

# The Complexity Trap: How Complex CEO Compensation Fuels Managerial Myopia

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## Abstract

This study examines the impact of CEO compensation complexity on managerial short-termism using S&P 1500 firms over the 2006–2022 period. We find a positive association between compensation complexity and R&D cuts, especially in firms with strong incentives to avoid small earnings declines. This positive effects are more pronounced in firms with weaker governance, less market competition, and among younger or less outside wealth CEOs. Further analysis suggests that complex contracts amplify managerial short-termism and worsen future performance through less sensitive pay-performance linkage. Overall, our study highlights the dark side of CEO compensation complexity and emphasizes the need for simpler executive compensation.

**JEL Classification:** G30, G32

**Keywords:** CEO compensation complexity, managerial short-termism, R&D cutting

*“CEOs are grappling with an ever-expanding set of priorities, often with overlapping or conflicting demands, which can make it difficult to maintain strategic focus.”*  
— McKinsey, *“Priorities for CEOs in the Next Normal”* (2021)

## 1. Introduction

There has recently been a marked increase in the complexity of executive compensation packages, with modern contracts evolving from relatively straightforward salary and bonus arrangements into complicated combinations of base salary, annual bonuses, stock options, restricted stock, long-term incentive plans, and various perquisites. Albuquerque et al. (2025) show that CEO compensation complexity has doubled between 2006 and 2019, driven primarily by the incorporation of more performance measures, an increased number of performance-measurement periods, and a greater use of relative performance conditions within CEO contracts.<sup>1</sup> This evolution reflects well-intentioned efforts by boards to better align executive incentives with shareholder interests and to attract and retain top talent in an increasingly competitive market for executive talent. However, more than half of this complexity increase appears to stem from external factors beyond efficient contracting, including pressure from compensation consultants, institutional investors, proxy advisors, and peer benchmarking practices (Albuquerque et al., 2025).

Most compensation committees support the inclusion of multiple performance metrics in incentive plans, surrendering to the pressures from external stakeholders. Complex compensation structures are advocated on the basis that compensation is a "powerful tool" to achieve various goals and provide comprehensive incentive alignment (Jensen and Murphy 1990). For example, linking executive compensation to multiple performance measures has been proposed as a solution to the multitasking problem inherent in modern corporate management.

Yet, prominent scholars have argued that overly complex compensation structures may undermine their intended purpose and lead to unintended consequences for corporate decision-

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<sup>1</sup> The authors define a contract as more complex based on four dimensions: the types of compensation used (e.g., cash or equity), the number of performance metrics, the number of performance-measurement periods, and the reference points for these measures (absolute and relative)

making and outcomes (Jensen and Murphy 1990; Burkert et al. 2024; Albuquerque et al. 2025). They make two main points that cannot be easily dismissed, even in well-governed firms, and which are not captured by standard models of executive compensation. First, they argue that complex contracts can cognitively overburden CEOs and impede efficient managerial decision-making. When executives face intricate compensation structures with multiple, potentially conflicting performance metrics, they may struggle to process and respond optimally to the embedded incentives, leading to suboptimal resource allocation decisions. Second, they argue that the driving forces behind compensation complexity often stem from external pressures, including compensation consultants, institutional investors, proxy advisors, and peer benchmarking practices, rather than from optimal contracting considerations. This externally driven complexity creates distraction from conflicting objectives that hampers CEO decision-making, as managers must navigate competing demands that may not align with long-term value creation.

In this paper, we investigate whether CEO compensation complexity can affect managers' incentives to engage in myopic behavior and, hence, influence the extent of managerial short-termism. When CEOs face pressure to shore up near-term performance, they are more likely to focus on easily measurable short-term metrics even when they are aware that this does not improve actual long-term value creation. Complex contracts, involving multiple performance measures and potential conflicting objectives, may consume too much of the managers' time and energy and in turn, managers fail to pay attention to all goals simultaneously and easily lean to easier-to-achieve short-term measures, harming long-term outcomes (e.g., Dikolli et al., 2009; Gabaix and Landier, 2008; Edmans and Gabaix, 2016; Burney et al., 2009). Thus, we predict that CEOs with complex compensation contracts are cognitively overladed by the multitude of performance metrics, vesting schedules, and incentive structures they must navigate and, thus, are more likely to engage in myopic behaviour.

We test our prediction using a sample of firms from the Incentive Lab database over the 2006–2022 period, from which we extract data to compute CEO compensation complexity from

compensation contracts. Following previous studies (e.g., Bushee, 1998; Chen et al., 2015), in the main analyses, we capture managerial short-termism using the likelihood of cutting R&D expenditures. We choose this proxy because the trade-off between meeting current earnings targets and increasing long-term firm performance is particularly salient in the case of cutting R&D (e.g., Graham et al., 2005). We then investigate the differential effect of CEO compensation complexity for firms whose managers have particularly strong incentives to engage in myopic behavior. We follow prior literature (Bushee, 1998; Cheng, 2004; Lai et al., 2020) and focus on firms in which a potential earnings decrease can be averted by cutting R&D. Specifically, we split the sample into two groups. The small earnings decrease (SD) group includes firm-years with pre-tax, pre-R&D incomes in year  $t$  that are lower than those in year  $t-1$ , and the pre-tax, pre-R&D incomes in year  $t$  are higher than pre-tax incomes in year  $t-1$ . The other group (Other) includes the firm-years with earnings increases and large earnings decreases that cannot be averted by cutting R&D expenses. We expect the effect of CEO compensation complexity to be stronger for the SD group than for the other group. We find that within the SD group, CEO compensation complexity is positively associated with the likelihood of cutting R&D; the coefficient on complexity is 0.027 ( $t=2.29$ ) for the SD group compared to 0.014 ( $t=1.84$ ) for the other group. In sum, the effect of CEO compensation complexity in exacerbating managerial short-termism is primarily driven by the SD group, where the incentives for managerial short-termism are particularly strong.

Our results are robust to alternative measures of both compensation complexity and R&D cutting behavior and survive extensive endogeneity tests. We employ three identification strategies to establish causality: difference-in-differences analyses exploiting the Tax Cuts and Jobs Act and exogenous CEO turnovers, instrumental variable estimation using compensation consultant usage, and omitted variable bias tests following Oster (2019). The difference-in-differences results show that firms more affected by the TCJA are less likely to cut R&D expenditures after the Act's implementation, while transitions from low-to-high compensation complexity significantly increase R&D cutting probability. The instrumental variable approach confirms the positive causal

relationship between compensation complexity and R&D cutting. The omitted variable tests indicate that unobservable factors would need to be more than ten times as important as observables to nullify our results.

We perform three lines of cross-sectional tests to corroborate our main results. First, when corporate governance is weaker, the adverse effects of compensation complexity on investment decisions should be more pronounced. Strong governance mechanisms can mitigate the confusing signals embedded in complex contracts by providing clearer oversight and long-term orientation, while weak governance allows CEOs to prioritize easily achievable short-term targets over uncertain long-term investments. Corresponding to this reasoning, we find that the CEO compensation complexity effect on myopia is greater when firms have higher co-opted board ratios and lower socially responsible institutional ownership. Second, when market competition is less intense, CEOs may have more latitude to pursue short-term objectives embedded in complex contracts rather than focusing on long-term competitive advantages. In highly competitive markets, the imperative to invest in R&D for survival and competitive positioning may override the short-term incentives created by complex compensation, whereas in less competitive environments, CEOs can afford to sacrifice long-term investments for immediate performance gains. Indeed, our tests show that the CEO compensation complexity effect on myopia is greater when firms operate in less competitive markets as measured by industry concentration, and product similarity. Third, younger CEOs with stronger career concerns may be more susceptible to the confusing signals embedded in complex compensation contracts as they seek to demonstrate competence and secure future opportunities. Complex contracts make it difficult for these CEOs to discern which actions truly maximize their compensation, leading them to focus on visible short-term metrics rather than uncertain long-term R&D investments that may not pay off within their tenure or may be difficult to attribute to their efforts. In contrast, CEOs approaching retirement have less need to signal their ability to the market and may be more willing to sacrifice short-term gains for the firm's long-term benefit. Our tests show that the CEO compensation complexity effect on myopia is greater among CEOs who are not close

to retirement compared to those approaching retirement age. In addition, CEOs with limited external wealth may be more susceptible to the corporate compensation influence than their wealthier counterparts, thereby exhibiting stronger myopic tendencies under short-term market pressures. Our tests indicate that the impact of compensation complexity on managerial short-termism is more pronounced among CEOs with lower external wealth who are more dependent on the firm-based compensation. Importantly, in complementing our primary results with a path analysis, we find that the direct effect of compensation complexity on R&D cutting plays a critical role relative to the indirect effect through pay-performance sensitivity. This evidence corroborates that the compensation complexity effect we estimate reflects an incremental influence of contract design beyond traditional pay-performance mechanisms.

Our decomposition analysis reveals that the structural complexity of compensation contracts, particularly the number of compensation components, performance measures, evaluation periods, and the use of mixed performance criteria, drives the positive association between CEO compensation complexity and R&D cutting. Additionally, we find that CEO compensation complexity is associated with worse future firm performance, with this negative effect being particularly pronounced for firms where managers face strong incentives to engage in myopic behaviour.

Our work contributes to the ongoing debate concerning the design of executive compensation contracts and their effects on managerial behaviour. While extensive research has explored the relationship between pay-performance sensitivity and managerial decision-making (Jensen and Murphy, 1990; Core et al., 2008), it does not address how the structural complexity of compensation contracts may independently influence managerial incentives, despite concerns that such complexity leads to short-termist behaviours that undermine long-term firm value. By explicitly controlling for CEO equity incentives and firm governance characteristics in the analyses, we provide evidence on the incremental effect of CEO compensation complexity in the forms of multiple compensation components, complicate performance metrics, and opaque vesting conditions, all of which are widely used in practice. We note that while both CEO equity incentives and compensation simplicity can

address myopic behaviour, the underlying reasons are different. While the former enhances the upside potential so that CEOs enjoy the benefits of successful long-term investments, the latter reduces cognitive load and information asymmetry so that they can better understand and pursue long-term value creation (Bebchuk and Fried, 2004; Edmans and Gabaix, 2009).

Our findings also contribute to the literature that investigates the relationship between compensation design and managerial horizons. Extant agency theory models suggest that managers will respond to clearer incentive structures by aligning their actions more closely with shareholder interests (e.g., Jensen and Murphy, 1990). While the popular press often associates complex compensation arrangements with managerial power and rent extraction, our evidence suggests that *ex ante*, such complexity can narrow managers' horizons and exacerbate the agency problem of managerial short-termism. This speaks to the costs of complex compensation structures. One caveat is that simplified compensation also has costs; for example, simpler contracts may provide insufficient incentives for CEOs to undertake complex value-creating activities.

On the normative side, we emphasize that wanting to encourage long-term performance is not a sufficient condition for including multiple complex metrics in incentive plans. Instead, boards should carefully consider whether the benefits of comprehensive measurement outweigh the costs of complexity-induced myopia. This perspective suggests that boards should better understand the cognitive limitations of executives and the practical effects of complex incentive structures before designing compensation packages.

## **2. Empirical predictions**

CEO compensation complexity is designed to align manager and shareholder interests and provide comprehensive incentive alignment across multiple performance dimensions (e.g., Jensen and Murphy, 1990; Holmström and Milgrom, 1991; Albuquerque et al., 2025). However, the cognitive demands imposed by complex compensation structures may exacerbate managerial myopia since executives have limited capacity to process multiple, potentially conflicting performance

signals simultaneously (e.g., Sweller, 1988; Hirshleifer and Teoh, 2003; Burkert et al., 2024). The concern is that too much compensation complexity or too many performance metrics in compensation contracts (e.g., multiple measurement periods with conflicting incentives) encourages CEO short-termism that can destroy long-term firm value. This in turn will decrease firm performance and innovation, assuming managers rationally respond to cognitive overload by focusing on easily achievable short-term targets.

However, too much compensation complexity may also discourage short-termism because complex contracts may simply be ignored by CEOs who cannot process the embedded signals. Indeed, when compensation contracts become overly complex, CEOs may revert to simple rules or focus primarily on the most salient performance measures, which could actually reduce myopic behavior if those measures emphasize long-term value creation. Of course, this so-called simplification effect can be mitigated, if not eliminated, by strong governance mechanisms. However, frictions make it costly for boards to design and monitor optimal complex contracts (Burkert et al., 2024).

One important friction is the cognitive load that complex contracts place on both CEOs and boards (Sweller, 1988). Specifically, a CEO may face multiple performance metrics with different measurement periods, vesting schedules, and performance thresholds that create conflicting incentives. The cognitive overload effect suggests that higher CEO compensation complexity will overwhelm executives' information processing capacity and thereby incentivize them to pursue easier-to-achieve short-term policies (Burkert et al., 2024). Although this drives a misalignment of incentives with shareholders, since short-term performance is often more visible and measurable, we anticipate that this complexity-induced cognitive overload—the CEO complexity burden—will increase the likelihood of managerial myopia. Focusing on R&D investment decisions, we predict:

**H: The likelihood of cutting R&D expenditures will increase with the level of CEO compensation complexity.**

### **3. Methodology**

### 3.1. *Sample and data*

Our initial sample consists of all companies covered by the Incentive Lab database from 2006 to 2022 with available data to compute the CEO compensation complexity. We obtain financial data from Compustat, institutional ownership data from Thomson Reuters Institutional (13F) holdings, analyst-related data from IBES, board co-option and CEO delta data from Lalitha Naveen's website, socially responsible institutional ownership data from Hwang et al. (2022),<sup>2</sup> Herfindahl-Hirschman Index (HHI) and product similarity data from the Hoberg-Phillips data library, and our estimates of CEO outside wealth are derived from ExecuComp database. Table 1 reports our detailed sample selection process. The initial sample comprises 20,850 observations related to CEO compensation complexity. Following Chen et al. (2015), we exclude firm-year observations with missing or insignificant R&D expenditures. We define insignificant R&D expenditures as situations where a firm's R&D expenditures in the current year are less than 1 percent of sales in the previous year. We also exclude observations with missing values for control variables. After merging with financial data and removing missing values of firm and CEO characteristics, our final sample includes 624 unique firms and 6,170 firm-year observations.

**[Insert Table 1 Here]**

### 3.2. *Measures*

#### 3.2.1. *Measure of managerial myopia*

We follow extensive prior research in relying on R&D expenditure reduction to measure managerial myopia for each firm-year observation (e.g., Bushee 1998; Chen et al. 2015; Lai et al. 2020). We define *CutR&D* as an indicator variable that equals one if a firm decreases R&D expenditures in the current year compared to the previous year, and zero otherwise. A higher probability of R&D cutting implies more myopic managerial behavior.

#### 3.2.2. *Measure of CEO compensation complexity*

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<sup>2</sup> We thank Chuan Yang Hwang, Sheridan Titman, and Ying Wang for graciously sharing their data with us.

The key variable of interest in our empirical models, *Complexity*, represents the degree of complexity in CEO compensation contracts. The data underlying this measure is available from the Incentive Lab database, which provides detailed information on executive compensation contract provisions. From a conceptual perspective, compensation complexity reflects the multi-dimensional nature of modern executive pay packages designed to motivate and restrain executives through various performance metrics and time horizons. From a practical econometric perspective, our sample timeframe from 2006 to 2022 captures significant variation in compensation design practices across different market conditions and regulatory environments.

Following Albuquerque et al. (2025), we quantify CEO compensation complexity across four dimensions of compensation contracts and calculate a score for each dimension. The first dimension focuses on the types of CEO compensation, counting the number of performance-based compensation types including short-term cash bonus, long-term cash bonus, stock, and stock options. The second dimension considers the use of performance measures, assigning scores within each compensation type according to specific contract provisions: a point for time-vesting conditions, a point for absolute performance conditions, and a point for relative performance conditions. The third dimension calculates the number of qualitative or quantitative performance measures contained in the contract for each performance condition and compensation type. The final dimension captures time periods, allocating points based on the duration of performance measurement periods. We calculate the total of all points assigned across the four dimensions to construct our measure of compensation complexity (*Complexity*). A higher aggregate score represents a more complex compensation contract. Importantly, this measure captures the multi-faceted nature of executive compensation design and is likely to influence managerial decision-making horizons.

### 3.2.3. *Control variables*

To account for various factors that may affect R&D expenditures, we include a comprehensive set of control variables that have been proven in the prior research to be key determinants of R&D

investment decisions (Bushee, 1998; Chen et al., 2015; Lai et al., 2020). We capture the dynamic nature of R&D investment by including the previous year's change in R&D investments ( $\Delta R\&D$ ) to control for firm-specific trends in R&D spending. To account for industry-level investment opportunities, we employ the change in industry R&D intensity ( $\Delta Ind\_R\&D$ ), as firms operating in industries with increasing R&D intensity are expected to be less likely to reduce their R&D expenditures. We also include the change in GDP ( $\Delta GDP$ ) to capture broader economic growth conditions that may influence firms' overall investment opportunities.

To control for earnings management incentives, we measure the distance of expected earnings to the earnings goal using the change in pre-tax and pre-R&D earnings scaled by R&D expenditures in the previous year ( $Distance\_Goal$ ). We expect that firms with greater distances from their earnings targets are less likely to engage in R&D cuts to meet short-term earnings goals. We employ the change in capital expenditures ( $\Delta CAPX$ ) as a proxy for firm life cycle and growth opportunities and include the change in sales ( $\Delta Sales$ ) to measure the funds available for R&D investment, following Berger (1993) who documents that R&D budgets are typically based on sales. We anticipate negative correlations between R&D investment and both  $\Delta CAPX$  and  $\Delta Sales$ .

Moreover, we control for firm-specific characteristics that may influence R&D investment decisions. We include firm size ( $Size$ ) as smaller firms are more likely to face cash constraints and reduce R&D investment due to financial shortfalls, consistent with Jalilvand and Harris (1984). The market-to-book ratio ( $MB$ ) captures growth opportunities, as managers of growth firms may maintain longer investment horizons and be less inclined to cut R&D expenditures. We employ the leverage ratio ( $Leverage$ ) to account for firms' incentives to reduce R&D spending to avoid debt default. Free cash flows ( $FCF$ ) capture funding availability, with firms having sufficient free cash flow being less likely to cut R&D expenditures to meet short-term earnings targets.

Finally, we include institutional ownership ( $Inst$ ) and analyst following ( $Analysts$ ) to control for monitoring effects on managerial short-termism behavior. All continuous variables are winsorized at

the upper and lower 1% level to mitigate the influence of outliers. The detailed definitions of these variables are provided in Appendix A.

### 3.3. Empirical Model

We examine the association between CEO compensation complexity and managerial short-termism using the following model:

$$CutR\&D_{i,t} = \alpha_0 + \beta * Complexity_{i,t} + \gamma * X_{i,t} + \delta * Industry_{i,t} + \theta * Year_{i,t} + \varepsilon_{it} \quad (1)$$

where  $CutR\&D_{i,t}$  is proxy for managerial short-termism, which equals one if R&D expenditures in fiscal year  $t$  decrease compared to fiscal year  $t-1$ , and zero otherwise. The variable of interest,  $Complexity_{i,t}$ , measures CEO compensation complexity as defined in Section 3.2.2.  $X$  represents a set of control variables discussed in Section 3.2.3 and measured in year  $t$ . The coefficient ( $\beta$ ) on  $Complexity$  is expected to be positive, indicating that greater CEO compensation complexity is associated with a higher likelihood of R&D cuts. We include two-digit SIC industry fixed effects ( $Industry$ ) to control for heterogeneity across industries and year fixed effects ( $Year$ ) to account for macro-economic factors that influence corporate R&D investment decisions. The standard errors of the estimated coefficients allow for clustering of observations by firm to control for potential autocorrelation.<sup>3</sup>

## 4. Main Results

### 4.1. Descriptive statistics

In Table 2, we present descriptive statistics based on firm-year observations in Panel A. Our main sample consists of 6,170 firm-year observations spanning the period from 2006 to 2022. The mean (median) value of our primary independent variable  $Complexity$  is 13.980 (14.000) with a standard deviation of 6.280, which is consistent with the statistics documented in Albuquerque et al. (2025). Our primary dependent variable  $CutR\&D$  has an average value of 0.288, indicating that

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<sup>3</sup> Our conclusions remain robust when we allow clustering by both firm and year (untabulated).

approximately 28.8% of sample firms reduce R&D expenditures in the current year compared to the previous year.

The mean (median) value of *Size* is 8.772 (8.706), which corresponds to US\$6,451.06 (US\$6,039.04) million in market value. The book leverage (*Leverage*), defined as the ratio of long-term debt to total assets, has an average value of 0.217. The average market-to-book ratio (*MB*) for our sample firms is 5.655, and free cash flow (*FCF*) has a mean value of 0.189. The firms in our sample have substantial coverage by sophisticated market participants, with each firm followed by approximately 15 analysts on average, as indicated by the mean natural logarithm of analyst following of 2.693. Moreover, institutional investors hold, on average, 73.6% of the shares in these firms. Overall, the summary statistics of our control variables are broadly consistent with those reported in previous studies examining myopic behaviour (Bushee, 1998; Chen et al., 2015; Lai et al., 2020).

In Panel B, we provide a correlation matrix for the key variables used in our study, with Spearman correlation coefficients in the upper triangle and Pearson correlation coefficients in the lower triangle, respectively. Both correlation coefficients between *Complexity* and *CutR&D* are positive and significant, providing preliminary evidence supporting our hypothesis that CEO compensation complexity increases the likelihood of cutting R&D expenditures.

**[Insert Table 2 Here]**

#### 4.2. Baseline regression results

Table 3 reports the multivariate regression results examining the relationship between CEO compensation complexity and R&D expenditure cuts. Our hypothesis predicts that CEO compensation complexity increases managerial short-termism, implying a positive relationship between CEO compensation complexity and the likelihood of cutting R&D expenditures. Column (1) reports the results using logistic regression, while column (2) presents OLS regression results, with t-values calculated using firm-level clustered standard errors to address potential autocorrelation.

The coefficient on *Complexity* is 0.018 ( $t = 2.96$ ) in column (1) and 0.003 ( $t = 2.74$ ) in column (2), both statistically significant and positive, indicating that CEO compensation complexity

increases the likelihood of cutting R&D expenditures.<sup>4</sup> To assess the economic significance, we calculate the marginal effect of *Complexity* on *CutR&D* using the logistic regression. Based on the untabulated marginal effect of 0.003 for *Complexity* in column (1), a one-standard-deviation increase in *Complexity* (6.280) is associated with a 6.54% ( $0.003 \times 6.280/0.288$ ) increase in the likelihood of cutting R&D expenditures relative to the base rate of 0.288. Thus, the effect of CEO compensation complexity on managerial short-termism is both statistically and economically significant.

For the control variables in column (1), the coefficients are consistent with those reported in prior studies examining managerial short-termism (Bushee, 1998; Chen et al., 2015; Lai et al., 2020). The negative coefficients on change in capital expenditures ( $\Delta CAPX$ ), change in sales ( $\Delta Sales$ ), distance from earnings goal (*Distance\_Goal*), firm size (*Size*), and market-to-book ratio (*MB*) indicate that firms with greater investment scale and stronger growth prospects are less likely to cut R&D expenditures. The significantly negative coefficient on the previous year's R&D change ( $\Delta R\&D$ ) is consistent with the notion that firms with expanding R&D opportunity sets are less likely to reduce R&D spending (Bushee, 1998). The negative coefficient on institutional ownership (*Inst*) suggests that firms with greater institutional investor presence are less likely to cut R&D expenditures. Furthermore, the positive coefficient on leverage (*Leverage*) indicates that firms with higher leverage ratios have greater incentives to cut R&D expenditures to avoid debt covenant violations. Overall, the baseline results are consistent with our hypothesis.

**[Insert Table 3 Here]**

#### 4.3. *Subsample analyses*

To further explore the mechanisms underlying CEO incentives for cutting R&D investment, we examine whether the effect of CEO compensation complexity varies based on managers' incentives to engage in myopic behavior. While our main analysis tests the average effect of CEO compensation

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<sup>4</sup> The results remain robust when we employ the lagged key independent variable in the baseline regression, i.e., regressing *CutR&D* in year t+1 on *Complexity* in year t.

complexity on R&D cutting, this effect should be stronger when CEOs face particular pressure to achieve short-term earnings targets.

Following Baber et al. (1991), Bushee (1998) and Cheng (2004), we identify situations where managers have especially strong incentives to cut R&D to avoid earnings decreases. The key insight is that not all firms facing earnings pressure have the same ability or motivation to use R&D cuts as a tool for earnings management. We therefore partition our sample based on whether R&D cuts could realistically help firms avoid reporting earnings declines.

Specifically, we classify firm-years into the Small Earnings Decrease group (SD) and the Other group (Other). Firms in the SD group must satisfy two criteria: (1) Pre-tax, pre-R&D incomes in year  $t$  are lower than those in year  $t-1$ ; (2) Pre-tax, pre-R&D incomes in year  $t$  are higher than pre-tax incomes in year  $t-1$ . For these firms, cutting R&D could potentially eliminate the earnings decrease entirely, creating strong managerial incentives for myopic R&D reductions. The remaining firm-years fall into the Other group where such incentives are weaker. The Other group includes the firms with larger earnings declines that cannot be mitigated by cutting R&D expenditures and those with earnings growth in the current year, eliminating the need to cut R&D for earnings management purposes. While managers in the Other group might still cut R&D for other reasons, such as resource constraints in the firms with larger earnings declines or opportunistic behavior in the firms with earnings growth, they lack the specific short-term earnings pressures that characterize the SD group.

If CEO compensation complexity affects R&D investment primarily through its impact on managerial myopia, we expect its effect to be strongest in the SD group, where the incentives for short-term earnings management are most pronounced. Conversely, if CEO compensation complexity affects R&D decisions through other channels unrelated to short-termism, we would expect similar effects across both groups.

Table 4 reports the regression results separately for the two groups. The coefficient on *Complexity* is 0.027 ( $t = 2.29$ ) for the SD group and 0.014 ( $t = 1.84$ ) for the Other group. The coefficient magnitude and significance level are higher in the SD group, with the effect becoming

progressively weaker in the Other group. This pattern strongly supports our hypothesis that CEO compensation complexity affects R&D investment decisions primarily through its influence on managerial short-termism rather than through alternative mechanisms. The results demonstrate that complex compensation arrangements are most problematic precisely when managers face the strongest temptations to sacrifice long-term value creation for short-term earnings targets.

**[Insert Table 4 Here]**

#### *4.4. Robustness tests*

##### *4.4.1. Alternative measure for independent variable*

As CEO compensation arrangements may vary in their complexity across different components, we examine whether our baseline results are sensitive to alternative measures that account for the relative economic importance of each compensation element. Specifically, we address a potential limitation of our primary measure by constructing an alternative variable, *WTD\_Complexity*, that weights the complexity of each compensation component by its proportion in total CEO pay. Following Albuquerque et al. (2025), this weighted measure assigns greater importance to complex compensation components that represent a larger share of total compensation.

The rationale for this alternative measure is that compensation components with high complexity scores but minimal economic significance may not meaningfully influence CEO decision-making. For instance, a highly complex stock option plan that represents only 5% of total compensation may have limited behavioral impact compared to a moderately complex plan that constitutes 40% of total pay. The weighted measure allows us to test whether CEO compensation complexity remains significantly associated with R&D cutting when we account for the economic materiality of each component.

We then replace our test variable in Equation (1) with *WTD\_Complexity* and re-estimate the regression. Panel A of Table 5 provides the results. Similarly to the findings in the baseline regression, the estimated coefficients of *WTD\_Complexity* are positive and economically and statistically

significant in both logistic and OLS model specifications. These results indicate that our baseline findings are robust to this alternative measure of CEO compensation complexity.

**[Insert Table 5 Here]**

#### 4.4.2. *Alternative measure for dependent variable*

In this section, we examine the robustness of our baseline findings using four alternative measures of myopic behaviour.

First, we address a potential sample selection concern identified by Chen et al. (2015). In our baseline regression, we exclude firm-year observations with missing R&D data in the current year. However, this approach may inadvertently exclude cases where CEOs reduce R&D expenditures to zero, potentially biasing our estimation. To address this concern, we retain observations with missing current-year R&D data and replace missing values with zero. Using this expanded sample, we construct an alternative dependent variable following the same definition (*CutR&D\_Alter*).

Second, following previous studies (Driver and Coelho Guedes, 2012; Guan et al., 2021; Chen et al., 2025), we employ R&D scaled by total operating revenue as an alternative measure for R&D investment intensity. We define an indicator variable, *CutR&D\_Sales*, which equals one if the ratio of R&D expenditures to total operating revenue in the current year decreases compared to the previous year, and zero otherwise.

Third, following Lai et al. (2020), we employ an alternative proxy for managerial myopia that specifically captures R&D cuts aimed at meeting analyst forecasts. *BeatByCutR&D* is an indicator that equals one if the firm's reported earnings in year *t* exceed the analysts' median consensus forecast through cutting R&D expenditures, and zero otherwise.

Fourth, following Roychowdhury (2006), Cohen et al. (2008), and Cohen and Zarowin (2010), we use comprehensive measures of real earnings management (*REM*) as alternative proxies for managerial short-termism. We measure the extent of real earnings management activities using sales manipulation, managing discretionary expenses, and abnormal production costs. APPENDIX B provides detailed information on the estimation procedure. Since firms that inflate reported earnings

via *REM* tend to use one or two of the three *REM* strategies (Cohen et al., 2008). Following Zang (2012), we construct two comprehensive measures to capture the overall extent of real earnings management. For the first measure (*REMI*), we multiply abnormal discretionary expenses by negative one and add it to abnormal production costs. For the second measure (*REM2*), we multiply both abnormal discretionary expenses and abnormal cash flows from operations by negative one and then aggregate them into a single metric. Higher values of these metrics indicate greater likelihood of real earnings management activities.

Panel B of Table 5 presents the results using these alternative dependent variables in columns (1) through (6). The positive coefficients on *Complexity* across all specifications suggest that our baseline results are robust to alternative measures of managerial short-termism. This consistency strengthens our confidence that CEO compensation complexity indeed increases the propensity for myopic managerial behaviour, regardless of how we capture such behaviour.

## **5. Endogeneity threats**

Our baseline regression shows that CEO compensation complexity is positively associated with managerial short-termism after controlling for numerous observed firm characteristics and various fixed effects. However, this analysis is vulnerable to potential endogeneity between CEO compensation complexity and R&D cutting for several reasons. For starters, although we control for observable firm characteristics in our main regressions, there might exist unobservable heterogeneity when omitted unobservable variables affect both CEO compensation complexity and the likelihood of cutting R&D expenditures. Additionally, given that firms usually do not dramatically alter their compensation policies, CEO compensation complexity tends to be auto-correlated across years. Although we examine the impact of CEO compensation complexity on future R&D cutting decisions in our main analyses, which mechanically mitigates the reverse causality and simultaneity issues, our results could still spuriously reflect potential endogeneity biases. Accordingly, in this section, we apply three econometric approaches to tackle potential endogeneity threats to reliable identification:

(i) exogenous variations due to the Tax Cut and Jobs Act and sudden CEO turnovers using a difference-in-differences (DID) design, (ii) an instrumental variable estimation, and (iii) a test for the omitted variable problem.

### *5.1. Difference-in-differences test*

#### *5.1.1. The Tax Cut and Jobs Act*

In order to further establish causality and mitigate concerns regarding endogeneity between CEO compensation complexity and R&D investment, we exploit the setting of the Tax Cuts and Jobs Act (TCJA) as an exogenous shock to CEO compensation complexity through its effect on performance-based pay.

Prior to the TCJA, Section 162(m) of the Omnibus Budget Reconciliation Act of 1993 stipulated that compensation paid to the CEO and the three highest-paid executives exceeding \$1 million per year was not deductible for tax purposes. Importantly, performance-based compensation (including stock options) and commission-based pay were fully deductible without regard to the \$1 million limit. However, the TCJA, passed on December 27, 2017, revised Section 162(m) by repealing the exceptions that allowed companies to deduct executives' performance-based compensation over \$1 million. Since then, all compensation paid to "covered employees" (including CEOs, CFOs, and other highly-paid officers) in excess of \$1 million is non-deductible for tax purposes, effectively eliminating firms' tax incentive to structure pay above \$1 million as performance-based pay.

If the motivation to include more performance measures to meet tax deductibility requirements resulted in more complex compensation contracts before the TCJA, we would expect a decline in compensation complexity after the Act's implementation, with this decline being caused by an exogenous shock. Since the tax deductibility threshold under Section 162(m) was \$1 million, we expect a more pronounced effect on firms with CEO compensation exceeding this threshold. Thus, we define our treatment firms as those with CEO compensation exceeding \$1 million in each of the four years (2014-2017) before the new Act. We predict that treatment firms will reduce compensation

complexity more in the post-TCJA period (2018-2021) and will have a lower likelihood of cutting R&D expenditures.

We then use a difference-in-differences (DID) regression model to empirically examine the impact of changes in CEO compensation complexity on the likelihood of cutting R&D owing to the TCJA shock:

$$CutR\&D_{i,t} = \alpha_0 + \beta * Treat_i \times Post_{i,t} + \gamma * X_{i,t} + \delta * Industry_{i,t} + \theta * Year_{i,t} + \varepsilon_{it} \quad (2)$$

where  $Treat_i$  is an indicator variable that equals one if CEO compensation exceeds \$1 million in each of the four years (2014-2017) and zero otherwise.  $Post_{i,t}$  is an indicator variable that equals one if year  $t$  is after 2017 and zero otherwise. The independent variable of interest in this analysis is the interaction term,  $Treat_i \times Post_{i,t}$ , which captures the effect of the TCJA on R&D cutting. We maintain the same control variables as in our baseline regression.

Table 6 presents the results. The coefficient of the  $Treat \times Post$  is -0.252 ( $t=-2.18$ ), indicating that our treatment firms have lower possibility to cut R&D expenditures in the post period relative to other firms. Consistent with our prediction, the result shows that firms more affected by the TCJA are less likely to cut R&D expenditures after the Act's implementation owing to the reduced complexity of CEO compensation brought about by the TCJA.

**[Insert Table 6 Here]**

### 5.1.2. Exogenous CEO turnover events

Following Shang (2021), our second identification test employs a difference-in-differences (DID) analysis that utilizes exogenous shocks from sudden CEO turnovers to identify the causal effect of changes in CEO compensation complexity on managerial short-termism. The potential endogeneity of CEO turnovers concerning corporate outcomes necessitates focusing on transitions where the timing and necessity of appointing a new CEO are quasi-randomly determined.

Gentry et al. (2021) document CEO departure reasons and classify them into eight categories: (1) CEO death, (2) CEO illness, (3) CEO dismissed for job performance, (4) CEO dismissed for

personal issues, (5) CEO retired, (6) New opportunity, (7) Other, and (8) Missing. We focus on CEO turnover events owing to exogenous reasons, specifically categories (1), (2), (5), and (6). These exogenous CEO turnover events allow us to more accurately evaluate the impact of CEO compensation complexity on managerial short-termism, as CEO changes driven by these reasons are less likely to be influenced by underlying factors that might simultaneously affect the firm's R&D investment decisions.

We employ a DID framework to examine changes in the likelihood of cutting R&D before and after executives transition from low to high compensation complexity, using a control group of firms with stable compensation complexity transitions (low-low or high-high) or reversed changes (high-low) for comparison. We require our sample firms to have at least three years of data before and three years after a CEO turnover event, including the transition year  $t$  and excluding firms with continuous CEO turnover observations, which ensures sufficient time for CEOs to implement changes in R&D investment policies.

We classify CEO turnovers based on compensation complexity changes by comparing the average CEO compensation complexity over years  $[t-3, t-1]$  with that over years  $[t+1, t+3]$ . If the post-turnover complexity exceeds the pre-turnover complexity, we classify the turnover as a low-to-high compensation complexity transition. We identify 71 exogenous CEO turnovers within our six-year observation window, of which 51 involve transitions from low to high CEO compensation complexity. We assign the exogenous low-to-high CEO compensation complexity transitions to our treatment group and the other exogenous CEO transitions to our control group.

We then estimate the following DID regression model to examine the impact of changes in CEO compensation complexity owing to exogenous CEO turnover on the likelihood of cutting R&D:

$$CutR\&D_{i,t} = \alpha_0 + \beta * Treat_i \times Post_{i,t} + \gamma * X_{i,t} + \delta * Industry_{i,t} + \theta * Year_{i,t} + \varepsilon_{it} \quad (3)$$

where  $Treat_i$  is an indicator variable that equals one if firm  $i$  experiences a low-to-high CEO compensation complexity transition and zero otherwise.  $Post_{i,t}$  is an indicator variable that equals

one if year  $t$  is either the event year or after the turnover event and zero otherwise. The independent variable of interest in this analysis is the interaction term,  $Treat_i \times Post_{i,t}$ , since its coefficient  $\alpha_1$  compares the changes in R&D cutting behavior over time between firms undergoing exogenous CEO turnovers with an increase in compensation complexity and those undergoing other types of exogenous CEO turnovers. We maintain the same control variables as in our baseline regression.

Table 7 presents the results of our DID tests for the CEO turnover sample. The coefficient of  $Treat \times Post$  is 0.153 ( $t = 2.09$ ), indicating that higher compensation complexity following CEO turnover increases the likelihood of cutting R&D expenditures. This finding provides robust causal evidence supporting the positive relation between CEO compensation complexity and managerial short-termism.

**[Insert Table 7 Here]**

## 5.2. Instrument variable estimation

In order to further mitigate endogeneity concerns that stem from reverse causality and the omitted-variable problem, we employ a two-stage least squares (2SLS) estimation as our third identification method. An ideal instrument should capture the variation in CEO compensation complexity but be exogenous to firm-level R&D cutting decisions.

We rely on two instrumental variables based on the role of compensation consultants in determining executive pay structures. First, Albuquerque et al. (2025) point out that the use of compensation consultants can increase additional complexity in compensation contracts; however, compensation consultants are unlikely to directly influence the firm's R&D investment decisions. Thus, our first instrument *Consultant\_dum* is an indicator variable that equals one if a firm uses a compensation consultant in year  $t$ , and zero otherwise. Second, the same compensation consultant may provide similar suggestions to different client firms they serve, thus leading to greater similarity of CEO compensation complexity across different firms. Nonetheless, shared compensation consultants cannot influence the R&D investment strategies of different firms. Therefore, our second

instrument *Complexity\_ave* is the average CEO compensation complexity among public companies that share the same compensation consultant in a given year.

Table 8 reports the 2SLS regression results. Columns (1) and (2) present the first-stage results with *Complexity* as the dependent variable, while columns (3) and (4) report the second-stage results. In the first-stage regression, the coefficient on *Consultant\_dum* is 2.585 ( $t = 3.53$ ), as presented in column (1) of Table 8, indicating that the use of compensation consultants indeed increases CEO compensation complexity and satisfies the relevance condition for a valid instrument. The significantly positive coefficient on *Complexity\_ave* in column (2) is consistent with our prediction, verifying similar CEO compensation complexity among different firms when they share common compensation consultants. The F-statistics in both first-stage regressions are statistically significant, lending support for the joint relevance of our instruments and allowing us to reject the null hypothesis of weak instruments.

**[Insert Table 8 Here]**

In the second-stage regressions, the coefficients on instrumented *Complexity* remain positive and statistically significant in both columns (3) and (4), supporting our baseline results. These findings indicate that even after addressing potential endogeneity concerns through instrumental variable estimation, CEO compensation complexity continues to be positively associated with the likelihood of cutting R&D expenditures, strengthening the causal interpretation of our main results.

### 5.3. *Omitted variables test*

We next examine whether our baseline results are susceptible to omitted-variable bias. Although our baseline model includes numerous control variables commonly used in prior studies to capture observable firm characteristics, and we further incorporate industry and year fixed effects in our regression analyses, the positive association between CEO compensation complexity and R&D cutting identified in our baseline results could be entirely driven by unobserved confounding factors.

Since fully accounting for all relevant variables is practically impossible, we employ the coefficient sensitivity test proposed by Oster (2019) to investigate the importance of omitted variable bias.

Oster (2019) proposes a method to address concerns about omitted-variable bias, based on the idea that when existing control variables effectively capture information about unobserved variables, smaller changes in estimated coefficients relative to increases in the model's explanatory power ( $R^2$ ) upon including new controls imply a lower likelihood of bias from omitted variables. The Oster test has two components. The first component tests whether unobserved variables as impactful as observed ones (including fixed effects) could nullify or reverse the coefficient of *Complexity* on *CutR&D* ( $\beta$ ). We estimate the bounds of *Complexity*'s coefficient,  $[\beta_{\text{baseline}}, \beta * (\min\{1.3 * R^2, 1\}, 1)]$  and check whether the interval excludes zero. According to Oster (2019), we define  $R_{\text{max}}$  as equal to 1.3 times the  $R^2$  and  $\delta$  as equal to 1, where  $\delta$  measures the ratio of the observable variables' impact on *Complexity*'s coefficient to the unobservable variables' impact on *Complexity*'s coefficient.

The second component examines how important unobserved variables need to be relative to observed ones (including fixed effects) to make  $\beta$  equal to zero by calculating the value of  $\delta$ . We make two assumptions: (1) the attainable  $R^2$  ( $R_{\text{max}}$ ) equals 1.3 times the  $R$ -squared of the specification with all controls; and (2) the coefficient of *Complexity* on *CutR&D* ( $\beta$ ) is zero.

Table 9 presents the estimation results. Rows (1)-(2) of Table 9 report the estimated coefficients of *Complexity* from Table 3 and the corresponding  $R^2$ . Rows (3)-(4) report the assumptions of  $R_{\text{max}}$  and  $\delta$  used in estimating the bounds. Row (5) shows that the bounds of *Complexity*'s coefficient exhibit very limited movement at  $[0.0029, 0.0035]$ , which falls within the 99.5% confidence interval for  $\beta$  in column (2) of Table 3  $[0.0008, 0.0050]$  and excludes zero. This suggests that controlling for both observable and unobservable variables would not lead to a substantially different conclusion than only controlling for the observable variables in our baseline regressions.

**[Insert Table 9 Here]**

Row (6) reports Oster's  $\delta$  of -10.433, indicating that unobservable variables would need to be 10.4 times more important than the observable variables and operate in the opposite direction to fully explain our result through omitted variable bias. Based on Oster's (2019) recommendation, we compare the absolute value of  $\delta$  to 1 and confirm that it is substantially greater than 1. Given that our baseline regression already controls for several important variables and fixed effects, it is very unlikely that unobservable variables are 10.4 times as important as all the observable variables included in our baseline regressions.

Overall, our four identification tests suggest that after controlling for selection bias and omitted variable bias, the positive relation between CEO compensation complexity and managerial short-termism remains robust.

## 6. Cross-sectional Analyses

In an effort to further investigate whether the relation between CEO compensation complexity and the likelihood of R&D cutting can be explained by variations in different firm and CEO characteristics, we examine cross-sectional heterogeneity based on corporate governance, market competition, CEO retirement proximity and CEO outside wealth. If the positive association between CEO compensation complexity and managerial short-termism stems from exacerbated agency problems and reduced monitoring effectiveness, we should observe a larger increase in R&D cutting propensity for firms with weaker *ex ante* governance mechanisms and more severe agency conflicts. We focus on several characteristics that influence information quality and agency problems: corporate governance quality, market competition intensity, CEO career horizon incentives and CEO outside wealth.

### 6.1. Corporate governance

We first examine whether the impact of CEO compensation complexity on R&D cutting is moderated by corporate governance quality. Building on prior research that good corporate governance promotes long-term strategic investment such as increased R&D expenditure (Baysinger

and Kosnik, 1991; Becker-Blease, 2011; Aghion et al., 2013), we argue that corporate governance quality influences how CEOs respond to complex incentives and make R&D investment decisions. In firms with weak corporate governance, insufficient oversight and misaligned incentives amplify the short-termism embedded in complex compensation structures. Without strong governance mechanisms, CEOs face fewer constraints on cutting R&D in pursuit of short-term targets tied to higher compensation. Conversely, strong corporate governance can mitigate this adverse effect by aligning compensation with long-term value creation. Thus, we expect the positive relationship between compensation complexity and R&D cutting to be more pronounced in firms with weaker corporate governance.

Following Coles et al. (2014) and Hwang et al. (2022), we use two proxies for corporate governance quality. *TW\_COP* is defined as the fraction of co-opted directors on the board, weighted by the CEO's tenure, where co-opted directors refer to those appointed after the current CEO assumes office. As the proportion of co-opted directors increases, board monitoring effectiveness decreases, indicating weaker corporate governance. *SRIO* represents the proportion of a firm's shares held by socially responsible investors relative to total outstanding shares, excluding hedge fund ownership, where a higher *SRIO* indicates better corporate governance. We divide our sample into two subsamples by retaining the highest and lowest quartile values in a year of our corporate governance proxies and re-estimate the baseline regression in each subsample.

Panel A of Table 10 presents the regression results. Consistent with our expectation, we find that the coefficient on *Complexity* is positive and statistically significant in the subsamples of firms with high *TW\_COP* and low *SRIO*, indicating weaker corporate governance. Additionally, the coefficients of *Complexity* differ significantly between the low and high corporate governance subsamples, further supporting our expectation that the positive relation between CEO compensation complexity and the likelihood of R&D cutting is stronger in firms with weaker corporate governance.

**[Insert Table 10 Here]**

## 6.2. Market competition

We next examine whether the relationship between CEO compensation complexity and R&D cutting varies among firms in more and less competitive markets. Market competition serves as an effective external corporate governance mechanism that can reduce managerial slack and quiet-life agency conflicts (Hart, 1983; Schmidt, 1997; Giroud and Mueller, 2010). In highly competitive market environments, CEOs are motivated to increase R&D investment to sustain competitive advantages and prevent their firms from being forced out (Nickel, 1996; Hou and Robinson, 2006). Conversely, absence of competition may allow complex compensation contracts to exacerbate managerial myopia, as CEOs might prefer a "quiet life" (Hoberg and Maksimovic, 2022). Thus, we posit that the positive association between compensation complexity and R&D cutting is stronger in less competitive markets.

We utilize two different approaches to measure firms' market competitive environments. First, we use the Herfindahl-Hirschman Index (*HHI*) computed as the sum of squared market shares based on firm sales in the text-based network industry classification framework. Second, we employ product similarity (*Similarity*) developed by Hoberg and Phillips (2016), where higher similarity scores indicate more competitive product markets.

Panel B of Table 10 reports the results. We find that the coefficient on *Complexity* is positive and significant for firms with high *HHI* (less competitive), and low *Similarity* (less competitive), but insignificant for their respective counterparts. The coefficients of *Complexity* differ significantly between the high and low competition subsamples across both measures. Overall, these findings are consistent with the idea that the impact of CEO compensation complexity on R&D cutting is more pronounced when firms face less market competition.

### 6.3. *CEO characteristic*

Finally, we examine how CEO career concerns and outside wealth influence the relationship between compensation complexity and R&D cutting. Prior research indicates that managers' concern about career development significantly influences their investment decisions (Narayanan, 1985).

CEOs attentive to career prospects face evaluation pressures in the labor market and tend to prioritize short-term performance goals to demonstrate competence rather than taking the uncertainty risks of long-term R&D investments (Graham et al., 2005; Porter, 1992). Regarding CEOs' outside wealth, we conjecture that, compared to those with little outside wealth, CEOs with substantial outside wealth have a lower dependence on corporate compensation. Consequently, they are less susceptible to the impact of compensation complexity and less likely to exhibit myopic behavior due to short-term market pressures. We expect the impact of compensation complexity on managerial short-termism to be more pronounced among younger executives who have stronger incentives to demonstrate performance quickly for career advancement and among CEOs with less outside wealth who are more reliable on the companies' compensation.

First, following Chen et al. (2015), we set an indicator variable *CEO\_retire* that equals one if the CEO is 63 or older, and zero otherwise. We divide our sample into two groups based on *CEO\_retire* and re-estimate our baseline regression using the two subsamples. Second, following prior literature (Dittmann and Maug, 2007; Underwood and Yost, 2025), we calculate CEOs' outside wealth and construct an indicator variable *Outside\_Wealth* that equals one if the CEO with an above-median share of their total wealth held outside of the firm's shares in a given year, and zero otherwise. Panel C of Table 10 reports the results. Consistent with our expectation, the coefficient of *Complexity* is positive and statistically significant for firms whose CEOs are not near retirement and have less outside wealth, but insignificant for firms with near-retirement CEOs or those with more outside wealth. The result further supports our expectation that the positive relation between CEO compensation complexity and managerial short-termism is stronger in firms with younger CEOs and less outside wealth CEOs.

Collectively, these cross-sectional results help validate the agency explanation underlying our main analyses; that is, CEO compensation complexity exacerbates managerial short-termism particularly when governance mechanisms are insufficient to constrain such behavior.

## 7. Path analysis

In this section, we conduct a path analysis to explore the potential mechanism through which CEO compensation complexity impacts the likelihood of R&D cutting. Specifically, we investigate whether the reduction in CEO pay-performance sensitivity (PPS), triggered by CEO compensation complexity, leads to an increase in R&D cutting decisions.

We propose a two-step mechanism linking CEO compensation complexity to R&D cutting through pay-performance sensitivity. First, complex compensation contracts with multiple metrics, conditions, and formulas render the link between CEO pay and performance less transparent. When the relationship between executives' specific actions and compensation outcomes becomes ambiguous due to this opacity, it becomes difficult for CEOs to accurately assess how their efforts translate into pay. Thus, we expect that CEO compensation complexity can reduce PPS. Second, Jensen and Murphy (1990) argue that performance-based incentives align managers' and shareholders' interests to promote efficient managerial investment. Based on this view, lower PPS may undermine this alignment. Since R&D investments typically have long-term uncertain payoffs, executives with low PPS, unable to clearly link their efforts to corresponding compensation, face limited gain from such long-term investments. Consequently, they are more likely to cut R&D investment.

Following prior studies (Chava and Purnanandam, 2010; Jiang et al., 2010; Jayaraman and Milbourn, 2012; Collins et al., 2019), we use CEO delta as a proxy for CEO pay-performance sensitivity. CEO delta is defined as the dollar change in a CEO's wealth for a 1% change in the firm's stock price, scaled by the CEO's total compensation (Core and Guay, 2002; Coles et al., 2006).

To conduct our path analysis, we employ Baron and Kenny's (1996) causal step regression to capture both the direct effect of CEO compensation complexity on R&D cutting and the indirect effect through the mediating variable. The analysis consists of three regressions: (1) *CutR&D* regressed on *Complexity* to confirm the main finding previously reported in Table 3, (2) the mediating variable (*PPS*) regressed on *Complexity* to demonstrate that our independent variable affects the

mediator, and (3) *CutR&D* regressed on both *Complexity* and *PPS* to examine the extent to which the mediator variable explains the relation between *Complexity* and *CutR&D*. All regressions include the same set of control variables used in Table 3. We calculate the indirect effect of *Complexity* on *CutR&D* by multiplying the effect of *Complexity* on the mediating variable by the effect of the mediating variable on *CutR&D*. To assess statistical significance, we employ Sobel's (1982) test.

Our mediated path analysis in Table 11 reveals that CEO compensation complexity has a statistically significant positive direct effect on R&D cutting, consistent with our primary finding. In the mediation analysis, we find a negative and significant relationship between *Complexity* and *PPS*, with *PPS* showing a significantly negative effect on *CutR&D*. Notably, the total indirect effect of *Complexity* on *CutR&D*, mediated by *PPS*, is statistically significant. Approximately 17.38% of the total effect of *Complexity* on *CutR&D* is attributable to the mediated path through reduced pay-performance sensitivity, while the remaining 82.62% stems from the direct path. These results suggest that pay-performance sensitivity serves as an important channel through which CEO compensation complexity increases firms' propensity to cut R&D investment.

**[Insert Table 11 Here]**

## **8. The Components of CEO Compensation Complexity**

In this section, we provide further evidence on how different components of CEO compensation complexity affect firms' R&D cutting decisions. To better understand which specific aspects of compensation complexity drive our main findings, we decompose our primary measure *Complexity* into its constituent elements. Following Albuquerque et al. (2025), we focus on four key dimensions that capture the structural complexity of compensation contracts: *num\_components* (number of main compensation components), *num\_measure* (number of different performance measures), *num\_periods* (maximum number of performance periods), and *abs\_rel\_dummy* (indicator of whether compensation contracts include both absolute and relative performance criteria). We then regress *CutR&D* on each individual complexity component along with the control variables used in our baseline regression.

Table 12 reports the results. The coefficients of *num\_components*, *num\_measure*, *num\_periods*, and *abs\_rel\_dummy* are all positive and statistically significant in columns (1)-(4), indicating that firms are more likely to cut R&D expenditures when their CEO compensation contracts involve more compensation components, more performance measures, more evaluation periods, and both absolute and relative performance criteria. Our findings highlight that the structural complexity of compensation contracts, particularly the multidimensional nature involving numerous components, measures, periods, and mixed performance criteria, drives the positive association between CEO compensation complexity and managerial short-termism. These results suggest that it is the overall architectural complexity of compensation design, rather than complexity within individual compensation elements, that primarily contributes to myopic R&D investment decisions.

**[Insert Table 12 Here]**

## **9. CEO Compensation Complexity and Firm Performance in the Future**

Our findings indicate that CEO compensation complexity can exacerbate managerial short-termism, especially for the SD group. One question, then, is whether CEO compensation complexity leads to deterioration in firm performance in the future. For firm-years in which managers have strong incentives to engage in myopic behavior, CEO compensation complexity can amplify managerial myopia and potentially lead to worse performance in the future. In this section, we examine whether firms with higher CEO compensation complexity experience worse performance in the future than those with lower complexity.

Table 13 reports the regression results, first for the full sample and then examining the differential effect for the SD group. The dependent variable is the average industry-adjusted *ROA* (return on assets) in the subsequent three and four years. The choice of control variables follows prior research. For the full sample, we find that the coefficient on *Complexity* is significantly negative (columns (1) and (3)), suggesting that, on average, CEO compensation complexity is associated with worse performance in the future.

We further examine whether this effect is more pronounced for the SD group by including the indicator *SD* and its interaction with *Complexity*. *SD* is a dummy variable that equals one if the pre-tax, pre-R&D income in year *t* is lower than in year *t*-1 but the pre-tax, pre-R&D income in year *t* is higher than pre-tax income in year *t*-1, and zero otherwise. The coefficients on the interaction term *Complexity*  $\times$  *SD* in columns (2) and (4) are significantly negative. This indicates that within the SD group, where CEOs are more inclined toward short-termism, firms with more complex compensation contracts tend to exhibit significantly worse performance in the future compared to other firms. F-tests indicate that the coefficient on *Complexity*  $\times$  *SD* is significantly different from zero, confirming the differential effect.

**[Insert Table 13 Here]**

In sum, we find that while CEO compensation complexity is associated with worse future performance on average, this negative effect is particularly pronounced within the SD group, where the incentive to engage in myopic behavior is strongest. This result speaks to the economic costs of exacerbating managerial short-termism through complex compensation arrangements.

## **10. Conclusion**

Building on agency theory and the growing literature on CEO compensation design, we examine the impact of CEO compensation complexity on managerial short-termism in a panel sample of S&P 1500 firms between 2006 and 2022. We find that CEO compensation complexity is positively associated with the likelihood of cutting R&D expenditures, consistent with complex compensation arrangements exacerbating managerial myopia. To establish causality and mitigate potential endogeneity concerns that compensation complexity may not be randomly assigned to firms, we employ three identification strategies: difference-in-differences analyses exploiting the Tax Cuts and Jobs Act and exogenous CEO turnovers, instrumental variable estimation using compensation consultant usage, and Oster's (2019) coefficient stability test. Our identification tests indicate a causal effect of CEO compensation complexity on R&D cutting behavior. The positive relation remains

robust after controlling for various firm characteristics, CEO traits, and other factors known to affect R&D investment decisions. Consistent with the notion that complex compensation contracts obscure pay-performance relationships and create conflicting incentives, we find that the effect of compensation complexity on R&D cutting is stronger among firms with weaker corporate governance, less market competition, as well as among younger CEOs and those with less outside wealth. We also find that the relation between compensation complexity and R&D cutting is more prominent among firms where managers face strong incentives to avoid earnings decreases, supporting the view that complex compensation arrangements amplify short-term pressures.

Porter (1992) and Graham et al. (2005) suggest that short-term pressures have a material impact on firms' long-term value creation and that investors are concerned about managerial myopia. Our findings suggest that investors would be well served to invest in firms with simpler compensation structures and avoid firms with overly complex CEO pay arrangements. Hence, our study offers investors an effective strategy to identify and avoid firms prone to value-destroying short-termism in their portfolio investment decisions.

This study complements the existing literature on the benefits and costs of complex executive compensation. Our results highlight that CEO compensation complexity undermines long-term investment decisions and increases the propensity for myopic behavior. Our findings have implications for agency theory that complex compensation contracts may exacerbate rather than alleviate agency problems due to obscured incentive structures. Our findings also have implications for the design of managerial compensation that corporate boards and other stakeholders should prioritize simplicity and clarity when aligning CEOs' interests with shareholders' long-term value creation objectives. While we show a negative effect of compensation complexity on R&D investment, we need to be cautious when generalizing our results. As compensation design involves multiple trade-offs, simpler contracts may have limitations in other contexts where multifaceted performance measurement is essential for effective governance.

## APPENDIX A. Variable Definitions

This table provides names and definitions of all variables used in the empirical analysis.

| Variable                     | Definition and measurement                                                                                                                                                                                                                                                                                                                                                       | Source        |
|------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------|
| <b>Dependent Variables</b>   |                                                                                                                                                                                                                                                                                                                                                                                  |               |
| <i>RD_Decrease</i>           | A dummy variable that equals one if R&D expenditure in fiscal year t decreases compared to fiscal year t-1, and zero otherwise. (Bushee et al., 1998; Chen et al., 2015; Lai et al., 2020).                                                                                                                                                                                      | Compustat     |
| <b>Independent Variables</b> |                                                                                                                                                                                                                                                                                                                                                                                  |               |
| <i>Complexity</i>            | The CEOs' compensation complexity calculated using data from Incentive Lab, as described in Section 2.2.2. Specifically, we aggregate the complexity scores for each type of compensation. (Albuquerque et al., 2025)                                                                                                                                                            | Incentive Lab |
| <b>Control Variables</b>     |                                                                                                                                                                                                                                                                                                                                                                                  |               |
| $\Delta R\&D$                | Change in R&D expenditure per share in fiscal year t-1, calculated as the difference in the natural logarithm of R&D expenditure per share between the fiscal year t-1 and year t-2. (Bushee et al., 1998; Chen et al., 2015; Lai et al., 2020)                                                                                                                                  | Compustat     |
| $\Delta Ind\_R\&D$           | Change in industry R&D intensity, calculated as the difference in the natural logarithm of the ratio of total industry R&D expenditure to total industry sales between the fiscal year t and year t-1. The industry metrics are derived from all firms within the same four-digit SICs, excluding the firm concerned. (Bushee et al., 1998; Chen et al., 2015; Lai et al., 2020) | Compustat     |
| $\Delta GDP$                 | Change in GDP, calculated as the difference in the natural logarithm of GDP between the fiscal year t and year t-1. (Bushee et al., 1998; Chen et al., 2015)                                                                                                                                                                                                                     | Bloomberg     |
| <i>Distance_Goal</i>         | The distance from earnings goal, calculated as the difference in the pre-tax, preR&D earnings per share between the fiscal year t and year t-1, scaled by the R&D expenditure per share in fiscal year t-1. (Bushee et al., 1998; Chen et al., 2015; Lai et al., 2020)                                                                                                           | Compustat     |
| $\Delta CAPX$                | Change in capital expenditures per share, calculated as the difference in the natural logarithm of capital expenditures per share between the fiscal year t and year t-1. (Bushee et al., 1998; Chen et al., 2015; Lai et al., 2020)                                                                                                                                             | Compustat     |
| $\Delta Sales$               | Change in sales per share, calculated as the difference in the natural logarithm of sales per share between the fiscal year t and year t-1. (Bushee et al., 1998; Chen et al., 2015; Lai et al., 2020)                                                                                                                                                                           | Compustat     |
| <i>Size</i>                  | The natural logarithm of market value of equity. (Bushee et al., 1998; Chen et al., 2015)                                                                                                                                                                                                                                                                                        | Compustat     |
| <i>MB</i>                    | The market value of equity divided by book value of equity. (Brochet et al., 2015; Alhusaini et al., 2023)                                                                                                                                                                                                                                                                       | Compustat     |
| <i>Leverage</i>              | The long-term debt divided by total assets. (Lai et al., 2020)                                                                                                                                                                                                                                                                                                                   | Compustat     |

|                 |                                                                                                                                                      |                 |
|-----------------|------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------|
| <i>FCF</i>      | Free cash flows, calculated as cash flows from operations minus capital, scaled by lagged current assets. (Chen et al., 2015; Lai et al., 2020)      | Compustat       |
| <i>Inst</i>     | Institutional ownership, measured as the percentage of shares held by institutional investors during the year. (Chen et al., 2015; Lai et al., 2020) | Thomson Reuters |
| <i>Analysts</i> | The natural logarithm of analysts following the firm during the year. (Lai et al., 2020)                                                             | IBES            |

#### Additional Variables in Table 5

|                         |                                                                                                                                                                                                                                                                                                                                                          |                   |
|-------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------|
| <i>WTD_Complexity</i>   | The weighted average scores of compensation complexity calculated using data from Incentive Lab, as described in Section 3.2. (Albuquerque et al., 2025)                                                                                                                                                                                                 | Incentive Lab     |
| <i>CutR&amp;D_Alter</i> | A dummy variable that equals one if R&D expenditure in fiscal year t decreases compared to fiscal year t-1, and zero otherwise. (Bushee et al., 1998; Chen et al., 2015; Lai et al., 2020), but is constructed from a new sample that do not drop the observations with missing R&D in the current year and replace them to be zero. (Chen et al., 2015) | Compustat         |
| <i>CutR&amp;D_Sales</i> | A dummy variable that equals one if R&D expenditures scaled by total operating revenue in fiscal year t decreases compared to fiscal year t-1, and zero otherwise.                                                                                                                                                                                       | Compustat         |
| <i>BeatByCutR&amp;D</i> | A dummy variable that equals one if the firm's reported earnings in year t exceed the analysts' median consensus forecast through cutting R&D expenditures, and zero otherwise.                                                                                                                                                                          | Compustat<br>IBES |
| <i>REM1</i>             | The first composite measure of <i>REM</i> (Multiply abnormal discretionary expenses by negative one and add it to abnormal production costs). APPENDIX B provides detailed information on the estimation procedure of <i>REM</i> .                                                                                                                       | Compustat         |
| <i>REM2</i>             | The second composite measure of <i>REM</i> (Multiply both abnormal discretionary expenses and abnormal cash flows from operations by negative one and then aggregate them into a single metric). APPENDIX B provides detailed information on the estimation procedure of <i>REM</i> .                                                                    | Compustat         |

#### Additional Variables in Table 8

|                       |                                                                                                                    |               |
|-----------------------|--------------------------------------------------------------------------------------------------------------------|---------------|
| <i>Consultant_dum</i> | A dummy variable that equals one if a firm use a compensation consultant in fiscal year t, and zero otherwise.     | Incentive Lab |
| <i>Complexity_ave</i> | The average of CEOs' compensation complexity in public companies with the same compensation consultants in a year. | Incentive Lab |

#### Additional Variables in Table 10

|               |                                                                                                                                                                         |                          |
|---------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------|
| <i>TW_COP</i> | The fraction of Co-opted directors on the board, weighted by the CEO's tenure. (Coles et al., 2014)                                                                     | Lalitha Naveen's website |
| <i>SRIO</i>   | The proportion of a firm's shares held by socially responsible investors relative to its total outstanding shares, excluding hedge fund ownership. (Hwang et al., 2022) |                          |

|                       |                                                                                                                                                                                                       |                              |
|-----------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------|
| <i>HHI</i>            | The Herfindahl-Hirschman Index (HHI) computed as the sum of squared market shares based on firm sales in the text-based network industry classification (TNIC) framework. (Hoberg and Phillips, 2016) | Hoberg-Phillips data library |
| <i>Similarity</i>     | Product similarity that calculates pairwise firm similarity scores by parsing the product text and forming word vectors. (Hoberg and Phillips, 2016)                                                  | Hoberg-Phillips data library |
| <i>CEO_retire</i>     | A dummy variable that equals one if the CEO is 63 and older, and zero otherwise. (Chen et al., 2015)                                                                                                  | CEO_trait                    |
| <i>Outside_Wealth</i> | A dummy variable that equals one if the CEOs with an above-median share of their total wealth held outside of the firm's shares in a given year, and zero otherwise.                                  | ExecuComp                    |

#### **Additional Variables in Table 11**

|            |                                                                                                                                                                                                                                          |                          |
|------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------|
| <i>PPS</i> | CEO pay-performance sensitivity, measured by CEO delta, which is defined as the dollar change in a CEO's wealth for a 1% change in the firm's stock price, scaled by CEO's total compensation. (Core and Guay, 2002; Coles et al., 2006) | Lalitha Naveen's website |
|------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------|

#### **Additional Variables in Table 12**

|                       |                                                                                                                                             |               |
|-----------------------|---------------------------------------------------------------------------------------------------------------------------------------------|---------------|
| <i>num_components</i> | The number of main compensation components in compensation contracts.                                                                       | Incentive Lab |
| <i>num_measure</i>    | The number of different performance measures in compensation contracts.                                                                     | Incentive Lab |
| <i>num_periods</i>    | The maximum number of performance periods in compensation contracts.                                                                        | Incentive Lab |
| <i>abs_rel_dummy</i>  | A dummy variable that equals one if the compensation contracts include both absolute and relative performance criteria, and zero otherwise. | Incentive Lab |

#### **Additional Variables in Table 13**

|            |                                                                                                                                                                                                                        |           |
|------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------|
| <i>ROA</i> | Earnings before interest and taxes divided by total assets.                                                                                                                                                            | Compustat |
| <i>SD</i>  | A dummy variable that equals one if the pre-tax, pre-R&D incomes in year t are lower than those in year t-1 and the pre-tax, pre-R&D incomes in year t are higher than pre-tax incomes in year t-1, and zero otherwise | Compustat |

## **APPENDIX B. Real Earnings Management**

Following prior research (Roychowdhury, 2006; Cohen et al., 2008; Cohen and Zarowin, 2010), we construct the proxies for real earnings management (*REM*) by examine three methods of manipulating real operational activities: sales manipulation, managing discretionary expenses and abnormal production. Sales manipulation lowers firms' operation cash flow by providing more price discounts and looser credit terms. Managing discretionary expenses can boost the reported earnings by reducing R&D expenses, advertising expenses, and SG&A expenses. Abnormal production often takes the form of overproduction: fixed manufacturing overhead is spread across more units, thereby lowering cost of goods sold (*COGS*) and increasing earnings.

The first measure of *REM* is firms' abnormal cash flow from operations. We capture the abnormal cash flow from operations by estimating the residuals for each industry and year using the following model:

$$\frac{CFO_{it}}{A_{i,t-1}} = \alpha_1 \frac{1}{A_{i,t-1}} + \alpha_2 \frac{Sales_{it}}{A_{i,t-1}} + \alpha_3 \frac{\Delta Sales_{it}}{A_{i,t-1}} + \varepsilon_{it} \quad (B.1)$$

where  $CFO_{it}$  is cash flow from operations in year  $t$ .  $A_{i,t-1}$  is the total assets of company  $i$  at the end of year  $t-1$ .  $Sales_{it}$  is the sales during year  $t$  and  $\Delta Sales_{it}$  is the change in sales from year  $t-1$  to  $t$ , and  $\varepsilon_{it}$  is the residual.

For the second measure of *REM*, we define  $DiscE_{it}$  as the sum of R&D expenses, advertising expenses, and SG&A expenses in year  $t$ . We capture the abnormal discretionary expenses by estimating the residuals for each industry and year using the following model:

$$\frac{DiscE_{it}}{A_{i,t-1}} = \alpha_1 \frac{1}{A_{i,t-1}} + \alpha_2 \frac{Sales_{i,t-1}}{A_{i,t-1}} + \varepsilon_{it} \quad (B.2)$$

For the third measure of *REM*, we define  $Prod_{it}$  as the sum of cost of goods sold and change in inventory in year  $t$ . We capture the abnormal production costs by estimating the residuals for each industry and year using the following model:

$$\frac{Prod_{it}}{A_{i,t-1}} = \alpha_1 \frac{1}{A_{i,t-1}} + \alpha_2 \frac{Sales_{it}}{A_{i,t-1}} + \alpha_3 \frac{\Delta Sales_{it}}{A_{i,t-1}} + \alpha_4 \frac{\Delta Sales_{i,t-1}}{A_{i,t-1}} + \varepsilon_{it} \quad (B.3)$$

We obtain three individual *REM* proxy variables through the above procedures. Since firms that inflate reported earnings via *REM* tend to use one or two of the three *REM* strategies (Cohen et al., 2008). Following Zang (2012), we use the comprehensive measure to capture the overall extent of real earnings management. For the first comprehensive measure of *REM* (*REM1*), we firstly multiply abnormal discretionary expenses by negative one and add it to abnormal production costs. Similarly, for the second measure of *REM* (*REM2*), we multiply abnormal discretionary expenses and abnormal cash flows from operations by negative one and then aggregate them into a single metric. The higher value of these two metrics, the more likely the firms engaged in real earnings management activities.

## References

- Aghion, P., Van Reenen, J., & Zingales, L. (2013). Innovation and institutional ownership. *American Economic Review*, 103(1), 277–304.
- Albuquerque, A., Carter, M. E., Guo, Z. (Michael), & Lynch, L. J. (2025). Complexity of CEO compensation packages. *Journal of Accounting and Economics*, 79(1), 101709.
- Baber, W., P. Fairfield, & J. Haggard. (1991). The effect of concern about reported income on discretionary spending decisions: The case of research and development. *The Accounting Review*, 66, 818-829.
- Baron, R. M., & Kenny, D. A. (1986). The Moderator–Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations. *Journal of Personality and Social Psychology*, 51, 1173.
- Baysinger, B. D., Kosnik, R. D., & Turk, T. A. (1991). Effects of board and ownership structure on corporate R&D strategy. *Academy of Management Journal*, 34(1), 205-214.
- Bebchuk, L. A., & Fried, J. M. (2004). *Pay without performance*. Cambridge, MA: Harvard University Press.
- Becker-Blease, J. R. (2011). Governance and Innovation. *Journal of Corporate Finance*, 17 (4), 947–58.
- Berger, P. G. (1993). Explicit and implicit tax effects of the R&D tax credit. *Journal of Accounting Research*, 31(2), 131-171.
- Burkert, S., Oberpaul, T., Tichy, N., & Weller, I. (2024). Executive compensation complexity and firm performance. *Academy of Management Discoveries*, 10(2), 273–306.
- Burney, L., Henle, C., & Widener, S. K. (2009). A Path Model Examining the Relations among Strategic Performance Measurement System Characteristics, Organizational Justice, and Extra- and In-Role Performance. *Accounting, Organizations and Society*, 34(3-4), 305-321.
- Bushee, B. (1998). The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review*, 73 (3), 305–333.
- Chava, S., & Purnanandam, A. (2010). CEOs versus CFOs: Incentives and corporate policies. *Journal of Financial Economics*, 97 (2), 263–278.
- Chen, J. Z., Li, Z., Mao, T., & Yoon, A. (2025). Global versus local ESG ratings: Evidence from China. *The Accounting Review*, 1–32.
- Chen, X., Cheng, Q., Lo, A. K., & Wang, X. (2015). CEO contractual protection and managerial short-termism. *The Accounting Review*, 90(5), 1871–1906.
- Cheng, S. (2004). R&D expenditures and CEO compensation. *The Accounting Review*, 79(2), 305–328.
- Cohen, D., Dey, A., & Lys, T. (2008). Real and accrual-based earnings management in the pre- and post-Sarbanes-Oxley period. *The Accounting Review*, 83 (3), 757–787.
- Cohen, D.A., & Zarowin, P. (2010). Accrual-based and real earnings management activities around seasoned equity offerings. *Journal of Accounting and Economics*, 50 (1), 2–19.
- Coles, J.L., Daniel, N.D., & Naveen, L., 2006. Managerial Incentives and Risk-Taking. *Journal of Financial Economics*, 79, 431-468.
- Coles, J. L., Daniel, N. D., & Naveen, L. (2014). Co-opted boards. *Review of Financial Studies*, 27(6), 1751–1796.
- Collins, D., Marquardt, B. B., & Niu, X. (2019). Equity-based incentives and shareholder say-on-pay. *Journal of Business Finance & Accounting*, 46(5-6), 739-761.
- Core, J., & Guay, W. (2002). Estimating the value of employee stock option portfolios and their sensitivities to price and volatility. *Journal of Accounting Research*, 40, 613-630.
- Core, J. E., Guay, W., & Larcker, D. F. (2008). The power of the pen and executive compensation. *Journal of Financial Economics*, 88(1), 1-25.
- Dikolli, S. S., Kulp, S. L., & Sedatole, K. L. (2009). Transient Institutional Ownership and CEO Contract Design. *The Accounting Review*, 84(3), 737-770.
- Dittmann, I., & Maug, E. (2007). Lower salaries and no options? On the optimal structure of executive pay. *The Journal of Finance*, 62(1), 303–343

- Driver, C., & Guedes, M. J. C. (2012). Research and development, cash flow, agency and governance: UK large companies. *Research Policy*, 41(9), 1565–1577.
- Edmans, A., & Gabaix, X. (2009). Is CEO pay really inefficient? A survey of new optimal contracting theories. *European Financial Management*, 15(3), 486–496.
- Edmans, A., & Gabaix, X. (2016). Executive Compensation: A Modern Primer. *Journal of Economic Literature*, 54(4), 1232–1287.
- Gabaix, X., & Landier, A. (2008). Why Has CEO Pay Increased So Much? *The Quarterly Journal of Economics*, 123(1), 49–100.
- Gentry, R. J., Harrison, J. S., Quigley, T. J., & Boivie, S. (2021). A database of CEO turnover and dismissal in S&P 1500 firms, 2000–2018. *Strategic Management Journal*, 42(5), 968–991.
- Giroud, X., & Mueller, H. M. (2011). Corporate governance, product market competition, and equity prices. *The Journal of Finance*, 66(2), 563–600.
- Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, 40(1–3), 3–73.
- Guan, Y., Zhang, L., Zheng, L., & Zou, H. (2021). Managerial liability and corporate innovation: Evidence from a legal shock. *Journal of Corporate Finance*, 69, 102022.
- Hart, Oliver. (1983). The market mechanism as an incentive scheme. *Bell Journal of Economics*, 14, 366–82.
- Hirshleifer, D., & Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, 36(1–3), 337–386.
- Hoberg, G., & Phillips, G. (2016). Text-Based Network Industries and Endogenous Product Differentiation. *Journal of Political Economy*, 124 (5), 1423–1465.
- Hoberg, G., & Maksimovic, V. (2022). Product life cycles in corporate finance. *The Review of Financial Studies*, 35(9), 4249–4299.
- Holmstrom, B., & Milgrom, P. (1991). Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design. *Journal of Law Economics and Organization*, 7, 24–52.
- Hou, K., & Robinson, D. T. (2006). Industry concentration and average stock returns. *The Journal of Finance*, 61(4), 1927–1956.
- Hwang, C. Y., Titman, S., & Wang, Y. (2022). Investor tastes, corporate behavior, and stock returns: An analysis of corporate social responsibility. *Management Science*, 68(10), 7131–7152.
- Jalilvand, A., & Harris, R. S. (1984). Corporate behavior in adjusting to capital structure and dividend targets: An econometric study. *The Journal of Finance*, 39(1), 127–145.
- Jayaraman, S., & Milbourn, T. T. (2012). The role of stock liquidity in executive compensation. *The Accounting Review*, 87(2), 537–563.
- Jensen, M. C., & Murphy, K. J. (1990). Performance pay and top-management incentives. *Journal of Political Economy*, 98, 225–264.
- Jiang, J., Petroni, K. & Wang, I. Y. (2010). CFOs and CEOs: Who have the most influence on earnings management? *Journal of Financial Economics*, 96 (3), 513–526.
- Lai, S., Li, Z., & Yang, Y. G. (2020). East, west, home's best: Do local CEOs behave less myopically? *The Accounting Review*, 95(2), 227–255.
- Narayanan, M. (1985). Managerial incentives for short-term results. *The Journal of Finance*, 40(5), 1469–1484.
- Nickell, S. J. (1996). Competition and corporate performance. *Journal of Political Economy*, 104(4), 724–746.
- Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, 37(2), 187–204.
- Porter, M. E. (1992). Capital choices: Changing the way America invests in industry. *The Journal of Applied Corporate Finance*, 5(2), 4–16.
- Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, 42 (3), 335–370.

- Schmidt, K. M. (1997). Managerial incentives and product market competition. *The Review of Economic Studies*, 64(2), 191.
- Shang, C. (2021). Dare to play with fire? Managerial ability and the use of short-term debt. *Journal of Corporate Finance*, 70, 102065.
- Sobel, M. E. (1982). Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models. *Sociological Methodology*, 13, 290–312.
- Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, 12(2), 257–285.
- Underwood, J., & Yost, B. (2025). CEO taxes and share pledging. SSRN.
- Zang, A.Y. (2012). Evidence on the trade-off between real activities manipulation and accrual-based earnings management. *The Accounting Review*, 87 (2), 675–703.

**Table 1.**

## Sample selection

This table describes the sample selection process. We start with 20,850 firm-years observations related to compensation contract complexity and drop the firm-years with R&D data in the current year. We exclude firm-years with missing or insignificant R&D data in the previous year and firm-years without the data to calculate the regression variables. Our final sample consists of 6,170 firm-years.

| Selection procedure                                                                                | Obs     |
|----------------------------------------------------------------------------------------------------|---------|
| Complexity                                                                                         | 20,850  |
| Less:                                                                                              |         |
| Firm-years with missing R&D data in the current year                                               | -10,042 |
| Firm-years with missing or insignificant R&D data in the previous year (i.e., $R\&D/Sales < 1\%$ ) | -3,787  |
| Firm-years without the data to calculate the regression variables                                  | -857    |
| Final Sample                                                                                       | 6,170   |

**Table 2**

Summary statistics and correlation analysis

Panel A: Summary Statistics

This table reports the summary statistics of main variables used in the empirical tests. The sample consists of 6,170 firm-year observations over the period 2006-2022. The number of observations, mean, standard deviation, P25 value, median, P75 value are reported from left to right, in sequence for each variable. Detailed definitions of all variables are described in Appendix A.

| VarName             | Obs   | Mean   | SD     | P25    | Median | P75    |
|---------------------|-------|--------|--------|--------|--------|--------|
| <i>CutR&amp;D</i>   | 6,170 | 0.288  | 0.453  | 0.000  | 0.000  | 1.000  |
| <i>Complexity</i>   | 6,170 | 13.980 | 6.280  | 10.000 | 14.000 | 17.000 |
| <i>ΔR&amp;D</i>     | 6,170 | 0.072  | 0.246  | -0.022 | 0.073  | 0.169  |
| <i>ΔInd_R&amp;D</i> | 6,170 | 0.005  | 0.106  | -0.033 | 0.013  | 0.053  |
| <i>ΔGDP</i>         | 6,170 | 0.018  | 0.019  | 0.018  | 0.023  | 0.027  |
| <i>Distance</i>     | 6,170 | 0.274  | 2.466  | -0.302 | 0.254  | 0.893  |
| <i>ΔCAPX</i>        | 6,170 | 0.052  | 0.469  | -0.172 | 0.059  | 0.275  |
| <i>ΔSales</i>       | 6,170 | 0.072  | 0.252  | -0.010 | 0.074  | 0.157  |
| <i>Size</i>         | 6,170 | 8.772  | 1.547  | 7.732  | 8.706  | 9.775  |
| <i>MB</i>           | 6,170 | 5.655  | 10.360 | 2.103  | 3.436  | 6.051  |
| <i>Leverage</i>     | 6,170 | 0.217  | 0.184  | 0.065  | 0.197  | 0.315  |
| <i>FCF</i>          | 6,170 | 0.189  | 0.244  | 0.076  | 0.190  | 0.317  |
| <i>Inst</i>         | 6,170 | 0.736  | 0.291  | 0.684  | 0.827  | 0.920  |
| <i>Analysts</i>     | 6,170 | 2.693  | 0.666  | 2.398  | 2.773  | 3.135  |

Panel B: Correlation matrix

This table reports the correlation matrix of all of the key variables in Equation (1), with Spearman correlation coefficients in the upper right triangle and Pearson correlation coefficients in the lower left triangle. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|                      | <i>CutR&amp;D</i> | <i>Complexity</i> | <i>ΔR&amp;D</i> | <i>ΔInd R&amp;D</i> | <i>ΔGDP</i> | <i>Distance Goal</i> | <i>ΔCAPX</i> | <i>ΔSales</i> | <i>size</i> | <i>MB</i> | <i>leverage</i> | <i>FCF</i> | <i>Inst</i> | <i>Analysts</i> |
|----------------------|-------------------|-------------------|-----------------|---------------------|-------------|----------------------|--------------|---------------|-------------|-----------|-----------------|------------|-------------|-----------------|
| <i>CutR&amp;D</i>    | 1                 | 0.02*             | -0.13***        | 0.01                | -0.10***    | -0.15***             | -0.25***     | -0.37***      | -0.11***    | -0.20***  | 0.10***         | -0.10***   | -0.06***    | -0.09***        |
| <i>Complexity</i>    | 0.02*             | 1                 | -0.04***        | 0.01                | 0.09***     | 0.03**               | -0.01        | -0.03**       | 0.33***     | 0.08***   | 0.19***         | 0.11***    | 0.08***     | 0.20***         |
| <i>ΔR&amp;D</i>      | -0.08***          | -0.03**           | 1               | 0.07***             | -0.06***    | -0.07***             | 0.04***      | 0.14***       | 0.07***     | 0.15***   | -0.11***        | 0.07***    | 0.07***     | 0.12***         |
| <i>ΔInd R&amp;D</i>  | 0.01              | 0.01              | 0.04***         | 1                   | -0.12***    | -0.12***             | -0.05***     | -0.09***      | -0.00       | -0.03**   | -0.01           | -0.00      | 0.05***     | 0.02*           |
| <i>ΔGDP</i>          | -0.16***          | 0.10***           | -0.04***        | -0.10***            | 1           | 0.12***              | 0.10***      | 0.13***       | 0.11***     | 0.10***   | 0.06***         | 0.01       | 0.02        | 0.04***         |
| <i>Distance Goal</i> | -0.10***          | 0.01              | -0.06***        | -0.10***            | 0.11***     | 1                    | 0.18***      | 0.42***       | 0.08***     | 0.13***   | -0.02           | 0.20***    | 0.01        | -0.00           |
| <i>ΔCAPX</i>         | -0.22***          | -0.01             | 0.01            | -0.03***            | 0.15***     | 0.12***              | 1            | 0.41***       | 0.04***     | 0.10***   | -0.05***        | -0.00      | 0.01        | 0.02*           |
| <i>ΔSales</i>        | -0.24***          | -0.02*            | 0.06***         | -0.07***            | 0.12***     | 0.25***              | 0.38***      | 1             | 0.09***     | 0.27***   | -0.09***        | 0.12***    | 0.06***     | 0.10***         |
| <i>Size</i>          | -0.11***          | 0.32***           | 0.04***         | -0.00               | 0.11***     | 0.04***              | 0.04***      | 0.05***       | 1           | 0.34***   | 0.16***         | 0.42***    | -0.05***    | 0.65***         |
| <i>MB</i>            | -0.10***          | 0.05***           | 0.08***         | -0.01               | 0.04***     | 0.04***              | 0.04***      | 0.12***       | 0.15***     | 1         | 0.04***         | 0.22***    | 0.05***     | 0.18***         |
| <i>Leverage</i>      | 0.10***           | 0.14***           | -0.08***        | -0.00               | 0.05***     | -0.02                | -0.04***     | -0.04***      | 0.08***     | 0.05***   | 1               | 0.02*      | 0.06***     | 0.03**          |
| <i>FCF</i>           | -0.08***          | 0.08***           | 0.03**          | 0.00                | -0.00       | 0.12***              | -0.00        | 0.05***       | 0.41***     | 0.04***   | 0.00            | 1          | 0.05***     | 0.22***         |
| <i>Inst</i>          | -0.07***          | 0.12***           | 0.04***         | 0.01                | 0.03**      | 0.00                 | 0.02         | 0.02*         | 0.12***     | 0.05***   | 0.04***         | 0.14***    | 1           | 0.03**          |
| <i>Analysts</i>      | -0.10***          | 0.20***           | 0.08***         | 0.01                | 0.05***     | -0.00                | 0.02         | 0.04***       | 0.60***     | 0.10***   | -0.02           | 0.21***    | 0.17***     | 1               |

**Table 3**

Baseline regression: CEO compensation complexity and managerial short-termism

This table reports the regression results on the relationship between CEO compensation complexity and managerial short-termism. *CutR&D* is a proxy for managerial short-termism, which equals one if R&D expenditures in fiscal year *t* decreases compared to fiscal year *t*-1, and zero otherwise. *Complexity* is CEO compensation complexity as defined in Section 2.2.2. We use logistic regression in column (1) and OLS regression in column (2). The  $R^2$  in column (1) is a Pseudo  $R^2$  obtained from the logistic regression. Industry and year fixed effects are controlled in both regressions. *t*-statistics in parentheses are calculated using standard errors clustered at the firm level. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

| Dependent variables     | <i>CutR&amp;D</i>    |                      |
|-------------------------|----------------------|----------------------|
|                         | (1)<br>Logistic      | (2)<br>OLS           |
| <i>Complexity</i>       | 0.018***<br>(2.96)   | 0.003***<br>(2.74)   |
| $\Delta R\&D$           | -0.514***<br>(-3.58) | -0.081***<br>(-3.30) |
| $\Delta Ind\_R\&D$      | -0.234<br>(-0.70)    | -0.021<br>(-0.35)    |
| $\Delta GDP$            | -12.165<br>(-0.47)   | -2.221<br>(-0.56)    |
| <i>Distance_Goal</i>    | -0.027*<br>(-1.85)   | -0.005**<br>(-2.05)  |
| $\Delta CAPX$           | -0.638***<br>(-8.28) | -0.110***<br>(-8.55) |
| $\Delta Sales$          | -1.508***<br>(-6.64) | -0.251***<br>(-7.46) |
| <i>size</i>             | -0.119***<br>(-3.28) | -0.023***<br>(-3.67) |
| <i>MB</i>               | -0.016***<br>(-4.49) | -0.002***<br>(-4.72) |
| <i>Leverage</i>         | 0.892***<br>(4.34)   | 0.163***<br>(4.48)   |
| <i>FCF</i>              | -0.129<br>(-0.67)    | -0.036<br>(-1.16)    |
| <i>Inst</i>             | -0.258**<br>(-2.16)  | -0.056**<br>(-2.54)  |
| <i>Analysts</i>         | -0.108<br>(-1.51)    | -0.018<br>(-1.45)    |
| Constant                | 0.848<br>(1.14)      | 0.651***<br>(5.32)   |
| Industry                | Controlled           | Controlled           |
| Year                    | Controlled           | Controlled           |
| N                       | 6,170                | 6,170                |
| Pseudo $R^2$ /R-squared | 0.132                | 0.150                |

**Table 4**

## Subsample analyses

This table reports the regression results on subsample analyses. The SD (Small Decreases in Pre-R&D Earnings) subsample in column (1) includes firm-years satisfy two criteria: (1) Pre-tax, pre-R&D incomes in year  $t$  are lower than those in year  $t-1$ ; (2) Pre-tax, pre-R&D incomes in year  $t$  are higher than pre-tax incomes in year  $t-1$ . The Other subsample in column (2) include firm-years with larger earnings declines that cannot be mitigated by cutting R&D expenditures and those with earnings growth in the current year. *CutR&D* is a proxy for managerial short-termism, which equals one if R&D expenditures in fiscal year  $t$  decreases compared to fiscal year  $t-1$ , and zero otherwise. *Complexity* is CEO compensation complexity as defined in Section 2.2.2. The control variables are the same as those reported in Table 3. Industry and year fixed effects are controlled in both regressions.  $t$ -statistics in parentheses are calculated using standard errors clustered at the firm level. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

| Dependent variables   | <i>CutR&amp;D</i>    |                      |
|-----------------------|----------------------|----------------------|
|                       | (1)<br>SD            | (2)<br>Other         |
| <i>Complexity</i>     | 0.027**<br>(2.29)    | 0.014*<br>(1.84)     |
| $\Delta R\&D$         | -0.682**<br>(-2.20)  | -0.477***<br>(-2.66) |
| $\Delta Ind\_R\&D$    | -1.210*<br>(-1.78)   | 0.089<br>(0.22)      |
| $\Delta GDP$          | 65.210<br>(1.17)     | -37.472<br>(-1.22)   |
| <i>Distance_Goal</i>  | 0.771***<br>(4.25)   | -0.019<br>(-1.29)    |
| $\Delta CAPX$         | -0.590***<br>(-4.19) | -0.649***<br>(-7.17) |
| $\Delta Sales$        | -1.977***<br>(-4.36) | -1.536***<br>(-6.28) |
| <i>size</i>           | -0.019<br>(-0.31)    | -0.152***<br>(-3.57) |
| <i>MB</i>             | -0.012*<br>(-1.66)   | -0.017***<br>(-4.05) |
| <i>Leverage</i>       | 0.863**<br>(2.23)    | 0.877***<br>(3.91)   |
| <i>FCF</i>            | 0.742**<br>(2.15)    | -0.423*<br>(-1.89)   |
| <i>Inst</i>           | -0.156<br>(-0.73)    | -0.243*<br>(-1.71)   |
| <i>Analysts</i>       | -0.285**<br>(-2.16)  | -0.080<br>(-0.95)    |
| Constant              | -0.165<br>(-0.09)    | 1.492<br>(1.56)      |
| Industry              | Controlled           | Controlled           |
| Year                  | Controlled           | Controlled           |
| N                     | 1,362                | 4,791                |
| Pseudo R <sup>2</sup> | 0.128                | 0.147                |

**Table 5.****Alternative variable**

This table reports the regression results for robustness checks on alternative measures. Panel A presents the results of alternative independent measure, *WTD\_Complexity*, which assigns weights to the complexity score of each compensation component based on its proportion of total CEO pay. Panel B presents the results of four alternative dependent measures. The first alternative dependent variable is *CutR&D\_Alter*, which shares the same definition as *CutR&D* but is constructed from a new sample that do not drop the observations with missing R&D in the current year and replace them to be zero. The second alternative dependent variable is *CutR&D\_Sales*, which equals one if R&D expenditures scaled by total operating revenue in fiscal year *t* decreases compared to fiscal year *t*-1, and zero otherwise. The third alternative dependent variable is *BeatByCutR&D*, which equals one if the firm's reported earnings in year *t* exceed the analysts' median consensus forecast by cutting R&D expenditures, and zero otherwise. The fourth alternative dependent variable is real earnings management (*REMI/REM2*). *Complexity* is CEO compensation complexity as defined in Section 2.2.2. We use logistic regression in column (1) of Panel A, column (1), (3) and (5) of Panel B, and OLS regression in column (2) of Panel A, column (2), (4), (6), (7) and (8) of Panel B. The  $R^2$  in column (1) of Panel A, column (1), (3) and (5) of Panel B is a Pseudo  $R^2$  obtained from the logistic regression. The control variables are the same as those reported in Table 3. Industry and year fixed effects are controlled in all regressions. *t*-statistics in parentheses are calculated using standard errors clustered at the firm level. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

**Panel A: Alternative Independent Variable**

| Dependent variables   | <i>CutR&amp;D</i>    |                      |
|-----------------------|----------------------|----------------------|
|                       | (1)<br>Logistic      | (2)<br>OLS           |
| <i>WTD_Complexity</i> | 0.040***<br>(3.81)   | 0.006***<br>(3.45)   |
| <i>ΔR&amp;D</i>       | -0.504***<br>(-3.53) | -0.080***<br>(-3.27) |
| <i>ΔInd_R&amp;D</i>   | -0.221<br>(-0.66)    | -0.019<br>(-0.32)    |
| <i>ΔGDP</i>           | -1.491<br>(-0.06)    | -0.647<br>(-0.16)    |
| <i>Distance_Goal</i>  | -0.027*<br>(-1.84)   | -0.005**<br>(-2.05)  |
| <i>ΔCAPX</i>          | -0.639***<br>(-8.33) | -0.110***<br>(-8.58) |
| <i>ΔSales</i>         | -1.507***<br>(-6.64) | -0.249***<br>(-7.43) |
| <i>size</i>           | -0.116***<br>(-3.22) | -0.022***<br>(-3.61) |
| <i>MB</i>             | -0.015***<br>(-4.22) | -0.002***<br>(-4.39) |
| <i>Leverage</i>       | 0.869***<br>(4.24)   | 0.159***<br>(4.37)   |
| <i>FCF</i>            | -0.137<br>(-0.71)    | -0.038<br>(-1.22)    |
| <i>Inst</i>           | -0.258**<br>(-2.16)  | -0.056**<br>(-2.53)  |
| <i>Analysts</i>       | -0.111<br>(-1.56)    | -0.019<br>(-1.49)    |

|                                  |                 |                    |
|----------------------------------|-----------------|--------------------|
| Constant                         | 0.626<br>(0.85) | 0.619***<br>(5.10) |
| Industry                         | Controlled      | Controlled         |
| Year                             | Controlled      | Controlled         |
| N                                | 6,170           | 6,170              |
| Pseudo R <sup>2</sup> /R-squared | 0.133           | 0.151              |

Panel B: Alternative Dependent Variable

| Dependent variables              | <i>CutR&amp;D_Alter</i> |                      | <i>CutR&amp;D_Sales</i> |                      | <i>BeatbyCutR&amp;D</i> |                      | <i>REMI</i>          | <i>REM2</i>          |
|----------------------------------|-------------------------|----------------------|-------------------------|----------------------|-------------------------|----------------------|----------------------|----------------------|
|                                  | (1)                     | (2)                  | (3)                     | (4)                  | (5)                     | (6)                  | (7)                  | (8)                  |
|                                  | Logistic                | OLS                  | Logistic                | OLS                  | Logistic                | OLS                  | OLS                  | OLS                  |
| <i>Complexity</i>                | 0.018***<br>(2.95)      | 0.003***<br>(2.74)   | 0.012**<br>(2.45)       | 0.003**<br>(2.42)    | 0.022**<br>(2.30)       | 0.001*<br>(1.95)     | 0.016***<br>(2.89)   | 0.011**<br>(2.36)    |
| <i>ΔR&amp;D</i>                  | -0.506***<br>(-3.51)    | -0.080***<br>(-3.24) | -0.279**<br>(-2.16)     | -0.051*<br>(-1.87)   | -0.504**<br>(-2.33)     | -0.033**<br>(-2.36)  | -0.092<br>(-0.73)    | -0.061<br>(-0.55)    |
| <i>ΔInd_R&amp;D</i>              | 0.017<br>(0.06)         | 0.018<br>(0.37)      | -1.273***<br>(-4.65)    | -0.276***<br>(-4.72) | 0.121<br>(0.25)         | 0.016<br>(0.42)      | 0.139<br>(0.52)      | 0.309<br>(1.36)      |
| <i>ΔGDP</i>                      | -12.348<br>(-0.48)      | -2.199<br>(-0.55)    | -52.093**<br>(-2.48)    | -12.057**<br>(-2.52) | 56.289<br>(1.14)        | 2.289<br>(0.96)      | 87.901***<br>(3.19)  | 64.649***<br>(2.68)  |
| <i>Distance_Goal</i>             | -0.026*<br>(-1.80)      | -0.005**<br>(-2.01)  | 0.061***<br>(4.38)      | 0.014***<br>(4.99)   | 0.116***<br>(5.96)      | 0.009***<br>(5.56)   | 0.014<br>(1.38)      | 0.003<br>(0.37)      |
| <i>ΔCAPX</i>                     | -0.637***<br>(-8.27)    | -0.110***<br>(-8.54) | -0.506***<br>(-7.26)    | -0.101***<br>(-7.24) | -0.658***<br>(-5.22)    | -0.045***<br>(-5.22) | 0.071<br>(1.06)      | 0.003<br>(0.05)      |
| <i>ΔSales</i>                    | -1.500***<br>(-6.64)    | -0.250***<br>(-7.45) | 2.555***<br>(12.50)     | 0.482***<br>(18.68)  | -0.126<br>(-0.46)       | -0.011<br>(-0.57)    | 0.040<br>(0.25)      | -0.064<br>(-0.47)    |
| <i>size</i>                      | -0.119***<br>(-3.28)    | -0.023***<br>(-3.67) | -0.035<br>(-1.26)       | -0.007<br>(-1.04)    | 0.039<br>(0.63)         | 0.001<br>(0.28)      | 0.034<br>(0.98)      | 0.025<br>(0.85)      |
| <i>MB</i>                        | -0.016***<br>(-4.50)    | -0.002***<br>(-4.73) | -0.002<br>(-0.88)       | -0.000<br>(-0.58)    | 0.005<br>(0.95)         | 0.000<br>(1.11)      | -0.007*<br>(-1.96)   | -0.007**<br>(-2.16)  |
| <i>Leverage</i>                  | 0.893***<br>(4.35)      | 0.164***<br>(4.49)   | 0.060<br>(0.38)         | 0.008<br>(0.24)      | -0.184<br>(-0.50)       | -0.007<br>(-0.28)    | -0.193<br>(-0.96)    | -0.102<br>(-0.62)    |
| <i>FCF</i>                       | -0.131<br>(-0.68)       | -0.036<br>(-1.17)    | 0.367***<br>(2.78)      | 0.079***<br>(2.96)   | -0.065<br>(-0.25)       | -0.012<br>(-0.69)    | 0.010<br>(0.06)      | -0.112<br>(-0.80)    |
| <i>Inst</i>                      | -0.257**<br>(-2.15)     | -0.056**<br>(-2.54)  | -0.056<br>(-0.61)       | -0.011<br>(-0.53)    | -0.037<br>(-0.19)       | -0.005<br>(-0.39)    | 0.020<br>(0.16)      | 0.028<br>(0.29)      |
| <i>Analysts</i>                  | -0.106<br>(-1.50)       | -0.018<br>(-1.44)    | -0.100*<br>(-1.79)      | -0.023*<br>(-1.81)   | -0.360***<br>(-2.64)    | -0.022**<br>(-2.43)  | 0.110*<br>(1.70)     | 0.069<br>(1.26)      |
| Constant                         | 0.855<br>(1.15)         | 0.652***<br>(5.31)   | 1.925***<br>(2.95)      | 0.937***<br>(6.44)   | -2.627*<br>(-1.81)      | -0.037<br>(-0.49)    | -3.161***<br>(-4.52) | -2.151***<br>(-3.73) |
| Industry                         | Controlled              | Controlled           | Controlled              | Controlled           | Controlled              | Controlled           | Controlled           | Controlled           |
| Year                             | Controlled              | Controlled           | Controlled              | Controlled           | Controlled              | Controlled           | Controlled           | Controlled           |
| N                                | 6,169                   | 6,169                | 6,168                   | 6,170                | 6,039                   | 6,101                | 5,847                | 5,869                |
| Pseudo R <sup>2</sup> /R-squared | 0.132                   | 0.150                | 0.082                   | 0.103                | 0.087                   | 0.050                | 0.167                | 0.150                |

**Table 6****The Tax Cut and Jobs Act**

This table reports the regression results of the effect of TCJA. *CutR&D* is a proxy for managerial short-termism, which equals one if R&D expenditures in fiscal year *t* decreases compared to fiscal year *t*-1, and zero otherwise. *Treat* is an indicator variable that equals one if the CEO compensation excess \$1 million in each of the four years (2014-2017) and zero otherwise. *Post* is an indicator variable that equals to one if year *t* is after 2017 and zero otherwise. The independent variable of interest in this analysis is the interaction term, *Treat*×*Post*. The control variables are the same as those reported in Table 3. Firm and year fixed effects are controlled in the regression. *t*-statistics in parentheses are calculated using standard errors clustered at the firm level. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

| Dependent variables        | <i>CutR&amp;D</i>    |
|----------------------------|----------------------|
| <i>Treat</i> × <i>Post</i> | -0.252**<br>(-2.18)  |
| <i>ΔR&amp;D</i>            | 0.016<br>(0.22)      |
| <i>ΔInd_R&amp;D</i>        | 0.172<br>(1.18)      |
| <i>Distance_Goal</i>       | -0.012*<br>(-1.91)   |
| <i>ΔCAPX</i>               | -0.083***<br>(-3.02) |
| <i>ΔSales</i>              | -0.362***<br>(-3.80) |
| <i>size</i>                | -0.118***<br>(-4.43) |
| <i>MB</i>                  | -0.001<br>(-0.53)    |
| <i>Leverage</i>            | -0.040<br>(-0.25)    |
| <i>FCF</i>                 | 0.134<br>(1.51)      |
| <i>Inst</i>                | 0.096<br>(0.96)      |
| <i>Analysts</i>            | -0.040<br>(-0.67)    |
| Constant                   | 1.565***<br>(5.77)   |
| Firm                       | Controlled           |
| Year                       | Controlled           |
| N                          | 1,512                |
| Adj R-squared              | 0.310                |

**Table 7**

## Exogenous CEO turnover events

This table reports the regression results of the exogenous CEO turnover events. The sample covers firm-year observations three years before and three years after an exogenous CEO turnover, including the turnover year. *CutR&D* is a proxy for managerial short-termism, which equals one if R&D expenditures in fiscal year *t* decreases compared to fiscal year *t*-1, and zero otherwise. *Treat* is an indicator variable that equals one if firm *i*'s transition year *t* is a low-to-high CEO compensation complexity transition and zero otherwise. *Post* is an indicator variable that equals to one if year *t* is either an event year or after the turnover event and zero otherwise. The independent variable of interest in this analysis is the interaction term, *Treat*×*Post*. The control variables are the same as those reported in Table 3. Firm and year fixed effects are controlled in the regression. *t*-statistics in parentheses are calculated using standard errors clustered at the firm level. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

| Dependent variables        | <i>CutR&amp;D</i>    |
|----------------------------|----------------------|
| <i>Treat</i> × <i>Post</i> | 0.153**<br>(2.09)    |
| $\Delta R\&D$              | 0.165<br>(1.29)      |
| $\Delta Ind\_R\&D$         | 0.146<br>(0.72)      |
| $\Delta GDP$               | 15.364<br>(0.33)     |
| <i>Distance_Goal</i>       | -0.008<br>(-0.65)    |
| $\Delta CAPX$              | -0.200***<br>(-3.92) |
| $\Delta Sales$             | -0.345***<br>(-2.74) |
| <i>size</i>                | -0.084<br>(-1.21)    |
| <i>MB</i>                  | -0.002<br>(-1.28)    |
| <i>Leverage</i>            | -0.080<br>(-0.29)    |
| <i>FCF</i>                 | -0.005<br>(-0.03)    |
| <i>Inst</i>                | 0.410**<br>(2.42)    |
| <i>Analysts</i>            | 0.040<br>(0.26)      |
| Constant                   | 0.154<br>(0.10)      |
| Firm                       | Controlled           |
| Year                       | Controlled           |

|               |       |
|---------------|-------|
| N             | 497   |
| Adj R-squared | 0.208 |

**Table 8**

Instrument variable

This table reports the estimates of the two-stage IV probit model. Our first instrument *Consultant\_dum* is an indicator variable that equals one if a firm use a compensation consultant in year *t*, and zero otherwise. Our second instrument *Complexity\_ave* is the average of CEO compensation complexity in public companies with the same compensation consultants in a year. Column (1) and (2) show results from the first-stage regression in which the dependent variable is *Complexity*, which is CEO compensation complexity as defined in Section 2.2.2. Column (3) and (4) show results from second-stage regressions in which the dependent variable is *CutR&D*, an indicator equals one if R&D expenditures in fiscal year *t* decreases compared to fiscal year *t*-1, and zero otherwise. The key independent variable in column (3) and (4) are the predicted value of *Complexity* from the first-step regression. The control variables are the same as those reported in Table 3. Industry and year fixed effects are controlled in all regressions. *t*-statistics in parentheses are calculated using standard errors clustered at the firm level. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

| Dependent variables   | <i>Complexity</i>       |                     | <i>CutR&amp;D</i>    |                      |
|-----------------------|-------------------------|---------------------|----------------------|----------------------|
|                       | First stage             |                     | Second stage         |                      |
|                       | (1)                     | (2)                 | (3)                  | (4)                  |
| <i>Complexity</i>     |                         |                     | 0.133***<br>(6.37)   | 0.039***<br>(3.47)   |
| <i>Consultant_dum</i> | 2.585***<br>(3.53)      |                     |                      |                      |
| <i>Complexity_ave</i> |                         | 0.905***<br>(15.08) |                      |                      |
| $\Delta R\&D$         | -0.786**<br>(-2.50)     | -0.589**<br>(-2.08) | -0.115<br>(-1.35)    | -0.273***<br>(-3.31) |
| $\Delta Ind\_R\&D$    | 0.619<br>(1.00)         | 0.267<br>(0.45)     | -0.186<br>(-1.14)    | -0.157<br>(-0.81)    |
| $\Delta GDP$          | -635.355***<br>(-10.48) | 7.619<br>(0.11)     | 82.590***<br>(4.05)  | 15.306<br>(0.91)     |
| <i>Distance_Goal</i>  | 0.015<br>(0.57)         | 0.015<br>(0.57)     | -0.014**<br>(-1.96)  | -0.017**<br>(-2.09)  |
| $\Delta CAPX$         | -0.097<br>(-0.64)       | -0.021<br>(-0.15)   | -0.253***<br>(-4.01) | -0.361***<br>(-8.01) |
| $\Delta Sales$        | -0.752**<br>(-2.00)     | -0.435<br>(-1.22)   | -0.499***<br>(-3.44) | -0.784***<br>(-6.78) |
| <i>size</i>           | 0.691***<br>(4.79)      | 0.510***<br>(3.81)  | -0.142***<br>(-5.66) | -0.093***<br>(-4.10) |
| <i>MB</i>             | -0.013<br>(-1.31)       | -0.011<br>(-1.12)   | -0.005**<br>(-2.17)  | -0.009***<br>(-4.77) |
| <i>Leverage</i>       | 0.723<br>(0.88)         | 0.264<br>(0.34)     | 0.298*<br>(1.85)     | 0.522***<br>(4.37)   |
| <i>FCF</i>            | -0.469<br>(-0.73)       | -0.300<br>(-0.50)   | 0.004<br>(0.04)      | -0.066<br>(-0.61)    |
| <i>Inst</i>           | 0.815*<br>(1.78)        | 0.813*<br>(1.78)    | -0.230***<br>(-3.44) | -0.187***<br>(-3.44) |

|                 |            |            |            |            |
|-----------------|------------|------------|------------|------------|
|                 | (1.74)     | (1.85)     | (-3.08)    | (-2.66)    |
| <i>Analysts</i> | 0.681***   | 0.619***   | -0.141***  | -0.082*    |
|                 | (2.90)     | (2.65)     | (-3.23)    | (-1.90)    |
| Constant        | 16.774***  | -6.456**   | -2.158***  | -0.128     |
|                 | (5.58)     | (-2.00)    | (-3.09)    | (-0.25)    |
| Industry        | Controlled | Controlled | Controlled | Controlled |
| Year            | Controlled | Controlled | Controlled | Controlled |
| N               | 6,170      | 6,170      | 6,170      | 6,170      |

**Table 9**

## Omitted variables test

This table reports the results of Omitted variables test proposed by Oster's (2019). Rows (1) and (2) present the coefficients of *Complexity* and  $R^2$  reported in column (2) of Table 4. Rows (3) and (4) present the assumption of  $\delta$  and  $R_{\max}$ . Referring to the suggestion of Oster (2019), we define  $R_{\max}$  as 1.3 times  $R^2$  from our baseline regressions that controls for all observable variables. Rows (5) and (6) report the bounds on "true" coefficient of *Complexity* and judge whether the bounding estimate excludes zero. Rows (7) and (8) report the value of  $\delta$  when and judge whether the it exceeds one. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively.

|     | Dependent variables            | <i>CutR&amp;D</i> |
|-----|--------------------------------|-------------------|
| (1) | <i>Complexity</i>              | 0.003             |
| (2) | $R^2$                          | 0.150             |
| (3) | $\delta$                       | 1                 |
| (4) | $R_{\max}=1.3R^2$              | 0.195             |
| (5) | Bounds on the treatment effect | [0.0029, 0.0035]  |
| (6) | Treatment effect excludes 0    | Yes               |
| (7) | Oster's $\delta$               | -10.433           |
| (8) | $ \delta >1$                   | Yes               |

**Table 10**

## Cross-sectional analyses

Panel A reports the regression results of cross-sectional analyses using corporate governance. We divide our sample into two subsamples based on the annual quartile value of two variables. The first variable is *TW\_COP*, which is defined as the fraction of Co-opted directors on the board, weighted by the CEO's tenure (Coles et al., 2014). The second variable is *SRIO*, which represents the proportion of a firm's shares held by socially responsible investors relative to its total outstanding shares, excluding hedge fund ownership (Hwang et al., 2022). Panel B reports the regression results of cross-sectional analyses using market competition. We divide our sample into two subsamples based on the annual quartile value of two variables. The first variable is the Herfindahl-Hirschman Index (*HHI*) computed as the sum of squared market shares based on firm sales in the text-based network industry classification (TNIC) framework (Hoberg and Phillips, 2016). The second variable is product similarity (*Similarity*) that calculates pairwise firm similarity scores by parsing the product text and forming word vectors (Hoberg and Phillips, 2016). Panel C reports the regression results of cross-sectional analyses using CEO characteristic. We divide our sample into two subsamples based on the *CEO\_retire* and *CEO\_outside wealth* variable. *CEO\_retire* equals one if the CEO is 63 and older, and zero otherwise (Chen et al., 2015). *Outside\_Wealth* equals one if the CEOs with an above-median (below-median) share of their total wealth held outside of the firm's shares in a given year, and zero otherwise. The control variables are the same as those reported in Table 3. Industry and year fixed effects are controlled in all regressions. *t*-statistics in parentheses are calculated using standard errors clustered at the firm level. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

| <b>Panel A: Corporate governance</b> |                           |                          |                               |                              |
|--------------------------------------|---------------------------|--------------------------|-------------------------------|------------------------------|
| Dependent variables                  | <i>CutR&amp;D</i>         |                          |                               |                              |
|                                      | (1)<br><i>High TW_COP</i> | (2)<br><i>Low TW_COP</i> | (3)<br><i>High SRIO</i>       | (4)<br><i>Low SRIO</i>       |
| <i>Complexity</i>                    | 0.034***<br>(3.14)        | 0.006<br>(0.42)          | -0.012<br>(-0.94)             | 0.026**<br>(2.24)            |
| Constant                             | 3.433*<br>(1.78)          | -1.414<br>(-0.82)        | 1.468<br>(0.88)               | 3.487**<br>(2.42)            |
| Control variables                    | Controlled                | Controlled               | Controlled                    | Controlled                   |
| Industry                             | Controlled                | Controlled               | Controlled                    | Controlled                   |
| Year                                 | Controlled                | Controlled               | Controlled                    | Controlled                   |
| P-value                              | 0.044                     |                          | 0.012                         |                              |
| N                                    | 1,441                     | 1,451                    | 1,493                         | 1,507                        |
| Pseudo R <sup>2</sup>                | 0.173                     | 0.130                    | 0.152                         | 0.163                        |
| <b>Panel B: Market competition</b>   |                           |                          |                               |                              |
| Dependent variables                  | <i>CutR&amp;D</i>         |                          |                               |                              |
|                                      | (1)<br><i>High HHI</i>    | (2)<br><i>Low HHI</i>    | (3)<br><i>High Similarity</i> | (4)<br><i>Low Similarity</i> |
| <i>Complexity</i>                    | 0.034***<br>(3.14)        | 0.006<br>(0.42)          | 0.009<br>(0.73)               | 0.034***<br>(2.79)           |
| Constant                             | 3.433*<br>(1.78)          | -1.414<br>(-0.82)        | 3.875***<br>(2.83)            | -1.236<br>(-0.94)            |
| Control variables                    | Controlled                | Controlled               | Controlled                    | Controlled                   |
| Industry                             | Controlled                | Controlled               | Controlled                    | Controlled                   |
| Year                                 | Controlled                | Controlled               | Controlled                    | Controlled                   |
| P-value                              | 0.098                     |                          | 0.079                         |                              |
| N                                    | 1,441                     | 1,451                    | 1,529                         | 1,539                        |
| Pseudo R <sup>2</sup>                | 0.173                     | 0.130                    | 0.137                         | 0.158                        |

| <b>Panel C: CEO characteristic</b> |                     |                     |                         |                         |
|------------------------------------|---------------------|---------------------|-------------------------|-------------------------|
| Dependent variables                | <i>CutR&amp;D</i>   |                     |                         |                         |
|                                    | (1)                 | (2)                 | (3)                     | (4)                     |
|                                    | <i>CEO_retire=1</i> | <i>CEO_retire=0</i> | <i>Outside_wealth=1</i> | <i>Outside_wealth=0</i> |
| <i>Complexity</i>                  | 0.014               | 0.024***            | 0.021                   | 0.072***                |
|                                    | (0.71)              | (2.98)              | (1.03)                  | (3.83)                  |
| Constant                           | 1.375               | 1.504               | 4.583***                | 2.965                   |
|                                    | (0.58)              | (1.61)              | (4.42)                  | (1.38)                  |
| Control variables                  | Controlled          | Controlled          | Controlled              | Controlled              |
| Industry                           | Controlled          | Controlled          | Controlled              | Controlled              |
| Year                               | Controlled          | Controlled          | Controlled              | Controlled              |
| P-value                            | 0.327               |                     | 0.031                   |                         |
| N                                  | 504                 | 4,010               | 718                     | 829                     |
| Pseudo R <sup>2</sup>              | 0.173               | 0.130               | 0.268                   | 0.176                   |

**Table 11**

## Path analysis

This table reports the results of mediation test exploring the mediation of CEO pay-performance sensitivity (*PPS*) on the relation between CEO compensation complexity (*Complexity*) and the likelihood of R&D cutting (*CutR&D*). The control variables are the same as those reported in Table 3. Industry and year fixed effects are controlled in the regression. z-statistics in parentheses are calculated using standard errors clustered at the firm level. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

| Dependent variables                         | <i>CutR&amp;D</i> |        |
|---------------------------------------------|-------------------|--------|
|                                             | Coefficient       | Z-stat |
| <b>Direct path</b>                          |                   |        |
| <i>P(Complexity, CutR&amp;D)</i>            | 0.002*            | 1.70   |
| <b>Indirect path</b>                        |                   |        |
| <i>P(Complexity, PPS)=a</i>                 | -0.012***         | -3.77  |
| <i>P(PPS, CutR&amp;D)=b</i>                 | -0.039***         | -3.13  |
| <b>Total indirect path for PPS (=a × b)</b> | 0.001***          | 2.41   |
| Proportion of total effect that is mediated | 17.38%            |        |
| Control variables                           | Controlled        |        |
| Industry                                    | Controlled        |        |
| Year                                        | Controlled        |        |
| N                                           | 4,189             |        |

**Table 12**

Decompose CEO compensation complexity

This table reports the regression results on the relationship between the components of CEO compensation complexity and managerial short-termism. *CutR&D* is a proxy for managerial short-termism, which equals one if R&D expenditures in fiscal year *t* decreases compared to fiscal year *t*-1, and zero otherwise. *num\_components* is the number of main compensation components in compensation contracts. *num\_measure* is the number of different performance measures in compensation contracts. *num\_periods* is the maximum number of performance periods in compensation contracts, and *abs\_rel\_dummy* is a dummy variable that equals one if the compensation contracts include both absolute and relative performance criteria, and zero otherwise. The control variables are the same as those reported in Table 3. Industry and year fixed effects are controlled in all regressions. t-statistics in parentheses are calculated using standard errors clustered at the firm level. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

| Dependent variables   | <i>CutR&amp;D</i>    |                      |                      |                      |
|-----------------------|----------------------|----------------------|----------------------|----------------------|
|                       | (1)                  | (2)                  | (3)                  | (4)                  |
| <i>num_components</i> | 0.107**<br>(2.04)    |                      |                      |                      |
| <i>num_measure</i>    |                      | 0.035***<br>(3.21)   |                      |                      |
| <i>num_periods</i>    |                      |                      | 0.067***<br>(4.36)   |                      |
| <i>abs_rel_dummy</i>  |                      |                      |                      | 0.441***<br>(5.46)   |
| $\Delta R\&D$         | -0.524***<br>(-3.66) | -0.514***<br>(-3.59) | -0.518***<br>(-3.61) | -0.510***<br>(-3.52) |
| $\Delta Ind\_R\&D$    | -0.210<br>(-0.63)    | -0.219<br>(-0.66)    | -0.225<br>(-0.67)    | -0.250<br>(-0.74)    |
| $\Delta GDP$          | -16.724<br>(-0.65)   | -23.392<br>(-0.92)   | -10.714<br>(-0.41)   | -5.209<br>(-0.20)    |
| <i>Distance_Goal</i>  | -0.027*<br>(-1.85)   | -0.027*<br>(-1.83)   | -0.027*<br>(-1.87)   | -0.025*<br>(-1.69)   |
| $\Delta CAPX$         | -0.639***<br>(-8.29) | -0.641***<br>(-8.32) | -0.637***<br>(-8.25) | -0.646***<br>(-8.32) |
| $\Delta Sales$        | -1.519***<br>(-6.75) | -1.506***<br>(-6.65) | -1.515***<br>(-6.65) | -1.497***<br>(-6.55) |
| <i>size</i>           | -0.106***<br>(-2.95) | -0.114***<br>(-3.15) | -0.115***<br>(-3.17) | -0.128***<br>(-3.48) |
| <i>MB</i>             | -0.016***<br>(-4.42) | -0.016***<br>(-4.54) | -0.016***<br>(-4.53) | -0.015***<br>(-4.19) |
| <i>Leverage</i>       | 0.902***<br>(4.35)   | 0.894***<br>(4.35)   | 0.901***<br>(4.38)   | 0.862***<br>(4.21)   |
| <i>FCF</i>            | -0.152<br>(-0.79)    | -0.157<br>(-0.81)    | -0.120<br>(-0.63)    | -0.134<br>(-0.69)    |
| <i>Inst</i>           | -0.245**<br>(-2.04)  | -0.254**<br>(-2.12)  | -0.248**<br>(-2.07)  | -0.258**<br>(-2.15)  |
| <i>Analysts</i>       | -0.096<br>(-1.37)    | -0.091<br>(-1.29)    | -0.113<br>(-1.60)    | -0.104<br>(-1.46)    |
| Constant              | 1.004<br>(1.36)      | 0.889<br>(1.20)      | 0.848<br>(1.14)      | 1.000<br>(1.37)      |
| Industry              | Controlled           | Controlled           | Controlled           | Controlled           |
| Year                  | Controlled           | Controlled           | Controlled           | Controlled           |

|                       |       |       |       |       |
|-----------------------|-------|-------|-------|-------|
| Observations          | 6,170 | 6,170 | 6,140 | 6,170 |
| Pseudo R <sup>2</sup> | 0.131 | 0.132 | 0.133 | 0.136 |

**Table 13**

CEO compensation complexity and firm performance in the future

This table reports the regression results on the relationship between CEO compensation complexity and firm performance in the future. *ROA* is a proxy for firm performance, which is the average industry-adjusted *ROA* (return on assets) in the subsequent three or four years. *Complexity* is CEO compensation complexity as defined in Section 2.2.2. *SD* is a dummy variable, which equals one if the pre-tax, pre-R&D incomes in year *t* are lower than those in year *t*-1 and the pre-tax, pre-R&D incomes in year *t* are higher than pre-tax incomes in year *t*-1, and zero otherwise. The control variables are the same as those reported in Table 3. Industry and year fixed effects are controlled in all regressions. *t*-statistics in parentheses are calculated using standard errors clustered at the firm level. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

| Dependent variables           | <i>ROA</i>           |                      |                      |                      |
|-------------------------------|----------------------|----------------------|----------------------|----------------------|
|                               | T+3                  |                      | T+4                  |                      |
|                               | (1)                  | (2)                  | (3)                  | (4)                  |
| <i>Complexity</i>             | -0.001*<br>(-1.86)   | -0.000<br>(-0.95)    | -0.001**<br>(-1.99)  | -0.000<br>(-1.07)    |
| <i>Complexity</i> × <i>SD</i> |                      | -0.001**<br>(-2.26)  |                      | -0.001**<br>(-2.09)  |
| <i>SD</i>                     |                      | 0.012*<br>(1.79)     |                      | 0.010<br>(1.42)      |
| <i>ΔCAPX</i>                  | -0.008**<br>(-2.31)  | -0.008**<br>(-2.30)  | -0.010***<br>(-3.41) | -0.010***<br>(-3.38) |
| <i>ΔSales</i>                 | -0.015*<br>(-1.69)   | -0.015*<br>(-1.71)   | -0.011<br>(-1.42)    | -0.012<br>(-1.50)    |
| <i>size</i>                   | 0.006***<br>(5.20)   | 0.006***<br>(5.26)   | 0.006***<br>(4.59)   | 0.006***<br>(4.65)   |
| <i>MB</i>                     | 0.000**<br>(2.58)    | 0.000**<br>(2.54)    | 0.000**<br>(2.51)    | 0.000**<br>(2.48)    |
| <i>Leverage</i>               | 0.015<br>(1.63)      | 0.015*<br>(1.65)     | 0.016<br>(1.58)      | 0.016<br>(1.61)      |
| <i>Inst</i>                   | 0.021***<br>(4.00)   | 0.021***<br>(4.02)   | 0.025***<br>(4.53)   | 0.025***<br>(4.54)   |
| <i>ROA</i>                    | 0.613***<br>(32.02)  | 0.613***<br>(32.19)  | 0.584***<br>(29.62)  | 0.582***<br>(29.84)  |
| Constant                      | -0.166***<br>(-7.51) | -0.170***<br>(-7.61) | -0.162***<br>(-8.70) | -0.166***<br>(-8.78) |
| Industry                      | Controlled           | Controlled           | Controlled           | Controlled           |
| Year                          | Controlled           | Controlled           | Controlled           | Controlled           |
| N                             | 5,050                | 5,050                | 4,569                | 4,569                |
| R-squared                     | 0.679                | 0.679                | 0.669                | 0.670                |