Do stock analysts' monitoring activities increase firm value? Evidence from accounting restatements

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Abstract

We examine whether the reputations of monitoring agents affect firm value. We exploit value-destroying accounting fraud cases as negative exogenous shocks to the reputations of equity analysts who positively covered the fraudulent firm right before the fraud revelation. We show that the non-fraudulent firms covered by the same affected analysts (i.e., connected firms) experience a 1% decline in stock value on the revelation date. This effect is amplified for connected firms with fewer other non-affected analysts following or with lower institutional ownership. Our analysis also reveals that the connected firms experience a reduction in stock liquidity after the revelation. Overall, our results underscore that the reputations of monitoring agents constitute an important determinant of firm value.

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1. Introduction

Prior studies claim that stock analysts' information acquisition efforts increase firm value by facilitating the monitoring of firm activities, thereby reducing agency costs (e.g., Jensen and Meckling 1976; Healy and Palepu 2001). Several recent empirical studies have focused on verifying analysts' role of monitoring management. For example, using closures and mergers of brokerage firms as exogenous shocks, Chen, Harford, and Lin (2015) find evidence that stock analysts create value by playing the role of effective monitoring agents. By contrast, Li and You (2015) argue that analysts create value mostly through an increase in investor recognition. In light of these disparate findings, our understanding of how analyst monitoring can increase firm value is still incomplete.

In this study, we investigate another unexplored channel through which analyst monitoring can affect firm value. Specifically, we investigate whether the *reputation* of an analyst as a skilled monitoring agent affects the value of the firms covered by the analyst. To the best of our knowledge, our paper is the first to rigorously study the causal effect of analyst reputation on firm value.

To derive the empirical predictions, we develop a simple model based on the Rational Expectation Equilibrium (REE) framework of Easley and O'Hara (2004), which connects the information asymmetry with the cost of capital. In so doing, we augment the Easley and O'Hara (2004) REE model by introducing analyst reputation, modeled as the distribution of analyst skill perceived by investors. In the model, an analyst experiences an external shock that tarnishes his reputation. This reputation shock reduces the investors' confidence on the analyst's recommendation of the firms covered by the analyst. Subsequently, the firms covered by the analyst become more opaque to their investors, who believe that the analyst's report is not as credible as it used to be. This insight yields the main prediction of our paper: The increased information asymmetry owing to a negative shock to the monitoring agent's reputation as a skillful monitoring agent leads to an increase in the cost of capital and a reduction in the firm value in the covered firms. We refer to this prediction as *reputation hypothesis*.

To empirically test the reputation hypothesis, we exploit value-destroying accounting fraud cases as negative exogenous shocks to the reputations of analysts who positively covered an eventual fraudulent firm right before the fraud revelation date. Specifically, for each accounting fraud case, if an analyst has published a "Buy" recommendation for the fraud firm prior to the fraud revelation date, we consider that analyst as having a negative reputation shock at the revelation event. By contrast, if a stock analyst has issued a "Sell" recommendation before the fraud revelation, we consider that analyst as having a positive reputation shock. Then, we identify non-fraudulent firms covered by the same affected analyst within 180 days prior to the revelation date on the fraud firms. We refer to the non-fraudulent firms as connected firms throughout the paper. Our sample consists of 4,360 connected firm observations for 224 unique first-time fraud revelation events between 1994 and 2011. Using the connected firm sample, we examine how stock investors react when their confidence about the analyst's effectiveness as a monitoring agent has plausibly deteriorated. We find that the connected firms followed by the negatively affected analysts experience a negative stock return over the period immediately following the fraud revelation. This result is consistent with the prediction of the reputation hypothesis.

We further perform three cross-sectional analyses to corroborate our main findings. First, we examine whether our results are more pronounced for firms with lower analyst coverage. The idea is that if firm value is indeed negatively affected by the presence of analysts with negative reputation shocks, then the impact should be mitigated if the firm is also covered by other analysts whose reputations are unaffected. Second, we hypothesize that our results are more pronounced for firms with lower institutional ownership. The idea is that if there are more highly sophisticated owners in institutions monitoring the management of the firms, the deleterious impact on firm value of a negative reputation shock to a stock analyst will be mitigated. We find evidence consistent with these predictions.

We posit that retail investors are more heavily reliant on analysts producing information when a firm exhibits a greater level of information asymmetry. This leads to the prediction that the negative impact of a reputation shock should be more pronounced in the connected firms' information asymmetry. Using pre-event idiosyncratic volatility and bid-ask spread as proxies for the extent of information asymmetry, we find that the negative and positive shocks on the analyst's quality are more significant for firms with higher information asymmetry. Finally, we test whether a negative reputation shock experienced by a stock analyst affects the connected firms' stock liquidity. The idea is that a rise in uncertainty due to increased information asymmetry would induce reduced participation from investors, which would result in a decline in overall trading volume. Indeed, we find evidence consistent with this conjecture.

We contribute to the literature in at least two ways. First, we extend the literature on stock analysts' monitoring role in firm valuation. As mentioned earlier, empirical results are mixed thus far. By using an exogenous shock on analysts' reputations as effective monitoring agents, we show that stock analysts' reputations indeed improve firm value. Second, our study sheds new light on asset pricing literature, especially the literature on asymmetric-information asset pricing models (Grossman and Stiglitz 1980; Hellwig 1980; Admati 1985; Easley and O'Hara 2004; Kelly and Ljungqvist 2012). Specifically, Kelly and Ljungqvist (2012) empirically show that a reduced number of analysts covering a stock leads to a lower stock price. Our study complements that of Kelly and Ljungqvist (2012) by showing that a firm's cost of capital is affected not only by the *quantity* but also by outside investors' perceptions on the *quality* of analysts.

Lastly, our study is related to, but distinct from, that of Lee and Lo (2016), which finds that positive opinion by bullish analysts prior to the misstatement revelation hurt their reputation, leading investors to react less strongly to the analysts' earnings forecast revisions on non-misstatement firms *after* the misstatement revelation. Notably, unlike Lee and Lo (2016), we focus on stock investors' *immediate* reactions to the connected firms followed by analysts involved in the fraud revelation events. We show that the connected firms' values are negatively affected even *without* the analysts' forecast revisions on the connected firms. In that sense, our study is more closely related to that of Fernando, May, and Megginson (2012), which documents that Lehman's collapse negatively affected industrial firms that received underwriting, advisory, analyst, and market-making services from it.

The remainder of this paper proceeds as follows. In Section 2, we describe the model construction and derive the main empirical predictions. In Section 3, we describe the sample data and methodology. We present the empirical findings in Section 4. Finally, we conclude in Section 5.

2. Hypothesis Development

2.1. Theoretical model

Consider a two-period risk-neutral economy with a riskless return R_f. The economy contains two publicly traded firms indexed by $i \in \{1,2\}$, each facing two sources of risks. First, there is uncertainty in the firm's productivity $y_i \sim N(\mu, \sigma_y^2)$. We can interpret μ as the average present value of the future cash flow and σ_y as the standard deviation of the present value. Moreover, the firm is subject to corporate governance issues, such as mismanagement, misallocation, or even misappropriation of the firm's capital and productivity. Following the setup of CEO governance (Hermalin and Wisbach 2012), we let corporate governance risk create an additional layer of uncertainty $z_i \sim N(0, \sigma_z^2)$, which is independent of the uncertainty in the firm's productivity y_i. The firm with $z_i = 0$ is the one with average corporate governance. The firm with $z_i < 0$ (or $z_i > 0$) is the one with worse-than-average (or better-than-average) corporate governance, so the realized firm value $x_i = y_i + z_i$ is lower (or better) than that of the average firm. Apparently, we have the firm value $x_i \sim N(\mu, \sigma_x^2)$, where $\sigma_x^2 = \sigma_y^2 + \sigma_z^2$.

There are two types of agents in the economy: representative investors and a sell-side analyst who covers both stocks. We assume that representative investors do not have their private signals about the firm's productivity and corporate governance risk. Meanwhile, the analyst can act as a monitor of corporate governance. The analyst can collect and process the corporate governance structure, as well as the productivity that is not easily accessible to the investors, and extract a noisy signal that correlates with the firm value. We denote the noisy signal for stock i as $\omega_i = z_i + \epsilon_i$, where $\epsilon_i \sim N(0, \sigma^2)$, which is independent of y_i and z_i. The parameter $\sigma^2 \in (0, +\infty)$ reflects the capability of the analyst. An analyst with $\sigma^2 \rightarrow 0$ has a perfect insight about the risk of corporate governance, whereas an analyst with $\sigma^2 \rightarrow +\infty$ gives an opinion that is uncorrelated with the underlying fundamental value. Furthermore, we assume that most of the analysts neither have close to perfect insight nor are completely clueless, but fall somewhere in between. In other words, the analysts' capabilities follow a distribution.

We let the representative investor observe the sell-side analyst's forecasts ω_i and make the investment decision at $t = 0$. Notably, at $t = 0$, the investor is not aware of the sell-side analyst's capability σ^2, except for a prior belief that the analyst's capability σ^2 follows an inverse Gamma distribution $IG(\alpha, \bar{\sigma}^2(\alpha-1))$ with p.d.f.

$$\iota\big(x; \alpha, \bar{\sigma}^2(\alpha-1)\big) = \frac{1}{x\Gamma(\alpha)}\left[\frac{\bar{\sigma}^2(\alpha-1)}{x}\right]^{\alpha} e^{-\frac{\bar{\sigma}^2(\alpha-1)}{x}}.$$

The parameter $\bar{\sigma}^2$ is the average capability of the analyst and the parameter $\alpha > 1$ determines the shape of distribution: a lower α leads to a more diverse capability distribution among the population of analysts.

In summary, the representative investor decides his $t = 0$ investment based on two random factors: the distribution of analyst capabilities and the distribution of possible future firm value based on the analyst's forecast. Once the firm value is revealed at $t = 1$, the investor can review the performance of the analyst by checking how far ω_i deviated from the realized x_i. Subsequently, the investor can update his/her belief about the distribution of analyst capability. Such an update of belief will affect the price of stock i at $t = 1$.

Finally, each investor has a CARA utility function $u(w) = -e^{-\rho w}$, where w is wealth at $t = 1$ and the investor chooses to optimally invest in stocks or riskless assets using an initial wealth w_0 at $t = 0$. The household optimally allocates θ_i amount of its wealth in stock i and the rest to the riskless asset. Hence, the investor's wealth in the following period is $w = \sum_i \theta_i x_i + R_f(w_0 - \sum_i p_i \theta_i)$. The optimal choice of investment θ_i satisfies

$$\widehat{\theta_i} = \underset{\theta_i}{\operatorname{argmax}}\, \mathbb{E}_I[-e^{-\rho w}].$$

Moreover, demand θ_i determines the stock price depending on the analyst's report p_i. The expectation is across the investor's information set I, which contains the ω_i, and a belief about σ_j for all j.

2.2. Stock price

We first look at the stock price when the representative investors observe the analyst's opinion ω_i.

Proposition 1. When representative investors hold a prior belief that the analyst's capability follows the inverse Gamma distribution $IG(\alpha, \bar{\sigma}^2(\alpha-1))$, the stock price p_i given the analyst's opinion ω_i is

$$p_i(x_i; \omega_i) = \frac{1}{R_f}\left(\mu + \phi\omega_i - \frac{\rho}{2}(1-\phi)\sigma_x^2\right).$$

The parameter ϕ measures the "weight" of the analyst's opinion in household investment decisions. In particular,

$$\phi = \frac{\alpha e^{\varphi}\sigma_x^2}{\sigma_x^2 + \sigma_y^2}\int_1^{+\infty}\frac{e^{-\varphi t}}{t^{\alpha+1}}dt \in [0,1], \varphi = \frac{(\alpha-1)\bar{\sigma}^2}{\sigma_x^2 + \sigma_y^2}$$

Further, $\frac{\partial\phi}{\partial\bar{\sigma}^2} < 0$ and $\frac{\partial\phi}{\partial\alpha} < 0$: so ϕ is decreasing in $\bar{\sigma}^2$ and α.

Proposition 1 differentiates our work from that of Lee and Lo (2016). In our framework, Lee and Lo (2016) show that after an analyst gets his reputation tarnished (which corresponds to a lower ϕ in our model), the market later reacts less to his/her opinion ω_i, as the market response is modulated by the factor $\phi < 1$. On the other hand, our work focuses on the investor's elevated level of perceived firm risk after losing faith in the analyst's capability, which is captured by the $-\frac{\rho}{2}(1-\phi)\sigma_x^2$ term. Our objective is to investigate whether the tarnished reputation of an analyst spills over not only to the analyst's future credibility, as in Lee and Lo (2016), but also to the value of the firms followed by the analyst.

To answer the more general question, we focus on the change in the average price across all realizations of analyst opinion ω_i. Specifically, we investigate how the average stock price

$\mathbb{E}_{\Omega_i}[p_i(x_i;\omega_i)]$ varies with the firm's opaqueness σ_x^2 and the analyst's average capability $\bar{\sigma}^2$, where Ω_i is the set of all possible realizations of the analyst's opinion ω_i.

Proposition 2. The stock price presents the following properties:

- The stock price lowers with the firm's opaqueness $\mathbb{E}_{\Omega_i}\left[\frac{\partial p_i(x_i;\omega_i)}{\partial \sigma_x^2}\right] < 0$.

- A sell-side analyst with a better reputation, i.e., a lower $\bar{\sigma}^2$, leads to a higher average stock price $\mathbb{E}_{\Omega_i}\left[\frac{\partial p_i(x_i;\omega_i)}{\partial \bar{\sigma}^2}\right] < 0$.

2.3. Analyst reputation

Analysts cover more than one stock. How does an analyst's past performance affect the future return of other stocks covered by the same analyst? We first study how representative investors update their beliefs about analyst capability.

Proposition 3. The representative investors, after observing a reporting error $\delta = \omega_i - x_i$, update the distribution of analyst capability from $IG(\alpha, \bar{\sigma}^2(\alpha-1))$ to $IG(\alpha', \overline{\sigma'}^2(\alpha-1))$, where $\alpha' = \alpha + \frac{1}{2}$ and $\overline{\sigma'}^2 = \bar{\sigma}^2 - \frac{\bar{\sigma}^2-\delta^2}{2\alpha-1}$.

Therefore, if at $t = 0$, the analyst's prediction error is δ, then the household will change its belief by $-\frac{\bar{\sigma}^2-\delta^2}{2\alpha-1}$. Specifically, if $\delta > \bar{\sigma}$, then the household will update its belief that the analyst has a worse capability than what the household used to believe: $\overline{\sigma'}^2 > \bar{\sigma}^2$. Together with Proposition 2, Proposition 3 gives us the following corollary.

Corollary 1. If the sell-side analyst's report at $t = 0$ deviates from the revealed firm value by $\delta > \bar{\sigma}$, then the household updates its belief about the analyst's capability to be $\overline{\sigma'}^2 > \bar{\sigma}^2$. Hence, the connected company's stock price $\mathbb{E}_{\Omega_i}[p_i(x_i;\omega_i)]$ will be lower.

From Proposition 2 and **Corollary 1**, we derive the first two hypotheses of this paper:

Hypothesis 1: The reputation loss (gain) of a financial analyst is associated with the value loss (gain) of a firm followed by the analyst.

Hypothesis 2: The impact of a reputation shock to a financial analyst on the covered firm's value is more pronounced if information asymmetry (such as bid-ask spread and idiosyncratic risk) is more severe.

2.4. Multiple analysts

When we introduce multiple additional analysts to the economy, the household updates its belief towards each of the analysts based on each of the analyst's δ at $t = 0$. As a result, if an analyst was proven to lack capability in monitoring the firm governance, the household still has the other analysts' opinions, which it would believe to be as accurate as usual. As a result, the single failing analyst's impact to the household's value of firms will not be as substantial. This analysis leads to our second and third hypotheses:

Hypothesis 3: The impact of a reputation shock to a financial analyst on the covered firm's value is more pronounced when few other analysts follow the firm.

Hypothesis 4: The impact of a reputation shock to a financial analyst on the covered firm's value is more pronounced if other monitoring mechanisms (such as institutional shareholders) are not available.

2.5. Discussion

Our study is closely related to, but distinct from that of Lee and Lo (2016), which finds that positive opinion by bullish analysts prior to the misstatement revelation hurt their reputation, leading investors to react less to their earnings forecast revisions on non-misstatement firms after the misstatement revelation (i.e., negative spillover). They also document that for bearish analysts issuing more negative opinions prior to the misstatement revelation, investors react more strongly to their earnings forecast revisions on non-misstatement firms after the misstatement revelation (i.e., positive spillover). While Lee and Lo (2016) examine stock investors' reactions to earnings forecast revisions at 180 days *after* the misstatement revelation (i.e., time-series analysis), we focus on stock investors' *immediate* reactions to connected firms followed by analysts of misstatement firms around the misstatement revelation. Given the nature of the research design, we don't require such analysts' research output to examine investors' reactions to more ineffective monitoring. Rather, our study is more closely related to that of Fernando, May, and Megginson (2012), who document that Lehman's collapse negatively affected industrial firms that received underwriting, advisory, analyst, and market-making services from it.

As a final remark, it is easy to see that although we are using a two-period economy, this structure allows us to extend the model recursively to an infinite period.

3. Sample Development, Variables, and Descriptive Statistics

3.1. Sample development

Our main empirical strategy in this study is the event study approach surrounding the revelation events of corporate accounting frauds. This approach requires us to identify the first revelation dates of major corporate fraud cases. First, we obtain detailed information about the financial fraud cases from the dataset constructed for Call, Martin, Sharp, and Wilde (2018)[1]. This dataset contains all of the SEC and DOJ enforcement actions for financial misrepresentation pursued between 1973 and 2012. Then, using the information provided on the timings of violations, enforcements, and regulatory proceedings, we narrow down the time periods in which the information about the violations first became public knowledge. Then, we manually search

[1] The dataset is available for download at the following link: https://research.chicagobooth.edu/arc/journal-of-accounting-research/online-supplements

the details of the violations in the sample firms' 10-Q, 10-K, and 8-K filings, as well as news feeds available in Nexus Uni using keywords such as "litigation," "restatement," "investigation," "review," and "indictment" to determine the first public revelation dates of the violations.

Once we identify the revelation dates of the fraud cases, we merge the dataset with Thomson Reuters I/B/E/S Detail Recommendations, such that only the cases in which at least one analyst produces stock recommendations within 180 days prior to the first revelation dates remain in the dataset. We refer to these analysts as the "affected analysts." Then, for each fraud case-affected analyst pair, we keep the recommendation on the fraud firm published closest to the revelation date and determine whether the recommendation is associated with a negative shock ("Strong Buy" or "Buy") or a positive shock ("Neutral," "Sell," or "Strong Sell") on the analyst. Next, we identify non-fraudulent firms in which the affected analysts produced stock recommendations within 180 days prior to the revelation dates on the fraud firms. We refer to the non-fraudulent firms as "connected firms." The datasets of the connected firms are then merged with Compustat annual data for firm characteristics and with CRSP for daily stock return information.

We implement the following additional filters on the preliminary dataset to generate the baseline data for our empirical tests. To ensure that the sample fraud cases have substantially negative effects on the wealth of investors who follow the affected analysts' recommendations, we drop a subset of the initial fraud cases that have a three-day cumulative return, adjusted for the value-weighted market return measured during the first three days of the post-revelation periods, greater than -10%.[2] In addition, the fraud cases are required to have non-missing Compustat and CRSP data. The connected firms with market equity measured seven days prior

[2] We re-estimate the empirical models using alternative thresholds (e.g., 0%, -5%, -20%, etc.) and find that the results are similar to the one based on the initial -10%.

to the first revelation dates of less than $50 million or the connected firms operating in the financial sector (i.e., one-digit SIC is "6") are also discarded. To mitigate the confounding effect of multiple fraud revelation events that are closely located along the timeline, we drop all connected firm observations for fraud revelation events occurring within 30 days of one another. Finally, for clean identification, connected firm observations within seven days before and after their quarterly earnings reports are dropped. These filters leave 2,980 connected firm observations for 224 unique first-time fraud revelation events between 1994 and 2011.

3.2. Measure for reputation shock

The key explanatory variable in this study is the measure for reputation shock to a sell-side analyst. To capture a plausibly exogenous shock to an analyst's reputation, we use the first public revelation event of a major financial fraud involving a firm (i.e., "fraud firm") followed by the analyst as the main experimental setting of the paper. Specifically, we define an *affected analyst* as an analyst who published a stock recommendation within 180 days prior to the first revelation date of a financial fraud by a firm. We define *reputation shock* as a binary variable that takes the value 1 if an affected analyst's stock recommendation before the fraud revelation event was either "Strong Buy" or "Buy" and 0 if the analyst's recommendation was any one of the following: "Neutral," "Sell," or "Strong Sell." By design, an analyst is considered to receive a negative reputation shock when *reputation shock* takes the value 1 and a positive reputation shock when *reputation shock* takes the value 0. Then, using reputation shock as a proxy for an exogenous change in an analyst's reputation, we investigate the relationship between the perceived quality of a financial analyst as a monitoring agent and the value of a firm followed by the analyst by testing the three main hypotheses of the paper. Empirically, we employ an event study setting where we test whether the firms, other than the fraud firms, followed by the analyst whose reputation was negatively affected experience a negative stock return over a period immediately following the fraud revelation.

3.3. Descriptive statistics

Figure 1 presents the average daily market-adjusted cumulative return of the 224 fraud firms' stocks during the [-22 +22]-day period surrounding event date 0 of the fraud revelation events. The equity value loss surrounding the fraud revelation events is visibly substantial and the pre-event 10-day cumulative market-adjusted return ([-10 -1] days) is -5.6%, implying that there is a moderate level of rundowns before the revelation events. Table 1 shows that the three-day ([-1 +1] days) cumulative loss surrounding the revelation date [0] is -32.6%, and a zero-mean t-test result confirms that the value is statistically different from zero at less than the 0.01% level. These results indicate that the first fraud revelation dates in our sample capture the unexpectedness and the economic significance of the events.

Table 1 also presents the summary statistics on the firm characteristics of the 2,980 sample connected firm observations. For each variable, Columns 1 and 2 report the means and the standard deviations for the sample of connected firms, while Columns 3 to 7 report their distributions. The average number of affected analysts covering the sample connected firms is 1.2 with a standard deviation of 0.68, while the average number of analysts covering the firms is 9.8. Due to the low affected-to-total analyst ratio, the effect of analyst reputation losses on firms with high analyst coverage should be minimal.

4. Research Design and Empirical Results

4.1. Baseline results

In this section, we test the first main empirical prediction (*H1*) which states that the reputation loss (gain) of a financial analyst is associated with the value loss (gain) of a firm followed by the analyst. To test this prediction, we employ the following baseline OLS model specification.

$$CAR_{i,t} = \beta \times NSR(PSR)_{j,t-1} + X_{i,t-1}B_{i,t-1} + F + \varepsilon_{i,t} \quad \text{(Eq. 1)}$$

where $CAR_{i,t}$ are the five-day cumulative abnormal returns (FFCAR5) of a non-fraudulent connected firm i over the fraud revelation period of [0 +5] days, estimated using the Fama and French five-factor model presented in Fama and French (2015). $NSR(PSR)_{j,t-1}$ is the key explanatory variable. It is the ratio of the number of analysts who are covering the non-fraudulent connected firm i and experiencing a negative (positive) reputation shock to the total number of analysts covering the firm i. $X_{i,t-1}$ is a vector of control variables for firm characteristics and F is a vector of industry and year fixed effects. The empirical prediction is that β is negative for the model with $NSR_{j,t-1}$ and positive for the model with $PSR_{j,t-1}$.

[Insert Table 2 here.]

Table 2 reports the estimation results obtained using Eq. 1. Panel A shows the results of the full sample, with Column 1 showing results using negative shock ratio and Column 3 showing results using positive shock ratio. As predicted in H1, the columns indicate that the coefficients of the negative (positive) shock ratio are negative (positive) and statistically significant.

A possible confounding explanation for the results in Panel A is that perhaps the analysts tend to cover firms that are similar to one another, and the firms' performance measures tend to co-move with one another. Thus, it is possible that the analysts' pre-event recommendations on the fraud firms may be correlated with the connected firms' performance measures, thereby explaining the correlation between the shock ratios and the stock returns shown in Table 1 Panel A. To address this concern, the extended models in Columns 2 and 4 include additional control variables that capture the connected firms' financial conditions that can potentially be correlated with the event returns.[3] The results indicate that the inclusion of additional control variables has almost no effect on the shock ratio coefficients across the different model specifications. In Panel B of Table 2, we estimate the same model in Eq. 1 but with alternative event windows. Columns 1 and 3 report estimation results based on the event period of [0 +22] days, and the estimates of NSR and PSR are comparable to those found in Panel A. The results reported in Columns 2 and 4, which are based on the event period of [+23 +66] days, show little sign of a reversal of the market reaction. Overall, the results in Table 1 demonstrate that changes in the analysts' reputations have a lasting impact on the value of the connected firms.

There are concerns that the baseline results reported in Table 2 can be counted as products of spurious factors. For example, various time-invariant firm and industry characteristics could be correlated both with the revelation return and the key explanatory variables NSR and PSR. To address these concerns, we augment Eq. 1 with more fixed effects: fraud firm, connected firm industry interacted with year, as well as connected and fraud firm states. The results in Table 3 show that an inclusion of a battery of fixed effects does not affect the results in a meaningful way.

[Insert Table 3 here.]

Next, we investigate whether the closeness between the connected firms and the fraud firms causes more significant changes in investors' perceptions about the analysts' abilities as monitoring agents. The idea is that a negative reputation shock experienced by an analyst may impact more negatively the connected firms that operate in the same industry as the fraud firm. To test this conjecture, we use three different proxies to capture the closeness between the fraud

[3] Alternatively, we also estimate a model with Altman-Z score as a performance measure. The results are virtually the same.

firms and the connected firms. Same industry is a binary variable that takes the value of 1 if a connected firm operates in the same three-digit SIC code as the fraud firm. Proximity is a binary variable that takes the value of 1 if a connected firm operates in the same state as the fraud firm. Lastly, product similarity is a binary variable that takes the value of 1 if a connected firm shares product similarity with the fraud firm, as defined by the Text-based Network Industry Classifications (TNIC) from Hoberg and Phillips (2010).

[Insert Table 4 here.]

Panels A and B of Table 4 report the estimation results. The interaction term between NSR (PSR) and each closeness variable reflects an incremental effect of the closeness to the sensitivity of the event return to the reputation variable NSR (PSR). The results show that only Column 2 in Panel A exhibits a statistically significant coefficient of the interaction terms. This indicates that only when the connected firms' products are similar to those of the fraud firms will the connected firms experience an additional value loss due to negative reputation shock.

4.2. Effect of information asymmetry

In this section, we test the prediction (*H2*) which states that pre-event information asymmetry surrounding the firm amplifies the effect of a reputation shock to a financial analyst on the value of the firm covered by the analyst.

We use the idiosyncratic volatility of the connected firms' equity to capture pre-shock information asymmetry (Wurgler and Zhuravskaya 2002; Ali, Hwang, and Trombley 2003; Mashruwala, Rajgopal, and Shevlin 2006; Gilchrist, Sim, and Zakrajsek 2014). We construct the variable as follows. For idiosyncratic volatility, we first fit the market model on each connected firm's daily return data over a [-250 -7]-day period to obtain the residuals. Then, we compute the standard deviation of the residuals for each connected firm. The unconditional median volatility is 29%. We classify connected firms with idiosyncratic volatility values greater (smaller) than the median as firms with more (less) severe information asymmetry. Then, we estimate Eq. 1 for each connected firm group. The empirical prediction is that the economic and statistical significance of β is greater for firms classified with more severe information asymmetry.

Table 5 reports the estimation results. Only the coefficients of the reputation variables in Columns 1 and 3, which are based on the connected firm group with more severe information asymmetry, are statistically significant. This is consistent with the prediction in H3 and suggests that investors tend to rely more on analysts' reports when the firms' information environments are opaque. Thus, a negative shock to the reputations of the analysts has a more substantial impact on the value of these firms.

[Insert Table 5 here.]

4.3. Alternative monitoring mechanisms

The previous section tests the prediction that pre-event information asymmetry surrounding the connected firms amplifies the effect of a reputation shock on firm value. For this section, we test the prediction in H3 which states that the impact of a reputation shock to a financial analyst on the firm's value is mitigated in the presence of other information-producing agents, such as institutional investors. The results in Columns 2 and 4 of Table 2 Panel B show that the presence of other sell-side analysts covering the same firms unaffected by the fraud revelation events dilutes the effect of the reputation shock to the affected analysts. This is consistent with the prediction in H3. In this section, we test the conjecture that simply having more analysts covering the firm is correlated with a higher-quality information environment. Thus, a greater number of analysts will mitigate the value impact of the analysts' reputation shocks. We construct the measure *total analysts*, which reflects the average monthly number of analyst coverage during the 180-day period that end one day before the revelation date.

Next, we test the prediction in H4 which states that the impact of a reputation shock to a financial analyst on the covered firm's value is more pronounced if other monitoring mechanisms (such as institutional shareholders) are not available. Many studies find evidence that institutional investors have a superior ability to produce and process information compared with individual retail investors (e.g., Bartov, Radhakrishnan, and Krinsky 2000; Bonner, Walther, and Young 2003; Jung, Kumar, Lim, and Yoo 2018). We construct the measure *institutional ownership* to capture institutional presence in the connected firms. First, we merge the sample connected firm data with the Thomson Reuters 13F filings data. The 13F data are updated quarterly, so we combine the two datasets by the latest quarter that ends before the fraud revelation dates. Then, institutional ownership is constructed by computing the ratio of the total institutional ownership to the total market capitalization of the firms in the latest quarter before the fraud revelation dates. We classify connected firms with a number of analysts (institutional ownership) that is less than eight (60%), which is the unconditional median, as firms with weaker alternative monitoring mechanism. H3 and H4 predict that connected firms with weaker alternative monitoring mechanisms will experience greater impacts from the analyst reputation shock.

[Insert Table 6 here.]

Panels A and B of Table 6 present the estimation results. As predicted, in Panel A, the coefficients of NSR shown in Columns 1 and 3 are negative and statistically significant, consistent with the predictions in H3 and H4. Conversely, the coefficients of NSR are not significant in Columns 2 and 4, which are based on the connected firms with stronger alternative monitoring mechanisms. Panel B reports the estimates from using PSR as the key explanatory variable. The results are also consistent with H3 and H4 in that only the firm groups with weaker alternative monitoring mechanisms show significant effects of analyst reputation shock on shareholder value. Overall, the results in this section yield strong support to the notion that the existing information environment surrounding the connected firms plays an important role in either amplifying or mitigating the impact of reputation shock to the analysts.

4.4. Alternative dependent variable: Stock liquidity

In this section, we test whether increased uncertainty stemming from analyst reputation shock will lead to a reduction in demand for trading the connected firms' stocks. To test this conjecture, we construct three liquidity variables that are widely used in stock liquidity literature: Amihud, ZeroRet, and FHT.[4] Then, for each liquidity variable, we construct three different versions with varying event windows: changes in liquidity over two months, six months, and two years surrounding the revelation date. To capture the changes in liquidity over a two-month period, we first compute the pre-event (post-event) average liquidity by averaging the daily liquidity measure over the 22-trading day period that ends (starts) 10 days before (after) the revelation date. Then, we subtract the pre-event average liquidity from the post-event average liquidity to capture the changes in liquidity over the two-month period. The other liquidity variables with different event windows are similarly constructed. Using the nine dependent variables that capture stock liquidity, we estimate Eq. 1 to examine how analyst reputation shock affects the overall liquidity of the connected firms' stocks.

[Insert Table 7 here.]

Panels A and B in Table 6 report the estimation results. In Panel A, across all the different model settings with various measures for stock liquidity, all of the coefficients of NSR

[4] Fong, Holden, and Trzcinka (2017) provide detailed descriptions on how the three variables are constructed.

are positive and seven out of nine estimates are statistically significant at the conventional level. This indicates that the negative reputation shock leads to greater illiquidity in the connected firms' stocks. On the contrary, in Panel B, all of the coefficients of PSR are negative and eight out of nine estimates are statistically significant at the conventional level. This indicates that the positive reputation shock leads to an increase in liquidity in the connected firms' stocks. Overall, the results reported in Table 6 confirm that reputation shocks to stock analysts have material impacts on the connected firms' values through a reduction in value and liquidity of the stocks.

5. Conclusion

Since prior studies claim that stock analysts' information acquisition efforts reduce agency costs (e.g., Jensen and Meckling 1976; Healy and Palepu 2001), several recent empirical studies have focused on verifying analysts' role of monitoring management. However, our understanding of how analyst monitoring can increase firm value is still incomplete. In this study, we investigate whether another unexplored channel, the *reputation* of an analyst as a skilled monitoring agent, can affect the value of the firms covered by the analyst. To the best of our knowledge, our paper is the first to rigorously study the causal effect of analyst reputation on firm value.

We exploit value-destroying accounting fraud cases as negative exogenous shocks to the reputations of analysts who positively covered the fraudulent firms right before the fraud revelations. We show that the non-fraudulent firms covered by the same affected analysts (i.e., connected firms) experience a 1% decline in stock value on the revelation date. This effect is amplified for the connected firms with fewer other non-affected analysts following or with lower institutional ownership. Our analysis also reveals that the connected firms experience a reduction in stock liquidity after the revelation. Overall, the results reported in this paper underscore that reputation shocks to stock analysts have material impacts on the covered firms' values through a change in the value and liquidity of the equity.

Appendix A: Variable definitions (in alphabetical order)

All analysts is the total number of analysts who published recommendation on an connected firm′s stock between -180 days and -1 day prior to the fraud revelation date.

CAR[0,+5] is connected firms′ six-day [0, +5] cumulative abnormal returns starting on the fraud revelation date [0], estimated using the daily Fama-French-Carhart daily 4-factor returns available on Kenneth French′s website. The estimation window is established as [-210, -11] days relative to the announcement date with a minimum 100 non-missing CRSP stock return observations required.

Cash/AT is the ratio of an connected firm′s cash and cash equivalents to the total book assets.

Firm age is a log-transformed count variable that reflects the number of years an acquirer (target) appears in the COMPUSTAT universe before the merger announcement date.

Institutional ownership is the ratio of all of an connected firm′s outstanding shares owned by all of the form-13F filing institutional investors to the firm′s total shares outstanding, as observed in the 13F filings reported in the last quarter-end prior to the merger announcement.

Market leverage is the ratio of an connected firm′s short-term debt plus long-term debt to *Market assets*.

Size is a continuous variable for the connected firms′ market value of equity and is constructed by multiplying the stock price and the number of common shares outstanding observed 10 trading days prior to the fraud revelation dates.

Q is the ratio of an acquirer′s (target′s) *Market assets* to book assets.

Past return is the buy-and-hold connected firm′s stock return minus the buy-and-hold return of the value-weighted market portfolio during a 12-month period ending 1 (?) month prior to the merger announcement date.

ROA is the ratio of an connected firm′s operating income before depreciation to the total book assets.

NSR *(i.e. Negative Reputation Shock Ratio)* is a continuous variable that takes the value between 0 and +1 and captures the proportion of analysts covering the connected firm who experienced a negative reputation shock. For example, suppose that firm ABC is covered by five analysts and two of the analysts also cover firm DEF, whose management were just found to be fraudulent. If the latest recommendations given by the two analysts on firm DEF are either "BUY" or "STRONG BUY" (thus experienced negative reputation shock), then NSR for firm ABC = 2/5 = 40%.

PSR *(i.e. Positive Reputation Shock Ratio)* is a continuous variable that takes the value between 0 and +1 and captures the proportion of analysts covering the connected firm who experienced a positive reputation shock. For example, suppose that firm ABC is covered by five analysts and two of the analysts also cover firm DEF, whose management were just found to be fraudulent. If the latest recommendations given by the two analysts on firm DEF are both either "NUTRAL", "SELL" or "STRONG SELL", (thus experienced negative reputation shock), then PSR for firm ABC = 2/5 = 40%.

Market assets is book assets minus book equity plus market equity.

Same state is a binary variable that takes the value 1 if the corporate headquarters of the acquirer and the target are located in the same state and take 0 otherwise.

Same industry is a binary variable that takes the value 1 if the primary businesses of the acquirer and the target share the same two-digit SIC code and take 0 otherwise.

Proximity is a binary variable that takes the value 1 if the headquarters of the fraudulent firm and the connected firm are located within a 100 miles radius of each other.

Z-Score is computed following Altman (1968) as:

$$Z\text{-}score = 1.2\times WC/TA + 1.4\times RE/TA + 3.3\times EBIT/TA + 0.6\times ME/TL + SALE/TA$$

where *WC* is working capital, *RE* is retained earnings, *EBIT* is earnings before interest and taxes, *ME* is market value of equity, *TL* is book value of total liabilities, *SALE* is total sales, and *TA* is total book value of assets.

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Figure 1: Daily cumulative stock returns surrounding the fraud revelation events

This graph shows the cumulative daily market-adjusted abnormal returns of fraudulent firms over the [-22 +22] days relative to the fraud revelation date [0].

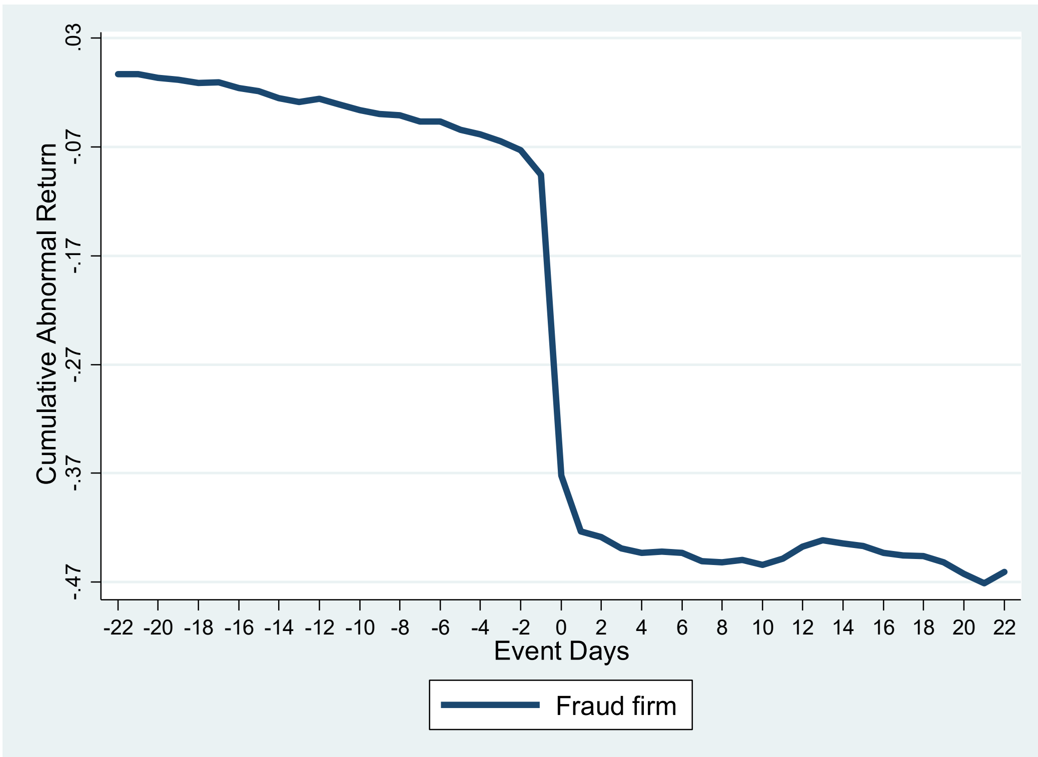

Table 1: Summary statistics

This table reports the summary statistics of the firm characteristic variables of the sample non-fraudulent firms covered by the same analyst whose reputation as an effective monitoring agent was affected during the fraud revelation of a firm also covered by the analysts. We refer to these non-fraudulent firms as connected firms throughout the paper.

	Mean	S.D.	5th percentile	25th	Median	75th	95th percentile
Size	13.797	1.758	11.286	12.444	13.587	14.954	17.048
Q	2.924	2.643	0.936	1.356	2.022	3.276	8.637
Past return	0.132	0.636	-0.695	-0.270	0.028	0.369	1.469
ROA	0.157	0.163	-0.147	0.107	0.172	0.247	0.358
Mkt leverage	0.111	0.137	0.000	0.001	0.056	0.178	0.404
Z-score	8.193	10.544	0.863	2.646	4.780	9.214	29.051
Cash/AT	0.222	0.232	0.004	0.029	0.127	0.366	0.702
Tangibility	0.249	0.214	0.031	0.083	0.174	0.353	0.710
Firm age	16.204	15.149	2	5	9	23	50
Affected analysts	1.227	0.675	1	1	1	1	3
All analysts	9.778	7.214	2	4	8	14	25
Bid_ask spread	0.047	0.024	0.018	0.028	0.042	0.060	0.097
Idiosyncatic σ	0.034	0.018	0.012	0.021	0.031	0.044	0.070
Institutional ownership	0.575	0.246	0.132	0.394	0.604	0.766	0.940
Same industry	0.364	0.481	0	0	0	1	1
Product similarity	0.320	0.466	0	0	0	1	1
Fraud firm return [-1, +1]	-0.326	0.190	-0.703	-0.412	-0.283	-0.164	-0.115
N	2,980						

Table 2: Baseline results

Panel A: Using FFC4CAR[0,+5] as the dependent variable

This table reports the estimation results of the baseline OLS model in Eq. 1 using the non-fraudulent connected firm sample. The dependent variables in Panel A are the five-day cumulative abnormal returns (FFCAR5) of a non-fraudulent connected firm over the fraud revelation period of [0 +5] days, estimated using the Fama and French five-factor model presented in Fama and French (2015). Panel B reports the estimation results of the same model and the dependent variables but with alternative event periods. See Appendix A for the detailed variable definitions. Student t-statistics from the standard errors clustered by merger deal group are enclosed in the parentheses. ***, **, * indicate significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(4)	(5)
Dependent variable:	CAR[0,+5]	CAR[0,+5]	CAR[0,+5]	CAR[0,+5]
NSR	**-0.0425*** **	**-0.0426*** **		
	(-3.1497)	**(-3.3661)**		
PSR			**0.0291** **	**0.0297*** **
			(2.6242)	**(2.7918)**
Control variables:				
Size	0.0026*	0.0028*	0.0014	0.0015
	(1.9301)	(1.7670)	(0.9386)	(0.9091)
Q	-0.0013	-0.0016	-0.0013	-0.0016
	(-1.1972)	(-1.5325)	(-1.2104)	(-1.4949)
Past return	-0.0152***	-0.0155***	-0.0144***	-0.0148***
	(-4.1508)	(-4.8176)	(-3.8771)	(-4.5218)
All analysts	-0.0112***	-0.0118***	-0.0008	-0.0013
	(-5.3739)	(-5.3827)	(-0.2712)	(-0.4734)
ROA		0.0234***		0.0237***
		(3.7690)		(3.7226)
Mkt leverage		-0.0006		-0.0002
		(-0.0426)		(-0.0169)
Cash/AT		0.0062		0.0060
		(0.6238)		(0.6260)
Firm age		-0.0020		-0.0019
		(-0.8975)		(-0.8370)
Same industry		-0.0016		-0.0021
		(-0.4032)		(-0.5145)
Same state		-0.0018		-0.0022
		(-0.2920)		(-0.3571)
Constant	-0.0078	-0.0077	-0.0195	-0.0190
	(-0.4740)	(-0.4124)	(-1.3037)	(-1.1574)
N	2,980	2,980	2,980	2,980
R-squared	0.0724	0.0742	0.0688	0.0707
Fraud firm ind. FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel B: Various return horizons

Dependent variable:	(1) CAR[0,+22]	(2) CAR[+23,+66]	(3) CAR[0,+22]	(4) CAR[+23,+66]
NSR	**-0.0323****	**-0.0064**		
	(-2.2550)	**(-0.1865)**		
PSR			**0.0754*****	**-0.0020**
			(3.8336)	**(-0.0525)**
Size	-0.0030	-0.0193***	-0.0045*	-0.0194***
	(-1.1063)	(-4.6698)	(-1.7034)	(-4.0578)
Q	-0.0093***	-0.0048	-0.0093***	-0.0049
	(-7.1813)	(-1.2313)	(-7.4001)	(-1.2283)
Past return	-0.0360***	-0.0880***	-0.0357***	-0.0879***
	(-5.9032)	(-11.1305)	(-5.9571)	(-11.1873)
All analysts	0.0054	0.0350***	0.0182**	0.0361***
	(0.7879)	(3.6955)	(2.5757)	(4.8564)
ROA	0.0467*	0.1066***	0.0497*	0.1062***
	(1.8325)	(3.0159)	(1.9884)	(3.0470)
Mkt leverage	-0.0597*	-0.0439	-0.0589*	-0.0438
	(-1.7365)	(-1.2133)	(-1.7222)	(-1.2094)
Cash/AT	0.0303	0.0303	0.0306	0.0302
	(1.4524)	(0.7416)	(1.4684)	(0.7429)
Firm age	-0.0017	0.0200***	-0.0017	0.0200***
	(-0.3689)	(2.8016)	(-0.3710)	(2.7937)
Same state	-0.0149*	0.0229*	-0.0148*	0.0228*
	(-1.7409)	(1.7083)	(-1.7485)	(1.7124)
Same industry	-0.0137	0.0158	-0.0135	0.0156
	(-1.6577)	(1.4191)	(-1.6471)	(1.4012)
Constant	0.0663**	0.1389**	0.0502*	0.1380***
	(2.1955)	(2.4125)	(1.6956)	(2.7556)
N	2,759	2,628	2,759	2,628
R-squared	0.0980	0.1472	0.1009	0.1472
Fraud firm Ind. FE	Yes	Yes	Yes	Yes
Conn..firm's ind FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 3: Baseline results with various fixed effects

This table reports the estimation results of the baseline OLS model in Eq.1 using the non-fraudulent connected firm sample. The dependent variable is the five-day cumulative abnormal returns (FFCAR5) of an non-fraudulent connected firm over the fraud revelation period of [0 +5] days, estimated using the Fama and French five-factor model presented in Fama and French (2015). See Appendix A for the detailed variable definitions. Student t-statistics from standard errors clustered by merger deal group is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	CAR[0,+5]	CAR[0,+5]	CAR[0,+5]	CAR[0,+5]	CAR[0,+5]	CAR[0,+5]
NSR	**-0.0474*** **	**-0.0499*** **	**-0.0480*** **			
	(-3.2612)	**(-3.2303)**	**(-3.1345)**			
PSR				**0.0323*** **	**0.0320** **	**0.0283***
				(2.7302)	**(2.3870)**	**(1.6990)**
Size	0.0024*	0.0028	0.0020	0.0010	0.0014	0.0006
	(1.6847)	(1.6462)	(1.1591)	(0.6518)	(0.8001)	(0.3740)
Q	-0.0009	-0.0008	-0.0006	-0.0009	-0.0007	-0.0005
	(-0.9625)	(-0.9114)	(-0.6653)	(-0.8891)	(-0.7937)	(-0.5611)
Past return	-0.0160***	-0.0179***	-0.0181***	-0.0154***	-0.0174***	-0.0174***
	(-4.9597)	(-7.5975)	(-8.5171)	(-4.6958)	(-7.2688)	(-8.1620)
All analysts	-0.0133***	-0.0146***	-0.0129***	-0.0019	-0.0028	-0.0016
	(-6.1257)	(-5.0361)	(-4.2629)	(-0.6002)	(-0.8483)	(-0.4055)
ROA	0.0172***	0.0177**	0.0304***	0.0178***	0.0183**	0.0305***
	(3.1032)	(2.4265)	(3.4747)	(3.0310)	(2.4267)	(3.3217)
Mkt leverage	-0.0058	-0.0098	-0.0149	-0.0047	-0.0085	-0.0132
	(-0.3705)	(-0.5409)	(-0.8571)	(-0.3000)	(-0.4744)	(-0.7477)
Cash/AT	0.0028	0.0075	0.0120	0.0025	0.0071	0.0117
	(0.2598)	(0.8221)	(1.3069)	(0.2364)	(0.7977)	(1.2904)
Firm age	-0.0002	-0.0002	0.0024	-0.0002	-0.0001	0.0025
	(-0.0944)	(-0.0716)	(0.9336)	(-0.0599)	(-0.0553)	(0.9335)
Same industry	-0.0009	0.0004	-0.0012	-0.0015	-0.0002	-0.0020
	(-0.1722)	(0.0937)	(-0.2174)	(-0.2756)	(-0.0411)	(-0.3560)
Same state	-0.0029	0.0034	0.0085	-0.0034	0.0035	0.0085
	(-0.4021)	(0.5250)	(1.0480)	(-0.4784)	(0.5414)	(1.0501)
Constant	-0.0030	-0.0077	-0.0089	-0.0156	-0.0210	-0.0213
	(-0.1563)	(-0.4249)	(-0.5738)	(-1.0059)	(-1.3560)	(-1.3869)
N	2,980	2,980	2,980	2,980	2,980	2,980
R-squared	0.1696	0.2004	0.2735	0.1662	0.1966	0.2704
Fraud firm ind. FE	Yes	Yes	No	Yes	Yes	No
Conn..firm's ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Conn. ind ×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Conn. firm state FE	No	Yes	Yes	No	Yes	Yes
Fraud firm state FE	No	Yes	No	No	Yes	No
Fraud firm FE	No	No	Yes	No	No	Yes

Table 4: Incremental effect from the closeness between fraud firms and connected firms

This table reports the estimation results of the baseline OLS model in Eq.1 augmented with the closeness interaction terms using the non-fraudulent connected firm sample. The dependent variable is the five-day cumulative abnormal returns (FFCAR5) of an non-fraudulent connected firm over the fraud revelation period of [0 +5] days, estimated using the Fama and French five-factor model presented in Fama and French (2015). See Appendix A for the detailed variable definitions. Student t-statistics from standard errors clustered by merger deal group is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

Panel A: Using NSR

Dependent variable:	(1) CAR[0,+5]	(2) CAR[0,+5]	(3) CAR[0,+5]
NSR × Same industry	-0.0135		
	(-0.3913)		
NSR × Product similarity		-0.0353**	
		(-2.0738)	
NSR × Proximity			-0.0026
			(-0.1417)
NSR	-0.0376***	-0.0321***	-0.0429***
	(-3.2838)	(-2.9554)	(-3.2084)
Same industry	0.0002		
	(0.0310)		
Product similarity		0.0039	
		(0.9150)	
Proximity			0.0036
			(0.6349)
Constant	-0.0085	-0.0102	-0.0082
	(-0.4842)	(-0.5854)	(-0.4447)
N	2,980	2,980	2,980
R-squared	0.0744	0.0755	0.0742
Control variables?	Yes	Yes	Yes
Fraud firm ind. FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Panel B: Using PSR

Dependent variable:	(1) CAR[0,+5]	(2) CAR[0,+5]	(3) CAR[0,+5]
PSR × Same industry	0.0141		
	(0.4310)		
PSR × Product similarity		-0.0123	
		(-0.6199)	
PSR × Proximity			-0.0420
			(-0.9162)
PSR	0.0257*	0.0323***	0.0340***
	(1.9911)	(2.7554)	(3.2454)
Same industry	-0.0034		
	(-0.5597)		
Product similarity		-0.0010	
		(-0.2002)	
Proximity			0.0062
			(0.7389)
Constant	-0.0188	-0.0196	-0.0199
	(-1.1358)	(-1.2175)	(-1.2194)
N	2,980	2,980	2,980
R-squared	0.0708	0.0707	0.0711
Control variables?	Yes	Yes	Yes
Fraud firm ind. FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 5: Information asymmetry

This table reports the estimation results of the baseline OLS model in Eq.1 using the non-fraudulent connected firm sample. The dependent variable is five-day cumulative abnormal returns (FFCAR5) of an non-fraudulent connected firm over the fraud revelation period of [0 +5] days, estimated using the Fama and French five-factor model as in Fama and French (2015). To construct Idiosyncratic volatility, we first fit the market model on each connected firm's daily return data over [-250 -7] days period to obtain the residuals. Then, we compute the standard deviation of the residuals for each connected firms. See Appendix A for the detailed variable definitions. Student t-statistics from standard errors clustered by merger deal group is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

	(1)	(2)	(5)	(6)
Dependent variable:	CAR[0,+5]	CAR[0,+5]	CAR[0,+5]	CAR[0,+5]
Sample group:	Idiosync.σ> 29%	Idiosync.σ≤ 29%	Idiosync.σ> 29%	Idiosync.σ≤ 29%
NSR	**-0.0640*** **	**-0.0043**		
	(-4.2396)	**(-0.4104)**		
PSR			**0.0391*** **	**0.0153**
			(2.8588)	**(1.2544)**
Size	0.0044*	0.0013	0.0024	0.0010
	(1.7695)	(0.8117)	(0.8766)	(0.6350)
Q	-0.0014	-0.0009	-0.0013	-0.0009
	(-0.8883)	(-0.6306)	(-0.8064)	(-0.5945)
Past return	-0.0173***	-0.0137**	-0.0163***	-0.0137**
	(-3.8592)	(-2.1155)	(-3.6389)	(-2.1128)
All analysts	-0.0169***	-0.0056*	-0.0005	-0.0036
	(-5.0325)	(-1.9782)	(-0.1069)	(-1.5788)
ROA	0.0209*	0.0077	0.0216*	0.0065
	(1.7800)	(0.4568)	(1.8275)	(0.3875)
Mkt leverage	-0.0076	0.0108	-0.0073	0.0112
	(-0.3805)	(0.8345)	(-0.3532)	(0.8663)
Cash/AT	0.0027	0.0034	0.0026	0.0034
	(0.1728)	(0.4105)	(0.1682)	(0.4283)
Firm age	-0.0020	-0.0004	-0.0024	-0.0002
	(-0.5619)	(-0.1847)	(-0.6344)	(-0.1142)
Same industry	-0.0055	0.0021	-0.0066	0.0021
	(-1.0905)	(0.4206)	(-1.2576)	(0.4289)
Same state	-0.0103	0.0048	-0.0102	0.0044
	(-1.0573)	(1.0639)	(-1.0384)	(1.0000)
Constant	-0.0122	-0.0083	-0.0286	-0.0109
	(-0.5906)	(-0.4451)	(-1.3865)	(-0.6072)
N	1,490	1,490	1,490	1,490
R-squared	0.1153	0.1302	0.1091	0.1311
Fraud firm ind. FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 6: Monitoring mechanism

This table reports the estimation results of the baseline OLS model in Eq.1 using the non-fraudulent connected firm sample. The dependent variable is five-day cumulative abnormal returns (FFCAR5) of an non-fraudulent connected firm over the fraud revelation period of [0 +5] days, estimated using the Fama and French five-factor model as in Fama and French (2015). We construct Total analysts, which reflects the average monthly total number of analyst coverage during the 180 day period that end one day before the revelation date. Institutional ownership is constructed by computing the ratio of the total institutional ownership to the total market capitalization of the firms in the latest quarter before the fraud revelation dates. See Appendix A for the detailed variable definitions. Student t-statistics from standard errors clustered by merger deal group is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

Panel A: Using NSR

	(1)	(2)	(3)	(4)
Dependent variable:	CAR[0,+5]	CAR[0,+5]	CAR[0,+5]	CAR[0,+5]
Sample group:	Total analysts<8	Total analysts≥8	Inst.Ownership<60%	Inst.Ownership≥60%
NSR	**-0.0402*** **	**-0.0475**	**-0.0498*** **	**-0.0120**
	(-3.1199)	**(-1.3357)**	**(-4.2118)**	**(-0.5481)**
Size	0.0008	0.0037	0.0006	0.0076***
	(0.3168)	(1.5093)	(0.2105)	(3.7022)
Q	-0.0010	-0.0020	-0.0012	-0.0022
	(-0.7489)	(-1.4345)	(-0.9350)	(-1.6516)
Past return	-0.0159**	-0.0148***	-0.0117**	-0.0210***
	(-2.5341)	(-3.6162)	(-2.4725)	(-4.2253)
All analysts	-0.0127***	-0.0117	-0.0083**	-0.0165***
	(-3.4879)	(-1.3884)	(-2.0348)	(-2.8021)
ROA	0.0274***	0.0134	0.0195	0.0252*
	(3.4321)	(0.8850)	(1.4746)	(1.6822)
Mkt leverage	-0.0010	0.0099	-0.0109	-0.0001
	(-0.0584)	(0.4259)	(-0.5920)	(-0.0055)
Cash/AT	0.0156	-0.0057	0.0106	-0.0001
	(1.4826)	(-0.3141)	(0.8528)	(-0.0059)
Firm age	-0.0002	-0.0053*	-0.0021	-0.0026
	(-0.0565)	(-1.6804)	(-0.5792)	(-0.9855)
Same industry	-0.0068	0.0051	-0.0073	0.0024
	(-1.1771)	(1.1220)	(-1.2249)	(0.4553)
Same state	-0.0054	-0.0001	-0.0099	0.0037
	(-0.7495)	(-0.0140)	(-1.4324)	(0.4784)
Constant	0.0107	-0.0095	0.0186	-0.0657**
	(0.4457)	(-0.3708)	(0.6132)	(-2.4185)
N	1,451	1,529	1,490	1,490
R-squared	0.0966	0.0982	0.0791	0.1498
Fraud firm ind. FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel B: Using PSR

	(1)	(2)	(3)	(4)
Dependent variable:	CAR[0,+5]	CAR[0,+5]	CAR[0,+5]	CAR[0,+5]
Sample group:	Total analysts<7	Total analysts≥7	Inst.Ownership<60%	Inst.Ownership≥60%
PSR	**0.0304****	**-0.0251**	**0.0369*****	**0.0041**
	(2.3777)	**(-0.6851)**	**(3.2356)**	**(0.1854)**
Size	0.0002	0.0039	-0.0016	0.0075***
	(0.0849)	(1.6499)	(-0.5325)	(3.7502)
Q	-0.0010	-0.0021	-0.0011	-0.0022
	(-0.7651)	(-1.4843)	(-0.8430)	(-1.6494)
Past return	-0.0154**	-0.0149***	-0.0106**	-0.0209***
	(-2.4127)	(-3.6725)	(-2.2362)	(-4.1419)
All analysts	0.0027	-0.0110	0.0065	-0.0148***
	(0.5272)	(-1.3942)	(1.2675)	(-3.8017)
ROA	0.0270***	0.0142	0.0201	0.0251*
	(3.2491)	(0.9773)	(1.5135)	(1.6863)
Mkt leverage	-0.0013	0.0113	-0.0106	0.0002
	(-0.0791)	(0.4770)	(-0.5698)	(0.0113)
Cash/AT	0.0157	-0.0044	0.0105	-0.0003
	(1.4896)	(-0.2463)	(0.8480)	(-0.0213)
Firm age	-0.0000	-0.0055*	-0.0023	-0.0026
	(-0.0002)	(-1.6920)	(-0.6223)	(-0.9884)
Same industry	-0.0074	0.0044	-0.0078	0.0022
	(-1.2666)	(0.9893)	(-1.2765)	(0.4314)
Same state	-0.0051	-0.0010	-0.0096	0.0035
	(-0.7051)	(-0.0951)	(-1.3677)	(0.4590)
Constant	-0.0150	-0.0149	0.0101	-0.0693***
	(-0.6587)	(-0.5735)	(0.3480)	(-2.8072)
N	1,451	1,529	1,490	1,490
R-squared	0.0936	0.0972	0.0745	0.1495
Fraud firm ind. FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 7: Changes in stock liquidity

This table reports the estimation results of an OLS regression model. The dependent variables are three stock liquidity measures that are widely used in the stock liquidity literature: Amihud, ZeroRet, and FHT. Fong, Holden, and Trzcinka (2017) provide detailed descriptions on how the three variables are constructed. See Appendix A for the detailed variable definitions for the control variables. Student t-statistics from standard errors clustered by merger deal group is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

Panel A: Using NSR

	(1) Amihid [-1,+1]M	(2) Amihid [-3,+3]M	(3) Amihid [-12,+12]M	(4) ZeroRet [-1,+1]M	(5) ZeroRet [-3,+3]M	(6) ZeroRet [-12,+12]M	(7) FHT [-1,+1]M	(8) FHT [-3,+3]M	(9) FHT [-12,+12]M
NSR	**0.0239****	**0.0202***	**0.0444*****	**0.3504****	**1.3608*****	**3.1580*****	**0.0008**	**0.0015****	**0.0012**
	(2.3433)	**(1.9714)**	**(2.7921)**	**(2.1477)**	**(4.0260)**	**(2.8771)**	**(0.8992)**	**(2.0506)**	**(1.5334)**
Size	-0.0020**	-0.0038***	-0.0063**	-0.0102	-0.1131**	-0.2490	-0.0001	-0.0002	-0.0003**
	(-2.2621)	(-4.3247)	(-2.3770)	(-0.3473)	(-2.0053)	(-1.6615)	(-0.3369)	(-1.5641)	(-2.6482)
Q	0.0004	0.0002	0.0009	0.0155	0.0511**	0.3090***	0.0000	0.0000	0.0002***
	(1.6498)	(0.3838)	(1.0812)	(1.2298)	(2.0424)	(4.6881)	(0.2697)	(0.5640)	(4.1132)
Past return	-0.0037***	-0.0096***	-0.0321***	-0.1029**	-0.3847***	-3.8713***	-0.0004	-0.0006***	-0.0024***
	(-2.8208)	(-3.7510)	(-7.8212)	(-2.4527)	(-4.1390)	(-11.4463)	(-1.4929)	(-3.2007)	(-10.3155)
All analysts	0.0018	0.0022	0.0028	0.0129	0.2950**	1.7000***	-0.0000	0.0004	0.0008***
	(0.9049)	(1.3577)	(1.0124)	(0.2060)	(2.3471)	(4.5838)	(-0.0609)	(1.5187)	(2.8969)
ROA	-0.0040	-0.0307*	-0.0816***	0.4732**	0.7132	-0.3787	0.0025**	0.0016*	-0.0023*
	(-0.5883)	(-1.8979)	(-3.5737)	(2.0786)	(1.5022)	(-0.1398)	(2.3087)	(1.6744)	(-1.7005)
Mkt leverage	-0.0035	-0.0198**	0.0152	0.5088	0.4288	-1.5791	0.0022	0.0011	0.0024*
	(-0.4222)	(-2.5148)	(0.7755)	(1.4147)	(0.5415)	(-0.9706)	(1.2452)	(0.9444)	(1.7509)
Cash/AT	-0.0102	-0.0036	0.0122	0.4814***	0.9635***	2.4494*	0.0025***	0.0019***	0.0004
	(-1.4572)	(-0.4464)	(1.1710)	(3.5299)	(3.3708)	(1.9061)	(3.8171)	(2.7119)	(0.6098)
Firm age	-0.0002	-0.0005	-0.0015	0.0428	0.1296	-0.0789	0.0003**	0.0002	-0.0000
	(-0.1498)	(-0.2923)	(-0.5261)	(1.0501)	(1.2683)	(-0.2883)	(2.0322)	(1.0301)	(-0.2647)
Same state	0.0019	0.0008	-0.0045	0.0597	0.0206	0.2367	0.0004	0.0002	-0.0001
	(0.7879)	(0.2936)	(-0.6813)	(0.7430)	(0.1455)	(0.4927)	(1.6336)	(0.5438)	(-0.3263)
Same industry	-0.0022	-0.0005	0.0038	-0.0185	0.0201	0.2408	-0.0001	-0.0000	0.0001
	(-1.3050)	(-0.1984)	(0.7442)	(-0.2419)	(0.1914)	(0.6118)	(-0.3980)	(-0.2207)	(0.6179)
Constant	0.0287***	0.0617***	0.1025***	-0.3653	-0.0741	-2.2057	-0.0014	0.0009	0.0030**
	(3.4594)	(5.2927)	(3.7545)	(-1.3643)	(-0.1443)	(-1.4253)	(-1.1061)	(0.7403)	(2.4719)
N	2,969	2,969	2,969	2,969	2,969	2,969	2,967	2,967	2,967
R-squared	0.0678	0.1216	0.2272	0.0471	0.0698	0.1787	0.0417	0.0556	0.1401
Fraud firm ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Using PSR

	(1) Amihid [-1,+1]M	(2) Amihid [-3,+3]M	(3) Amihid [-12,+12]M	(4) ZeroRet [-1,+1]M	(5) ZeroRet [-3,+3]M	(6) ZeroRet [-12,+12]M	(7) FHT [-1,+1]M	(8) FHT [-3,+3]M	(9) FHT [-12,+12]M
PSR	**-0.0177***	**-0.0167***	**-0.0406*****	**-0.4430****	**-1.3081*****	**-5.0307*****	**-0.0012**	**-0.0017****	**-0.0021*****
	(-1.9227)	**(-1.7954)**	**(-3.4628)**	**(-2.1482)**	**(-3.9676)**	**(-3.9566)**	**(-1.2580)**	**(-2.0518)**	**(-3.0616)**
Size	-0.0013	-0.0031***	-0.0048*	0.0025	-0.0674	-0.1251	-0.0000	-0.0002	-0.0003**
	(-1.4023)	(-3.2300)	(-1.7759)	(0.0920)	(-1.1065)	(-0.8648)	(-0.1429)	(-1.0369)	(-2.2318)
Q	0.0004*	0.0002	0.0009	0.0154	0.0506**	0.3078***	0.0000	0.0000	0.0002***
	(1.6843)	(0.3726)	(1.0736)	(1.2159)	(2.0517)	(4.7055)	(0.2659)	(0.5586)	(4.1278)
Past return	-0.0041***	-0.0099***	-0.0328***	-0.1084**	-0.4076***	-3.9172***	-0.0004	-0.0006***	-0.0024***
	(-3.0992)	(-3.9524)	(-8.1327)	(-2.6055)	(-4.3838)	(-11.6748)	(-1.4976)	(-3.3830)	(-10.5432)
All analysts	-0.0042**	-0.0030	-0.0090***	-0.0907*	-0.0721	0.6779**	-0.0003	-0.0000	0.0004
	(-2.1003)	(-1.4786)	(-2.9151)	(-1.7932)	(-0.5260)	(2.3150)	(-1.1225)	(-0.1101)	(1.4765)
ROA	-0.0041	-0.0309*	-0.0822***	0.4633**	0.6914	-0.5104	0.0025**	0.0015	-0.0023*
	(-0.5974)	(-1.9359)	(-3.6567)	(2.0177)	(1.4446)	(-0.1915)	(2.2535)	(1.6191)	(-1.7876)
Mkt leverage	-0.0036	-0.0200**	0.0149	0.5065	0.4195	-1.5995	0.0022	0.0011	0.0023*
	(-0.4476)	(-2.5494)	(0.7653)	(1.4169)	(0.5326)	(-0.9859)	(1.2486)	(0.9389)	(1.7556)
Cash/AT	-0.0101	-0.0035	0.0123	0.4809***	0.9654***	2.4365*	0.0025***	0.0019***	0.0004
	(-1.4644)	(-0.4427)	(1.1929)	(3.5064)	(3.3930)	(1.8901)	(3.8073)	(2.7140)	(0.5939)
Firm age	-0.0003	-0.0005	-0.0016	0.0414	0.1250	-0.0926	0.0003**	0.0002	-0.0000
	(-0.1956)	(-0.3291)	(-0.5711)	(1.0181)	(1.2168)	(-0.3442)	(2.0132)	(0.9956)	(-0.3017)
Same state	0.0021	0.0010	-0.0041	0.0623	0.0319	0.2572	0.0004	0.0002	-0.0001
	(0.8625)	(0.3520)	(-0.6084)	(0.7883)	(0.2319)	(0.5243)	(1.6558)	(0.5998)	(-0.3051)
Same industry	-0.0020	-0.0003	0.0042	-0.0176	0.0300	0.2334	-0.0001	-0.0000	0.0001
	(-1.2235)	(-0.1260)	(0.7933)	(-0.2295)	(0.2892)	(0.5949)	(-0.4149)	(-0.1950)	(0.5986)
Constant	0.0351***	0.0674***	0.1156***	-0.2443	0.3356	-0.9630	-0.0011	0.0014	0.0035***
	(3.9075)	(5.7190)	(3.8656)	(-0.8559)	(0.6179)	(-0.6325)	(-0.8117)	(1.2196)	(2.8692)
N	2,969	2,969	2,969	2,969	2,969	2,969	2,967	2,967	2,967
R-squared	0.0644	0.1200	0.2255	0.0475	0.0686	0.1815	0.0420	0.0556	0.1417
Fraud firm ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes