the equity analysts transmission mechanism by showing that analysts' recommendation are more favorable for peer firms during the scandal period only when unexplained overlap in analyst coverage is high.

We provide evidence consistent with the suboptimal investment argument by showing that these investments have weaker associations with future cash flows, suggesting that investments made during the scandal period are less efficient. Finally, our results suggest that peer firms' insiders were in fact misled by the falsified rosy prospects portrayed in the scandal firm's fraudulent financial reports, and manifested their optimistic expectations by increasing their ownership.

Overall, our findings are consistent with distorted accounting signals generated by high-profile scandal firms on average increasing investment by industry peers. Our paper makes contributions to the accounting and investment efficiency literatures by showing that accounting information not only plays an important role in firms' own investment, it also affects other firms' investments.

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Appendix A: Relation between peer capital expenditures and leading firms' earnings growth in non-scandal periods

		Model 1	Model 2
Variable	Sign	Coefficient (clustered t)	Coefficient (clustered t)
Intercept	?	0.0165 (2.70)***	0.0260 (3.87)***
PEER	?	-0.0085 (-2.00)**	-0.0107 (-2.42)**
SHOCK	?	-0.0013 (-0.32)	-0.0015 (-0.26)
GROWTH	?		-0.0145 (-4.20)***
PEER*SHOCK	+	0.0115 (2.34)**	-0.0015 (-0.26)
PEER*SHOCK *GROWTH	+		0.0125 (3.47)***
SIZE	?	0.0015 (1.81)*	0.0013 (1.49)
MTB	+	0.0098 (7.71)***	0.0098 (7.71)***
LEV	?	0.0723 (8.42)***	0.0723 (8.42)***
CFO	?	0.0628 (5.65)***	0.0612 (5.55)***
RATING	?	-0.0019 (-0.44)	-0.0030 (-0.69)
SG	+	0.0704 (12.16)***	0.0701 (12.17)***
LEAD_SHOCK	+	0.0853 (4.62)***	0.1431 (6.18)***
N		7,874	7,874
R-Squared		0.1802	0.1858

Variable Definition:

CAPEX (dependent variable): the ratio of capital expenditure (COMPUSTAT "capx") to lagged assets.

PEER: an indicator variable equal one for firms in the same 3-digit SIC codes as the fraudulent firms, and zero for control firms that have the same 2-digit SIC codes as the fraudulent firms (but different 3-digit SIC codes).

SHOCK: an indicator variable equal one for years during which the lead firm experience very high real revenue growth , and zero for 3 years prior to the shock period.

GROWTH: actual growth in lead firm earning in the shock period

SIZE: the natural log of lagged total assets (COMPUSTAT "at").

MTB: lagged ratio of market value of total assets (COMPUSTAT "at" – "ceq" + "prcc_f" * "csho") to book value of total assets (COMPUSTAT "at").

LEV: long-term debt (COMPUSTAT “dltt”) divided by total assets (COMPUSTAT “at”), measured at the beginning of the year.

CFO: cash flow from operations (COMPUSTAT “oancf”) divided by lagged total assets (COMPUSTAT “at”).

RATING: an indicator variable for firms with S&P credit ratings.

SG: change in revenues (COMPUSTAT “revt”) divided by lagged total assets

Table 1: Descriptive statistics for restatements and industry exits and entries

Panel A: Restatement Amounts

	Revenue Recognition Related Restatements		Other Restatements	
	Restatement Amount ($000,000)	Restatement Amount/Average Pre-scandal period Sales	Restatement Amount ($000,000)	Restatement Amount/Average Pre-scandal period Sales
Median	49.00	0.021	128.25	0.018
Mean	423.65	0.160	282.20	0.076
Maximum	2794	1.214	2063	0.429
Minimum	0.69	0.001	1.12	0.001
Standard Deviation	834.66	0.358	565.79	0.125
N	14		21	

Panel B: Industry exits and entries

	Exit Ratio	Entry Ratio
Variable	Coefficients (clustered t-stats)	Coefficients (clustered t-stats)
Intercept	0.057 (7.74)***	0.144 (8.65)***
PEER	0.015 (2.87)***	-0.029 (-3.02)***
SCAN	0.009 (0.92)	-0.032 (-1.60)
PEER*SCAN	-0.021 (-2.14)**	0.032 (1.89)*
N	310	310
Adjusted R-squared	0.014	0.011

Note: Standard errors are clustered at the year level. ***, ** and * represent 1%, 5% and 10% significance levels, respectively. Exit is defined as the ratio of the number of firms that exited the industry to the total number of firms in the industry and entry is defined as the ratio of the number of firms that enter the industry to the total number of firms in that industry.

Variable Definition:

PEER: an indicator variable equal one for firms in the same 3-digit SIC codes as the fraudulent firms, and zero for control firms that have the same 2-digit SIC codes as the fraudulent firms (but different 3-digit SIC codes).

SCAN: an indicator variable equal one for years during which fraudulent firms committed frauds, and zero for 3 years prior to the scandal period.

Table 2: Descriptive statistics of peer firms and control group firms

	Pre-scandal period		Scandal period	
	Peer firms	Control firms	Peer firms	Control firms
Variables	Mean	Mean (t-stat Peer-Control)	Mean	Mean (t-stat Peer-Control)
CAPEX	0.400	0.343 (5.54)***	0.449	0.319 (14.38)***
SIZE	4.789	4.803 (-0.29)	4.742	4.971 (-5.10)***
MTB	2.207	2.249 (-0.84)	2.876	2.131 (13.82)***
LEV	0.166	0.174 (-1.83)*	0.171	0.186 (-3.75)***
CFO	0.280	0.008 (3.63)***	-0.038	0.006 (-7.47)***
RATING	0.218	0.223 (-0.58)	0.219	0.245 (-3.11)***
SG	0.136	0.135 (0.17)	0.081	0.105 (-2.02)**
Number of Observations	3,170	6,091	4,428	7,361

***, ** and * represent 1%, 5% and 10% significance levels, respectively.

Variable Definition:

CAPEX: the ratio of capital expenditure (COMPUSTAT "capx") to lagged properties, plants and equipment (COMPUSTAT "ppent").
SIZE: the natural log of lagged total assets (COMPUSTAT "at").
MTB: lagged ratio of market value of total assets (COMPUSTAT "at" – "ceq" + "prcc_f" * "csho") to book value of total assets (COMPUSTAT "at").
LEV: long-term debt (COMPUSTAT "dltt") divided by total assets (COMPUSTAT "at"), measured at the beginning of the year.
CFO: cash flow from operations (COMPUSTAT "oancf") divided by lagged total assets (COMPUSTAT "at").
RATING: an indicator variable for firms with S&P credit ratings.
SG: change in revenues (COMPUSTAT "revt") divided by lagged total assets (COMPUSTAT "at").

Table 3: Pearson Correlation (and P-value) for investment model variables, for both scandal and pre-scandal periods

	(2) PEER	(3) SCAN	(4) SIZE	(5) MTB	(6) LEV	(7) CFO	(8) RAT	(9) SG	(10) COM	(11) RES	(12) I_FACTOR
(1) CAPEX	0.101 (0.001)	0.005 (0.470)	-0.177 (0.001)	0.325 (0.001)	-0.173 (0.001)	-0.167 (0.001)	-0.129 (0.001)	0.288 (0.001)	0.075 (0.001)	0.072 (0.001)	0.157 (0.001)
(2) PEER		0.034 (0.001)	-0.029 (0.001)	0.077 (0.001)	-0.028 (0.001)	-0.030 (0.001)	-0.019 (0.005)	-0.012 (0.001)	0.119 (0.001)	0.375 (0.001)	0.346 (0.001)
(3) SCAN			0.020 (0.004)	0.032 (0.001)	0.025 (0.001)	-0.041 (0.001)	0.017 (0.011)	-0.042 (0.001)	0.078 (0.001)	0.186 (0.001)	0.147 (0.001)
(4) SIZE				-0.265 (0.001)	0.277 (0.001)	0.409 (0.001)	0.656 (0.001)	-0.016 (0.017)	-0.031 (0.001)	0.051 (0.001)	-0.111 (0.001)
(5) MTB					-0.102 (0.001)	-0.485 (0.001)	-0.120 (0.001)	0.106 (0.001)	-0.041 (0.001)	0.062 (0.001)	0.122 (0.001)
(6) LEV						0.049 (0.001)	0.372 (0.001)	-0.032 (0.001)	-0.069 (0.001)	0.001 (0.977)	-0.093 (0.001)
(7) CFO							0.162 (0.001)	0.057 (0.001)	0.082 (0.001)	-0.013 (0.068)	-0.025 (0.001)
(8) RATING								-0.004 (0.593)	-0.065 (0.001)	0.041 (0.001)	-0.095 (0.001)
(9) SG									0.064 (0.001)	-0.011 (0.120)	0.024 (0.001)
(10) COMOVE										0.105 (0.001)	0.044 (0.001)
(11) RESTATE											0.469 (0.001)

***, ** and * represent 1%, 5% and 10% significance levels, respectively.

Variable Definition:

CAPEX: the ratio of capital expenditure (COMPUSTAT “capx”) to lagged properties, plants and equipment (COMPUSTAT “ppent”).

PEER: an indicator variable equal one for firms in the same 3-digit SIC codes as the fraudulent firms, and zero for control firms that have the same 2-digit SIC codes as the fraudulent firms (but different 3-digit SIC codes).

SCAN: an indicator variable equal one for years during which fraudulent firms committed frauds, and zero for 3 years prior to the scandal period.

SIZE: the natural log of lagged total assets (COMPUSTAT “at”).

MTB: lagged ratio of market value of total assets (COMPUSTAT “at” – “ceq” + “prcc_f” * “csho”) to book value of total assets (COMPUSTAT “at”).

LEV: long-term debt (COMPUSTAT “dltt”) divided by total assets (COMPUSTAT “at”), measured at the beginning of the year.

CFO: cash flow from operations (COMPUSTAT “oancf”) divided by lagged total assets (COMPUSTAT “at”).

RATING: an indicator variable for firms with S&P credit ratings.

SG: change in revenues (COMPUSTAT “revt”) divided by lagged total assets (COMPUSTAT “at”).

RESTATE: tercile rankings of the amount of overstatement by the scandal firms.

COMOVE: tercile rankings of the co-movement of change in market-to-book ratios between the fraudulent firms and sample or control firms in the pre-scandal period (at the 3-digit SIC code level). The co-movement is measured as β in the regression $\Delta MTB = \alpha + \beta \Delta MTB\_S + \varepsilon$, where ΔMTB is defined as annual change in MTB and ΔMTB_S represents fraudulent firms’ change in MTB.

I_FACTOR: an indicator variable for firms in the industries (defined by 3-digit SIC codes) that have investor sentiments higher than the median of all industries, earnings-to-price ratio (measured at the median of the industry) lower than the median of all industries and higher counts of M&A activities than the median.

Table 4: Causality analysis of peer firm capital expenditures and lead firms' frauds

Panel A: Lead-lag analysis

		Model 1	Model 2	Model 3	Model 4	Model 5
		$SCAN_{-1}$ (one year before fraud inception)	$SCAN_{0}$ (the year of fraud inception)	$SCAN_{+1}$ (the first year after fraud inception)	$SCAN_{+2}$ (the second year after fraud inception)	$SCAN_{PS1}$ (one year after the end of fraud period)
Variable	Prediction	Coefficient (clustered-t)	Coefficient (clustered-t)	Coefficient (clustered-t)	Coefficient (clustered-t)	Coefficient (clustered-t)
Intercept	?	0.266 (12.57)***	0.253 (15.96)***	0.267 (18.17)***	0.261 (9.31)***	0.271 (16.09)***
PEER	?	0.034 (2.86)***	0.020 (1.64)	0.019 (1.59)	0.017 (1.20)	0.021 (1.63)
$SCAN_t$	?	0.001 (0.01)	0.005 (0.54)	0.007 (0.34)	0.000 (0.00)	-0.014 (-0.82)
$PEER*SCAN_t$	+	-0.029 (-1.22)	0.010 (0.58)	0.054 (2.23)**	0.060 (2.17)**	-0.014 (-0.71)
SIZE	?	-0.014 (-2.64)***	-0.011 (-2.80)***	-0.012 (-2.99)***	-0.011 (-2.10)**	-0.010 (-1.54)
MTB	+	0.050 (8.18)***	0.047 (8.94)***	0.046 (9.96)***	0.044 (6.40)***	0.040 (8.25)***
LEV	?	-0.296 (-7.63)***	-0.261 (-7.00)***	-0.298 (-2.68)***	-0.285 (-7.79)***	-0.286 (-8.17)***
CFO	?	-0.034 (-1.22)	-0.053 (-1.27)	-0.059 (-2.68)**	-0.069 (-1.44)	-0.035 (-1.06)
RATING	?	0.002 (0.07)	-0.010 (-0.43)	0.005 (0.24)	-0.001 (-0.07)	-0.017 (-0.56)
SG	+	0.292 (17.07)***	0.294 (12.72)***	0.275 (13.54)***	0.304 (20.35)***	0.304 (19.54)***
CAPEX_S	+	0.048 (4.99)***	0.047 (3.79)***	0.050 (3.17)***	0.059 (2.83)**	0.048 (3.38)***
COMOVE	+	0.033 (4.69)***	0.037 (4.49)***	0.037 (4.18)***	0.033 (3.21)***	0.032 (3.77)***
N		10,971	13,017	12,945	12,426	12,951
R-Squared		0.2020	0.1960	0.1970	0.2171	0.1995

Note: ***, ** and * represent 1%, 5% and 10% significance, respectively, based on a one- or two-tailed test, as appropriate. Standard errors are clustered by fiscal year. In Model 1, the pre-scandal period is from 4 years to 2 years before the scandal; in other models, the pre-scandal period is from 3 years to 1 year before the scandal.

Panel B: Partitions by competitiveness and revenue growth

		Competitive Industries	Concentrated Industries	High Growth	Low Growth
Variable	Prediction	Coefficient (clustered t)	Coefficient (clustered t)	Coefficient (clustered t)	Coefficient (clustered t)
Intercept	?	0.204 (9.67)***	0.289 (14.03)***	0.203 (7.12)***	0.265 (16.60)***
PEER	?	0.075 (5.33)***	-0.043 (-2.93)***	0.009 (0.68)	-0.036 (-1.90)*
SCAN	?	0.024 (2.61)***	-0.019 (-1.95)*	-0.000 (-0.03)	0.000 (0.00)
PEER* SCAN	+	0.032 (1.87)**	0.029 (1.51)*	0.063 (3.55)***	0.059 (3.23)***
SIZE	?	-0.007 (-2.00)**	-0.009 (-2.88)***	-0.004 (-0.80)	-0.009 (-2.33)**
MTB	+	0.040 (10.09)***	0.046 (11.32)***	0.051 (12.01)***	0.038 (6.36)***
LEV	?	-0.221 (-7.43)***	-0.304 (-10.25)***	-0.323 (-11.65)***	-0.203 (-4.81)***
CFO	?	-0.091 (-2.29)**	-0.031 (-0.93)	-0.086 (-1.82)*	-0.077 (-1.75)*
RATING	?	0.001 (0.06)	-0.027 (-2.26)**	-0.009 (-0.75)	-0.023 (-1.41)
SG	+	0.311 (16.67)***	0.256 (15.34)***	0.277 (17.07)***	0.271 (14.95)***
CAPEX_S	+	0.063 (7.28)***	0.047 (3.18)***	0.062 (3.65)***	0.068 (2.41)**
COMOVE	+	0.035 (4.86)***	0.022 (3.85)***	0.050 (7.99)***	0.008 (1.27)
N		10,415	10,635	10,557	10,493
R-Squared		0.2335	0.1829	0.2416	0.1668
		Test of coefficient equality on PEER*SCAN: $\chi2$=0.0144 p-value=0.9039		Test of coefficient equality on PEER*SCAN: $\chi2$=0.3364 p-value=0.5743	

Note: ***, ** and * represent 1%, 5% and 10% significance, respectively, based on a one- or two-tailed test, as appropriate. Standard errors are clustered by fiscal year. “Competitive Industries” vs. “Concentrated Industries” partition is based on the peer industries’ ratio of top 5 firms in revenue to the total revenue of each year-industry, classified by 3-digit SIC code. Both peer and control industries are classified as “Competitive Industries” if the peer industries’ ratio is lower than the annual median; otherwise as “Concentrated Industries”. “High Growth” vs. “Low Growth” is defined by peer industries’ sales growth (SG) at the beginning year of the scandal period. Peer and control industries are classified as “High Growth” if the peer industries’ median sales growth is higher than the median; otherwise, classified as “Low Growth”.

Variable Definition:

CAPEX (dependent variable): the ratio of capital expenditure (COMPUSTAT "capx") to lagged properties, plants and equipment (COMPUSTAT "ppent").

PEER: an indicator variable equal one for firms in the same 3-digit SIC codes as the fraudulent firms, and zero for control firms that have the same 2-digit SIC codes as the fraudulent firms (but different 3-digit SIC codes).

SCAN: an indicator variable equal one for years during which fraudulent firms committed frauds, and zero for 3 years prior to the scandal period.

RESTATE: tercile rankings of the ratio of fraudulent firms' total restatement to the average revenues of the pre-scandal period.

I_FACTOR: an indicator variable for firms in the industries (defined by 3-digit SIC codes) that have investor sentiments higher than the median of all industries, earnings-to-price ratio (measured at the median of the industry) lower than the median of all industries and higher counts of M&A activities than the median.

SIZE: the natural log of lagged total assets (COMPUSTAT "at").

MTB: lagged ratio of market value of total assets (COMPUSTAT "at" – "ceq" + "prcc_f" * "csho") to book value of total assets (COMPUSTAT "at").

LEV: long-term debt (COMPUSTAT "dltt") divided by total assets (COMPUSTAT "at"), measured at the beginning of the year.

CFO: cash flow from operations (COMPUSTAT "oancf") divided by lagged total assets (COMPUSTAT "at").

RATING: an indicator variable for firms with S&P credit ratings.

SG: change in revenues (COMPUSTAT "revt") divided by lagged total assets (COMPUSTAT "at").

CAPEX_S: fraudulent firms' CAPEX.

COMOVE: tercile rankings of the co-movement of change in market-to-book ratios between the fraudulent firms and sample or control firms in the pre-scandal period (at the 3-digit SIC code level). The co-movement is measured as β in the regression $\Delta MTB = \alpha + \beta \Delta MTB\_S + \varepsilon$, where ΔMTB is defined as annual change in MTB and ΔMTB_S represents fraudulent firms' change in MTB.

Table 5: Determinants of firms' capital expenditure

		Firm level analysis Controls share 2-digit SIC codes			Segment level analysis Controls are other segments		
		Model1	Model 2	Model 3	Model1	Model 2	Model 3
Variable	Sign	Coefficient (clustered t)	Coefficient (clustered t)	Coefficient (clustered t)	Coefficient (clustered t)	Coefficient (clustered t)	Coefficient (clustered t-)
Intercept	?	0.253 (15.18)***	0.255 (15.60)***	0.249 (16.85)***	0.146 (6.89)***	0.167 (8.06)***	0.170 (5.40)***
PEER	?	0.018 (1.06)	0.021 (1.36)	0.008 (0.53)	0.071 (3.48)***	0.070 (3.49)***	0.070 (3.44)***
SCAN	?	-0.006 (-0.47)	-0.006 (-0.51)	-0.015 (-1.08)	-0.014 (-0.92)	-0.011 (-0.75)	-0.015 (-1.03)
RESTATE	?		-0.002 (-0.29)			-0.009 (-1.08)	
I_FACTOR	?			0.049 (2.97)**			0.021 (1.91)*
PEER* SCAN	+	0.054 (2.60)**	-0.011 (-0.46)	0.001 (0.02)	0.057 (1.67)*	-0.000 (-0.00)	0.009 (0.36)
PEER* SCAN* RESTATE	+		0.044 (2.88)***			0.053 (2.51)**	
PEER* SCAN* I_FACTOR	+			0.085 (3.07)***			0.121 (3.18)***
SIZE	?	-0.009 (-3.48)***	-0.009 (-3.55)***	-0.008 (-3.80)***	-0.015 (-5.57)***	-0.0166 (-4.76)***	-0.016 (-4.73)***
MTB	+	0.044 (9.17)***	0.044 (9.15)***	0.043 (8.77)***	0.045 (4.50)***	0.042 (4.84)***	0.036 (4.69)***
LEV	?	-0.260 (-10.17)***	-0.259 (-10.01)***	-0.250 (-10.09)***	-0.094 (-3.23)***	-0.100 (-3.38)***	-0.103 (-3.60)***
CFO	?	-0.059 (-1.63)	-0.057 (-1.61)	-0.064 (-1.83)*	-0.196 (-2.56)**	-0.193 (-2.61)**	-0.194 (-2.53)**
RATING	?	-0.011 (-0.88)	-0.011 (-0.93)	-0.010 (-0.84)	0.034 (4.57)***	0.036 (5.13)***	0.040 (5.84)***
SG	+	0.279 (19.17)***	0.280 (19.16)***	0.280 (19.48)***	0.120 (5.24)***	0.121 (5.46)***	0.126 (5.97)***
CAPEX_S	+	0.065 (2.73)***	0.062 (2.76)***	0.048 (2.45)**	0.055 (4.56)***	0.053 (3.49)***	0.037 (3.57)***
COMOVE	+	0.032 (5.40)***	0.031 (5.43)***	0.029 (4.95)***			
N		21,050	21,050	21,050	3,179	3,179	3,179
R-Squared		0.2084	0.2092	0.2134	0.1735	0.1789	0.1895

Note: ***, ** and * represent 1%, 5% and 10% significance, respectively, based on a one- or two-tailed test, as appropriate. Standard errors are clustered by fiscal year.

Variable Definition:

CAPEX (dependent variable): the ratio of capital expenditure (COMPUSTAT “capx”) to lagged properties, plants and equipment (COMPUSTAT “ppent”).

PEER: an indicator variable equal one for firms in the same 3-digit SIC codes as the fraudulent firms, and zero for control firms that have the same 2-digit SIC codes as the fraudulent firms (but different 3-digit SIC codes). For segment level analysis, PEER=1 for segments of the peer firm that share the same 3-digit SIC codes as the scandal firm, and PEER=0 for segments of the peer firm that operate in other industries.

SCAN: an indicator variable equal one for years during which fraudulent firms committed frauds, and zero for 3 years prior to the scandal period.

RESTATE: tercile rankings of the ratio of fraudulent firms’ total restatement to the average revenues of the pre-scandal period.

I_FACTOR: an indicator variable for firms in the industries (defined by 3-digit SIC codes) that have investor sentiments higher than the median of all industries, earnings-to-price ratio (measured at the median of the industry) lower than the median of all industries and higher counts of M&A activities than the median.

SIZE: the natural log of lagged total assets (COMPUSTAT “at”).

MTB: lagged ratio of market value of total assets (COMPUSTAT “at” – “ceq” + “prcc_f” * “csho”) to book value of total assets (COMPUSTAT “at”).

LEV: long-term debt (COMPUSTAT “dltt”) divided by total assets (COMPUSTAT “at”), measured at the beginning of the year.

CFO: cash flow from operations (COMPUSTAT “oancf”) divided by lagged total assets (COMPUSTAT “at”).

RATING: an indicator variable for firms with S&P credit ratings.

SG: change in revenues (COMPUSTAT “revt”) divided by lagged total assets (COMPUSTAT “at”).

CAPEX_S: fraudulent firms’ CAPEX.

COMOVE: tercile rankings of the co-movement of change in market-to-book ratios between the fraudulent firms and sample or control firms in the pre-scandal period (at the 3-digit SIC code level). The co-movement is measured as β in the regression $\Delta MTB = \alpha + \beta \Delta MTB\_S + \varepsilon$, where ΔMTB is defined as annual change in MTB and ΔMTB_S represents fraudulent firms’ change in MTB.

Table 6: The effects of overlapping analysts on peer firms' investment

	Model1		Model 2		Model 3	
	High Overlap_R	Low Overlap_R	High Overlap_R	Low Overlap_R	High Overlap_R	Low Overlap_R
Variables	Coefficient (clustered-t)	Coefficient (clustered-t)	Coefficient (clustered-t)	Coefficient (clustered-t)	Coefficient (clustered-t)	Coefficient (clustered-t)
Intercept	0.235 (11.53)***	0.274 (14.03)***	0.236 (12.25)***	0.278 (12.67)***	0.239 (13.61)***	0.265 (11.53)***
PEER	-0.017 (-1.01)	0.061 (1.42)	-0.014 (-1.10)	0.066 (1.59)	-0.043 (-3.92)***	0.055 (1.49)
SCAN	-0.037 (-3.27)***	0.009 (0.42)	-0.037 (-3.42)***	0.012 (0.79)	-0.052 (-4.42)***	0.001 (0.04)
RESTATE			0.001 (0.14)	-0.008 (-0.72)		
I_FACTOR					0.083 (4.62)***	0.038 (1.55)
PEER* SCAN	0.126 (4.46)***	-0.063 (-1.16)	0.039 (1.80)**	-0.016 (-0.24)	0.057 (4.90)***	-0.042 (-0.93)
PEER*SCAN* RESTATE			0.057 (2.77)**	-0.033 (-1.70)*		
PEER*SCAN* I_FACTOR					0.085 (2.25)**	-0.038 (-0.45)
SIZE	-0.004 (-1.39)	-0.014 (-3.61)***	-0.004 (-1.31)	-0.013 (-3.22)***	-0.003 (-1.00)	-0.013 (-3.63)***
MTB	0.043 (9.15)***	0.044 (7.26)***	0.042 (8.88)***	0.044 (7.18)***	0.041 (8.46)***	0.044 (7.35)***
LEV	-0.260 (-7.71)***	-0.256 (-8.11)***	-0.261 (-7.76)***	-0.257 (-7.88)***	-0.240 (-7.26)***	-0.259 (-7.85)***
CFO	-0.099 (-2.25)**	-0.013 (-0.55)	-0.098 (-2.25)**	-0.016 (-0.70)	-0.103 (-2.36)**	-0.019 (-0.83)
RATING	-0.026 (-2.43)**	0.005 (0.21)	-0.028 (-2.54)**	0.005 (0.21)	-0.024 (-2.16)**	0.005 (0.20)
SG	0.297 (14.52)***	0.262 (18.74)***	0.298 (14.20)***	0.262 (18.92)***	0.299 (14.59)***	0.26 (18.68)***
CAPEX_S	0.078 (4.24)***	0.051 (2.43)**	0.071 (4.27)***	0.055 (2.67)**	0.053 (3.80)***	0.041 (1.97)**
COMOVE	0.034 (7.57)***	0.029 (3.35)***	0.036 (8.64)***	0.030 (3.57)***	0.023 (3.84)***	0.033 (3.09)***
N	10,522	10,528	10,522	10,528	10,522	10,528
R-Squared	0.2379	0.1742	0.2400	0.1747	0.2459	0.1755
Test of Equality of Coefficients	PEER*SCAN: $\chi 2$=47.89 p-value=0.001		PEER*SCAN*RESTATE: $\chi 2$=14.06 p-value=0.001		PEER*SCAN*I_FACTOR: $\chi 2$=10.96 p-value=0.001	

Note: ***, ** and * represent 1%, 5% and 10% significance, respectively, based on a one- or two-tailed test, as appropriate. Standard errors are clustered by fiscal year.

<u>Variable Definition:</u>

Overlap_R: the residual from the following regression: $Overlap = \alpha + \beta_1 Comove\_return + \beta_2 SIZE\_m + \beta_3 MTB\_m + \beta_4 LEV\_m + \beta_5 SG\_m + \varepsilon$ for each industry-year, where

Overlap is measured as the ratio of the number of firms that have at least one analyst also covering the scandal firm to the total number of firms that have any analyst coverage at the 3-digit SIC code level,

Comove_return is the R-squared of the regression of peer/control firms' daily returns on scandal firms' returns, measured annually, and

SIZE_m is measured as the industry median size, etc.

High Overlap_R: Industries with above the median Overlap_R

Low Overlap_R: Indutries with below the median Overlap_R

CAPEX (dependent variable): the ratio of capital expenditure (COMPUSTAT "capx") to lagged properties, plants and equipment (COMPUSTAT "ppent").

PEER: an indicator variable equal one for firms in the same 3-digit SIC codes as the fraudulent firms, and zero for control firms that have the same 2-digit SIC codes as the fraudulent firms (but different 3-digit SIC codes).

SCAN: an indicator variable equal one for years during which fraudulent firms committed frauds, and zero for 3 years prior to the scandal period.

RESTATE: tercile rankings of the ratio of fraudulent firms' total restatement to the average revenues of the pre-scandal period.

I_FACTOR: an indicator variable for firms in the industries (defined by 3-digit SIC codes) that have investor sentiments higher than the median of all industries, earnings-to-price ratio (measured at the median of the industry) lower than the median of all industries and higher counts of M&A activities than the median.

SIZE: the natural log of lagged total assets (COMPUSTAT "at").

MTB: lagged ratio of market value of total assets (COMPUSTAT "at" – "ceq" + "prcc_f" * "csho") to book value of total assets (COMPUSTAT "at").

LEV: long-term debt (COMPUSTAT "dltt") divided by total assets (COMPUSTAT "at"), measured at the beginning of the year.

CFO: cash flow from operations (COMPUSTAT "oancf") divided by lagged total assets (COMPUSTAT "at").

RATING: an indicator variable for firms with S&P credit ratings.

SG: change in revenues (COMPUSTAT "revt") divided by lagged total assets (COMPUSTAT "at").

CAPEX_S: fraudulent firms' CAPEX.

COMOVE: tercile rankings of the co-movement of change in market-to-book ratios between the fraudulent firms and sample or control firms in the pre-scandal period (at the 3-digit SIC code level). The co-movement is measured as β in the regression $\Delta MTB = \alpha + \beta \Delta MTB\_S + \varepsilon$, where ΔMTB is defined as annual change in MTB and ΔMTB_S represents fraudulent firms' change in MTB.

Table 7: Ordered probit model of analyst recommendations

		Overall	High Overlap_R	Low Overlap_R
Variable	Sign	Coefficient (clustered z-stats)	Coefficient (clustered z-stats)	Coefficient (clustered z-stats)
PEER	?	0.086 (1.66)*	0.183 (1.80)*	-0.062 (-0.72)
SCAN	?	0.004 (0.06)	0.125 (1.71)*	-0.077 (-1.10)
PEER*SCAN	-	-0.142 (-1.72)**	-0.297 (-2.31)**	0.009 (0.07)
SIZE	?	0.085 (5.65)***	0.076 (3.76)***	0.092 (0.07)
MTB	?	-0.041 (-4.09)***	-0.035 (-5.06)***	-0.055 (-2.77)**
LEV	?	-0.325 (-4.46)***	-0.383 (-3.69)***	-0.213 (-1.85)*
CFO	?	-0.202 (-1.96)**	-0.096 (-0.73)	-0.286 (-1.84)*
RATING	?	-0.006 (-0.21)	0.037 (0.79)	-0.049 (-1.64)
SG	?	-0.615 (-16.80)***	-0.600 (-12.89)***	-0.636 (-13.61)***
CAPEX_S	?	-0.035 (-1.42)	-0.049 (-2.25)**	-0.078 (-1.56)
COMOVE	?	-0.055 (-1.88)*	-0.096 (-2.90)***	-0.020 (-0.66)
N		11,278	5,907	5,371
Pseudo R-Squared		0.0302	0.0330	0.0298
Test of Equality of Coefficient PEER*SCAN			$\chi 2$=3.13 p-value=0.076	

Note: ***, ** and * represent 1%, 5% and 10% significance, respectively, based on a one- or two-tailed test, as appropriate. Standard errors are clustered by fiscal year.

Variable Definition:

Overlap_R: the residual from the following regression: $Overlap = \alpha + \beta_1 Comove\_return + \beta_2 SIZE\_m + \beta_3 MTB\_m + \beta_4 LEV\_m + \beta_5 SG\_m + \varepsilon$ for each industry-year, where

Overlap is measured as the ratio of the number of firms that have at least one analyst also covering the scandal firm to the total number of firms that have any analyst coverage at the 3-digit SIC code level,

Comove_return is the R-squared of the regression of peer/control firms' daily returns on scandal firms' returns, measured annually, and

SIZE_m is measured as the industry median size, etc.

High Overlap_R: Industries with above the median Overlap_R

Low Overlap_R: Indutries with below the median Overlap_R

Recom (Dependent Variable): the median value of all analysts' recommendations during a year. 1 represents strong buy and 5 represents strong sell.

PEER: an indicator variable equal one for firms in the same 3-digit SIC codes as the fraudulent firms, and zero for control firms that have the same 2-digit SIC codes as the fraudulent firms (but different 3-digit SIC codes).

SCAN: an indicator variable equal one for years during which fraudulent firms committed frauds, and zero for 3 years prior to the scandal period.

RESTATE: tercile rankings of the ratio of fraudulent firms' total restatement to the average revenues of the pre-scandal period.

I_FACTOR: an indicator variable for firms in the industries (defined by 3-digit SIC codes) that have investor sentiments higher than the median of all industries, earnings-to-price ratio (measured at the median of the industry) lower than the median of all industries and higher counts of M&A activities than the median.

SIZE: the natural log of lagged total assets (COMPUSTAT "at").

MTB: lagged ratio of market value of total assets (COMPUSTAT "at" – "ceq" + "prcc_f" * "csho") to book value of total assets (COMPUSTAT "at").

LEV: long-term debt (COMPUSTAT "dltt") divided by total assets (COMPUSTAT "at"), measured at the beginning of the year.

CFO: cash flow from operations (COMPUSTAT "oancf") divided by lagged total assets (COMPUSTAT "at").

RATING: an indicator variable for firms with S&P credit ratings.

SG: change in revenues (COMPUSTAT "revt") divided by lagged total assets (COMPUSTAT "at").

CAPEX_S: fraudulent firms' CAPEX.

COMOVE: tercile rankings of the co-movement of change in market-to-book ratios between the fraudulent firms and sample or control firms in the pre-scandal period (at the 3-digit SIC code level). The co-movement is measured as β in the regression $\Delta MTB = \alpha + \beta \Delta MTB\_S + \varepsilon$, where ΔMTB is defined as annual change in MTB and ΔMTB_S represents fraudulent firms' change in MTB.

Table 8: Association between investment and future cash flows

		Model 1			Model 2		
		Dependent Variable: CFO_{t+1}	Dependent Variable: CFO_{t+2}	Dependent Variable: CFO_{t+3}	Dependent Variable: CFO_{t+1}	Dependent Variable: CFO_{t+2}	Dependent Variable: CFO_{t+3}
Variables	Pred	Coefficient (clustered-t stats)	Coefficient (clustered-t stats)	Coefficient (clustered-t stats)	Coefficient (clustered-t stats)	Coefficient (clustered-t stats)	Coefficient (clustered-t stats)
Intercept	?	-0.160 (-5.92)***	-0.161 (-5.69)***	-0.163 (-5.47)***	-0.158 (-6.16)***	-0.158 (-5.86)***	-0.154 (-5.31)***
PEER	?	-0.006 (-0.40)	-0.018 (-1.08)	-0.025 (-1.82)*	-0.006 (-0.40)	-0.019 (-1.24)	-0.027 (-2.02)**
SCAN	?	-0.019 (-0.96)	-0.018 (-0.92)	-0.030 (-1.44)	-0.003 (-0.20)	-0.002 (-0.14)	-0.008 (-0.43)
PEER*SCAN	?	-0.009 (-0.36)	-0.005 (-0.18)	0.026 (1.01)	-0.010 (-0.38)	-0.004 (-0.16)	0.027 (1.02)
CAPEX	+	0.027 (1.12)	0.006 (0.21)	-0.005 (-0.17)	0.027 (1.14)	0.006 (0.21)	-0.004 (-0.15)
CAPEX*PEER	?	0.033 (1.17)	0.069 (2.26)**	0.091 (2.50)**	0.034 (1.17)	0.069 (2.24)**	0.088 (2.54)**
CAPEX* SCAN	?	0.012 (0.46)	0.043 (1.18)	0.078 (2.13)**	0.012 (0.42)	0.042 (1.15)	0.077 (2.17)**
CAPEX* PEER*SCAN	-	-0.045 (-1.59)*	-0.073 (-2.03)**	-0.111 (-2.61)**	-0.071 (-1.70)**	-0.107 (-2.41)**	-0.171 (-2.33)**
Post	?				-0.044 (-1.54)	-0.028 (-0.98)	-0.036 (-1.31)
CAPEX*PEER *SCAN*Post	?				0.074 (1.60)	0.054 (1.39)	0.069 (1.34)
SIZE	?	0.055 (13.23)***	0.054 (15.91)***	0.053 (11.64)***	0.055 (13.78)***	0.054 (15.82)***	0.053 (11.60)***
MTB	?	-0.034 (-8.60)***	-0.031 (-8.75)***	-0.031 (-10.78)***	-0.035 (-8.70)***	-0.031 (-9.22)***	-0.031 (-12.07)***
LEV	?	-0.036 (-3.35)***	-0.028 (-1.72)*	0.017 (0.99)	-0.036 (-3.26)***	-0.027 (-1.74)*	0.018 (1.01)
RATING	?	-0.098 (-12.67)***	-0.091 (-12.62)***	-0.091 (-8.51)***	-0.097 (-12.41)***	-0.091 (-12.34)***	-0.091 (-8.55)***
N		19,279	17,701	16,326	19,279	17,701	16,326
R-Squared		0.2570	0.2205	0.1980	0.2597	0.2220	0.1998

Note: ***, ** and * represent 1%, 5% and 10% significance, respectively, based on a one- or two-tailed test, as appropriate. Standard errors are clustered by fiscal year.

Variable Definition:

CFO_{t+1}(dependent variable): one-year (or two, three-year) ahead CFO, where CFO is defined as cash flow from operations (COMPUSTAT "oancf") divided by lagged total assets (COMPUSTAT "at").

PEER: an indicator variable equal one for firms in the same 3-digit SIC codes as the fraudulent firms, and zero for control firms that have the same 2-digit SIC codes as the fraudulent firms (but different 3-digit SIC codes).

SCAN: an indicator variable equal one for years during which fraudulent firms committed frauds, and zero for 3 years prior to the scandal period.

CAPEX: the ratio of capital expenditure (COMPUSTAT "capx") to lagged properties, plants and equipment (COMPUSTAT "ppent").

Post: an indicator variable if CFO of interest is observed after the scandal period.
SIZE: the natural log of lagged total assets (COMPUSTAT “at”).
MTB: lagged ratio of market value of total assets (COMPUSTAT “at” – “ceq” + “prcc_f” * “csho”) to book value of total assets (COMPUSTAT “at”).
LEV: long-term debt (COMPUSTAT “dltt”) divided by total assets (COMPUSTAT “at”), measured at the beginning of the year.
RATING: an indicator variable for firms with S&P credit ratings.

Table 9: Determinants of insider trading

Variables	Predictions	Coefficients	Clustered t-stats
Intercept	?	0.429	16.45***
PEER	?	-0.034	-1.94*
SCAN	?	-0.085	-7.28***
PEER*SCAN	+	0.052	2.36**
SIZE	?	-0.016	-3.39***
MTB	?	-0.051	-14.53***
LEV	?	0.159	4.59***
CFO	?	-0.301	-8.59***
RATING	?	0.032	1.60
RET	?	-0.076	-10.37***
N		17,514	
R-Squared		0.0425	

Note: ***, **, and * represent 1%, 5% and 10% significance levels, respectively.

Variable Definition:

NET_PURCHASE (dependent variable): net purchase in shares (total purchase-total sale) by insiders, divided by the sum of purchase and sale.

PEER: an indicator variable equal one for firms in the same 3-digit SIC codes as the fraudulent firms, and zero for control firms that have the same 2-digit SIC codes as the fraudulent firms (but different 3-digit SIC codes).

SCAN: an indicator variable equal one for years during which fraudulent firms committed frauds, and zero for 3 years prior to the scandal period.

SIZE: the natural log of lagged total assets (COMPUSTAT “at”).

MTB: lagged ratio of market value of total assets (COMPUSTAT “at” – “ceq” + “prcc_f” * “csho”) to book value of total assets (COMPUSTAT “at”).

LEV: total debts (COMPUSTAT “dltt” + “dlc”) divided by total assets (COMPUSTAT “at”).

RATING: an indicator variable for firms with S&P credit ratings.

RET: compounded market-adjusted returns of the 12-month period before the fiscal year end.

Table 10: The differential effects of restatement types on peers' investment

		Model1	Model 2	Model 3
Variables	Prediction	Coefficients (clustered t-stats)	Coefficients (clustered t-stats)	Coefficients (clustered t-stats)
Intercept	?	0.249 (14.78)***	0.249 (14.45)***	0.251 (16.31)***
PEER	?	0.016 (0.86)	0.019 (1.15)	0.009 (0.56)
SCAN	?	-0.009 (-0.64)	-0.009 (-0.74)	-0.016 (-1.09)
REV_REC	?	0.019 (2.13)**	0.015 (1.73)*	-0.002 (-0.15)
RESTATE	?		-0.001 (-0.18)	
I_FACTOR	?			0.051 (2.45)**
PEER*SCAN	+	-0.010 (-0.33)	-0.003 (-0.10)	0.001 (0.03)
PEER*SCAN* RESTATE	+		-0.021 (-2.50)**	
PEER*SCAN* I_FACTOR	+			-0.024 (-0.39)
PEER*SCAN* REV_REC	+	0.089 (3.57)***		
PEER*SCAN* RESTATE* REV_REC	+		0.076 (4.24)***	
PEER*SCAN* I_FACTOR* REV_REC	+			0.123 (2.14)**
SIZE	?	-0.009 (-3.63)***	-0.009 (-3.52)***	-0.009 (-3.95)***
MTB	+	0.044 (9.18)***	0.043 (9.13)***	0.043 (8.88)***
LEV	?	-0.250 (-10.05)***	-0.251 (-10.02)***	-0.278 (-9.73)***
CFO	?	-0.056 (-1.60)	-0.056 (-1.61)	-0.063 (-1.78)*
RATING	?	-0.008 (-0.74)	-0.008 (-0.72)	-0.009 (-0.78)
SG	+	0.281 (19.45)***	0.281 (19.38)***	0.280 (19.48)***
CAPEX_S	+	0.056 (3.01)***	0.053 (3.11)***	0.045 (2.81)***

COMOVE	+	0.029 (5.50)***	0.032 (5.95)***	0.029 (4.78)***
N		21,050	21,050	21,050
R-Squared		0.2108	0.2122	0.2134

Note: ***, ** and * represent 1%, 5% and 10% significance, respectively, based on a one- or two-tailed test, as appropriate. Standard errors are clustered by fiscal year.

Variable Definition:

CAPEX (dependent variable): the ratio of capital expenditure (COMPUSTAT "capx") to lagged properties, plants and equipment (COMPUSTAT "ppent").

PEER: an indicator variable equal one for firms in the same 3-digit SIC codes as the fraudulent firms, and zero for control firms that have the same 2-digit SIC codes as the fraudulent firms (but different 3-digit SIC codes).

SCAN: an indicator variable equal one for years during which fraudulent firms committed frauds, and zero for 3 years prior to the scandal period.

REV_REC: an indicator variable for restatements caused by revenue recognition related frauds.

RESTATE: tercile rankings of the ratio of fraudulent firms' total restatement to the average revenues of the pre-scandal period.

I_FACTOR: an indicator variable for firms in the industries (defined by 3-digit SIC codes) that have investor sentiments higher than the median of all industries, earnings-to-price ratio (measured at the median of the industry) lower than the median of all industries and higher counts of M&A activities than the median.

SIZE: the natural log of lagged total assets (COMPUSTAT "at").

MTB: lagged ratio of market value of total assets (COMPUSTAT "at" – "ceq" + "prcc_f" * "csho") to book value of total assets (COMPUSTAT "at").

LEV: long-term debt (COMPUSTAT "dltt") divided by total assets (COMPUSTAT "at"), measured at the beginning of the year.

CFO: cash flow from operations (COMPUSTAT "oancf") divided by lagged total assets (COMPUSTAT "at").

RATING: an indicator variable for firms with S&P credit ratings.

SG: change in revenues (COMPUSTAT "revt") divided by lagged total assets (COMPUSTAT "at").

CAPEX_S: fraudulent firms' CAPEX.

COMOVE: tercile rankings of the co-movement of change in market-to-book ratios between the fraudulent firms and sample or control firms in the pre-scandal period (at the 3-digit SIC code level). The co-movement is measured as β in the regression $\Delta MTB = \alpha + \beta \Delta MTB\_S + \varepsilon$, where ΔMTB is defined as annual change in MTB and ΔMTB_S represents fraudulent firms' change in MTB.