Relative Performance Evaluation and Contagion in Financial Reporting Quality

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Abstract

We examine the effect of relative performance evaluation contracts on a company's financial reporting quality. Using data on actual peer firms, we find that the adoption of relative performance evaluation provides financial incentives for earnings management. On average, higher earnings management in the set of peer firms leads to higher earnings management in the target firm. If the peer firm also uses the target firm as its peer in their incentive plans, this mutual benchmarking strengthens the earnings management contagion effect. The contagion effect is weaker if there are significant differences in performance, as well as in incentives and costs of earnings management between the target firm and its peers.

Keywords: Relative performance evaluation; Earnings management; Earnings quality contagion; Financial reporting quality

JEL Classifications : G34; G38; C3

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1. Introduction

Relative performance evaluation (RPE) is the use of peer performance to set executive compensation. Relative performance awards have become an increasingly important component of executive pay over the past decade. With relative performance grants, managers are rewarded based on improving shareholder value relative to a peer group of firms selected by the board. The theoretical justification for benchmarking performance against a set of peers was first proposed by Holmstrom (1982). Holmstrom shows that relative evaluation can be desirable if there are common shocks that influence the output of managers. By filtering out exogenous shocks that are unrelated to the effort of the manager, a firm can more objectively measure the manager's performance. This can prevent lucky managers from being mistakenly categorized as good managers when the firm benefits from positive exogenous shocks. Filtering out exogenous shocks can also improve the welfare of the manager by reducing the variability of her compensation.

In this paper we investigate contagion in financial reporting quality (FRQ) through the relative performance evaluation channel. We define target firms as those adopting RPE contracts in their managers' compensation. Decisions in the target firms are potentially influenced by firms in their RPE peer group. Several theoretical papers link reporting choices of firms to peer pressure emanating from capital markets and product market competition (Einhorn, Langberg, and Versano 2018 and Gao and Zhang 2019). More closely related, Bagnoli and Watts (2000) theoretically examine earnings management as a non-cooperative game and show that firms will engage in earnings management because they expect their peers to do the same.

Building on this prior theoretical work, we construct a stylized model to show how earnings management contagion can arise through the use of RPE in compensation contracts. When target firms expect peer firms to manipulate earnings, RPE provides incentives for the target manager to respond in kind. This is the central idea behind our empirical analyses. We test whether earnings management among peer firms leads to a contagion in the earnings management behavior among target firms. We identify a set of actual peer firms for 1,466 target firms in the S&P 1500 from 2006 to 2016 based on actual RPE compensation contracts. Using actual peers, rather than proxies like industry classification, increases the power of our tests, as the links between target firms and their RPE peer firms are more accurately identified and not contaminated by misclassified peers.

We find that the level of peer firm earnings management strongly influences the level of earnings management of the target firm. Specifically, the median discretionary accruals of RPE peer firms are significantly related to the discretionary accruals of their respective target firms. This basic result goes through when we use alternative specifications, including a specification that controls for the median industry level of discretionary accruals. It is important to control for industry-level discretionary accruals since the extant literature (Kedia, Koh, and Rajgopal 2015) often uses firms in the same two-digit SIC code as peers. This result also highlights the importance of identifying actual peer firms used in RPE compensation contracts as our peer identification is significant above and beyond the impact of industry-based peer identification. We conduct cross-sectional analyses to better understand the conditions under which earnings management contagion occurs. The earnings management game between the target firm and its peers often exhibits strategic complementarity, where managers increase earnings management in response to peers doing so. However, strategic substitutability can occur if the costs of earnings management exceed the benefits.

If a firm experiences negative shocks to its earnings, the manager may find it too costly or risky to manipulate earnings sufficiently to match or exceed peer performance. In such cases, the manager might choose to reduce earnings management or even manipulate earnings downward to create "cookie jar" reserves for future use. Consistent with this idea, we find that large differences in performance between the target firm and its peers lead to lower levels of correlation between the earnings management of the target firm and its peers.

Significant differences in incentives and costs between the target firm and its peers can dampen the responsiveness of managers to each other's earnings management practices. Conversely, when incentives and costs are similar, managers are more likely to mirror each other's actions, leading to a cycle of earnings management contagion. To test this idea, we use proxies for financial incentives and costs associated with earnings management. First, we use the proportion of a target CEO's compensation tied to RPE grants as a proxy for financial incentives. Second, we examine the number of peers used in the CEO's compensation contract; a larger number of peers dilutes the economic incentives and makes it more challenging for managers to anticipate and mimic each peer's earnings management strategies. Similarly, we would expect the contagion effect to be weaker when the target firm uses a broad index as a benchmark since the economic incentives to mimic earnings manipulation behavior are more diffuse. Third, we use an indicator variable representing whether the target firm had been investigated by the SEC in the past three years, serving as a proxy for higher costs due to increased scrutiny and potential penalties. Lastly, we consider whether peer firms also use RPE grants and include the target firm as a peer. Mutual referencing and similar compensation structures intensify the economic incentives to engage in earnings management, while the absence of RPE use by peer firms is expected to dampen the contagion effect. Overall, we find evidence that the contagion effect in earnings management is weaker when there are significant differences in financial incentives and costs between the target and peer firms.

Our benchmark tests use discretionary accruals as our main measure of earnings management, calculated following the modified Jones (1991) model which we estimate in line with Dechow et al. (1995). We conduct robustness tests using alternative measures of financial reporting quality including, the Dechow and Dichev (2002) quality of accruals, measures of real earnings management and restatements. We find that real earnings management by peer firms has a significant impact on the real earnings management behavior of the target firm. We also document that the incidence and the amount of earnings restatements of peer firms significantly influence the likelihood as well as the amount of restatements by the target firms.

Target firms may choose peers with similar financial reporting quality which could influence our empirical findings. Similarly, earnings management measures are estimated with error, and if these errors are correlated across selected peers based on omitted variables, this could lead to the appearance of contagion when none exists. We carry out two analyses to address these concerns. First, we demonstrate that introducing RPE into compensation contracts for the first time leads to an increase in contagion using a differences-in-differences analysis. We examine the change in the relationship between the target firm's own earnings management and the median discretionary accruals of its peers a year before and a year after RPE adoption. In the year before a target firm adopts RPE, we use the same set of peers the target firm chooses in their RPE contract. We find a significant increase in the relationship between the financial reporting quality of the target firm and its peer firms after the RPE adoption suggesting that our results are not likely to be explained by peer selection or measurement error.

Second, we create a set of counterfactual peer firms to use as a control group in our analyses. These counterfactual firms have similar characteristics to the actual peer firms we use in our analyses but are not listed as peers in the relevant RPE compensation contracts. By including counterfactual firms as controls in the analyses, we control for potential omitted variables and correlated estimation errors that also affect counterfactual peers.

We use three different approaches to selecting counterfactual peers. First, we identify counterfactual peers via propensity score matching using characteristics that have been shown to be important in peer selection. Second, we use the former peer firms of the target firm as counterfactual peers.

Former peer firms constitute a particularly strong control group since they match the target firm closely enough to once have been considered as peers, but as former peers should have no influence on the current decisions of target firm management if our main hypothesis is correct. Finally, we use two recently proposed approaches to identifying potential peer firms in the literature. Following Cadman and Carter (2014), we use the peer firms of actual peers, and following Bloomfield, Guay and Timmermans (BGT, 2022), we construct a set of counterfactual peers from among the firms in the same industry that have the largest return correlations with the target firm.

We find that the earnings management of the actual RPE peer firms is always a significant predictor of the earnings management decisions of the target firm after controlling for counterfactual peers. Excepting the BGT counterfactual peers, the earnings management behavior of counterfactual peers has no significant effect on the intensity of earnings management by the target firm. Through these tests we provide compelling evidence that the relationship between the earnings management decisions of the target firm and those of the target firm's RPE peers is unlikely to be driven by omitted variables or measurement error.

Our paper contributes to a growing literature that examines the determinants and the economic impact of RPE in executive compensation contracts. Carter, Ittner and Zechman (2009) examine how firms design their relative performance grants. De Angelis and Grinstein (2020) show that RPE can be used as a commitment device to pay CEOs for their revealed relative talent. Albuquerque (2009), Ball, Bonham and Hemmer (2020), Bizjak, Kalpathy, Li and Young (2022), Drake and Martin (2020) and Gong, Li and Shin (2011) examine determinants of RPE peer selection and highlight some of the inefficiencies and biases that can arise in peer selection due to incentives faced by executives and board members. A strand of this literature examines how RPE compensation contracts can affect firms' financial and business decisions. Feichter, Moers and Timmermans (2022) show that competitive aggressiveness increases within the same peer group when two firms use each other as peers. Park and Vrettos (2015) and Timmermans (2024) show that greater RPE usage leads firms to take on more idiosyncratic risk. Do, Zhang and Zuo (2022) suggest that RPE contracts provide a tournament-like incentive mechanism that causes poorly performing firms to take on more risk.

Related to our study, Gong, Li, and Yin (2019) examine the impact of RPE based compensation on the timing of earnings release. They find that CEOs prefer peers whose earnings they can observe before reporting their own earnings. This allows the CEO to better estimate the performance level required to achieve RPE targets. They do this by last minute reporting discretion. This paper complements and extends Gong et al. (2019) by presenting evidence consistent with target firms engaging in earnings management in response to earnings management by peer firms in addition to potential report date management by target firms documented in Gong et al. (2019).

This paper also contributes to the literature that examines contagion in earnings management. Kedia, Koh, and Rajgopal (2015) show contagion in earnings management through an analysis of earnings restatements from 1997 to 2008. They find that firms are more likely to begin managing earnings after the public announcement of a restatement by another firm in the same geographical area. Chiu, Teoh, and Tian (2013) find that a firm is more likely to restate earnings in the future if one of its directors is also on the board of another firm that restates its earnings. These results are consistent with interlocking boards having similar corporate practices with directors acting as conduits for unethical behavior. Gleason, Jenkins, and Johnson (2008) find that stock prices react quickly to peer firms' restatement announcements. They show that price declines at peer firms are unrelated to changes in analysts' earnings forecasts, but instead reflect investors' concern about earnings management contagion within an industry. In a related paper, Du and Shen (2018) report that the performance of peer firms, measured using idiosyncratic stock returns as in Leary and Roberts (2014), can lead to higher discretionary accruals. They show that the idiosyncratic capital market performance of peer firms in the same 3-digit SIC code is significantly positively related to the target firm's discretionary accruals. In another stream of research which documents that peer firms' actions can influence the actions of target firms and vice versa, Beatty, Liao, and Yu (2013) show that fraudulent peer reports convince other same-industry firms that investment conditions are different than they appear from their own firm's observations. They show that investments of firms that share the same 3-digit SIC code with a high-profile firm that reports fraudulent earnings reports are greater during the fraud period.

We build on the contagion literature that most often uses SIC industry peer firms to identify peer firm effects.[1] In our empirical analyses, we carefully isolate the contagion effect of RPE peer firms on target firm earnings management through the direct identification of peer firms from actual RPE compensation contracts. We provide precise tests on the potential downside of using relative performance evaluation in compensation contracts: The race to keep up with the earnings management activities of peer firms can lead to greater target firm earnings management resulting in lower financial reporting quality. We ascribe this outcome to the financial motivations of the target-firm manager to reap the rewards of surpassing their peer firms, and to evade the adverse effects, such as termination from underperforming their peers. If RPE alters both the costs and benefits of earnings management behavior, our findings provide one explanation for the fact that many firms do not adopt RPE compensation, and when they do, why some firms opt for using a broad market benchmark like the S&P 500.

The rest of the paper is organized as follows. Section 2 briefly outlines the hypotheses we examine. Section 3 describes the data and defines the measures of earnings management we use in this paper. Section 4 presents the empirical results, and Section 5 concludes.

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[1] Albuquerque (2009) discusses the importance of identifying correct firms to use in peer groups in empirical tests. Jayaraman, Milbourn and Peters (2021), for instance, find that using the more sophisticated Hoberg and Phillips (2016) classification method to identify peers significantly improves the empirical evidence on the Holmstrom (1982) theory.

2. Hypotheses

A large body of literature shows that financial incentives in executive compensation contracts can lead to opportunistic earnings management by executives (Holthausen, Larcker, and Sloan 1995; Bergstresser and Philippon 2006; Burns and Kedia 2006; Efendi, Srivastava, and Swanson 2007; Do, Zhang, and Zuo 2022). Similarly, financial incentives associated with Relative Performance Evaluation (RPE) grants provide strong motivations for executives to manage earnings, especially when their peer firms are also engaging in such practices. When peers are managing earnings upwards, executives are incentivized to inflate their own firm's performance to meet or surpass the peer performance benchmarks specified in their compensation contracts.

Beyond the risk of losing compensation, executives face the grave danger of termination if they underperform relative to their peer group, which can further influence managers to manipulate earnings when peer firms manipulate theirs. Prior research suggests that relative performance significantly impacts whether a manager will be dismissed from their position. For instance, Jenter and Kanaan (2015) and DeFond and Park (1999) demonstrate that CEOs are more likely to be dismissed after poor performance relative to their industry benchmarks. Rajgopal, Shevlin, and Zamora (2006) show that a CEO's external career opportunities depend on their firm's performance relative to the industry. Thus, failing to match or exceed the performance of one's peers can have severe adverse consequences for a manager's career prospects. Facing such potentially negative outcomes, including job dismissal, influences managers' decisions to manipulate their earnings. Additionally, there is evidence that investors and analysts use relative performance with respect to peers when evaluating firms (De Franco, Hope, and Larocque 2015). This additional capital market pressure adds further incentives to outperform peer benchmarks, increasing the likelihood of earnings management by managers.

Given the financial incentives associated with RPE compensation contracts outlined above, the decision to manage earnings is likely influenced by the earnings management decisions of peer firms. Managers face both costs and benefits when considering whether to manipulate earnings, including in the context of relative performance evaluation. If peer firms are manipulating earnings, the manager must decide whether to follow suit. Earnings manipulation carries significant potential costs if discovered, such as reputational damage, dismissal from their position, monetary sanctions, and even potential criminal liability imposed by regulatory bodies like the SEC and the Department of Justice (DOJ). Given these substantial personal costs, a manager must weigh the potential gains from outperforming their peers through earnings manipulation against the risks of punishment if their manipulation is discovered.

From a game theory perspective, the situation often exhibits strategic complementarity, where the optimal response of the target firm's CEO, expecting earnings management in their set of peer firms, is to increase the level of earnings management in their own firm. However, there may also be cases where the interaction leads to strategic substitutability, with the optimal response being to reduce earnings management in reaction to higher earnings management by peers. This is particularly true when the target firm has little chance of outperforming its peers if the cost of earnings management exceeds the benefits. For instance, if the target firm experiences a significant negative idiosyncratic shock to its earnings, the CEO may find it too costly to manipulate earnings sufficiently to catch up with peer firms. In such instances, the CEO might choose to manipulate earnings downwards to create a "cookie jar" reserve that could be utilized in the future. The financial incentives and associated costs determine the strength and direction of the target firm's response. For example, the target firm's CEO may be less inclined to manipulate earnings if RPE accounts for only a small portion of their compensation or if the personal costs of manipulation are too severe.

Strategic complementarity in a repeated game of earnings management also depends on the financial incentives and costs faced by peer firms. If there are significant differences in incentives and costs between the target firm and its peers, this could reduce the responsiveness of both parties to each other's earnings management practices. Conversely, when incentives and costs are more closely aligned, we would expect greater complementarity in their responses. We anticipate that the earnings quality of firms that use RPE in their compensation contracts and cross-reference the target firm as a peer would have a greater impact on the earnings quality of the target firm. When peer firms manage earnings to outperform the target firm, managers at the target firm are motivated to inflate their own performance to achieve the benchmarks set in their compensation contracts, resulting in a cycle of earnings management contagion. Significant differences in costs between the peer and target firm can influence this dynamic. If the costs associated with earnings management differ substantially between the firms, the contagion effect may be dampened, as managers weigh the potential benefits against the unique risks and costs their firm faces.

To formally illustrate how an equilibrium can emerge in a dynamic game of earnings management, we outline a stylized model (details are provided in Appendix 1). In this model, the CEO of the target firm is rewarded based on relative performance. We assume that there is only one peer firm for simplicity. The compensation of the CEO in firm *i* in year *t* is $W_{i,t} = \gamma_{i,t} + b_t\left(x_{i,t} - x_{p,t}\right)^+$, where $\gamma_{i,t}$ is the fixed portion of the CEO's compensation, and $x_{i,t}$ and $x_{p,t}$ represent the reported earnings of the target firm and the peer firm, respectively. The CEO receives a reward when they outperform the peer firm, which occurs when $x_{i,t} - x_{p,t} > 0$. The reward factor for relative out-performance is denoted by b_t .

The target firm *i*'s reported earnings at time *t*, $x_{i,t}$ depend on three components, an industry-wide earnings shock I_t, a firm-specific idiosyncratic shock $\eta_{i,t}$, and earnings manipulation $m_{i,t}$: $x_{i,t} = I_t + \eta_{i,t} + m_{i,t}$. Similarly, the peer firm's earnings are: $x_{p,t} = I_t + \eta_{p,t} + m_{p,t}$. Both the target firm and the peer firm experience the same industry-wide shock to their earnings in any given year. The idiosyncratic shocks $\eta_{i,t}$ and $\eta_{p,t}$ are independent and normally distributed random variables: $\eta_{i,t} - \eta_{p,t} \sim N(\Delta\eta_t, 2\sigma^2)$.

The CEO maximizes their utility (U) over time using earnings management strategies: $\max_{\{m_{i,t}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t U(W_{i,t})$. β is the discount factor. The CEO's utility is defined as expected compensation minus the personal cost associated with earnings manipulation: $U(W_{i,t}) = E(W_{i,t}) - c_t m_{i,t}^2$. The costs reflect potential monetary penalties and reputational costs associated with dismissal and potential SEC and DOJ litigations and sanctions. The cost of manipulation is convex, reflecting the increasing likelihood of detection and larger penalties for higher levels of manipulation. To ensure that the manipulation is bounded, we impose the constraint $\sum_{t=0}^{\infty} m_t \leq M$, thereby limiting the cumulative manipulation that firms can engage in over time.

With the boundedness constraint on the aggregate level of manipulation the optimization problem for the CEO in the target firm becomes:

$$\mathcal{L}_i = \sum_{t=0}^{\infty} \beta^t U(W_{i,t}) - \lambda_i\left(\sum_{t=0}^{\infty} m_{i,t} - M\right) \tag{1}$$

where λ_i is the Lagrange multiplier. The CEO at the peer firm faces the same optimization problem. Both the target and peer firm CEOs optimize their manipulation strategies, treating the other's earnings as given. The first-order conditions for the target and peer CEOs are thus symmetric:

$$\begin{gathered} b_t \Phi\left(\frac{\Delta\eta_t + m_{i,t}^* - m_{p,t}}{\sqrt{2}\sigma}\right) - 2c_t m_{i,t}^* - \frac{\lambda_i}{\beta^t} = 0 \\ b_t \Phi\left(\frac{-\Delta\eta_t + m_{p,t}^* - m_{i,t}}{\sqrt{2}\sigma}\right) - 2c_t m_{p,t}^* - \frac{\lambda_p}{\beta^t} = 0 \end{gathered} \tag{2}$$

In equilibrium, these first-order conditions must hold for both firms. When the idiosyncratic shocks are identical for both firms ($\Delta\eta_t = 0$), we demonstrate (in Appendix 1) that the optimal level of manipulation for both the target and the peer firm is:

$$m_{i,t}^* = m_{p,t}^* = \frac{b_t/2 - \lambda/\beta^t}{2c_t} \quad (3)$$

where $\lambda = \lambda_i = \lambda_p$. The target and the peer firm mimic each other's earnings management practices in this equilibrium. This result is based on expectations whereby the target firm responds in kind to their peer's earnings management behavior without first observing their peer's earnings management behavior. This is consistent with Bagnoli and Watts (2000) who show that correlated earnings management behavior can take place as the interaction between the target firm and its peers is a repeated and continuous game.[2] The optimal manipulation level increases with the reward factor b_t and decreases with costs c_t and the shadow price of the constraint λ.

If the target firm receives a significantly higher idiosyncratic shock to its earnings than the peer firm ($\Delta\eta_t$ being much greater than zero), the equilibrium in this case is:

$$m_{i,t}^* = \frac{b_t - \lambda_i/\beta^t}{2c_t};\ m_{p,t}^* = -\frac{\lambda_p/\beta^t}{2c_t} \quad (4)$$

Conversely, if the peer firm receives a significantly higher positive idiosyncratic shock relative to the target firm (η_t being much less than zero), the equilibrium becomes:

[2] Bagnoli and Watts (2000) argue that "…if a firm is a member of a group of firms that will be compared by investors and creditors, it will manage its earnings simply because it expects its rivals to do the same…" even if there is uncertainty regarding how its peers will behave. The expectation that, in equilibrium, the peer firms will manage earnings to enhance their firm values would lead to similar earnings management behavior at the target firm over time.

$$m_{i,t}^{*} = -\frac{\lambda_i/\beta^t}{2c_t}, m_{p,t}^{*} = \frac{b_t - \lambda_p/\beta^t}{2c_t} \quad (5)$$

In both cases of significant positive or negative earnings shocks, we observe a divergence in the direction of manipulation, implying a breakdown in the correlation between the target and peer firm's earnings management. Intuitively, when faced with large negative idiosyncratic shocks, significant amounts of manipulation would be required to catch up with and outperform the peer firm. As this is very costly for the target firm's CEO, it is optimal for them to not mimic the peer firm's earnings management behavior when the target firm experiences large negative earnings shocks. The same rationale should also apply to the peer firm's management.

The first two hypotheses are motivated by the stylized results of the model. In equilibrium, we expect a positive relationship between the target and the peer firm's earnings management, implying a positive correlation in measures of earnings management:

H1*: Firms are more likely to engage in earnings management when the peer firms used in relative performance evaluation also engage in earnings management.*

The earnings manipulation relationship weakens when there are large idiosyncratic shocks to earnings of either the target firm or its peers. Since our focus is to model the earnings management behavior of the target firm, we are primarily concerned about the impact of large earnings shocks to the target firm on contagion in financial reporting quality:

H2*: The similarity in the earnings quality measures of a target firm and its peers will be lower in periods when the target firm experiences substantially different earnings shocks from the peer firms.*

To empirically test the first hypothesis, we examine the base-level correlation in earnings management between the target and the peer firms. We conduct a number of tests to address endogeneity concerns related to peer selection and measurement error in earnings management. To test the second hypothesis, we use absolute differences in accounting and price-based performance measures to assess how the base-level relationship changes when there is divergence in performance.

While our stylized model demonstrates how an equilibrium of strategic complementarity and substitutability can emerge based on performance shocks, it does have its limitations. To keep the model tractable, we assume that the financial incentives and the costs associated with earnings management (parameters b and c) are the same for both the target and peer firms. This assumption simplifies the analysis but overlooks the potential differences in incentives and costs across firms. As we have outlined earlier, variations in financial incentives can significantly influence whether strategic complementarity or substitutability occurs. Managers in firms facing significantly different financial incentives and costs may be less inclined to mimic their peers' earnings management practices, leading to strategic substitutability. For instance, if the target firm is under investigation by the SEC but its peers are not, then the target firm would be less likely to mimic the behavior of its peers. Similarly, when the expected pay-off to outperforming the peers is either very high or very low, we would expect divergence in earnings management practices. Thus, our third hypothesis focuses on the impact of firm-specific variations in incentives and costs on financial reporting quality. This allows us to better understand the conditions under which earnings management contagion occurs:

H3*: The similarity in the earnings quality measures of a target firm and its peers will be lower when there are significant differences in financial incentives and costs associated with earnings management between the target and peer firms.*

To test the third hypothesis, we use measures of financial incentives and costs associated with earnings management. First, we use the portion of a target CEO's compensation tied to RPE grants as a proxy for financial incentives to respond to their peers' earnings management practices. Second, we investigate whether the number of peers used in compensation contracts can affect the target firm's ability to mimic peer behaviors. A larger number of peers diffuses the economic incentives and makes it challenging for managers to anticipate and respond to each peer's earnings management strategies. It is also more likely that there will be greater divergence in financial incentives, costs, and shocks with a larger number of peers. Third, we investigate how costs of earnings manipulation affect contagion in financial reporting quality. In doing so we use an indicator variable representing whether the target firm was investigated by the SEC in the past three years. Prior investigations suggest increased scrutiny and higher potential costs if further manipulation is detected. Finally, we investigate the impact of offering similar financial incentives to both the management team of the target firm and the peer firm. In our sample, several peer firms use RPE grants in their own compensation contracts, and a subset of these firms cross-reference the target firm as a peer. When peer firms also use RPE grants and include the target firm as a peer, both sets of managers face mutual pressures to outperform each other. This mutual referencing should intensify the economic incentives to engage in earnings management, leading to a contagion effect where firms increasingly mimic each other's practices.

Identifying peer effects in corporate earnings management is empirically challenging as earnings management is an endogenous choice variable. The selection of peers by the target RPE firm is also endogenous and there could be unobserved factors that drive both peer selection and the earnings management decision. Unlike many studies that proxy for peers using industry classification and firm size, we identify actual peers from proxy statements exploiting the 2006 SEC mandate to disclose details of relative performance grants. Using actual peers allows us to control for industry and firm fixed effects and isolates RPE grants as the channel through which peers' behavior affects the firm's earnings reporting quality. By doing this, we can show that firms' contracting practices with management have a direct impact on earnings management decisions and contagion in financial reporting quality.

3. Data

Information about peer groups used in this study comes from Incentive Lab. The dataset contains information from DEF 14A proxy statements on the various aspects of stock, option and cash grants awarded to CEOs and other senior executives. Incentive Lab database covers S&P 1,500 firms for the years 1998 to 2016. We focus on the period after 2006. In that year, the SEC implemented new disclosure rules requiring firms to provide details on performance targets used in executive compensation contracts. Starting in 2006, we can obtain details about the characteristics of the relative performance evaluation (RPE) targets including the lists of peer firms.

Explicit relative performance awards have become a critical component of executive pay. As Figure 1 shows, there has been a steady increase in the use of RPE from 2006 to 2016. A significant percentage of the firms in the dataset use RPE in their executive compensation contracts. In 2016, for instance, 50% of the firms used some form of RPE. On average, RPE grants account for 38% of fair value of all grants awarded and 32% of the total compensation of the CEOs in 2016. The characteristics of the performance benchmark to evaluate relative performance are also specified in the dataset. Around 70% of the firms that implement RPE use peer firms as benchmarks.

On average, each firm has fifteen peers in a given year. There is significant turnover in selected peers over time. 14% of the peers are added or dropped from the peer list each year. Incentive Lab also provides information on the metrics used for performance evaluation. The majority of performance metrics used are either a firm's stock return or an accounting performance measure such as a firm's EPS.

Stock return is used as a metric in 61% of the RPE grants. In majority of the contracts, the median peer is specified as the target threshold.

Since we are interested in how the earnings quality of a firm is impacted by the earnings quality of its peers, we limit our sample to the set of firms that utilize RPE compensation contracts and in particular, to the subset of firms that use a set of peer firms to assess relative performance.[3] After matching with CRSP and Compustat, our final sample consists of 323 firms and 1,466 observations over the 2006 to 2016 time period.

Our principal measure of financial reporting quality is discretionary accruals using the modified Jones (1991) measure proposed by Dechow, Sloan, and Sweeney (1995). We compute discretionary accruals (DAM) by subtracting nondiscretionary accruals from total accruals. To do so, we run the following cross-sectional regression:

$$TA_{i,t} = b_1\left(\frac{1}{AT_{i,t-1}}\right) + b_2\left(\Delta REV_{i,t} - \Delta REC_{i,t}\right) + b_3 PPE_{i,t} + \varepsilon_{i,t} \qquad (6)$$

where $TA_{i,t}$ is total accruals in year t, $AT_{i,t-1}$ is total assets in year $t-1$, $\Delta REV_{i,t}$ is the change in revenues from year $t-1$ to year t scaled by total assets in year $t-1$, $\Delta REC_{i,t}$ is the change in net receivables from year $t-1$ to year t scaled by total assets in year $t-1$, and $PPE_{i,t}$ is the gross property plant and equipment in year t scaled by total assets in year $t-1$. Total accruals in year t are computed as:

$$TA_{i,t} = \frac{\Delta CA_{i,t} - \Delta CL_{i,t} - \Delta Cash_{i,t} + \Delta STD_{i,t} - Dep_{i,t}}{AT_{i,t-1}} \qquad (7)$$

[3] Although some firms use index level returns or industry level performance measures in their RPE compensation contracts, such firms would not be included in our sample.

where $\Delta CA_{i,t}$ is the change in current assets, $\Delta CL_{i,t}$ the change in current liabilities, $\Delta Cash_{i,t}$ the change in cash and cash equivalents, $\Delta STD_{i,t}$ the change in debt included in current liabilities, and $Dep_{i,t}$ the depreciation and amortization expense.

We estimate Equation (6) on an industry-year basis, where industry is defined using the first two digits of the SIC code. We require the number of firms in an industry in any given year to be at least ten and all three independent variables to be available to run the regression. Since the independent variables capture how changes in the firm's economic circumstances influence non-discretionary accruals, the residuals from this regression proxy for discretionary accruals.

Although the discretionary accrual measure described in Equation (6) is our main variable of interest, we also use a number of alternative real earnings management measures. To receive RPE grants, managers could overstate earnings through overproduction, channel-stuffing and reducing discretionary expenses. Following Huang et al. (2020), we estimate a company's degree of abnormal discretionary expenses and abnormal production costs and construct an aggregate index combining them. Following Huang et al. (2020) and Kothari et al. (2016), we run the following regression to estimate abnormal discretionary expenses:

$$DiscExp_{i,t} = b_0 + b_1 DiscExp_{i,t-1} + b_2\left(\frac{1}{AT_{i,t-1}}\right) + b_3 Sales_{i,t} + \varepsilon_{i,t} \tag{8}$$

where $DiscExp_{i,t}$ is the sum of advertising expense, R&D expense and SG&A expense, scaled by lagged total assets; $DiscExp_{i,t-1}$ is its lagged value; $AT_{i,t-1}$ is total assets in year $t-1$; $Sales_{i,t}$ is sales in year t scaled by lagged total assets. We estimate the model above each year. The residual reflects a firm's deviation from the cross-sectional mean for that year. After subtracting the mean value of the residual across all years for the firm, we obtain abnormal discretionary expenses for the firm.

Following Huang et al. (2020) and Kothari et al. (2016), we run the following regression to estimate abnormal production costs:

$$Prod_{i,t} = b_0 + b_1 Prod_{i,t-1} + b_2\left(\frac{1}{AT_{i,t-1}}\right) + b_3 Sales_{i,t} + b_4 \Delta Sales_{i,t} + b_5 \Delta Sales_{i,t-1} + \varepsilon_{i,t} \quad (9)$$

where $Prod_{i,t}$ is the sum of COGS and change in inventory during year t scaled by lagged total assets; $Prod_{i,t-1}$ is its lagged value; $AT_{i,t-1}$ is total assets in year $t-1$; $Sales_{i,t}$ is sales in year t scaled by lagged total assets; $\Delta Sales_{i,t}$ is sales growth scaled by lagged total assets; $\Delta Sales_{i,t-1}$ is the lagged value of $\Delta Sales_{i,t}$. We estimate the model each year. The firm-year residual minus the average of the residual across all years for the corresponding firm yields abnormal production costs for a given firm. Following Huang et al. (2020), we combine abnormal discretionary expenses and abnormal production costs to estimate a firm's overall real earnings management.

In addition to these measures, we also use in our analyses three additional financial reporting quality measures commonly utilized in the literature. The first of these is a financial reporting quality measure that captures the likelihood that a firm will restate its financial statements (Dechow, Ge, and Schrand 2010). *Restate* is a dummy variable set to 1 if a fiscal year overlaps with an identified restatement period as recorded by the Audit Analytics "Non-Reliance" database, and zero otherwise. The second is the *Restatement Amount*, which is the natural logarithm of the cumulative misstatement amount for a restatement event. The third additional measure of financial reporting quality we utilize is the Dechow and Dichev (2002) quality of accruals. Following Dechow and Dichev (2002), we run the firm-specific regressions as follows:

$$\Delta WC_{i,t} = b_0 + b_1 CFO_{i,t-1} + b_2 CFO_{i,t} + b_3 CFO_{i,t+1} + \epsilon_{i,t} \qquad (10)$$

where $\Delta WC_{i,t}$ is change in working capital, measured as $\Delta WC = \Delta Accounts\ Receivable + \Delta Inventory - \Delta Accounts\ Payable - \Delta Taxes\ Payable + \Delta Other\ Assets$, $CFO_{i,t-1}$ is one-period lag cash flow from operations, $CFO_{i,t}$ is cash flow from operations in the current year, and $CFO_{i,t+1}$ is cash flow from operations in the next year. The DD accruals are computed as the standard deviation of these residuals. A higher standard deviation indicates lower quality of earnings.

In all our analyses, we control for a number of firm characteristics commonly used in the literature. These firm level variables are obtained from CRSP and Compustat databases. *Size* is the natural logarithm of total assets. *BM* is the book value of equity divided by market value of equity. *ROA* is earnings before extraordinary items scaled by total assets. *EarningsVol* is the volatility of earnings over the past 3 years. *Leverage* is sum of market value of equity and book value of liabilities scaled by market value of equity. *Return* and *Return3y* are annual and annualized 3 year holding period returns. *Std* is annualized volatility computed using monthly stock returns over the past 3 years. *Beta* is the CAPM beta also computed using monthly returns over the past 3 years. *HHI* is the Herfindahl measure of customer concentration computed from Compustat "Customer Segments" database. It is computed as the sum of the square of sales to distinct customers as a percentage of revenues. *Institutional ownership* is the shares held by institutions divided by total shares outstanding. The data for institutional shares are obtained from Thomson Reuters and the data for total shares outstanding come from CRSP.

All the variables used in this paper are defined and explained in further detail in Table 1. In Table 2, we report the summary statistics of these variables for three samples. Panel A presents summary statistics for the sample of firms that use relative performance evaluation in executive compensation contracts. This is the sample of firms that we use in our analyses. Panel B presents summary statistics for all firms with data available in both the CRSP and Compustat databases. Panel C presents summary statistics for the S&P 1500 firms with data available in both the CRSP and Compustat databases. The latter sample is the sample of firms covered by Incentive Lab and includes firms that do not use RPE in executive contracts. As we would expect, compared to all the firms in the CRSP-Compustat universe, RPE firms are, on average, larger, and more profitable. RPE firms also have slightly higher leverage than the Incentive Labs sample average and have a slight growth tilt. Table 2 also shows that there is significant cross-sectional variation in RPE firm characteristics.

4. Empirical Results

4.1 The relation between earnings quality of RPE firms and their peers

We begin with a univariate analysis of how a given firm's earnings quality is correlated with the earnings quality of its peers. For each firm in our dataset, we compute the discretionary accruals using the modified Jones measure (*DAM*). We do the same for the firm's peers and compute the median accruals quality across the firm's peers (*Med Peer DAM*). We focus on the median peer performance, since, as mentioned earlier, a CEO is typically awarded grants based on the relative performance of her firm compared to the median performance of its peers.[4] We sort firms each year based on the target firm's DAM and form quintile portfolios. We then compute average Med Peer DAM values as well as averages for various firm characteristics for each quintile portfolio.

Table 3 reports mean values for the sorted portfolios. "L" in the table denotes the lowest discretionary accrual quintile and "H" corresponds to the highest discretionary accrual quintile. "H-L" column reports the difference between the highest and lowest discretionary accrual quintiles for each characteristic and the *t-Value* column reports the t-statistics of this difference. As the target firm's discretionary earnings management increases, there is a monotonic increase in the median peer firm's discretionary earnings management as well. The difference in Med Peer DAM between the high minus low portfolios is highly significant. Moreover, this relationship does not appear to be a simple function of other firm characteristics such as the book-to-market ratio, firm size, return on assets, earnings volatility, stock return, or leverage. The differences in these firm characteristics for the high minus low portfolios are all insignificant.

[4] The majority of RPE grants in our sample (roughly 70%) set the median as the target goal. Within our theoretical framework, in the absence of shocks, we would expect the firm's performance ranking to align with the target set by the company and while we believe that the median is a better measure than the average, we demonstrate that our results are robust when using the average peer discretionary accruals measure.

Next, we examine the relationship between target firm and peer earnings quality in a multivariate regression controlling for various firm characteristics. We run the following baseline regression:

$$DAM_{i,t} = \alpha + \theta Med\ Peer\ DAM_{i,t} + \beta X_{i,t} + \gamma_t + \delta_j + \varepsilon_{i,t} \tag{11a}$$

In Equation (11a) i, j, and t denote firm, industry, and year, respectively. $X_{i,t}$ are firm level controls described in Table 1 that are commonly used in explaining earnings management behavior (Du and Shen, 2017). Coefficients on the variables of interest in the second-stage of modified Jones accruals model regressions can be biased when there is non-zero covariance between the explanatory variables in the stage 1 regression (modified Jones model regression) and the control variables in the stage 2 regression. To control for this potential bias, we follow a solution suggested by Chen, Hribar, and Melessa (2018). Specifically, we include all the stage 1 regressors in the stage 2 regression (Equation 11a) as additional controls. All of the panel data regressions in the paper using discretionary accruals incorporate this methodology.

In the regression, γ_t controls for time (year) fixed effects and δ_j controls for industry fixed effects. We include time fixed effects to control for the impact of macroeconomic factors that could potentially lead to system-wide earnings management. Industry fixed effects control for all time-invariant industry related factors that could affect financial reporting quality for both the peer and the target firms. We would expect to find cross-sectional variation in earnings management across different industries. Since peer firms are selected mainly from the same industry as the target firm, peer effects could be driven by the common industry shocks shared by the RPE firm and its peer firms, hence the need to control for industry fixed effects.

In Equation (11a), we are interested in the coefficient θ which captures the effect of median peer earnings quality. The results from this regression are reported in column (1) of Table 4. The coefficient on the Med Peer DAM variable is both statistically and economically significant. A one standard deviation increase in the median peer discretionary accrual results in close to a 0.86 standard deviation increase in the discretionary accrual of the target firm. These results are consistent with our first hypothesis that earnings management by peers leads to greater earnings management by the target firm when performance goals in executive compensation contracts are set relative to the performance of the firm's peers.

Next, we show that our main result of peer effects in earnings management is robust to different specifications. First, we control for changes in median industry earnings quality. While industry fixed effects control for time-invariant levels of earnings quality at the industry level, a number of papers show evidence of industry-wide variation in earnings management.[5] We control for median industry earnings quality (Med Industry DAM) by running the following regression:

$$DAM_{i,t} = \alpha + \theta Med\ Peer\ DAM_{i,t} + \partial Med\ Industry\ DAM_{j,t} + \beta X_{i,t} + \gamma_t + \delta_j + \varepsilon_{i,t} \quad \text{(11b)}$$

The results are reported in column (2) of Table 4. Consistent with the findings in the literature, the coefficient on the Med Industry DAM variable is significant. The effect of the median peer earnings quality remains significant after controlling for industry wide earnings management. In other words, the impact of peers' financial reporting quality on the financial reporting quality of the target firm captures information regarding earnings management contagion above and beyond what is explained by industry effects.

To control for any time-varying industry effects, we include dummy variables ($\gamma_t \times \delta_j$) that interacts time and industry fixed effects. These fixed effects capture all time-varying heterogeneity within an industry including industry specific changes in technology and management, as well as changes in economic growth and volatility. We use the following regression specification:

[5] For example, Kedia, Koh, and Rajgopal (2015) show evidence of industry-wide contagion in earnings management. They link contagion to enforcement activity by the SEC.

$$DAM_{i,t} = \alpha + \theta Med\ Peer\ DAM_{i,t} + \beta X_{i,t} + \gamma_t \times \delta_j + \varepsilon_{i,t.} \tag{11c}$$

The results from this specification are reported in column (3) of Table 4. The coefficient on the Med Peer DAM variable again remains significant.

Next, we include firm fixed effects to control for firm specific factors that affect both the earnings management of the firm as well as the firm characteristics that could impact earnings management. Firm fixed effects would also control for omitted firm level factors that could affect the calculation of discretionary accruals. We run the following regression:

$$DAM_{i,t} = \alpha + \theta Med\ Peer\ DAM_{i,t} + \beta X_{i,t} + \gamma_t + \vartheta_i + \varepsilon_{i,t} \tag{11d}$$

In equation (11d), ϑ_i are firm fixed effects. The results are reported in column (4) of Table 4. After controlling for firm specific factors, the effect of peer earnings quality, once again, remains significant.

Next, we include firm fixed effects along with the interaction of industry and time fixed effects. This setting controls for potential peer selection biases that could result from time invariant firm characteristics as well as all time varying industry effects simultaneously. We run the following regression:

$$DAM_{i,t} = \alpha + \theta Med\ Peer\ DAM_{i,t} + \beta X_{i,t} + \gamma_t \times \delta_j + \vartheta_i + \varepsilon_{i,t.} \tag{11e}$$

Above, ϑ_i are firm fixed effects, while the $\gamma_t \times \delta_j$ term captures the interaction of time and industry fixed effects. The results are reported in column (5) of Table 4. After controlling for firm-specific factors as well as the interaction of time and industry fixed effects, the effect of peer earnings quality on target firm financial reporting quality again remains significant.

Next, we conduct a robustness test by replacing the median discretionary accruals measure of the target firm's peers with the average value of the discretionary accruals measure of the peer firms (*Avg Peer DAM*). We run the following regression with industry and time fixed effects:

$$DAM_{i,t} = \alpha + \theta Avg\ Peer\ DAM_{i,t} + \beta X_{i,t} + \gamma_t + \delta_j + \varepsilon_{i,t} \quad (11f)$$

Above, γ_t captures time fixed effects while δ_j captures industry fixed effects. The results are reported in column (6) of Table 4. The coefficient on *Avg Peer DAM* is economically and statistically similar to the coefficient on *Med Peer DAM* in column (1).

Finally, we conduct another robustness test by estimating the coefficient of interest using target-peer-year level regressions.[6] Nevertheless, to show that our results are robust to using target-peer level sample, we replicate our analysis in column (1) by conducting the analysis at the target-peer level, with results reported in column (7) of Table 4. The dependent variable $DAM_{i,t}$ is the same as in the rest of the columns as it captures the discretionary accrual level of a target firm in a given year while the independent variable of focus is $Peer\ DAM_{i,p,t}$ which is the discretionary accrual measure of a given peer (*p*) firm. The rest of the independent variables are the same as in other columns. We run regression 10 (g) with industry and time fixed effects using all target-peer pairs in a given year:

$$DAM_{i,t} = \alpha + \theta\ Peer\ DAM_{i,p,t} + \beta X_{i,t} + \gamma_t + \delta_j + \varepsilon_{i,t} \quad (11g)$$

Overall, the results are qualitatively similar and statistically highly significant. Although the average economic significance is lower, these results suggest that our main findings are robust to utilizing target-peer-year level regressions.

We also examine the impact of the metrics used in the RPE compensation contracts on the contagion effect between the target and peer firms. Our results show that the contagion effect is not

[6] Doing the analyses at the target-peer level has both advantages and disadvantages. Conducting the analysis at the peer level retains all available information. However, there is a downside as this information is one-sided: while there is variation in the peers' earnings management measures, the target firm's earnings management measure remains constant. Running a regression at the peer level can therefore inflate statistical significance. Additionally, the number of peers varies across firms, which can introduce additional biases into the estimation as it can lead to overweighing the influence of certain target firms with large numbers of peers.

significantly different between those using stock price metrics and those using other performance metrics. When focusing exclusively on accounting metrics, we find a significantly higher (lower) contagion effect for earnings-based metrics (non-financial performance metrics).

Results in Section 4.1, presented in Tables 3 and 4, confirm our prediction in hypothesis 1 since we verify that firms are more likely to engage in earnings management when the peer firms used in relative performance evaluation also engage in earnings management.

4.2 The impact of earnings shocks on FRQ contagion

Our model suggests that when there are large differences in the earnings shocks experienced by the target and the peer firms, we expect to observe a divergence in the direction of earnings manipulation by the target and the peer firms. This leads to a breakdown in the correlation between the target and peer firms' earnings manipulation choices.

To test hypothesis 2, we investigate the impact of performance differences between the target firm and each of its peers on the correlation of their financial reporting quality. Specifically, in Table 5, we run target-peer-year level regressions of the target firm's discretionary accrual measure (*DAM*) on each of the target firm's peers' discretionary accrual measures (*Peer DAM*) as well as the interaction of Peer DAM with the performance differential between the target firm and the peer firm in that period. Every period we calculate the absolute value of the performance differential between the target firm and each of its peers using an accounting (return on assets *ROA*) and a market based (*Stock Return*) performance metric. The absolute value difference between ROA and Stock Return values of the target firm and its peer in a given year is *Abs Difference ROA* and *Abs Difference Return*, respectively. Columns (1) and (2) report the regression results where the absolute performance difference measure is either *Abs Difference ROA* or *Abs Difference Return*.

In Table 5, we focus on the marginal impact of the absolute performance difference between the target and the peer firms on the strength of the contagion of financial reporting quality. Thus, the emphasis is on ∂ which is the coefficient on the interaction of the performance measure with the median discretionary accrual value of the target firm's peer firms. We control for industry and year fixed effects and run a regression model following Equation (12):

$$DAM_{i,t} = \alpha + \theta Peer\ DAM_{i,t} + \partial Peer\ DAM_{j,t}\ X\ Performance_{i,t} + \beta X_{i,t} + \gamma_t + \delta_j + \varepsilon_{i,t} \quad (12)$$

In column (1) of Table 5 *Performance* is calculated using an accounting based measure, $Abs\ Difference\ ROA_{i,t}$, while in column (2) we calculate *Performance* using a stock return based measure, $Abs\ Difference\ Return_{i,t}$. Both models (1) and (2) control for industry and year fixed effects. The coefficients on both interaction terms, where $Peer\ DAM_{j,t}$ is interacted with either $Abs\ Difference\ ROA_{i,t}$ or $Abs\ Difference\ Return_{i,t}$, are negative and statistically significant. These results suggest that when target firms experience earnings shocks that are significantly different from their peers, they are less likely to mimic their peers. Overall, results in Table (5) lend support to hypothesis 2.

To further verify our findings in Table 5 we conduct a robustness analysis in Appendix Table A1 and analyze the impact of experiencing extreme earnings surprises (*EES*) by the target firm on financial reporting quality contagion. *EES-dummy* is equal to one if the target firm's standardized unexpected earnings (*SUE*) ranks either in the top 5th (10th) percentile or in the bottom 5th (10th) percentile of all *SUE*'s in the cross section of all stocks in our sample in that given year. In Appendix Table A1, columns (1) and (2) report the regression results where the *EES-Dummy* is equal to 1 if the target firm's earnings surprise falls into either the top or the bottom 5th (10th) percentile of the earnings surprise in the sample. The coefficient on the $Med\ Peer\ DAM_{j,t}\ X\ EES - dummy_{i,t}$ is negative and statistically significant in both specifications suggesting that when target firms experience large idiosyncratic earnings shocks, rather than mimic their peers their earnings management choices deviate from them. Results in Table A1 are consistent with our findings in Table 5, further supporting our predictions in Hypothesis 2.

4.3 Impact of costs and benefits of earnings management on FRQ contagion

In, Hypothesis 3, we predict that FRQ contagion will be lower when the target and peer firms face different financial benefits and costs from earnings management. We use proxies for financial incentives and costs linked to earnings management. First, the proportion of a target CEO's compensation tied to RPE grants represents financial incentives. Second, the number of peers in a CEO's compensation contract, where more peers dilute incentives and make earnings strategies harder to predict. Third, an indicator of SEC investigations in the past three years signals higher costs from scrutiny and potential penalties. Finally, whether peer firms use RPE grants and include the target firm as a peer, where mutual referencing and similar compensation structures heighten incentives, while their absence likely reduces contagion effects.

To assess our hypothesis, we use the model in equation 13 and focus on ∂ which is the coefficient on the interaction of the variable of interest (*Interaction_Variable*) with the median discretionary accrual value of the target firm's peer firms ($Med\ Peer\ DAM$):

$$DAM_{i,t} = \alpha + \theta Peer\ DAM_{i,t} + \partial Peer\ DAM_{j,t} \times Interaction\_Variable_{i,t} + \beta X_{i,t} + \gamma_t + \delta_j + \varepsilon_{i,t} \tag{13}$$

In column (1) of Table 6, the $Interaction\_Variable_{i,t}$ is $RPE\ Percent\ dummy$ and the interaction term is $Med\ Peer\ DAM_{j,t} \times RPE\ Percent\ dummy$. *RPE Percent dummy* is equal to one if RPE grants account for 8% (70%) of a manager's total compensation, corresponding to the 10^{th} (90^{th}) percentile in the distribution of RPE compensation ratio as a percentage of the total managerial compensation. *RPE Percent dummy* is equal to one only for those firms that utilize RPE contracts either heavily or very little as a percentage of total executive compensation. The coefficient on the $Med\ Peer\ DAM_{j,t} \times\ RPE\ Percent\ dummy_{i,t}$ term is negative and economically significant, yet statistically insignificant. This result suggests that contagion of financial reporting quality is likely to be weaker for firms that are more dissimilar to their peers in their financial incentives. This finding is in line with the prediction of Hypothesis 3 as the benefit to mimic peers should be higher for those firm managers whose compensation depends more on outperforming their peers, but fails to provide statistical confirmation.

Next, we investigate the impact of the number of peer firms on financial reporting quality contagion. We hypothesize that the number of peers used in compensation contracts will affect the target firm's ability to mimic peer behaviors. A larger number of peers should diffuse the economic incentives and make it challenging for managers to anticipate and respond to each peer's earnings management strategies. We also expect greater divergence in financial incentives, costs, and shocks as the number of peer firms increases. Thus, we predict that such divergence should reduce contagion in financial reporting quality. We investigate this hypothesis empirically in column (2) of Table 6, using the same model set-up utilized in Equation (13). In this case the interaction term equals $Med\ Peer\ DAM_{j,t} \times\ Number\ of\ Peers\ Dummy$.

Number of Peers Dummy is equal to 1 if the target firm has more than thirty peers, corresponding to the 90th percentile of the number of peers in the sample. The independent variables of focus are the median discretionary accrual measure of peers ($Med\ Peer\ DAM$), the *Number of Peers of Dummy* and their interaction term. The coefficient on the $Med\ Peer\ DAM_{j,t} \times\ Number\ of\ Peers\ of\ Dummy_{i,t}$ interaction term is negative and statistically significant, indicating that contagion of financial reporting quality is weaker for firms that have too many peers as having a very large number of peers leads to divergent economic incentives, costs and shocks for the target firm with respect to their peers and such divergence leads to a reduction in financial reporting quality contagion, as predicted.

Next, we investigate how costs associated with earnings manipulation impact contagion in financial reporting quality. Specifically, we hypothesize and empirically show that contagion in FRQ is lower for firms that are under scrutiny, as these firms' earnings management activities are more likely to be discovered, and they are more likely to face harsher penalties if discovered. In column (3) of Table 6 *Interaction_Variable* is the *SEC Investigation Dummy*. *SEC Investigation Dummy* is equal to 1 if the target firm was investigated by the SEC at any point in the prior 3 years. The coefficient on the $Med\ Peer\ DAM_{j,t} \times SEC\ Investigation\ Dummy_{i,t}$ term is negative and statistically significant indicating that contagion of financial reporting quality is weaker for firms where the economic costs to manipulate financial reporting quality are higher. Managers under close scrutiny find it costly to mimic their peers.

The results in Table 6 document that there are cross sectional differences across firms in their willingness to mimic their RPE peers and that these differences in actions are ultimately tied to incentives, the costs and benefits of earnings manipulation.

Next, we test to see if the compensation practices of peer firms affect the strength of the relationship between the earnings management choices of peer and target firms. First, we examine the impact of having peer firms that use RPE in their own compensation contracts on the target firm's earnings management behavior. Second, we focus on peer firms that not only use RPE in their managers' compensation contracts but also cross-reference the target firm as their own peers in their managers' compensation contracts and analyze the impact of such cross-referencing on the earnings management decisions of target firms.

We expect the earnings quality of firms that cross-reference the target firm as a peer to have a greater impact on the earnings quality of the target firm. When peer firms manage earnings to outperform the target firm, managers at the target firm would also be motivated to inflate their own performance to meet or exceed market expectations or to achieve the benchmark set in the compensation contract. We expect this effect to be magnified when the peer firm has the target firm as its own peer. Since under our first hypothesis, peer firms also respond to the earnings management by the target firm, these joint ties should result in a cycle of earnings management contagion. A similar, but more subdued, effect could occur if the peer firm uses relative performance evaluation in its own contracts without cross-referencing the target firm.[7] To assess these conjectures, we run the following regression:

$$\begin{aligned} DAM_{i,t} = \alpha + \theta Med\ Peer\ DAM_{i,t} + \partial Med\ Mutual\ Peer\ DAM_{i,t} \\ + \varphi Med\ Non\_mutual\ RPE\ Peer\ DAM_{i,t} + \beta X_{i,t} + \gamma_t + \vartheta_i + \varepsilon_{i,t} \end{aligned} \tag{14}$$

In Equation (14), *Med Mutual Peer DAM* is the median DAM of the peer firms that also use the target firm as a peer in relative performance evaluation. *Non-mutual RPE Peer DAM* is the median DAM of the peer firms that use relative performance evaluation grants in executive compensation but do not cross-reference the target firm as their peer. Since we control for the median peer DAM in this regression, the coefficient on the *Med Mutual Peer DAM* variable captures the incremental impact of peers that mutually benchmark while the coefficient on the *Non-mutual RPE Peer DAM* variable captures the incremental impact of peers that use relative performance evaluation in their compensation contracts without mutual benchmarking.

[7] To illustrate, consider the following example: Firm A uses Firms B, C, and D as benchmarks for RPE grants. Firm B includes Firms A, C, and D in its RPE evaluations. Firm C uses RPE grants but does not reference Firms A, B, or D as peers. Firm D does not use RPE grants. In this example, we would expect the highest correlation in earnings management practices between Firms A and B (mutual referencing and use of RPE grants). A moderate correlation between Firms A and C (Firm C uses RPE grants but does not reference Firm A). The lowest correlation between Firms A and D (Firm D does not use RPE grants).

The results are reported in Table 7. In the first column, we report results for the specification that includes the *Med Mutual Peer DAM* variable but excludes the *Non-mutual RPE Peer DAM* variable. We find that the coefficient on *Med Mutual Peer DAM* is positive and economically as well as statistically significant, suggesting that the earnings quality of peer firms that mutually benchmark should have a significant incremental impact on the earnings quality of the target firm, even after controlling for the median of peer firms' discretionary accruals. This result supports hypothesis 3 finding enhanced contagion effects when peers benchmark each other. The specification reported in column (2) includes the *Non-mutual RPE Peer DAM* variable but excludes the *Med Mutual Peer DAM* variable. These firms are peers of the target firm and use RPE in compensation contracts, but they do not cite the target as a peer firm. After controlling for the median DAM of peers, we find the additional effect of these peers on the target firm's earnings management behavior to be insignificant. These results are consistent with our hypothesis stated in H3. Non-mutual peers have no incentive to respond to earnings management of the target firm, since the reward associated with beating the target firm is 0. Compared to mutual peers, the reward for non-mutual peers differs more from that of the target firm. This divergence causes the contagion effect between the non-mutual peers and the target firm to be smaller than that between mutual peers and the target firm. To confirm this result, in column (3), we include both the *Mutual Peer DAM* and the *Non-mutual RPE Peer DAM* variables. We find that the *Mutual Peer DAM* variable retains its significance in this specification.

Finally, we investigate how the contagion effect changes when the target firm uses a broad index as a benchmark. Similar to the impact of using a large number of peers on FRQ contagion we would expect the contagion effect to be lower when a target firm uses a broad index as a benchmark since the economic incentives to mimic the earnings manipulation behavior of index constituents would be much more diffuse. Table 8 provides an analysis of target firms that use the S&P 500 index as a benchmark.

The table reports the regression results of estimating the target firm's DAM on the median DAM for the S&P 500 firms (Column 1), the market capitalization weighted average DAM of S&P 500 firms (Column 2), and the asset value weighted average of DAM of S&P 500 firms (Column 3).

Consistent with the notion that it is harder to mimic financial reporting practices of a broad index, we find that the average and the median DAM of S&P 500 firms have no statistically significant impact on the DAM of the target firm. Contagion in financial reporting quality in RPE peer groups requires the target firm and its peers to compete against each other and to manage their actions accordingly. Such mutual interaction is very difficult when the target firm references a broad index.

4.4 RPE initiations in compensation contracts

Our analyses could suffer from a potential endogeneity problem in selecting peers. In particular, target firms may choose peers with similar financial reporting quality to theirs, which could influence our empirical findings.

We conduct additional analyses to address potential endogeneity issues associated with the selection of peers. Specifically, we examine the relationship between the target firm DAM and the median DAM of its peers a year before and a year after RPE adoption using a difference-in-difference specification. If our hypothesis is correct, we would expect a significant increase in the strength of the relationship between the earnings management behavior of the target firm and that of its peer firms after the target firm adopts RPE-based compensation contracts. For the year before a target firm adopts RPE, we use the same set of peers the target firm chooses in one year after adoption. We estimate the following difference-in-difference specification:

$$\begin{aligned} DAM_{i,t} = \alpha + \theta_1 Med\ Peer\ DAM_{i,t} + \theta_2 After_t + \theta_3 After_t \times Med\ Peer\ DAM_{i,t} \\ + \beta X_{i,t} + \gamma_t + \vartheta_i + \varepsilon_{i,t} \end{aligned} \tag{15}$$

Above, $X_{i,t}$ are firm level controls, ϑ_i and γ_t are the firm and year fixed effects described earlier. The variable *After* takes on a value of one for the year after a target firm adopts RPE. The variable of interest is the interaction term *After×Med Peer DAM* which captures the initiation of the contagion effect after the target firm adopts RPE in executive compensation. Column (1) in Table 9 reports the main results of this test. When we examine this coefficient, we find that the covariance between the earnings management behavior of the target firm and the median financial reporting quality of its peer firms increases significantly after the target firm adopts RPE-based compensation contracts for its executives.

To validate that our finding is attributable to the adoption of RPE based compensation contracts and not driven by other factors, we repeat the analyses conducted in column (1) using counterfactual RPE adoption years. Using counterfactual years after the actual RPE adoption is not possible since the increase in the covariance documented in column (1) would persist in the post actual RPE adoption year period. Therefore, we choose as counterfactual RPE adoption event years those years that precede the actual RPE adoption event. Specifically in column (2) we use three years prior to the actual RPE adoption as the counterfactual adoption year and in column (3) we denote five years prior to the actual RPE adoption as the counterfactual adoption year. In both columns (2) and (3) the "After" year dummy equals one in the years the target firm counterfactually adopts RPE based compensation contracts and zero otherwise. In both specifications we find the *After×Med Peer DAM* interaction term to be statistically insignificant. These results suggest that the increase in the documented covariance of the financial reporting quality measures of the target firm and its peers subsequent to the actual adoption of RPE based executive compensation contracts is unlikely to be random.

4.5 Alternative measures of earnings quality

We verify our main findings using three alternative measures of earnings quality. Specifically, we proxy the target firm's earnings quality with its real earnings management activity and three additional measures of reporting quality: One of the additional measures is the Dechow-Dichev (2002) accrual measure, the second measure captures the likelihood that a firm will restate its financial statements, and the third measure is the earnings restatement amount.

In Table 10, we first examine if there exists correlated behavior in the real earnings management activities of the target firm and its peer firms. Columns (1) through (3) report the regression results of the target firm's abnormal discretionary expenses, abnormal production costs, and abnormal real earnings management on the median of the RPE peers' corresponding values, respectively. These variables are described in detail in Section 3. For all three analyses we find that there is strong covariance in the real earnings management behaviors of the target firm and its peers, suggesting that the impact of RPE-based compensation contracts may lead not only to higher covariance in financial reporting quality amongst peers but also to significant co-movement in real earnings management behaviors.

In results reported in columns (4) and (5) we use the Dechow and Dichev (2002) discretionary accruals and restatements as alternative proxies of financial reporting quality. In column (4) we run the regression of the target firm's Dechow and Dichev (2002) discretionary accruals on the median level of their peers' Dechow and Dichev (2002) discretionary accruals. Results in column (4) suggest that using the Dechow and Dichev (2002) measure of discretionary accruals does not qualitatively change our main findings. In column (5), the *Restate* dummy is set to one in a fiscal year if the target firm restates earnings in that year. The *Peer Restate* dummy variable captures the impact of peers and is set to one if any peer firm restates earnings in the same fiscal year. As *Restate dummy* is a binary outcome variable, we run a logistic regression and report its pseudo-R squared value in the fifth column of Table 10. We find a significant association between the incidence of peers' restatements and the incidence of the target firm's restatements. Finally, in column (6) of Table 10 we investigate the relationship between the target firm's earnings restatement amount (*Restatement Amount*) and the median amount of restatement for the peer firms (*Med Peer Restate Amount*). We calculate the restatement amount as the natural logarithm of the cumulative misstatement amount for all firms. The regression includes only firms that have restated provided that the misstatement amount is available. We find an economically and statistically significant relationship between the target's restatement amount and the median restatement amount of its peers. Overall, the results in Table 10 show that our main findings are robust to alternative measures of financial reporting quality.

We expect that herding in earnings management behavior is correlated with herding in voluntary disclosure decisions as earnings management behavior and voluntary disclosure activity are closely related to each other. Kasznik (1999) documents an association between management earnings forecasts and earnings management activity. Since we contend that using RPE compensation contracts will lead to contagion in financial reporting quality of peer firms, we expect a similar contagion effect in voluntary reporting quality as well. We test this conjecture and report the results in Appendix Table A2.

We use frequency, timeliness, precision, accuracy, and bias of management earnings forecasts to capture voluntary disclosure quality. In the first column of Table A2 we use the frequency or the number of predictions a company makes during a fiscal year as our dependent variable. We measure the impact of peers using the variable *Freq pct* which is the percentage of peers having made at least one prediction during the same fiscal year. Consistent with Seo's (2021) results on industry peer effects, we find that the higher the percentage of peers making a prediction during a fiscal year, the higher the RPE target firm prediction frequency. In results reported in columns (2), (3), (4) and (5) of Table A2, we use the horizon, range, bias, and error of earnings forecasts by the target firm as alternative dependent variables that proxy for financial reporting quality. To control for the effect of peers, we use the median values of horizon, range, bias and error of earnings forecast of peer firms, respectively. Using all five alternative measures of voluntary reporting quality, we find a strong positive relationship between the voluntary reporting quality of peer firms and that of the target firm. All are statistically significant except for horizon. Taken together, these findings suggest that our results are robust to utilizing alternative measures of financial reporting quality.

4.6 Counterfactual peers as a control group

Although firm fixed effects control for time-invariant determinants, there could still be time-varying firm characteristics that are unobservable that could drive our findings. For instance, there could be changes in monitoring capacity or changes in the incentives of the board to monitor the CEO. These changes could simultaneously lead to both higher levels of earnings management at the firm as well as selection of peers that are likely to engage in earnings management. To address such potential endogeneity issues associated with the selection of peers, we create a set of counterfactual peers and examine if our main results continue to be significant when we control for earnings management of counterfactual peers.

We construct a set of counterfactual peers using three different approaches. First, we do propensity score matching (PSM) based on key firm characteristics that have been shown to drive peer selection. We choose counterfactual peers on how close they are to the actual peers based on these characteristics. These counterfactual peers represent peer firms that could have been selected by the firm but were not.

Second, we use the fact that firms are added and dropped over time from the RPE peer group. We create a list of counterfactual peers using firms that used to be in the peer group in the past but were dropped from the peer list at some point and are no longer listed as peers. If our main hypothesis is correct that compensation is the main channel through which peers affect the firm’s earnings quality, then we would expect earnings management by counterfactual peers to have no significant impact on the firm’s earnings quality. For instance, if a peer is managing earnings, we would expect it to have an impact on the firm’s earnings quality in the year in which it is in the firm’s peer group. But, once a peer firm is dropped from the peer list, we would not expect the dropped peer firm to have an impact on the target firm's earnings management behavior in the subsequent years.

Third, we follow Cadman and Carter (2014) and construct a list of counterfactual peers using peers' peers. If the contagion effect between the target firm's financial reporting quality and the peers' financial reporting quality is due to their similarity, we would expect that the target firm would also be similar to the peers of its own peers. In that case, we would expect to find a significant relationship between the discretionary accruals of the target firm and those of the peers of its peers. However, if the covariation between the discretionary accruals of the target firm and those of its peers can be explained through the RPE-based compensation channel, then we should not find a significant association between the financial reporting quality of the target firm and the earnings management behavior of its peers' peers.

Finally, following Bloomfield, Guay and Timmermans (2022), we construct a set of counterfactual peers from among firms in the same industry that have the largest return correlations with the target firm. We begin with a pool of potential peers from the same industry as the target firm. We calculate pairwise stock return correlations between each potential peer and the target firm, and add peers to the group iteratively, starting with the most highly correlated peer. We stop when the equal-weighted portfolio of peers exhibits the highest in-sample stock performance correlation with the target firm.

For the propensity score matching, we utilize key characteristics that have been shown to drive peer firm selection (Gong, Li, and Shin, 2011; Bizjak et al. 2022). Since the main motivation for using RPE-based compensation contracts is to filter out common shocks (Holmstrom 1982, Holmstrom and Milgrom 1987), counterfactual peer firms should be in the same industry, more likely to be included on the same stock index and should have stock returns that are highly correlated with those of the target firm. Furthermore, we also use firm characteristics that capture similarities in performance, risk, growth opportunities, and capital raising capacity to construct the counterfactual peer list. In particular, we use firm size (*Size*), book-to-market ratio (*BM*), average annual return over the past three years (*Return 3y*), annual volatility (*Std*), CAPM-beta (*Beta*), institutional ownership ratio (*IOR*) as well as customer concentration (*HHI*) in the creation of the propensity score.

We create three sets of firms– i) target firms, ii) actual peers of the target firms, and iii) all other firms in the CRSP-Compustat universe that are not target firms or peers of the target firms. Appendix Table A3 shows the mean values of firm characteristics for these three sets of firms. The mean values for firms in the CRSP-Compustat universe that are not target firms or their peers are denoted as “Non-selected” in the table.

In Panel B of Table A3, we report the summary statistics for joint characteristics between target firms and their peers, between target firms and “non-selected firms”, and the differences between these pairings. We report return correlations between these alternative pairings as well as their likelihood of belonging to the same 1-digit SIC industry, being listed on the S&P 500 index, or the S&P 1500 index. We find that selected peers have similar firm characteristics with the target firms. As expected, peer firms are more likely to be in the same index as the target firm and tend to have higher stock return correlations with the target firm than firms that are not peers. For instance, the return correlation between target firms and their RPE peers averages 0.545, while the correlation between target firms and all other non-peer firms averages only 0.286.

Each year we create a set of counterfactual peers for each target firm using propensity score matching (PSM). Since each target firm averages fifteen peers, matching each of these 15 peers to over 7,000 firms in the CRSP-Compustat universe results in an exceptionally large dataset to be used in the PSM exercise. To limit the sample used in PSM and to ensure that potential peer firms are meaningful in terms of their likelihood of being selected by the target firm, we first match by firm size, limiting the match to firms that are at least as large as the smallest actual peer of the target firm every year.

We then run a logistic regression to calculate the coefficients to be used in the propensity score matching process. First, we create a dummy variable that takes on a value of one if the matched firm is an actual peer and zero otherwise. Then, we run a logistic regression using this dummy variable as a dependent variable. The explanatory variables are joint characteristics such as the return correlation between the target firm and the matched firm, and differences in firm characteristics such as the size difference between the target firm and the matched firm.

The results from the logit regression are reported in column (1) of the Appendix Table (A4). All explanatory variables are significant. Not all the variables have the same sign as it is possible for target firms to choose aspirational peers that are industry leaders. For instance, target firms may choose more profitable firms in their industry as peers.

The sample utilized in the regression described in column (1) is large since we pair each target-peer firm with a large number of candidates that could potentially have been selected as peers. A large number of non-zero outcomes can lead to biases in logistic regressions (King and Zeng, 2001; Gong, Li, and Yin, 2019). To address this potential bias, we limit the sample size in results reported in columns (2) and (3) by randomly matching each target peer firm to a single potential counterfactual firm. Column (2) presents the results when we use such a limited counterfactual set. In this regression specification we use the same set of explanatory variables as in column (1). Although the number of observations is significantly lower, the coefficients on the explanatory variables are similar. Only two variables, *Return3y*, the difference in three-year stock returns, and the beta estimated from CAPM regressions lose significance in this smaller set. For the regression specification reported in column (3), we use only variables that have been previously used in the literature. Specifically, we control for the correlation of stock returns between the target and peer firms, firm size difference between the target and peer firms, as well as industry and index membership classifications (Bizjak et al. 2022). The pseudo R-squared value reported in column (2) is only slightly higher than the one reported in column (3), despite controlling for the full set of explanatory variables. Based on the pseudo R-squared observed in the regression conducted in column (3), we conclude that these five variables capture most of the variation in the estimated likelihood that a given firm will be selected as a peer.

Using the coefficients obtained from the logistic regressions, we calculate an expected likelihood of being selected as a peer for each match each year. For each target firm in a given year, we then select the matching firm that has the highest probability of being selected as a peer as the target firm's counterfactual peer. We repeat this separately using coefficients reported in each of the three regression models used in Table 6, providing us with three alternative sets of counterfactual peers.

Appendix Table (A5) reports correlations among discretionary accruals of different groups. RPE DAM has the highest correlation with Med industry DAM. The correlation between the target RPE DAM and Med Peer DAM is similar to the correlations between RPE DAM and the median DAMs of counterfactual peer groups, especially comparable to the correlation between RPE DAM and the median DAM of the first counterfactual peer group, when the counterfactual peers are estimated using model 1 in Appendix Table (A4). These results suggest that the contagion effect between the target firm's earnings management and their peers' earnings management is not likely to be driven by the similarities between the characteristics of the firms but rather appears to be a byproduct of the RPE-based executive compensation contracts.

We compute the median discretionary accrual values of the counterfactual peers from propensity score matching. In addition, we create a set of counterfactual peers created from peers that have been dropped by the target firm in the previous year and a set of counterfactual peers created from the peers of peers list. If our main hypothesis is correct, that compensation is the main channel through which peers affect the target firm's earnings quality, then we would expect earnings management by counterfactual peers to have limited impact on the firm's earnings quality. We also expect the median discretionary accruals of actual peers to remain significant after including the median discretionary accruals of counterfactual peers. We control for the median earnings quality of the counterfactual peers (*Med Counterfactual DAM*) by running the following regression:

$$DAM_{i,t} = \alpha + \theta Med\ Peer\ DAM_{i,t} + \partial Med\ Counterfactual\ DAM_{i,t} + \beta X_{i,t} + \gamma_t + \vartheta_i + \varepsilon_{i,t} \tag{16}$$

The results are reported in Table 11. The first three columns report results controlling for median counterfactual peer DAM using the propensity score matching approach. Counterfactual peers are selected using coefficients from corresponding columns in Appendix Table (A4). In column (4) we control for the median peer DAM of dropped peers. In column (5), we control for the median DAM of peers' peers. In all five specifications, the impact of earnings quality of counterfactual peers is insignificant. Moreover, the impact of the earnings quality of actual peers is always significant. Comparing the coefficients on the Med Peer DAM variable to those reported in Table 4 column (1), we find that they are very similar. These results suggest that it is unlikely that our results are driven by omitted variables or because of the similarity between the target firm and its peers.

In column (6), we construct counterfactual peers from amongst firms that are in the same industry as the target firm and that have the highest return correlations with the target firm following Bloomfield, Guay and Timmermans (2022). We observe in column (6) that when we regress the target firm's DAM measure on the set of controls, both the coefficient on the median DAM of Bloomfield, Guay and Timmermans (2022) counterfactual peers (median BGT DAM) as well as the coefficient on the median DAM of actual RPE peers (Med Peer DAM) remain statistically and economically significant. By design, the selection of BGT peers inherently captures the same shocks that affect the target firm. In addition, since the Bloomfield, Guay and Timmermans (2022) procedure chooses counterfactual peers that have the highest return correlations with the target firm within the target firm's industry, these counterfactual peers could also potentially be picking up the industry contagion documented in Kedia, Koh and Rajgopal (2015). Once we control for industry*year fixed effects, the median BGT DAM substantially declines in statistical and economic significance, yet this potential industry contagion does not impair the statistical significance of peer firm's earnings management behavior on that of the target firm.

5. Conclusion

Recently, academics have demonstrated that peer firms can have significant influences on the actions of a target firm. Most often, due to data constraints that exist, the set of peer firms is defined as a set of firms in the same industry defined by proximity in SIC codes. Using this set of peers, researchers have identified peer effects in a number of accounting and financial decisions made by firm management. Usually, these peer effects are attributed to either social conformity or economic rationale. This paper takes advantage of enhanced disclosure of peer firms introduced in 2006 to identify the actual peer firms the target firm uses for their relative performance evaluation. This disclosure removes the confounding influence of potentially misclassified non-peer firms that are in the same industry but are not peers. Using this new set of actual peers, we find that the amount of peer firms' earnings management is significantly positively related to the amount of target firm's earnings management. We attribute this result to the target-firm manager's economic incentives to earn the benefits of outperforming their peer firms, and to avoid the negative consequences, such as dismissal, from underperforming one's peers. If RPE changes both the costs and benefits or earnings management behavior, our results can help to explain why not all firms adopt RPE compensation, and why some firms use a less accurate, but more diverse set of peers such as the S&P 500.

One limitation of our study is that we estimate the level of earnings management for the target firm as well as for its peer firms using the unexplained errors in discretionary accruals, a measure of earnings management proposed by Dechow, Sloan, and Sweeney (1995). Although widely adopted as the state of the art, there is some concern that correlated errors between target and peer firms, rather than management activity, could be an alternative explanation for our results. Therefore, we devote a large part of the paper to ensuring that this unidentified error is an unlikely explanation for our results. To this end, we perform numerous robustness checks to validate our main result. Peer firm discretionary accruals are still significantly associated with target firm discretionary accruals when we control for the industry level of discretionary accruals, the most commonly used proxy in the literature for peer firm activity. We test our hypotheses controlling for alternative sets of counterfactual peer groups. These alternative peers include those estimated via propensity score matching, former peer firms, as well as peers of peers, a set of counterfactual peers proposed by Bloomfield, Guay and Timmermans (2022). Using counterfactual peers as a control group, we find that it is the earnings management behaviors of actual peer firms have an impact on the financial reporting quality of the target firm. Our finding of a significant increase in the contagion effect between the target firm and its peer firms after the target firm adopts RPE lends further support to our main hypothesis. Furthermore, we show that if the peer firm uses the target firm as its peer in their incentive plans, the contagion effect is even stronger.

Finally, we document that the target firm's real earnings management has a significant relationship with that of its peer firms. The incidence and the amount of earnings restatements of peer firms also significantly influence the likelihood of restatements and the amount of restatements by the target firms. Given this evidence, we conclude that there exists significant contagion in financial reporting quality among firms that use RPE in their compensation contracts.

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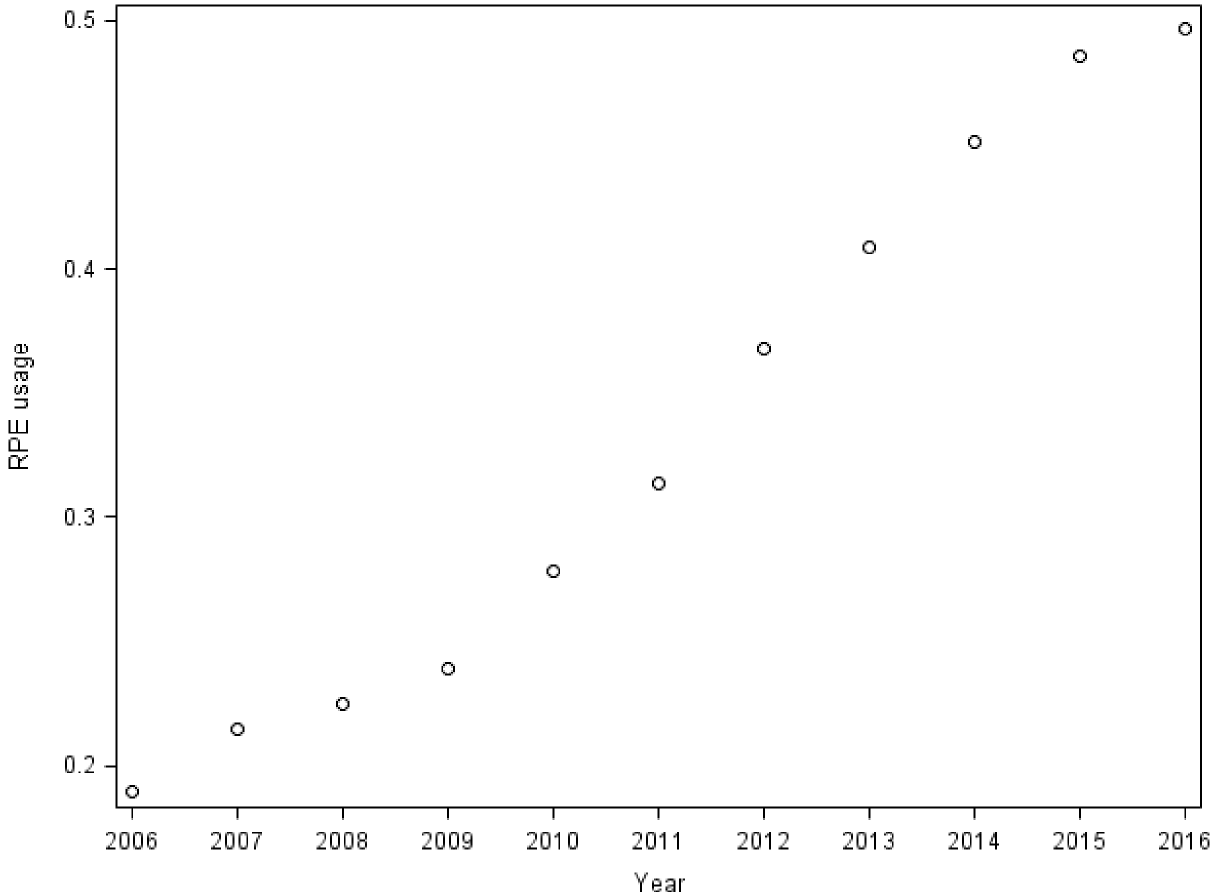
Figure 1: Ratio of firms that use RPE contracts in the full sample of S&P 1500



This figure plots the ratio of firms that use RPE in Incentive Lab for the years 2006 to 2016.

Table 1: Variable definitions

Variable	Definition
Firm characteristics:	
BM	BM is book value of equity divided by market value of equity.
Size	Size is the natural logarithm of total assets.
ROA	ROA is Earnings before extraordinary items divided by total assets.
EarningsVol	EarningsVol is Earnings volatility in the past 3 years.
Return	Return is annual return.
Leverage	Leverage is the sum of the market value of equity and the book value of liabilities divided by the market value of equity.
Performance measures, financial reporting quality measures and RPE contract characteristics:	
DAM	DAM is discretionary accrual computed using the modified Jones measure in Dechow, Sloan, and Sweeney (1995) without intercept.
Peer DAM	Peer DAM is the discretionary accrual of a peer firm in a given year computed using the modified Jones measure as in Dechow, Sloan, and Sweeney (1995) without intercept.
Med Peer DAM	Med Peer DAM is the median of discretionary accruals of peers, where discretionary accruals are computed using the modified Jones measure without intercept.
Avg Peer DAM	Avg Peer DAM is the mean of discretionary accruals of peers, where discretionary accruals are computed using the modified Jones measure without intercept.
Med Industry DAM	Med Industry DAM is the median of discretionary accruals of firms in the same Fama & French 12 industry, where discretionary accruals are computed using the modified Jones measure without intercept.
Med Counterfactual DAM	Med Counterfactual DAM is the median of discretionary accruals of firms with the highest propensity scores but were not selected as peers, where discretionary accruals are computed using the modified Jones measure without intercept. These are the so-called counterfactual peers.
Med Dropped DAM	Med Dropped DAM is the median of discretionary accruals of peers that are dropped in the previous year, where discretionary accruals are computed using the modified Jones measure without intercept

Med Peers' Peer DAM	Med Peers' Peer DAM is the median of discretionary accruals of peers' peers, where discretionary accruals are computed using the modified Jones measure without intercept.
Med BGT Peer DAM	Med BGT Peer DAM is the median of discretionary accruals of firms with the highest correlation with the target firm and from the same industry, following Bloomfield, Guay, and Timmermans (2022)
Med Mutual Peer DAM	Med Mutual Peer DAM is the median of discretionary accruals of peers that also use the target firm as their peer (cite it back), where discretionary accruals are computed using the modified Jones measure without intercept
Med Non-mutual RPE Peer DAM	Med Non-mutual RPE Peer DAM is the median of discretionary accruals of peers that use some form of RPE in their contracts but do not use the target firm as their peer, where discretionary accruals are computed using the modified Jones measure without intercept
Abnormal Discretionary Expenses	Abnormal discretionary expenditures are computed following Huang et al. (2020) and Kothari et al. (2016).
Abnormal Production Costs	Abnormal production costs are computed following Huang et al. (2020) and Kothari et al. (2016).
Abnormal Real Earnings	The sum of abnormal discretionary expenditures and abnormal production cost
DD accruals	The DD accruals are computed following the Dechow and Dichev (2002) approach as the standard deviation of residuals from the regression of accruals on current, past, and future cash flows.
Management Frequency	The number of predictions a company makes during a fiscal year
Horizon	The number of days between the management earnings forecast and the end of the fiscal period to which the prediction applies
Range	The high estimate of the earnings forecast minus the low estimate scaled by the midpoint of the range
Bias	Management's earning forecast minus actual earnings scaled by beginning of period price
Error	The absolute value of management's earnings forecast minus the actual scaled by beginning of period price

Restate Dummy	A dummy equal to 1 if fiscal year t overlaps with a restated period identified in Audit Analytics' 'Non-Reliance' database. Observations corresponding to restatements arising from clerical errors are deleted
Restatement Amount	Natural logarithm of the cumulative misstatement amount for a restatement event for the target firm
Med Peer Restate Amount	Median of the natural logarithm of the cumulative misstatement amounts for the restatement events of the target firm's peers
Extreme Earnings Surprise Dummy (EES-Dummy)	A dummy equal to 1 if the target firm's earnings surprise falls into the top or bottom 5^{th} /10^{th} percentile of the earnings surprise in the sample
RPE Percent Dummy	A dummy equal to 1 if RPE grants account for 8% of their total compensation, i.e., 5^{th} percentile of the RPE percentage of total compensation in the sample
Number of Peers Dummy	A dummy equal to 1 if the target firm has more than 30 peers, i.e., 95^{th} percentile of the number of peers in the sample
SEC Investigation Dummy	A dummy equal to 1 if the target firm has been investigated by SEC in the past 3 years
Med Peer ADE	Median of abnormal discretionary expenditures of peers
Med Peer APC	Median of abnormal production cost of peers
Med Peer REM	Median of abnormal real earnings of peers
Med Peer DD accruals	Median of DD accruals of peers
Freq Pct	The percentage of peers having made at least one prediction during a fiscal year
Med Peer Horizon	Median horizon of peers
Med Peer Range	Median range of peers
Med Peer Bias	Median bias of peers
Med Peer Error	Median error of peers
Peer Restate Dummy	A dummy equal to 1 if any peer restated during a given fiscal year.
Peer Restatement Amount	Median restatement amount of peers

Variables used in the propensity score matching:

Return 3y	Annualized return in the past 3 years
Std	Annualized volatility in the past 3 years computed using monthly returns

Beta	CAPM beta in the past 3 years computed using monthly returns
IOR	Institutional ownership ratio, the percentage of shares held by institutions.
HHI	Customer concentration, sum of the square of sales as a percentage of revenues
Correlation	Correlation between the returns of a target firm and its potential peer computed using monthly returns in the past 3 years
Same Industry	A dummy equal to 1 if a target firm and its potential peer are within the same one-digit SIC industry and 0 otherwise
Same S&P500	A dummy equal to 1 if a target firm and its potential peer both belong to the S&P 500 index and zero otherwise
Same S&P1500	A dummy equal to 1 if a target firm and its potential peer both belong to the S&P 1500 index and zero otherwise
Sizediff	Sizediff measures the difference in the market capitalizations of a target firm and a given potential peer, for all possible target firm to potential peer firm matches
BMdiff	BMdiff measures the difference in the book-to-market ratios of a target firm and a given potential peer, for all possible target firm to potential peer firm matches
Return 3ydiff	Return 3ydiff measures the difference in the three-year annual average returns of a target firm and a given potential peer, for all possible target firm to potential peer firm matches
Stddiff	Stddiff measures the difference in the annualized standard deviations of n target firm and a given potential peer, for all possible target firm to potential peer firm matches
Betadiff	Betadiff measures the difference in the CAPM betas of a target firm and a given potential peer, for all possible target firm to potential peer firm matches
IORdiff	IORdiff measures the difference in the institutional ownership levels of a target firm and a given potential peer, for all possible target firm to potential peer firm matches
HHIdiff	HHIdiff measures the difference in the customer concentration levels of a target firm and a given potential peer, for all possible target firm to potential peer firm matches

ROAdiff	ROAdiff measures the difference in the return on assets of a target firm and a given potential peer, for all possible target firm to potential peer firm matches
Variables used in the first stage of Instrumental Variable Analysis:	
1/AT	One divided by one-period lagged total assets
ΔREV-ΔREC	Change in revenues scaled by lagged total assets minus change in net receivables scaled by lagged total assets
PPE	Gross property plant and equipment scaled by lagged total assets
Lag CFO	One-period lag cash flow from operations
CFO	Cash flow from operations in the current year
Lead CFO	Cash flow from operations one year later
DiscExp	Sum of advertising expense, R&D expense, and SG&A expense, scaled by lagged total assets
Sales	Sales scaled by lagged total assets
ΔSales	Sales growth scaled by lagged total assets
lag ΔSales	Lagged value of ΔSales

This table describes the variables used in the analyses.

Table 2: Summary Statistics

Panel A: Target firms

Variables	Obs	Avg	Std	P25	P50	P75
BM	1469	0.634	0.430	0.324	0.555	0.836
Size	1469	9.155	1.274	8.326	9.056	10.071
ROA	1469	0.055	0.070	0.028	0.052	0.090
EarningsVol	1469	0.014	0.018	0.005	0.008	0.015
Return	1469	0.124	0.381	-0.079	0.113	0.294
Leverage	1469	1.995	0.957	1.396	1.735	2.288
DAM	1469	0.034	1.170	-0.035	0.007	0.075

Panel B: Firms in the interaction of Compustat and CRSP

Variables	Obs	Avg	Std	P25	P50	P75
BM	30830	0.762	1.112	0.290	0.512	0.873
Size	30830	6.278	2.080	4.736	6.203	7.721
ROA	30830	-0.033	0.312	-0.044	0.033	0.081
EarningsVol	30830	0.053	0.324	0.007	0.016	0.039
Return	30830	0.102	0.591	-0.258	0.039	0.328
Leverage	30830	2.021	3.979	1.176	1.426	1.974
DAM	30830	0.064	1.304	-0.053	0.008	0.106

Panel C: S&P 1500 Firms

Variables	Obs	Avg	Std	P25	P50	P75
BM	14629	0.625	0.826	0.286	0.473	0.763
Size	14629	7.525	1.650	6.354	7.426	8.605
ROA	14629	0.051	0.115	0.020	0.054	0.097
EarningsVol	14629	0.022	0.041	0.005	0.010	0.022
Return	14629	0.140	0.500	-0.139	0.097	0.338
Leverage	14629	1.866	2.337	1.214	1.459	1.954
DAM	14629	0.056	1.244	-0.043	0.006	0.078

This table reports the number of observations, average, standard deviation, 25th percentile, median, and 75th percentile of the firm characteristics used in the analyses. Panel A presents summary statistics from 2006 to 2016 for the sample of firms that use relative performance evaluation (RPE) in executive contracts. Panel B presents summary statistics from 2006 to 2016 for all firms with data available in both the CRSP and Compustat databases. Panel C presents summary statistics from 2006 to 2016 for S&P 1500 firms with data available in both the CRSP and Compustat databases. The reported variables are book-to-market ratio (*BM*), firm size (*Size*), return on assets (*ROA*), earnings volatility (*EarningsVol*), annual return (*Return*), leverage (*Leverage*) and discretionary accruals (*DAM*). All variables are described in detail in Table 1.

Table 3: Univariate sorts of firms that use RPE in executive contracts based on the level of their discretionary accruals

Quintile	DAM	Med Peer DAM	BM	Size	ROA	Earnings Vol	Return	Leverage
L	-0.706	-0.351	0.545	8.995	0.065	0.016	0.180	1.794
2	-0.034	-0.041	0.728	9.261	0.045	0.012	0.124	2.259
3	0.007	0.016	0.682	9.158	0.055	0.011	0.104	2.139
4	0.074	0.041	0.590	9.109	0.066	0.014	0.106	1.939
H	0.881	0.431	0.594	9.071	0.058	0.017	0.113	1.797
H-L	1.587	0.783	0.049	0.076	-0.007	0.001	-0.067	0.003
t-Value	5.572	4.441	0.460	0.515	-0.478	0.489	-1.434	0.035

This table reports over the 2006 to 2016 period portfolio-level mean values for a set of firm characteristics of the firms in a given portfolio as well as of the peers of the firms in that portfolio where portfolios are formed based on quintile sorts of discretionary accruals computed using the modified Jones measure without the intercept (*DAM*). Peer firms are those firms listed by the respective executive contracts that utilize RPE. *DAM* is the average discretionary accrual value per quintile for firms that use relative performance evaluation (RPE) in executive contracts, where L denotes the lowest accrual quintile, and H corresponds to the highest accrual quintile. *Med Peer DAM* is the average of the median discretionary accruals of the peer firms in each quintile. *BM* is the average of book-to-market ratio of all firms that use relative performance evaluation (RPE) in executive contracts for a given DAM-quintile portfolio. *Size* is the average of market capitalization of all firms that use relative performance evaluation (RPE) in executive contracts in the corresponding DAM-quintile portfolio. *ROA* is the average of return on assets of all firms that use relative performance evaluation (RPE) in executive contracts in each DAM-quintile portfolio. *EarningsVol* is the average of volatility of earnings of all firms that use relative performance evaluation (RPE) in executive contracts in each DAM-quintile portfolio. *Return* is the average of annual returns of all firms that use relative performance evaluation (RPE) in executive contracts in a given DAM-quintile portfolio. *Leverage* is the average of firm leverage of all firms that use relative performance evaluation (RPE) in executive contracts in a corresponding DAM-quintile portfolio. H-L reports for each characteristic the difference between the highest and lowest accrual quintiles and the *t-Value* reports the t-statistics (statistical significance) of this difference. All variables are described in detail in Table 1.

Table 4: The effect of peers' discretionary accruals

VARIABLES	(1) Mod Jones Accruals	(2) Mod Jones Accruals	(3) Mod Jones Accruals	(4) Mod Jones Accruals	(5) Mod Jones Accruals	(6) Mod Jones Accruals	(7) Mod Jones Accruals
1/AT	9.860	-3.062	1.755	208.014	309.686	42.213	30.778
	(69.117)	(66.496)	(69.593)	(377.004)	(408.271)	(78.328)	(76.862)
ΔREV-ΔREC	0.129	0.146	0.202	0.248	0.265	0.052	0.108
	(0.191)	(0.189)	(0.203)	(0.246)	(0.281)	(0.187)	(0.175)
PPE	0.065	0.054	0.051	0.027	-0.126	0.051	0.171**
	(0.078)	(0.077)	(0.084)	(0.162)	(0.167)	(0.081)	(0.086)
BM	0.088*	0.070	0.087*	0.041	0.038	0.085	0.085
	(0.053)	(0.054)	(0.049)	(0.077)	(0.092)	(0.053)	(0.065)
Size	0.017	0.006	0.004	-0.097	0.088	0.001	0.009
	(0.027)	(0.025)	(0.027)	(0.154)	(0.161)	(0.028)	(0.027)
ROA	0.635	0.616	0.508	0.414	0.524	0.517	0.336
	(0.560)	(0.563)	(0.648)	(0.885)	(1.133)	(0.559)	(0.595)
Return	0.082	0.086	0.051	0.184	0.189	0.079	0.008
	(0.075)	(0.076)	(0.087)	(0.132)	(0.137)	(0.076)	(0.085)
EarningsVol	0.290	0.402	0.350	-2.885	-1.003	0.574	0.535
	(1.246)	(1.215)	(1.312)	(3.010)	(3.289)	(1.281)	(1.153)
Leverage	-0.012	-0.016	-0.013	0.012	0.007	-0.007	0.004
	(0.019)	(0.021)	(0.028)	(0.033)	(0.057)	(0.021)	(0.026)
Med Peer DAM	0.862***	0.618***	0.539***	0.904***	0.517***		
	(0.103)	(0.113)	(0.112)	(0.123)	(0.124)		
Med Industry DAM		0.706***					
		(0.151)					
Avg Peer DAM						0.840***	
						(0.099)	
Peer DAM							0.276***
							(0.057)
Constant	-0.265	-0.100	-0.130	0.680	-0.739	-0.154	-0.366
	(0.331)	(0.320)	(0.352)	(1.481)	(1.550)	(0.340)	(0.320)
Observations	1,418	1,418	1,418	1,418	1,418	1,418	19,801
R-squared	0.379	0.450	0.504	0.548	0.677	0.388	0.184

FE	Industry+Year	Industry+Year	Industry*Year	Firm+Year	Firm + Industry*Year	Industry+Year	Industry+Year

This table reports results of annual regressions where the dependent variable is the discretionary accruals for firms that use some form of RPE in their executive compensation contracts. The independent variables in focus are the median of discretionary accruals of peers (*Med Peer DAM*) and the median of discretionary accruals of firms in the same Fama and French 12 industry group as the target firm studied (*Med Industry DAM*). All discretionary accrual measures are computed using the modified Jones measure without intercept. Models (1) and (2) control for industry and year fixed effects, model (3) controls for industry times year fixed effects, model (4) controls for firm and year fixed effects, and model (5) controls for firm + industry*year fixed effects. Model (6) replicates the analysis in model (1) by replacing the median of the discretionary accruals of peers (*Med Peer DAM)* with the average of the discretionary accruals of peer (*Avg Peer DAM*) as the independent variable in focus. Model (7) is different from the first six models as the regression model is run at the target firm – peer firm – year level with industry plus year fixed effects. The independent variable in focus in model (7) is the discretionary accrual level of a peer firm (*Peer DAM*) in a given year. Independent variables are described in further detail in Table 1. Standard errors are reported in parentheses and calculated after adjusting for firm-level clustering. Significance is denoted by ***, **, and * at the 1%, 5%, and 10% significance levels, respectively, using two-tailed tests.

Table 5: The impact of performance shocks on the contagion of earnings management

VARIABLES	(1) Mod Jones Accruals	(2) Mod Jones Accruals
1/AT	29.954	29.672
	(76.496)	(76.771)
ΔREV-ΔREC	0.108	0.109
	(0.176)	(0.175)
PPE	0.169*	0.171**
	(0.086)	(0.086)
BM	0.085	0.084
	(0.065)	(0.066)
Size	0.010	0.008
	(0.027)	(0.027)
ROA	0.339	0.340
	(0.585)	(0.594)
Return	0.008	0.010
	(0.084)	(0.095)
EarningsVol	0.446	0.506
	(1.127)	(1.144)
Leverage	0.004	0.006
	(0.026)	(0.026)
Peer DAM	0.295***	0.304***
	(0.061)	(0.062)
Abs Difference ROA	0.119	
	(0.244)	
Peer DAM × Abs Difference ROA	-0.252***	
	(0.096)	
Abs Difference Return		0.001
		(0.055)
Peer DAM × Abs Difference Return		-0.095*
		(0.056)
Constant	-0.374	-0.364
	(0.314)	(0.319)
Observations	19,801	19,798
R-squared	0.185	0.185
FE	Industry+Year	Industry+Year

This table examines how the covariation of earnings management behavior of the target firm with the earnings management behavior of its peer firms changes, based on the performance differential between them. The table reports results of annual regressions where the dependent variable is the discretionary accrual for target firms. Discretionary accrual measures for all firms are computed using the modified Jones measure without intercept. Every period we calculate the absolute value of the performance differential between the target firm and each of its peers using either return on assets (ROA) or stock return (Return). The absolute value difference between ROA (Return) values of the target firm and its peer in a given year is *Abs Difference ROA (Abs Difference Return)*. Column 1 (2) reports the regression results where the absolute performance difference measure is *Abs Difference ROA (Abs Difference Return)*. Both models (1) and (2) control for industry and year fixed effects. Table 1 describes the independent variables used in the regressions in further detail. Standard errors are reported in parentheses and calculated after adjusting for firm-level clustering. Significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels respectively, using two-tailed tests.

Table 6: Impact of RPE contract characteristics, peer group composition and SEC investigations on contagion in financial reporting quality

VARIABLES	(1) Mod Jones Accruals	(2) Mod Jones Accruals	(3) Mod Jones Accruals
1/AT	12.315	12.572	11.128
	(68.746)	(70.358)	(68.188)
ΔREV-ΔREC	0.134	0.126	0.129
	(0.192)	(0.191)	(0.190)
PPE	0.064	0.056	0.070
	(0.079)	(0.078)	(0.078)
BM	0.085	0.068	0.088
	(0.054)	(0.053)	(0.054)
Size	0.016	0.018	0.017
	(0.026)	(0.027)	(0.025)
ROA	0.603	0.695	0.602
	(0.557)	(0.560)	(0.561)
Return	0.081	0.082	0.077
	(0.074)	(0.075)	(0.075)
EarningsVol	0.138	0.269	0.393
	(1.233)	(1.249)	(1.224)
Leverage	-0.011	0.001	-0.015
	(0.019)	(0.016)	(0.020)
Med Peer DAM	0.888***	0.904***	0.922***
	(0.103)	(0.106)	(0.106)
RPE Percent Dummy	0.099		
	(0.090)		
Med Peer DAM × RPE Percent Dummy	-0.141		
	(0.279)		
Number of Peers Dummy		0.036	
		(0.042)	
Med Peer DAM × Number of Peers Dummy		-0.717***	
		(0.200)	
SEC Investigation Dummy			0.032
			(0.067)
Med Peer DAM × SEC Investigation Dummy			-0.398*
			(0.236)
Constant	-0.322	-0.348	-0.318
	(0.317)	(0.323)	(0.310)
Observations	1,418	1,418	1,418
R-squared	0.381	0.392	0.389
FE	Industry+Year	Industry+Year	Industry+Year

This table studies the impact of relative performance evaluation (RPE) contract characteristics, peer group composition and SEC investigations, respectively on contagion in financial reporting quality. The table reports results of annual regressions where the dependent variable is the discretionary accruals for firms that use RPE in their executive compensation contracts. The independent variables in focus are the interactions of median of discretionary accruals of peers (*Med Peer DAM*) with the RPE Percent dummy, the Number of Peers dummy and the SEC Investigation dummy, respectively. RPE Percent dummy is equal to 1 if RPE grants account for 8% (70%) of a manager's total compensation, corresponding to the 10^{th} (90^{th}) percentile in the distribution of RPE compensation ratio as a percentage of the total managerial compensation. Number of Peers dummy is equal to 1 if the target firm has more than thirty peers, corresponding to the 95^{th} percentile in the distribution of the number of peers in the sample. SEC Investigation dummy is equal to 1 if the target firm has ever been investigated by the SEC in the past 3 years. All discretionary accrual measures are computed using the modified Jones measure without intercept. All models control for industry and year fixed effects. Independent variables are described in further detail in Table 1. Standard errors are reported in parentheses and calculated after adjusting for firm-level clustering. Significance is denoted by ***, **, and * at the 1%, 5%, and 10% significance levels, respectively, using two-tailed tests.

Table 7: Effect of mutual benchmarking

VARIABLES	(1) Peers benchmarking back	(2) Peers using RPE but not benchmarking back	(3) Horse-race
1/AT	11.251	17.968	23.156
	(68.505)	(70.186)	(70.384)
ΔREV-ΔREC	0.128	0.123	0.118
	(0.191)	(0.191)	(0.192)
PPE	0.049	0.059	0.039
	(0.077)	(0.079)	(0.079)
BM	0.073	0.090*	0.074
	(0.051)	(0.053)	(0.051)
Size	0.018	0.017	0.020
	(0.027)	(0.027)	(0.027)
ROA	0.530	0.672	0.580
	(0.555)	(0.566)	(0.559)
Return	0.083	0.079	0.079
	(0.075)	(0.075)	(0.076)
EarningsVol	-0.083	0.341	-0.023
	(1.222)	(1.244)	(1.222)
Leverage	-0.008	-0.013	-0.010
	(0.018)	(0.020)	(0.018)
Med Peer DAM	0.703***	0.832***	0.652***
	(0.140)	(0.111)	(0.162)
Med Mutual Peer DAM	0.281**		0.292**
	(0.143)		(0.143)
Med Non-mutual RPE Peer DAM		0.062	0.091
		(0.090)	(0.086)
Constant	-0.253	-0.272	-0.263
	(0.329)	(0.333)	(0.332)
Observations	1,418	1,418	1,418
R-squared	0.406	0.381	0.410
FE	Industry+Year	Industry+Year	Industry+Year

This table reports results of annual regressions where the dependent variable is the discretionary accruals computed using the modified Jones measure without the intercept (*DAM*) for firms that use some form of RPE in their executive compensation contracts. The analyses examine the additional effects of i) peers that cite back the target firm as a peer and ii) peers that use some form of RPE in their contracts but do not cite back the target firm as a peer. After controlling for the median discretionary accruals of all peers regardless of their RPE usage (*Med Peer DAM*), model (1) controls for the median discretionary accruals of peers that cite back the target firm as a peer (*Med Mutual Peer DAM*). Model (2) controls for the median discretionary accruals of peers that do not cite back the target firm as a peer but use other firms as peers while utilizing RPE contracts (*Med Non-mutual RPE Peer DAM*), and model (3) runs a horse-race between *Med Mutual Peer DAM* and *Med Non-mutual RPE Peer DAM*. All three models use industry and year fixed effects. Table 1 describes the other independent variables used in the regression in further detail. Standard errors are reported in parentheses and calculated after adjusting for firm-level clustering. Significance is denoted by ***, **, and * at the 1%, 5%, and 10% significance levels, respectively, using two-tailed tests.

Table 8: The effect of aggregate index discretionary accruals

VARIABLES	(1) Mod Jones Accruals	(2) Mod Jones Accruals	(3) Mod Jones Accruals
1/AT	46.064	46.064	46.064
	(57.920)	(57.920)	(57.920)
ΔREV-ΔREC	0.260	0.260	0.260
	(0.294)	(0.294)	(0.294)
PPE	0.188	0.188	0.188
	(0.155)	(0.155)	(0.155)
BM	0.194**	0.194**	0.194**
	(0.081)	(0.081)	(0.081)
Size	-0.056*	-0.056*	-0.056*
	(0.030)	(0.030)	(0.030)
ROA	0.216	0.216	0.216
	(0.480)	(0.480)	(0.480)
Return	0.355	0.355	0.355
	(0.400)	(0.400)	(0.400)
EarningsVol	-1.070	-1.070	-1.070
	(2.201)	(2.201)	(2.201)
Leverage	-0.037*	-0.037*	-0.037*
	(0.019)	(0.019)	(0.019)
Median S&P500 DAM	16.150		
	(11.279)		
Mkt Cap weighted S&P500 DAM		1.769	
		(1.235)	
Assets weighted S&P500 DAM			2.305
			(1.610)
Constant	0.223	0.196	0.225
	(0.271)	(0.278)	(0.271)
Observations	1,057	1,057	1,057
R-squared	0.104	0.104	0.104
FE	Industry+Year	Industry+Year	Industry+Year

This table presents the impact of peer DAM on the target firms whose benchmark is S&P 500 index. Columns (1) to (3) reports the regression results on i) Median DAM for the S&P 500 firms, ii) market capitalization weighted average DAM of S&P 500 firms and iii) asset value weighted average DAM of S&P 500 firms, respectively. Standard errors are reported in parentheses and calculated after adjusting for firm-level clustering. Significance is denoted by ***, **, and * at the 1%, 5%, and 10% significance levels, respectively, using two-tailed tests.

Table 9: The impact of peer discretionary accruals after RPE initiation

VARIABLES	(1) Mod Jones Accruals	(2) Mod Jones Accruals	(3) Mod Jones Accruals
1/AT	-210.766	-401.552	-373.712
	(592.890)	(1,787.100)	(643.155)
ΔREV-ΔREC	-0.369	0.143	0.033
	(0.791)	(0.681)	(0.839)
PPE	-0.050	0.147	-0.610
	(0.690)	(0.325)	(1.279)
BM	-0.108	-0.205	0.274
	(0.263)	(0.819)	(0.665)
Size	-0.020	-0.809	-0.443
	(0.363)	(0.709)	(0.657)
ROA	3.493	-0.419	3.774
	(4.648)	(2.724)	(4.086)
Return	-0.042	0.412	-0.048
	(0.203)	(0.747)	(0.387)
EarningsVol	-1.504	-6.233	4.111
	(4.203)	(5.913)	(7.381)
Leverage	0.029	-0.073	-0.110
	(0.054)	(0.182)	(0.178)
After	0.041	1.060**	-0.086
	(0.356)	(0.407)	(0.303)
Med Peer DAM	0.526**	2.431	0.671
	(0.225)	(1.725)	(0.985)
After×Med Peer DAM	1.124***	-1.144	1.586
	(0.321)	(1.720)	(2.873)
Constant	0.030	6.134	3.879
	(3.480)	(6.137)	(4.879)
Observations	426	268	176
R-squared	0.882	0.849	0.771
FE	Firm + Year	Firm + Year	Firm + Year
Sample	Treated	Counter-factual	Counter-factual

This table reports the impact of peer discretionary accruals before versus after the target firm adopts RPE. Column (1) compares the impact one year before and one year after the target firm adopts RPE. Assuming that the target firm adopted RPE several years earlier, we further conduct some robustness checks. Columns (2) and (3) report the relationship between the target firm and its peers one year before and one year after the counterfactual treatment year, assuming that the target firm adopted RPE three years and five years earlier, respectively. Standard errors are reported in parentheses and calculated after adjusting for firm-level clustering. Significance is denoted by ***, **, and * at the 1%, 5%, and 10% significance levels, respectively, using two-tailed tests.

Table 10: Impact of peers' behavior on alternative measures of financial reporting quality

VARIABLES	(1) Abnormal Discretionary Expenses	(2) Abnormal Production Costs	(3) Abnormal Real Earnings Management	(4) DD accruals	(5) Restatement Dummy	(6) Re-statement Amount
1/AT	-12.229	26.634*	8.223			
	(7.953)	(14.457)	(11.614)			
Sales	0.045***	-0.098***	-0.033*			
	(0.009)	(0.028)	(0.020)			
DiscExp	-0.109***		0.020			
	(0.038)		(0.047)			
Lag Prod		0.022	0.000			
		(0.025)	(0.019)			
ΔSales		-0.060**	0.010			
		(0.024)	(0.018)			
lag ΔSales		0.024	0.033**			
		(0.020)	(0.016)			
Lag CFO				0.367		
				(0.280)		
CFO				-0.437		
				(0.427)		
Lead CFO				0.234		
				(0.287)		
BM	-0.015*	0.016	0.008	-0.004	0.439	-0.004
	(0.008)	(0.012)	(0.009)	(0.037)	(0.346)	(0.154)
Size	0.003	-0.005	0.001	0.004	-0.214*	0.019
	(0.003)	(0.003)	(0.003)	(0.016)	(0.117)	(0.037)
ROA	0.044	0.564***	0.567***	0.723**	-2.238	-0.566
	(0.042)	(0.083)	(0.085)	(0.304)	(1.656)	(0.656)
Return	0.003	-0.010	0.006	-0.008	0.090	0.076
	(0.006)	(0.011)	(0.009)	(0.022)	(0.264)	(0.088)
EarningsVol	-0.00	0.149	0.129	0.943*	4.586	-1.458
	(0.117)	(0.255)	(0.218)	(0.502)	(8.726)	(2.742)
Leverage	0.001	0.000	0.001	0.000	0.053	0.021
	(0.001)	(0.001)	(0.001)	(0.002)	(0.062)	(0.027)
Med Peer ADE	0.909***					
	(0.125)					
Med Peer APC		0.349**				
		(0.140)				
Med Peer REM			0.596***			
			(0.106)			
Med Peer DD accruals				0.768***		
				(0.134)		
Peer Restate Dummy					0.564**	
					(0.250)	
Med Peer Restate Amount						0.193**
						(0.076)
Constant	-0.029	0.042	-0.014	-0.096	1.981	13.512***
	(0.033)	(0.035)	(0.032)	(0.178)	(1.290)	(1.239)

Observations	1,560	1,590	1,358	544	511	206
(Pseudo) R-squared	0.463	0.408	0.377	0.563	0.064	0.162
FE	Industry+ Year	Industry+ Year	Industry+ Year	Industry+ Year	Industry+ Year	Industry+ Year

This table extends the main analyses by investigating the impact of peer behavior on alternative measures of financial reporting quality. Managers might overstate earnings via overproduction, channel-stuffing and reducing discretionary expenses. Following Huang et al. (2020), we estimate a company's degree of abnormal discretionary expenses and abnormal production costs and construct an aggregate index combining them (*Abnormal Real Earnings Management*). Columns (1)-(3) report the regression results of the target firm's abnormal discretionary expenses, abnormal production costs, and abnormal real earnings management on the median of peers' corresponding values, respectively. In column (4) we run the regression of the target firm's Dechow and Dichev (2002) discretionary accruals on the median level of their peers' Dechow and Dichev (2002) discretionary accruals. Using restatements, in column (5) we run a logistic regression and investigate the impact of peer restatements on the likelihood of the target firm re-stating its financials. Column (6) reports the regression of the target firm's restatement amount (*Restatement Amount*) on the median restatement amount (*Med Peer Restate Amount*) of the target firm's peers. *Restatement Amount* (*Med Peer Restate Amount)* is the natural logarithm of the cumulative misstatement amount for a restatement event for the target (peer) firm. Table 1 describes the independent variables used in the regressions in further detail. Standard errors are reported in parentheses and calculated after adjusting for firm-level clustering. Significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels respectively, using two-tailed tests.

Table 11: Controlling for discretionary accruals of matched firms and of dropped peers

VARIABLES	(1) Mod Jones Accruals	(2) Mod Jones Accruals	(3) Mod Jones Accruals	(4) Mod Jones Accruals	(5) Mod Jones Accruals	(6) Mod Jones Accruals
1/AT	12.124	20.745	9.284	10.980	150.747	-8.462
	(95.445)	(95.935)	(68.985)	(68.702)	(148.382)	(69.169)
ΔREV-ΔREC	0.124	0.121	0.137	0.125	0.491**	0.387*
	(0.194)	(0.193)	(0.193)	(0.192)	(0.206)	(0.218)
PPE	0.063	0.060	0.067	0.057	0.052	0.031
	(0.080)	(0.079)	(0.076)	(0.079)	(0.089)	(0.108)
BM	0.088	0.077	0.083	0.089*	0.097*	0.042
	(0.055)	(0.055)	(0.053)	(0.053)	(0.051)	(0.067)
Size	0.019	0.024	0.017	0.015	0.038	0.011
	(0.029)	(0.029)	(0.026)	(0.026)	(0.030)	(0.034)
ROA	0.790	0.821	0.666	0.641	0.625	0.506
	(0.584)	(0.584)	(0.565)	(0.560)	(0.581)	(0.688)
Return	0.054	0.074	0.091	0.086	0.069	0.120
	(0.072)	(0.074)	(0.075)	(0.075)	(0.078)	(0.087)
EarningsVol	0.551	0.492	0.327	0.258	0.534	-0.926
	(1.363)	(1.352)	(1.253)	(1.236)	(1.274)	(1.354)
Leverage	-0.009	-0.010	-0.011	-0.012	-0.016	-0.005
	(0.020)	(0.020)	(0.019)	(0.019)	(0.019)	(0.027)
Med Peer DAM	0.864***	0.847***	0.851***	0.828***	0.708***	0.571***
	(0.103)	(0.099)	(0.101)	(0.112)	(0.154)	(0.145)
Med Counterfactual DAM (1)	-0.033					
	(0.055)					
Med Counterfactual DAM (2)		0.246				
		(0.168)				
Med Counterfactual DAM (3)			0.163			
			(0.144)			
Med Dropped DAM				0.132		
				(0.190)		
Med Peers' Peer DAM					0.190	
					(0.142)	

	(1)	(2)	(3)	(4)	(5)	(6)
Med BGT Peer DAM						0.479***
						(0.134)
Constant	-0.302	-0.342	-0.265	-0.246	-0.553	-0.157
	(0.363)	(0.362)	(0.329)	(0.323)	(0.395)	(0.457)
Observations	1,392	1,392	1,416	1,418	1,280	1,029
R-squared	0.382	0.385	0.381	0.382	0.369	0.512
FE	Industry+Year	Industry+Year	Industry+Year	Industry+Year	Industry+Year	Industry+Year

This table reports results of annual regressions where the dependent variable is the discretionary accruals computed using the modified Jones measure without the intercept (*DAM*) for firms that use some form of RPE in their executive compensation contracts. The independent variables in focus are the median of discretionary accruals of peers (*Med Peer DAM*) as well as the median discretionary accrual values of those so-called counterfactual peers. Counterfactual peers are estimated using the logistic regression results from Table 6. Specifically using loadings on characteristics studied in Table 6 we estimate for each peer firm the most similar firm to it from the set of all firms covered by CRSP and COMPUSTAT and designate it the counterfactual peer. Counterfactual peers, by definition, should not be actual peers of the target firm but instead are those firms that could alternatively have been chosen as peer firms. In column 1 (2, 3) we utilize *Med Counterfactual DAM 1 (2, 3)* which is the median discretionary accrual values of counterfactual peers when the counterfactual peers are estimated using model 1 (2, 3) in Table 6. In column (4) we control for the median of discretionary accruals of peers that are dropped in the former period (Med Dropped DAM). Column (5) reports results controlling for the median of discretionary accruals of peers' peers (Med Peers' Peer DAM). Column (6) controls for the median of discretionary accruals of firms with the highest correlation with the target firm and from the same industry, following Bloomfield, Guay, and Timmermans (2022). Analyses in columns (1) through (6) control for industry and year fixed effects. All the models use industry and year fixed effects. Table 1 describes the other independent variables used in the regression in further detail. Standard errors are reported in parentheses and calculated after adjusting for firm-level clustering. Significance is denoted by ***, **, and * at the 1%, 5%, and 10% significance levels, respectively, using a two-tailed test.

APPENDICES

Model:

This appendix constructs the basic model considered in the paper. The model assumes symmetric incentives and costs for the target firm and its sole peer. Hypotheses 1 and 2 follow directly from the predictions of the model. The goal of the CEO in firm *i* is to maximize her whole-life utility via the management of earnings from *t*=0 to ∞:

$$\max_{\{m_{i,t}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t U(W_{i,t})$$

Assumption 1: $U(W_{i,t}) = E(W_{i,t})$ (A.1)

Assumption 2: The CEO is rewarded when the reported earnings of the company are greater than their peer companies'. The compensation of the manager in firm i is

$$W_{i,t} = \gamma_{i,t} + b_t(x_{i,t} - x_{p,t})^+ - c_t m_{i,t}^2 \quad \text{(A.2)}$$

where $\gamma_{i,t}$ is the fixed compensation, $x_{i,t}$ and $x_{p,t}$ are the reported earnings of the target firm and the peer firm, respectively. The CEO receives a reward of $b_t(x_{i,t} - x_{p,t})^+$ when she beats the peer, where $(x_{i,t} - x_{p,t})^+ = \max(x_{i,t} - x_{p,t}, 0)$ and b_t is the reward factor at time *t*. There is also a personal cost of earnings management $c_t m_t^2$ should the manipulation be discovered.

Assumption 3: The target firm *i*'s reported earnings at time *t*, $x_{i,t}$, depend on the industry shock to the earnings I_t, the firm-specific idiosyncratic shock $\eta_{i,t}$, and manipulation $m_{i,t}$, i.e.,

$$x_{i,t} = I_t + \eta_{i,t} + m_{i,t} \quad \text{(A.3)}$$

Assumption 4: There is only one peer firm and it also uses the target firm as the peer. Its earnings are also determined by the industry shock, the firm-specific idiosyncratic and the level of manipulation:

$$x_{p,t} = I_t + \eta_{p,t} + m_{p,t} \quad \text{(A.4)}$$

Assumption 5: The firm-specific idiosyncratic shocks are random variables, independent, and follow a normal distribution with a variance of σ^2 so that

$$\eta_{i,t} - \eta_{p,t} \sim N(\Delta\eta_t, 2\sigma^2) \quad \text{(A.5)}$$

Assumption 6: The sum of the earnings management is bounded, i.e.,

$$\sum_{t=0}^{\infty} m_t \leq M \quad \text{(A.6)}$$

Model solution:

The Lagrangian incorporating the constraint (A.6) of the target firm is

$$\mathcal{L}_i = \sum_{t=0}^{\infty} \beta^t U(W_{i,t}) - \lambda_i (\sum_{t=0}^{\infty} m_t - M) \quad \text{(A.7)}$$

Given the assumptions, the first-order condition is

$$\frac{d\mathcal{L}_i}{dm_{i,t}} = \beta^t \frac{dU(W_{i,t})}{dm_{i,t}} - \lambda_i = \beta^t \frac{dE(W_{i,t})}{dm_{i,t}} - \lambda_i. \quad \text{(A.8)}$$

Given $\eta_{i,t}$ *and* $\eta_{p,t}$ follow normal distributions and they are independent, we have

$$x_{i,t} - x_{p,t} \sim N(\Delta\eta_t + m_{i,t} - m_{p,t}, 2\sigma^2)$$

Thus $E(W_{i,t}) = \gamma_{i,t} + b_t(\Delta\eta_t + m_{i,t} - m_{p,t})\Phi\left(\frac{\Delta\eta_t + m_{i,t} - m_{p,t}}{\sqrt{2}\sigma}\right) + b_t\sqrt{2}\sigma\phi\left(\frac{\Delta\eta_t + m_{i,t} - m_{p,t}}{\sqrt{2}\sigma}\right) - c_t m_{i,t}^2$.[9]

where $\Phi(x)$ and $\phi(x)$ are the cumulative distribution function (CDF) and probability density function (PDF) of the standard normal distribution, respectively.

The derivative of $E(W_{i,t})$ with respect to $m_{i,t}$ is

[9] The proof uses the following property: Given $X \sim N(0,1)$ and $Y = \mu + \sigma X$, then

$$EY^+ = E(\mu + \sigma X)^+ = \int_{-\mu/\sigma}^{+\infty} (\mu + \sigma x)\phi(x)dx = \mu \int_{-\mu/\sigma}^{+\infty} \phi(x)dx + \sigma \int_{-\mu/\sigma}^{+\infty} x\phi(x)dx$$
$$= \mu \int_{-\infty}^{\mu/\sigma} \phi(x)dx + \sigma \int_{-\mu/\sigma}^{+\infty} x \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} dx = \mu\Phi(\frac{\mu}{\sigma}) + \frac{\sigma}{\sqrt{2\pi}} e^{-\frac{(\mu/\sigma)^2}{2}} = \mu\Phi(\frac{\mu}{\sigma}) + \sigma\phi(\frac{\mu}{\sigma})$$

$$\frac{dE(W_{i,t})}{dm_{i,t}} = b_t \Phi\left(\frac{\Delta\eta_t + m_{i,t} - m_{p,t}}{\sqrt{2}\sigma}\right) - 2c_t m_{i,t} \qquad \text{(A.9)}$$

Substituting (9) into (8), we get the optimal $m_{i,t}$ satisfying

$$b_t \Phi\left(\frac{\Delta\eta_t + m_{i,t}^* - m_{p,t}}{\sqrt{2}\sigma}\right) - 2c_t m_{i,t}^* = \lambda_i / \beta^t \qquad \text{(A.10)}$$

Similarly, the optimal choice of the peer's management satisfies

$$b_t \Phi\left(\frac{-\Delta\eta_t + m_{p,t}^* - m_{i,t}}{\sqrt{2}\sigma}\right) - 2c_t m_{p,t}^* = \lambda_p / \beta^t \qquad \text{(A.11)}$$

In the equilibrium, both equations (A.10) and (A.11) should be satisfied.

Case 1: the expected earnings of the target firm and the peer firm are similar. In the extreme case, we can assume $\Delta\eta_t$ is 0,

Taking the difference between (A.10) and (A.11), we have

$$b_t \Phi\left(\frac{m_{i,t} - m_{p,t}}{\sqrt{2}\sigma}\right) - b_t \Phi\left(\frac{m_{p,t} - m_{i,t}}{\sqrt{2}\sigma}\right) = 2c_t\left(m_{i,t} - m_{p,t}\right) + \frac{\lambda_i - \lambda_p}{\beta^t} \qquad \text{(A.12)}$$

Since $\Phi(-x) = 1 - \Phi(x)$, equation (A.12) is equivalent to

$$\Phi\left(\frac{m_{i,t} - m_{p,t}}{\sqrt{2}\sigma}\right) = \frac{c_t}{b_t}\left(m_{i,t} - m_{p,t}\right) + \frac{1}{2}\left(1 + \frac{\lambda_i - \lambda_p}{b_t \beta^t}\right) \qquad \text{(A.13)}$$

Denote $x = \frac{m_{i,t} - m_{p,t}}{\sqrt{2}\sigma}$, then we need to solve for *x* in the following equation

$$\Phi(x) = \frac{c_t}{b_t}\sqrt{2}\sigma x + \frac{1}{2}\left(1 + \frac{\lambda_i - \lambda_p}{b_t \beta^t}\right) \qquad \text{(A.14)}$$

The solution would be in the intersection of y=$\Phi(x)$ and y=$\frac{c_t}{b_t}\sqrt{2}\sigma x + \frac{1}{2}\left(1 + \frac{\lambda_i - \lambda_p}{b_t \beta^t}\right)$. *y*=$\Phi(x)$ is CDF of the standard normal distribution and $y = \frac{c_t}{b_t}\sqrt{2}\sigma x + \frac{1}{2}\left(1 + \frac{\lambda_i - \lambda_p}{b_t \beta^t}\right)$ is a liner function of *x*. Since the target firm and the peer firm face exactly the same incentives and shocks, we expect that $\lambda_i = \lambda_p = \lambda$. In this case, $\Phi(x)$ and $\frac{c}{b}\sqrt{2}\sigma x + \frac{1}{2}$ intersect at the point (0,1/2) and *x*=0 is at least one solution. In that case,

$m_{i,t}^{*} - m_{p,t}^{*} = 0$. Substituting $m_{i,t}^{*} - m_{p,t}^{*} = 0$ into equations (A.10) and (A.11), the optimal solution for $m_{i,t}$ and $m_{p,t}$ in the equilibrium is:

$$m_{i,t}^{*} = m_{p,t}^{*} = \frac{b_t/2 - \lambda/\beta^t}{2c_t} \tag{A.15}$$

In this case, the target firm and the peer firm would manage the same amount of earnings in the equilibrium, consistent with our hypothesis of the contagion effect between the target firm's earnings management and that of the peer firm's. The level of the management is higher as the reward increases and the penalty reduces.

Case 2: $\Delta\eta_t$ is much greater than 0, i.e., earnings of the target firm are expected to perform much stronger than the peer firm, then

$\Phi\left(\frac{\Delta\eta_t + m_{i,t} - m_{p,t}}{\sqrt{2}\sigma}\right) \rightarrow 1$ and the equilibrium $m_{i,t}^{*} \rightarrow \frac{b - \lambda_i/\beta^t}{2c}$, while

$\Phi\left(\frac{-\Delta\eta_t + m_{p,t} - m_{i,t}}{\sqrt{2}\sigma}\right) \rightarrow 0$ and $m_{p,t}^{*} \rightarrow -\frac{\lambda_p/\beta^t}{2c}$

Case 3: $\Delta\eta_t$ is much lower than 0, then

$\Phi\left(\frac{\Delta\eta_t + m_{i,t} - m_{p,t}}{\sqrt{2}\sigma}\right) \rightarrow 0$ and the equilibrium $m_{i,t}^{*} \rightarrow -\frac{\lambda_i/\beta^t}{2c}$, while

$\Phi\left(\frac{-\Delta\eta_t + m_{p,t} - m_{i,t}}{\sqrt{2}\sigma}\right) \rightarrow 1$ and $m_{p,t}^{*} \rightarrow \frac{b - \lambda_p/\beta^t}{2c}$

In these two cases, $m_{i,t}^{*}$ and $m_{p,t}^{*}$ have little relationship leading to the prediction in Hypothesis 2.

Table A1: The impact of experiencing extreme earnings surprises on the covariation of the earnings management level of the target firm with that of its median peer firm

VARIABLES	(1) Mod Jones Accruals	(2) Mod Jones Accruals
1/AT	88.566	83.313
	(106.178)	(105.708)
ΔREV-ΔREC	0.256	0.252
	(0.255)	(0.254)
PPE	0.047	0.056
	(0.081)	(0.082)
BM	0.103	0.124*
	(0.069)	(0.068)
Size	0.028	0.026
	(0.028)	(0.028)
ROA	0.501	0.454
	(0.569)	(0.576)
Return	0.079	0.086
	(0.074)	(0.078)
EarningsVol	0.203	0.136
	(1.217)	(1.217)
Leverage	0.002	0.001
	(0.021)	(0.020)
Med Peer DAM	0.923***	0.945***
	(0.108)	(0.109)
EES-Dummy	-0.047	-0.039
	(0.121)	(0.068)
Med Peer DAM × EES-Dummy	-0.344***	-0.407***
	(0.131)	(0.128)
Constant	-0.466	-0.431
	(0.350)	(0.345)
Observations	1,355	1,355
R-squared	0.387	0.391
FE	Industry+Year	Industry+Year

This table examines how the covariation of earnings management behavior of the target firm with the earnings management behavior of its median peer firm changes when the target firm experiences extreme earnings surprises. The table reports results of annual regressions where the dependent variable is the discretionary accrual for target firms. Discretionary accrual measures for all firms are computed using the modified Jones measure without intercept. Every period we rank firms based on their surprise unexpected earnings (SUE). Based on this ranking, we assign a value of one to the *Extreme Earnings Surprise Dummy (EES-Dummy)* if the target firm's SUE ranks either in the top 5th (10th) percentile or in the bottom 5th (10th) percentile of all SUE's. Column 1 (2) reports the regression results where the EES-Dummy is equal to 1 if the target firm's earnings surprise falls into either the top or the bottom 5th (10th) percentile of the earnings surprise in the sample. Both models (1) and (2) control for industry and year fixed effects. Table 1 describes the independent variables used in the regressions in further detail. Standard errors are reported in parentheses and calculated after adjusting for firm-level clustering. Significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels respectively, using two-tailed tests.

Table A2: Impact of peers' behavior on management forecasts

VARIABLES	(1) Frequency	(2) Horizon	(3) Range	(4) Bias	(5) Error
1/AT	141.017	3,305.079	-8.474	2.303	-2.576
	(242.971)	(5,259.727)	(5.486)	(1.466)	(3.224)
ΔREV-ΔREC	-0.254	-10.195	0.023**	0.001	0.005
	(0.422)	(9.643)	(0.009)	(0.004)	(0.004)
PPE	-0.257	-2.079	0.016	0.003	-0.007*
	(0.478)	(10.617)	(0.012)	(0.005)	(0.004)
BM	-0.328	-16.794**	0.043**	0.011	-0.008
	(0.416)	(8.238)	(0.017)	(0.008)	(0.007)
Size	0.228	3.084	-0.008***	-0.001	-0.000
	(0.164)	(2.896)	(0.003)	(0.001)	(0.001)
ROA	1.944	-28.570	-0.374***	0.175**	-0.139*
	(2.565)	(66.584)	(0.068)	(0.071)	(0.073)
Return	0.527*	2.724	-0.002	0.022***	-0.001
	(0.294)	(6.768)	(0.010)	(0.004)	(0.005)
EarningsVol	-10.428	-474.323*	0.098	-0.458**	0.404*
	(11.168)	(251.990)	(0.172)	(0.194)	(0.210)
Leverage	-0.045	-0.308	0.000	-0.002**	0.002***
	(0.036)	(0.588)	(0.001)	(0.001)	(0.001)
Freq Pct	1.863***				
	(0.481)				
Med Peer Horizon		0.196			
		(0.139)			
Med Peer Range			0.124*		
			(0.073)		
Med Peer Bias				0.754*	
				(0.447)	
Med Peer Error					0.850*
					(0.492)
Constant	2.064	253.364***	0.130***	0.003	0.023*
	(1.598)	(51.799)	(0.031)	(0.013)	(0.012)
Observations	818	800	739	778	778
R-squared	0.301	0.080	0.328	0.318	0.314
FE	Industry+Year	Industry+Year	Industry+Year	Industry+Year	Industry+Year

This table extends the analyses in the earlier tables by investigating the impact of peer behavior on the target firm's voluntary reporting. We utilize four alternative measures of financial reporting quality distinct from discretionary accruals. In column (1) the dependent variable is *Frequency*, which reports the number of predictions a company makes during a fiscal year. In column (2) our proxy for financial reporting quality is *Horizon*, which is equal to the number of trading days between the management earnings forecast and the end of the fiscal period to which the prediction applies. In column (3) we use *Range* as our proxy for forecasting precision, where *Range* is computed as the high estimate of the earnings forecast minus its low estimate, scaled by the midpoint of the range. In column (4) we utilize *Bias* as our alternative measure of financial reporting quality. *Bias* is equal to management's earning forecast minus actual earnings scaled by beginning of period price. In column (5) we use management's forecast error as our measure of financial reporting quality where *Error* is equal to the absolute value of management's earnings forecast minus the actual scaled by beginning of period price. Table 1 describes the independent variables used in the regressions in further detail. Standard errors are reported in parentheses and calculated after adjusting for firm-level clustering. Significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels respectively, using two-tailed tests.

Table A3: Firm characteristics of Target firms and other firms

Panel A: Individual characteristics

Variable	Target Firms	Peers	Non-selected	RPE–Peers	RPE–Non-selected
Size	9.234	9.231	5.811	0.003	3.423***
BM	0.643	0.882	1.388	-0.239	-0.745**
Return 3y	0.161	0.151	0.132	0.009	0.029
Std	0.314	0.316	0.464	-0.002	-0.150
Beta	1.164	1.152	1.276	0.012	-0.112
IOR	0.594	0.593	0.251	0.001	0.343
HHI	0.054	0.057	0.059	-0.002	-0.004

Panel B: Joint characteristics

Variable	Peers	Non-selected	Peers – Non-selected
Correlation	0.545	0.286	0.259
Same SIC-1	0.727	0.117	0.610***
Same S&P500	0.672	0.491	0.181
Same S&P1500	0.722	0.316	0.407

This table reports summary statistics of individual firm characteristics for all firms that use relative performance evaluation in executive compensation contracts (target firms), for the peers of such target firms as well as for all other firms that are covered by CRSP and COMPUSTAT but are not peers (denoted as Non-selected). A firm is denoted Non-selected if it is not listed as a peer of the target firm in focus. Panel A reports the mean values for firm size (*Size*), book-to-market ratio (*BM*), average annual return over the past three years (*Return 3y*), annual volatility (*Std*), CAPM-beta (Beta), institutional ownership ratio (*IOR*) as well as customer concentration (*HHI*)for target firms, their peers and all other non-peer (Non-selected) firms, as well as the mean differences target RPE firms and their peers, and the difference between target firms and non-selected firms. Panel B reports the summary statistics for joint characteristics between target firms and their peers as well as between target firms and non-selected firms as well as the differences between these pairings. We report return correlations between these alternative pairings as well as their likelihood of belonging to the same one digit SIC industry, S&P 500 index and S&P 1500 index. Table 1 describes the variables used in further detail. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels respectively, using two-tailed tests.

Table A4: Determining counterfactual peers

VARIABLES	(1) Peer dummy	(2) Peer dummy	(3) Peer dummy
Correlation	5.228***	4.076***	4.116***
	(0.044)	(0.096)	(0.095)
Sizediff	0.319***	0.534***	0.537***
	(0.004)	(0.009)	(0.008)
BMdiff	-0.118***	-0.120***	
	(0.005)	(0.007)	
Return 3ydiff	0.049***	0.026	
	(0.014)	(0.032)	
Stddiff	-0.997***	-0.998***	
	(0.051)	(0.099)	
Betadiff	0.030***	-0.013	
	(0.011)	(0.022)	
IORdiff	0.480***	0.583***	
	(0.020)	(0.040)	
HHIdiff	-0.138***	-0.218**	
	(0.048)	(0.097)	
ROAdiff	0.547***	0.794***	
	(0.063)	(0.127)	
Same Industry	2.704***	2.669***	2.654***
	(0.016)	(0.031)	(0.030)
SameS&P500	0.566***	0.522***	0.496***
	(0.015)	(0.030)	(0.029)
SameS&P1500	0.841***	0.751***	1.022***
	(0.017)	(0.031)	(0.029)
Constant	-8.818***	-2.720***	-2.980***
	(0.043)	(0.084)	(0.082)
Sample	Full sample	1 to 1 sample	1 to 1 sample
# of Observations	6,350,100	53,869	53,869
Pseudo R-squared	0.328	0.553	0.532
FE	Industry+Year	Industry+Year	Industry+Year

This table reports logistic regression results where the dependent variable is the *Peer dummy* which equals one if a matched firm is an actual RPE peer of the firm studied and zero otherwise. In model (1), we match each target firm-year with all possible firms in that year that have corresponding data on CRSP and Compustat as long as the matched firm is at least as large as the smallest peer of the target firm in that year. This setup yields an N x M matrix which implies multiple pairings between each target firm and peers to match from a larger set of candidates. We collapse this N x M matrix of all possible matches into an [N*M] x K matrix where [N*M] rows correspond to all the one-to-one matches between target firms and the universe of potential matches, while K columns include information regarding the independent and dependent variables utilized in this table. In models (2) and (3), we limit the sample size by randomly matching each target peer firm to a single potential matching firm. Loading on characteristics that determine the likelihood of being a peer firm are then used to determine counterfactual peers. Table 1 describes the independent variables used in the regressions in further detail. Standard errors are reported in parentheses and calculated after adjusting for firm-level clustering. Significance is denoted by ***, **, and * at the 1%, 5%, and 10% significance levels respectively, using two-tailed tests.

Table A5: Correlations between different measures of DAM

	RPE DAM	Med Peer DAM	Med industry DAM	Med Counter-factual DAM (1)	Med Counter-factual DAM (2)	Med Counter-factual DAM (3)	Med Dropped DAM	Med Peers' Peer DAM
Med Peer DAM	0.640	1						
Med industry DAM	0.680	0.559	1					
Med Counterfactual DAM (1)	0.663	0.736	0.584	1				
Med Counterfactual DAM (2)	0.530	0.655	0.601	0.803	1			
Med Counterfactual DAM (3)	0.524	0.629	0.545	0.786	0.803	1		
Med Dropped DAM	0.199	0.289	0.240	0.238	0.235	0.248	1	
Med Peers' Peer DAM	0.215	0.276	0.211	0.273	0.326	0.312	0.137	1
Med BGT DAM	0.597	0.646	0.541	0.600	0.517	0.437	0.251	0.182

This table reports correlations among the target firm's discretionary accruals (*RPE DAM*), median discretionary accruals of peers (*Med Peer DAM*), median discretionary accruals of the industry (*Med industry DAM*), *Med Counterfactual DAM 1 (2, 3),* which are median discretionary accrual values of counterfactual peers when the counterfactual peers are estimated using model 1 (2, 3) in Table 6, the median of discretionary accruals of peers that are dropped in the former period (*Med Dropped DAM*), the median of discretionary accruals of peers' peers (*Med Peers' Peer DAM*), and *Med BGT DAM*, i.e., the median of discretionary accruals of firms with the highest correlation with the target firm and from the same industry following Bloomfield, Guay, and Timmermans (2022).