Relative Performance Evaluation and Contagion in Financial Reporting Quality

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Abstract

We examine the effect of relative performance contracts on a manager's economic incentives to manipulate earnings. Using data on actual peer firms, we find that 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.

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

JEL Classifications: G34; G38; C33

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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 earnings management through the relative performance evaluation channel. We define target firms as those whose earnings management decisions are potentially influenced by the earnings management decisions of firms in their RPE peer group. Theoretically, both Gao and Zhang (2019) and Infuehr (2022) investigate the influence of peer firm earnings management behavior on the amount of earnings management by the target firm.

Gao and Zhang (2019) argue that when there are two firms with correlated fundamentals, investors can also use the peer firm's financial reports to improve their valuation of the target firm. They show that this informational spillover creates pressure to manipulate earnings. The incentive of the target firm's manager to manipulate increases in her expectation that the manager of the peer firm has already successfully manipulated his report. Gao and Zhang (2019) further show that if a target firm invests more in internal controls this would have positive externalities for the peer firm as well, leading to a reduction in earnings management for both the peer and the target firms. Since the target firm fails to internalize this positive externality, both the peer and the target firm underinvest in internal controls, failing to curb the correlation in earnings management behavior.

Infuehr (2022) proposes a model to explain why RPE compensation is not universal. He argues, under a relative performance contract with a benchmark, the manager could find it optimal at times to substitute earnings management for effort. He shows that when earnings management is possible, RPE contracts create stronger incentives for earnings management compared to non-RPE contracts that are not benchmarked against peers.

Building on this prior theoretical work, we empirically examine the relationship between RPE compensation contracts and earnings management contagion. Specifically, we test if 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 2006-2016 based on actual RPE compensation contracts. The use of actual peers, as opposed to using proxies such as membership in the same SIC industry, should increase the power of our tests as links between target firms and peer firms identified through actual RPE compensation contracts will not be contaminated by any firms that may be misclassified as peers.

We hypothesize that when peer firms manipulate earnings, there is increased pressure on the target firm to respond in kind. This is the central idea behind our initial test. In line with this prediction, 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 (e.g. 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 proceed to further develop the existence of earnings management contagion among peer firms by documenting that no such contagion exists among a set of counterfactual peer firms. 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. We find that the earnings management behavior of counterfactual peers has no significant effect on the likelihood or the intensity of earnings management by the target firm suggesting that it is the RPE compensation contract peers that matter to the earnings management behavior of the target firm.

To control for potential errors in identifying the set of counterfactual peer firms, we further test whether the earnings management behavior of former peer firms affects the earnings management decisions of the target firm. 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. We find that former peer firms' earnings management activity has no significant effect on the target firms' earnings management. Through these tests we establish that any variables omitted from our analysis are unlikely to influence the earnings management behavior of the target firm. In all these specifications we find that only the level of earnings management behavior of the concurrent set of actual peer firms has a significant effect on the management of target firm's earnings.

Our benchmark tests use discretionary accruals as a measure of earnings management. We conduct a robustness test using alternative measures of financial reporting quality. We find that target firm activity is significantly related to the forecast rate and horizon of managerial forecasts of peer firms, as well as the bias and error in these forecasts. We also document that the incidence and frequency of earnings restatements of peer firms significantly influence the likelihood of restatements by the target firms. Motivated by the theoretical assumptions of Gao and Zhang (2019) we also examine whether there is a strong correlation between peer firms' internal controls and the target firm internal control mechanisms, but find no such significant relation.

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 (2019) 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 (2022) show that greater RPE usage leads firms to take on more idiosyncratic risk.

Most 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 reporting 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 1997-2008. 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 between firms 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.

We contribute and build on the contagion literature that most often uses SIC identified 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 through actual RPE compensation contracts. We provide precise tests on the potential downsides of using relative performance evaluation in compensation contracts: The race to keep up with the earnings management activities of peer firms causes greater target firm earnings management.

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. Section 4 presents the empirical results, and Section 5 concludes.

2. Hypotheses

The choice of whether to manage earnings should be related to the management decisions of peer firms. Target management faces costs and benefits to manipulating earnings in all settings, but the case of relative performance evaluation presents a stark example of a Nash equilibrium problem. If peer firms manipulate earnings, then the manager is faced with a choice of whether to manipulate or not. Management carries a set of punishment costs should the management be discovered, so if peers do not manipulate the manager must trade off these costs against the gains that can be obtained from additional RPE compensation by outperforming her peers. If the manager observes that peer firms are manipulating, then the manager faces a higher risk of underperformance if she does not manipulate. In game theory terms, we assume that the game is *supermodular*.

[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 measure peers significantly improves the empirical evidence on the Holmstrom theory, allowing firms to improve the filtering out of common shocks.

Supermodular games exhibit strategic complementarity, where the optimal response of the target firm CEO upon observing earnings management in their set of peer firms, is to increase the level of earnings management of their firm.

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). Financial incentives associated with RPE grants similarly provide strong motivations for executives to manage earnings when the firm's peers are also managing earnings. When peers are managing earnings upwards, executives are motivated to inflate their own performance to meet or exceed the peer performance benchmark specified in their compensation contracts.

In addition to losing compensation, the grave danger of termination after underperforming one's peer group can also influence the target manager to manipulate when peer firms manipulate. Prior research suggests that relative performance can determine whether a manager will be dismissed from her job. Using industry and size benchmarks, Jenter and Kanaan (2015) and DeFond and Park (1999) show that CEOs are more likely to be dismissed from their jobs after poor performance relative to their industry. Rajgopal, Shevlin, and Zamora (2006) show that a CEO's outside career opportunities depend on her firm's performance relative to their industry. Thus, failing to match the performance of one's peers can have severe adverse consequences to a manager's career. Facing such potentially adverse outcomes, such as being dismissed from their jobs, likely influences managers' decision to manipulate their earnings. There is also evidence that investors and analysts use relative performance with respect to their peers when evaluating firms (De Franco, Hope and Laroucque 2015). This additional capital market pressure adds further incentives to outperform peer benchmarks hence increases the likelihood of earnings management by the managers.

Dovetailing into our hypothesis Gao and Zhang (2019) theoretically show that information spillovers they attribute to peer pressure lead target firms to manage earnings. Peer pressure is a social construct that could be present (Seo, 2001), but herein we emphasize the target firm's compensation-driven economic incentives to manage earnings. Further enhancing our predictions, Infuehr (2022), in another theoretical model, proposes and proves that the combination of inherent high correlation between target and peer firms' performances coupled with the asymmetric nature of the cost-benefit tradeoff within RPE contracts leads to contagion in earnings management among RPE firms relative to non-RPE firms. We argue that financial incentives associated with RPE compensation contracts will ultimately motivate managers to mimic their peers' earnings reporting quality. Thus, the first hypothesis (H1) we test in this paper is the following:

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

A number of firms listed as peers by the target firms in our sample use RPE grants in their managers' compensation contracts. Furthermore, a subset of these peer firms also cross-reference the target firm and use the target firm as a peer in their managers' compensation contracts. If, as we hypothesize, firms engage in earnings management in response to the behavior of their peers, which then leads to a contagion in earnings management, then we should expect this contagion effect to be more pronounced among groups of firms that mutually reference each other as peers in their RPE compensation contracts. Since managers in both firms that cross-reference each other will be pressured to mimic each other's earnings management behavior, the correlation in earnings reporting quality should be higher for such a pair of firms compared to other firm pairs where only the target firm lists the peer firm in the target firm's manager's RPE compensation contract but the peer firm does not cite back the target firm in its manager's RPE compensation contract. We would expect to see a similar effect (though to a lesser degree) between the target firm and the peer firm which uses RPE grants in compensation contracts but does not use the target firm as a peer.

Consider the following example. Suppose firm A uses the performance of firms B, C and D as benchmarks for RPE grants. Firm B uses firms A, C and D in its relative performance evaluation. Firm C uses RPE grants in their executives' compensation contracts but does not use firms A, B or D as peers. Firm D does not use RPE grants. In this example, we would expect the correlation in earnings reporting quality be highest between firms A and B, followed by between firms A and C, and the lowest between firms A and D. The more firms are interlinked through the compensation contracts the more the economic incentives to mimic increase. Thus, we would expect the correlation of earnings quality measures across firms to increase with greater interlinkages between firms. Thus, the second set of hypotheses we test in the paper are as follows:

> H2A: *The similarity in the earnings quality measures of a target firm and its peers increases if the peer firms use RPE grants in setting executive pay.*

> H2B: *The similarity in the earnings quality measures of a target firm and its peers increases if the peer firms and the target firm cross-reference each other as peers in RPE compensation contracts.*

Identifying peer effects in corporate earnings management is empirically challenging as earnings management is an endogenous choice variable. The selection of peers by the 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 the 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 contagion.

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 time 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 an important 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 executive compensation contracts. In 2016, for instance, 50% of the firms have 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 a benchmark.[2] On average, each firm has 15 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. Although, firms may select RPE peers opportunistically to increase award payout, Bizjak Kalpathy, Li and Young, (2022) find limited evidence of such bias in peer selection. Incentive Lab also provides information on the metric used for performance evaluation. The performance metric is either a firm's stock return or an accounting performance measure such as a firm's EPS.[3] Stock return is used as a metric in 61% of the RPE grants. Although there is some variation, typically, the CEO is awarded cash, stock or option grants if the firm beats the median peer based on the specified performance metric.

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 RPE firms that use a set of peer firms to assess relative performance. Although some firms use index level returns or industry level performance measures in their RPE compensation contracts, such firms wouldn't be included in our sample. 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 main measure of earnings quality is discretionary accruals using the modified Jones measure proposed by Dechow, Sloan and Sweeney (1995). To be exact, we compute discretionary accruals (DAM) by subtracting nondiscretionary accruals from total accruals. In order to do so we run the following cross-sectional regression:

[2] Most other firms use the market return or the average industry stock or accounting return as a compensation benchmark. A smaller percentage of firms use commodity prices as benchmarks for RPE compensation contracts.

[3] The accounting metrics vary, but majority are based on earnings, with EPS being the most common.

$$TA_t = b_1\left(\frac{1}{AT_{t-1}}\right) + b_2(\Delta REV_t - \Delta REC_t) + b_3 PPE_t + \varepsilon_t \tag{1}$$

where TA_t is total accruals in year t, AT_{t-1} is total assets in year $t-1$, ΔREV_t is the change in revenues from year $t-1$ to year t scaled by total assets in year $t-1$, ΔREC_t is the change in net receivables from year $t-1$ to year t scaled by total assets in year $t-1$, and PPE_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:

$$TA_t = \frac{\Delta CA_t - \Delta CL_t - \Delta Cash_t + \Delta STD_t - Dep_t}{AT_{t-1}} \tag{2}$$

where ΔCA_t is the change in current assets, ΔCL_t the change in current liabilities, $\Delta Cash_t$ the change in cash and cash equivalents, ΔSTD_t the change in debt included in current liabilities, and Dep_t the depreciation and amortization expense.

We estimate Equation (1) 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 10 and all three independent variables to be available to run the regression specified in Equation (1). 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.

In addition to the discretionary accruals measure, we also use in our analyses two additional mandatory financial reporting quality measures commonly utilized in the literature, namely the likelihood that a firm will report an internal control weakness, and the likelihood that a firm will restate its financial statements (Dechow and Dichev 2002; McGuire, Omer, and Sharp 2012).

Restate is a dummy variable set to 1 if a fiscal year overlaps with an identified restatement period as recorded by the AuditAnalytics "Non-Reliance" database, and 0 otherwise. Internal control weakness (ICW) is a dummy variable equal to 1 if a firm is reported as having an ineffective internal control according to AuditAnalytics "SOX 404 Internal Controls" database.

Although the discretionary accrual measure described in Equation (1) is our main variable of interest, we also use a number of alternative variables that capture a firm's voluntary reporting quality, in terms of the frequency, timeliness, accuracy, precision, and bias of management earnings forecasts. *Frequency* is the number of forecasts made by a firm during a fiscal year. *Horizon* is the number of days between the date of the first earnings forecast in a fiscal year and the end of the fiscal year. *Bias* measures the difference between management's earnings forecast and actual earnings scaled by price at the beginning of the period. *Error* is the absolute value of management's earnings forecast minus the actual earnings scaled by price at the beginning of the period. When there is only one forecast, we take that value as the forecast; if the period has multiple forecasts, we take the median as the forecast (Call et. al 2013). The forecast data is obtained from the IBES Management Guidance Detail file. We use these alternative measures of reporting quality to help validate our main conclusions using discretionary accruals.

In all of our analyses, we control for a number of firm characteristics commonly used in the literature. We use these same set of controls when we conduct a propensity score matching in an effort to create counterfactual set of peers. 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. *Rating* is the S&P Domestic Long Term Issuer Credit Rating from Compustat, and is assigned a numerical value of 1 for credit rating levels of D and SD. Alphabetical rating assignments are converted to numerical values by increasing by one each increment in credit rating above and beyond a rating level of D, up until we assign a numerical value of 22 for the rating level AAA. *Institutional ownership* is the shares held by institutions divided by total shares outstanding, where 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 also 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 performance of the CEO's firm with respect to the median performance of its peers. We sort firms each year based on the Med Peer DAM and form quintile portfolios. We then compute average DAM values as well as averages for various firm characteristics for each quintile portfolio.

Table 3 reports means of 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 Med Peer DAM increases, there is a monotonic increase in the target firm's discretionary earnings management as well. The differences in DAM between the high minus low Med Peer DAM portfolios is highly significant. Moreover, this relationship does not appear to be related to or be driven by other firm characteristics such as the book-to-market ratio, firm size, return on assets, earnings volatility, stock return, or leverage. We reach this conclusion as the differences in firm characteristics for the high minus low Med Peer DAM portfolios are all insignificant.

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

$$DAM_{i,t} = \alpha + \theta Med\ Peer\ DAM_{i,t} + \beta X_{i,t} + \gamma_t + \delta_j + \varepsilon_{i,t} \quad (3a)$$

Above, 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). γ_t control for time fixed effects and δ_j control 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 membership shared by the RPE firm and its peer firms, hence the need to control for industry fixed effects.

In Equation 3(a), 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 accruals results in a one standard deviation increase in the discretionary accruals of the firm.[4] These results are consistent with our first hypothesis that earnings management by peers lead to greater earnings management by the

[4]Based on standard deviations reported in Table 1, a one standard deviation increase in peer firm DAM results in a 0.905*1.304 = 1.18 increase in target firm DAM, which is roughly equivalent to one standard deviation (1.17) in DAM of the target firm.

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. Kedia, Koh, and Rajgopal (2015), for instance, show evidence of industry-wide contagion in earnings management. They link contagion to enforcement activity by the SEC. We control for median industry earnings quality (Med Industry DAM) by running the following regression:

$$DAM_{i,t} = \alpha + \theta Med\ Peer\ DAM_{i,t} + \partial Med\ Industry\ DAM_{j,t} + \beta X_{i,t} + \gamma_t + \delta_j + \varepsilon_{i,t} \tag{3b}$$

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 effect of peers on earnings quality captures information regarding earnings management behavior above and beyond what is explained by industry effects.

To control for all time varying industry effects, we include dummy variables ($\gamma_t \times \delta_j$) that interact 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:

$$DAM_{i,t} = \alpha + \theta Med\ Peer\ DAM_{i,t} + \beta X_{i,t} + \gamma_t \times \delta_j + \varepsilon_{i,t} \tag{3c}$$

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

Finally, we include firm fixed effects to control for potential peer selection biases that could result from time invariant firm characteristics. Firm fixed effects would control for firm specific factors that affect both the earnings management of the firm as well as the selection of peers that are likely to engage in 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:

$$DAM_{i,t} = \alpha + \theta Med\ Peer\ DAM_{i,t} + \beta X_{i,t} + \gamma_t + \vartheta_i + \varepsilon_{i,t} \qquad (3d)$$

Above, 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 again remains significant.

4.2 The relation between earnings quality of RPE firms and counterfactual peers

Although firm fixed effects control for time-invariant determinants, there could still be time-varying firm characteristics that are unobservable but 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. We carry out two additional analyses to address such potential endogeneity issues associated with the selection of peers. Specifically, we create a set of counterfactual peers using two 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. In this sense, 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 it is dropped from the peer list, under our hypothesis even when it is managing earnings, we would not expect the dropped peer firm to have an impact on the firm's earnings management behavior in the current year.

For the propensity score matching, we identify key characteristics that have been shown to drive peer firm selection (Gong, Li and Shin, 2011; Bizjak et al. 2022). As the main motivation for using RPE is to filter out common shocks (Holmstrom 1982, Holmstrom and Milgrom 1987), we find counterfactual firms that are in the same industry, listed in the same stock index, and firms whose stock returns are highly correlated with those of our target firm. For the propensity score matching, we also use firm characteristics that capture similarities in performance, risk, growth opportunities and capital raising capacity. 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*), credit rating (*Ratings*), 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. Table 5 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 5, 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 to 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 correlation 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.

Using the set of firm characteristics listed above, each year we create a set of counterfactual peers for each target firm using propensity score matching (PSM). Since each target firm averages 15 peers, matching each of these 15 peers to over 7,000 firms in the CRSP-Compustat universe results in a very large dataset to be used in PSM. 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 Table 6. All explanatory variables are significant. Not all of 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) uses a large number of matches 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 the variables that have been previously used in the literature. Specifically, we only 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 (see for instance 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 logit regressions, we calculate an expected likelihood of being selected as a peer for each match each year. For each target peer, 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.

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. 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. 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 median earnings quality of the counterfactual peers (*Med Counterfactual DAM*) by running the following regression:

$$DAM_{i,t} = \alpha + \theta Med\ Peer\ DAM_{i,t} + \partial Med\ Counterfactual\ DAM_{i,t} + \beta X_{i,t} + \gamma_t + \vartheta_i + \varepsilon_{i,t} \quad (4)$$

The results are reported in Table 7. 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 Table 6. In column (4) we control for the median peer DAM of dropped peers. In all four specifications, the impact of earnings quality of counterfactual peers is insignificant. Moreover, the impact of 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 confounding variables. Rather, our results support a causal link between the target firm's earnings quality and that of its peers, strongly supporting our first hypothesis.

4.3 Impact of mutual benchmarking

In this section, we test our second hypothesis that the compensation practices of peer firms could affect the strength of the relation 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 peer 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 are managing earnings to outperform the target firm, managers at the target firm will 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 perhaps more subdued, effect could occur if the peer firm uses relative performance evaluation in its own contracts without cross-referencing the target firm. To test these conjectures, we run the following regression:

$$\begin{aligned} DAM_{i,t} = {} & \alpha + \theta Med\ Peer\ DAM_{i,t} + \partial Med\ Mutual\ Peer\ DAM_{i,t} \\ & + \varphi Med\ Non\_mutual\ RPE\ Peer\ DAM_{i,t} + \beta X_{i,t} + \gamma_t + \vartheta_i + \varepsilon_{i,t} \end{aligned} \tag{5}$$

In Equation (5), *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 coefficients on the *Med Mutual Peer DAM* and the *Non-mutual RPE Peer DAM* variables capture the incremental impact of the peers who mutually benchmark or just use relative performance valuation in compensation contracts without mutual benchmarking above and beyond the impact of peers.

The results are reported in Table 8. In the first column, we report results for the specification that includes only the *Med Mutual Peer DAM*. We find the coefficient on this variable to be economically and 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 peer firm discretionary accruals. This result supports our hypothesis *H2B* regarding enhanced contagion effects when peers benchmark each other. The specification reported in column (2) includes only the *Non-mutual RPE 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 effect of these peers on the target firm's earnings management behavior to be insignificant. These results do not support our hypothesis *H2A* since non-mutual peers provide no additional incentive to manipulate, only mutual peers do. 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.

4.4 Alternative measures of earnings quality

We conclude the empirical tests in the paper using a number of alternative measures of earnings quality to make sure that our results are robust to using different measures. We use four alternative measures that can capture a firm's voluntary reporting quality, in terms of frequency, timeliness, accuracy, and bias of management earnings forecasts. We also use two additional measures of mandatory reporting quality: the likelihood that a firm will report an internal control weakness, and the likelihood that a firm will restate its financial statements. Voluntary and mandatory reporting quality variables are described in detail in Table 1. The results using these alternative measures are reported in Table 9. In the first column 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) and (4), we use the horizon, 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, bias and error of earnings forecast of peer firms respectively. Using all four 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.

In results reported in columns (5) and (6) we use the restatement and ineffective internal control dummies as alternative proxies of financial reporting quality. The *Restate* dummy is set to one in a fiscal year if the target firm restates earnings in that year. The *ICW* dummy variable is set to one in a fiscal year in which management reports ineffective internal controls. 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. Similarly, the *Peer ICW* dummy variable equals one if any of the peers is reported to suffer from ineffective internal controls. As these are binary outcome variables, we run a logistic regression and report pseudo-R squared values in the last two columns of Table 9. We find a significant association between peers' restatements and the target firm's restatements. Peers' internal control weakness also has a positive impact on the target firm's internal control weakness, though this effect is not statistically significant. Overall, the results in Table 9 show that our main findings are robust to alternative measures of financial reporting quality.

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 without the confounding influence of pseudo-peer firms that happen to be in the same industry. Using this set of peers, we find that the amount of peer firm's earnings management is significantly positively related to the amount of target firm 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.

We perform a number of 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 common literature proxy, the industry level of discretionary accruals. We also develop a number of counterfactual peer groups, including a set of former peer firms, and find that the discretionary accruals of these alternative peer groups do not have any significant influence on the target firm's discretionary accruals. Finally, we show that if the peer firm uses the target firm as its peer in their incentive plans, the contagion effect is even stronger. Given this evidence, we conclude that there exists significant contagion in earnings management behavior among firms that use RPE in their compensation contracts.

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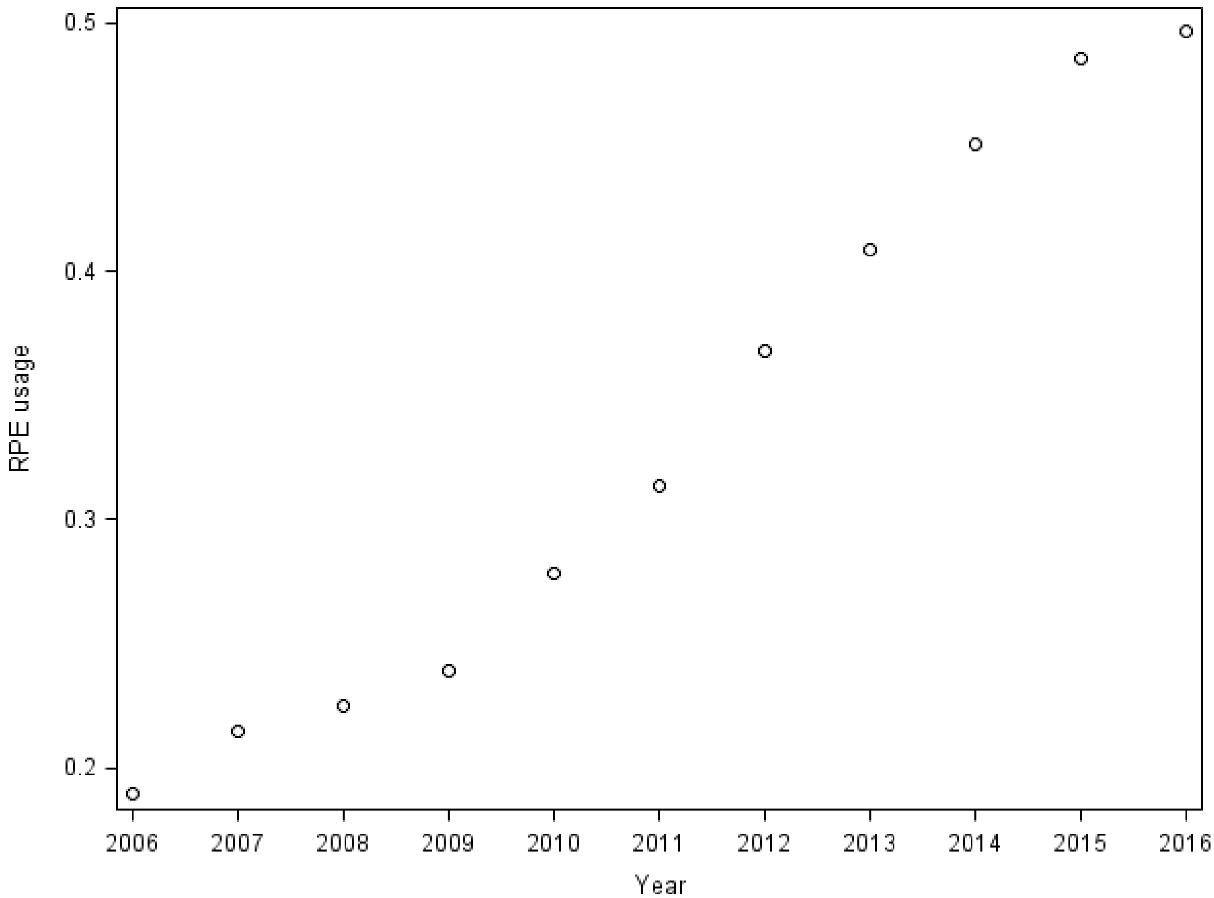
Figure 1: RPE usage



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

Table 1: Variable definitions

This table describes the variables used in the analyses.

Variable	Definition
Firm characteristics:	
BM	Book value of equity divided by market value of equity
Size	The natural logarithm of total assets
ROA	Earnings before extraordinary items divided by total assets
EarningsVol	Earnings volatility in the past 3 years
Return	Annual return
Leverage	Sum of the market value of equity and the book value of liabilities divided by the market value of equity
Accruals quality measures:	
DAM	Discretionary accruals computed using the modified Jones measure in Dechow, Sloan and Sweeney (1995) without intercept
Med Peer DAM	Median of discretionary accruals of peers, where discretionary accruals are computed using the modified Jones measure without intercept
Med Industry DAM	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
MedCounterfactual DAM	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.
MedDropped DAM	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 Mutual Peer DAM	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	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

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
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 AuditAnalytics' 'Non-Reliance' database. Observations corresponding to restatements arising from clerical errors are deleted
ICW Dummy	A dummy equal to 1 if for any period in which management reports ineffective internal controls.
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 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 ICW Dummy	A dummy equal to 1 if any management of the peers reported ineffective internal controls.
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
Rating	Credit rating is expressed as a number, where we assign a numeric value of 1 for the lowest S&P domestic long-term issuer credit rating quality of D or SD. The numerical equivalent of each rating increases by 1 for each subsequent increment reaching its highest for AAA at 22
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
SameS&P500	A dummy equal to 1 if a target firm and its potential peer both belong to the S&P 500 index and 0 otherwise
SameS&P1500	A dummy equal to 1 if a target firm and its potential peer both belong to the S&P 1500 index and 0 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
Ratingsdiff	Ratingsdiff measures the difference in the credit ratings 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

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 2016for the sample of firms that use relative performance evaluation (RPE) in executive contracts. Panel B presents summary statistics from 2006 to 2016for all firms with data available in both the CRSP and Compustat databases. Panel C presents summary statistics from 2006 to 2016for 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 on discretionary accruals

Quintile	DAM	Med Peer DAM	BM	Size	ROA	EarningsVol	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
BM	0.080	0.061	0.079	0.022
	(0.051)	(0.052)	(0.048)	(0.071)
Size	0.011	0.003	0.001	-0.082
	(0.021)	(0.020)	(0.021)	(0.110)
ROA	0.652	0.655	0.517	0.499
	(0.536)	(0.540)	(0.625)	(0.825)
Return	0.077	0.082	0.052	0.186
	(0.071)	(0.071)	(0.080)	(0.129)
EarningsVol	0.321	0.502	0.441	-2.934
	(1.227)	(1.194)	(1.275)	(2.868)
Leverage	-0.010	-0.012	-0.010	0.013
	(0.019)	(0.020)	(0.027)	(0.033)
Med Peer DAM	0.905***	0.624***	0.547***	0.948***
	(0.104)	(0.111)	(0.111)	(0.123)
Med Industry DAM		0.719***		
		(0.141)		
Constant	-0.138	-0.021	-0.059	0.674
	(0.222)	(0.215)	(0.233)	(1.044)
# of Observations	1,466	1,466	1,466	1,466
R-squared	0.409	0.484	0.533	0.568
FE	Industry+Year	Industry+Year	Industry*Year	Firm+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, and model (4) controls for firm 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 5: 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
Ratings	13.852	13.995	12.902	-0.143	0.950
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), credit rating (*Ratings*), 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 1 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 6: 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 a given 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 would 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 7: 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
BM	0.080	0.081	0.075	0.077
	(0.052)	(0.053)	(0.052)	(0.053)
Size	0.013	0.012	0.017	0.013
	(0.022)	(0.022)	(0.022)	(0.022)
ROA	0.793	0.795	0.844	0.782
	(0.555)	(0.555)	(0.556)	(0.557)
Return	0.050	0.047	0.071	0.054
	(0.068)	(0.067)	(0.070)	(0.068)
EarningsVol	0.579	0.580	0.571	0.527
	(1.336)	(1.339)	(1.334)	(1.354)
Leverage	-0.008	-0.007	-0.011	-0.009
	(0.020)	(0.020)	(0.020)	(0.020)
Med Peer DAM	0.907***	0.910***	0.893***	0.893***
	(0.104)	(0.104)	(0.103)	(0.101)
Med CounterfactualDAM(1)	-0.039			
	(0.056)			
Med CounterfactualDAM(2)		-0.077		
		(0.091)		
Med CounterfactualDAM(3)			0.226	
			(0.158)	
Med Dropped DAM				0.036
				(0.039)
Constant	-0.174	-0.171	-0.206	-0.174
	(0.231)	(0.231)	(0.232)	(0.230)
Observations	1,440	1,440	1,440	1,440
R-squared	0.411	0.412	0.414	0.412
FE	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*). All four 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: Effect of mutual benchmarking

	(1)	(2)	(3)
Case Analyzed:	Peers benchmarking back	Peers using RPE but not benchmarking back	Horse-race
VARIABLES	Mod Jones Accruals	Mod Jones Accruals	Mod Jones Accruals
BM	0.064	0.084*	0.068
	(0.048)	(0.050)	(0.048)
Size	0.012	0.010	0.011
	(0.021)	(0.021)	(0.021)
ROA	0.550	0.688	0.594
	(0.533)	(0.541)	(0.537)
Return	0.078	0.074	0.074
	(0.071)	(0.071)	(0.072)
EarningsVol	-0.055	0.390	0.024
	(1.203)	(1.225)	(1.203)
Leverage	-0.006	-0.013	-0.009
	(0.017)	(0.019)	(0.018)
Med Peer DAM	0.727***	0.864***	0.667***
	(0.137)	(0.110)	(0.159)
Med Mutual Peer DAM	0.297**		0.308**
	(0.142)		(0.141)
Med Non-mutual RPE Peer DAM		0.080	0.105
		(0.089)	(0.084)
Constant	-0.139	-0.134	-0.134
	(0.221)	(0.222)	(0.221)
Observations	1,466	1,466	1,466
R-squared	0.437	0.411	0.442
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 9: Impact of peers' behavior on alternative measures of financial reporting quality

VARIABLES	(1) Frequency	(2) Horizon	(3) Bias	(4) Error	(5) Restate Dummy	(6) ICW Dummy
BM	-0.210	-0.047	-0.009	0.015	0.439	0.195
	(0.332)	(0.038)	(0.013)	(0.012)	(0.346)	(0.344)
Size	0.261**	-0.005	-0.001	-0.001	-0.214*	-0.188
	(0.130)	(0.014)	(0.001)	(0.001)	(0.117)	(0.125)
ROA	1.981	-0.111	0.084	-0.037	-2.238	-3.238*
	(2.418)	(0.371)	(0.056)	(0.056)	(1.656)	(1.696)
Return	0.527*	-0.007	0.019***	0.004	0.090	0.200
	(0.303)	(0.044)	(0.005)	(0.004)	(0.264)	(0.270)
EarningsVol	-7.963	-2.574**	-0.274***	0.185*	4.586	0.806
	(9.912)	(1.228)	(0.083)	(0.100)	(8.726)	(7.386)
Leverage	-0.015	0.003	-0.002*	0.001*	0.053	0.064
	(0.025)	(0.002)	(0.001)	(0.001)	(0.062)	(0.075)
Freq Pct	2.049***					
	(0.520)					
Med Peer Horizon		0.002*				
		(0.001)				
Med Peer Bias			0.593***			
			(0.190)			
Med Peer Error				0.619***		
				(0.197)		
Peer RestateDummy					0.564**	
					(0.250)	
Peer ICW Dummy						0.168
						(0.269)
Constant	1.143	5.224***	0.012	0.010	1.981	2.184
	(1.157)	(0.326)	(0.008)	(0.008)	(1.290)	(1.371)
Observations	866	847	824	824	511	516
(Pseudo) R-squared	0.303	0.073	0.308	0.317	0.064	0.048
FE	Industry+Year	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 alternative measures of financial reporting quality. We utilize five alternative measures of financial reporting quality distinct from discretionary accruals. In columns (1) through (4) we run panel regressions with industry and year fixed effects. 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 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 (4) 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. In column (5) we add to our alternative measures of financial reporting quality by utilizing restatements. 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. In column (6) we run a logistic regression of the target firm's internal control weakness (ICW) on their peers' ICW. 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.