Economic Determinants and Consequences of Performance Target Difficulty

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ABSTRACT: Using data on earnings targets in annual bonus plans, we construct and validate an empirical measure of beginning-of-year target difficulty and show that it is negatively associated with market uncertainty, retention concerns, and CEO entrenchment. We then present several findings about the effect of target difficulty on future performance and compensation. First, greater target difficulty in annual bonus plans is associated not only with lower CEO cash compensation but also with lower equity grants. Second, moderately challenging targets (neither too easy nor too difficult to achieve) are associated with abnormal reversals in fourth-quarter performance, particularly reductions in fourth-quarter performance following abnormally favorable third-quarter performance. Third, greater target difficulty is associated with higher same-year abnormal earnings but at the same time with lower next-year earnings and stock returns. Combined, our findings suggest that target difficulty is an important incentive design choice that affects performance and executive compensation.

Keywords: *Performance targets, target difficulty, incentives*.

Data Availability: Data used in this study is publicly available.

I. INTRODUCTION

A wealth of prior research examines the effect of target difficulty on performance in various settings (Bonner and Sprinkle 2002; Locke and Latham 2002). Despite recent interest in how firms set performance targets in executive compensation contracts (Bennett, Bettis, Gopalan, and Milbourn 2017; Guay, Kepler, and Tsui 2019), it still remains an open question how to measure ex ante target difficulty and whether it affects performance of large public companies studied in the executive compensation literature. Armstrong, Chau, Ittner, and Xiao (2020) compare internal earnings targets and analyst forecasts and conclude that CEOs have stronger incentives to achieve analyst forecasts than internal earnings targets. Chen, Kim, Li, and Zhu (2021) consider multiple performance goals (thresholds, targets, and maximums) and show that less difficult thresholds and more difficult maximums go together with greater corporate risk-taking.

Our study provides new evidence on the economic determinants and consequences of the choice of ex ante target difficulty in CEO annual bonus plans. We build on prior literature suggesting that firms calibrate target difficulty to address information asymmetry issues, improve performance and risk sharing, and assure managerial retention (Matějka 2018; Casas-Arce, Indjejikian, and Matějka 2020). We know from the literature that challenging but achievable targets motivate greater effort and performance in simple single-period settings (Locke and Latham 1990; Arnold and Artz 2015; Matějka and Ray 2017). However, performance effects of challenging targets are much less obvious in complex dynamic settings such as those faced by executives in large companies—increasing the difficulty of internal performance targets could increase performance but it could also invite strategic responses and have the opposite effect, e.g., if executives reduce end-of-year performance out of concerns about future target difficulty (Leone and Rock 2002; Bouwens and Kroos 2011; Indjejikian, Matějka, and Schloetzer 2014a).

Our empirical analysis proceeds as follows. We hand-collect 2006–2014 data on earnings targets and actual performance relative to those targets in S&P 1500 firms. Our sample consists of 630 unique firms that disclose earnings targets and end-of-year performance in their proxy statement discussions of

CEO annual bonuses. We introduce a new measure of beginning-of-year target difficulty defined as abnormally large target increases given prior-year performance relative to target, peer performance, beginning-of-year analyst forecasts, and several other measures of expected future performance. Our validation analysis suggests that the measure is a good approximation of deviations from expected performance and inversely related to slack in performance targets (Antle and Fellingham 1990; Indjejikian and Matějka 2006). In particular, when compared to alternatives used in prior work, our measure is less biased and less noisy when predicting ex post performance relative to target.

We put forward three predictions about the economic determinants of ex ante target difficulty. First, we expect that greater uncertainty goes together with lower target difficulty and, therefore, higher expected compensation. This is because the risk premium associated with performance-contingent compensation is higher in uncertain environments and so is the information rent associated with greater information asymmetry between the CEO and the board (Murphy 2000; Banker, Darrough, Huang, and Plehn-Dujowich 2013). Second, we expect tight labor markets and the resulting concerns about CEO retention to be associated with lower target difficulty and higher expected compensation (Indjejikian, Matějka, Merchant, and Van der Stede 2014b; Cadman, Carter, and Peng 2021). Finally, we expect target difficulty to be lower when CEOs are more entrenched and have more power over compensation design choices (Bebchuk and Fried 2009; Abernethy, Kuang, and Qin 2015). We find some support for all three predictions using alternative measures of market uncertainty, retention concerns, and entrenchment.

Further, we examine the effect of ex ante target difficulty on executive compensation and performance. First, we find that beginning-of-year target difficulty is negatively associated with CEO compensation. In particular, greater target difficulty increases the likelihood of a failure to meet the annual target, which reduces average CEO cash compensation by $714,000 (about 29% of total cash compensation). In addition, failure to meet the target in annual bonus plans is associated with lower equity grants and other compensation, on average by about $639,000 over two years.

Second, we examine the effect of beginning-of-year target difficulty on abnormal fourth-quarter performance, which we measure as deviations from the firm-quarter-specific mean of quarterly earnings as a percentage of annual earnings. We show a strong reversal pattern in fourth-quarter performance—abnormally low third-quarter performance is often followed by abnormally high fourth-quarter performance and vice versa. Importantly, we find that this reversal pattern depends on ex ante target difficulty. Specifically, the reversal in fourth-quarter abnormal performance is relatively strong for moderately difficult targets and relatively weak when target difficulty is very low or very high. This is consistent with the theory that targets have the strongest incentive effects when they are neither too easy nor too difficult to achieve (Locke and Latham 1990; Matějka and Ray 2017). We also find some evidence that the abnormal fourth-quarter performance reversals are primarily driven by reductions in fourth-quarter performance following favorable third-quarter performance.

Third, we examine the effect of target difficulty on same- and next-year performance as reflected in stock returns and abnormal annual earnings. We find that target difficulty is associated positively with same-year abnormal earnings but negatively with next-year abnormal earnings. In addition, we find that target difficulty has no association with same-year stock returns but a negative association with next-year stock returns. This evidence suggests that greater target difficulty can increase current earnings but at least partly at the expense of next-period earnings.

Our findings contribute to the literature as follows. First, it is still unclear whether performance targets in annual bonus plans have meaningful incentive effects, given that cash bonus payouts are typically much smaller in magnitude than stock-based incentives (Core, Guay, and Verrecchia 2003; Guay et al. 2019). We show that failure to meet bonus plan targets is associated not only with significantly lower CEO cash compensation but also with lower current and future equity grants. In addition, several of our tests strongly reject the null hypothesis that targets in annual bonus plans have no performance effects. Thus, although we find no evidence that greater target difficulty increases long-term performance or firm value, our findings suggest that target difficulty is an important incentive design choice that affects performance and CEO compensation.

Second, we validate a new measure of ex ante target difficulty, an incentive design choice rarely examined in prior work on executive compensation. In contrast to concurrent work comparing internal earnings targets and analyst forecasts (Armstrong et al. 2020; Chen et al. 2021), we propose a comprehensive measurement model of ex ante target difficulty incorporating not only analyst forecasts but also other sources of forward-looking information. We show that this approach reduces measurement error and increases the ability of our measure to predict ex post performance relative to target. We also show that it alleviates biases arising when companies use non-GAAP earnings and targets for internal performance evaluation, which can invalidate comparisons with analyst forecasts.

Finally, our findings contribute to the literature on accrual and real earnings management (Roychowdhury 2006; Cohen and Zarowin 2010). We introduce a new method to detect unusual fourth-quarter performance based on reversals in quarterly performance. Using performance reversals in the second and third fiscal quarters as benchmarks, we can identify unusual fourth-quarter reversals. Such reversals comprehensively reflect all managerial actions that affect fourth-quarter performance, including value-enhancing activities as well as accrual and real earnings management. Thus, abnormal reversals are informative about both incentives to increase performance to meet annual earnings targets and incentives to reduce performance to prevent increases in future earnings targets (Holthausen, Larcker, and Sloan 1995; Murphy 2000; Bouwens and Kroos 2011).

II. THEORY AND HYPOTHESES

Prior literature

One of the basic tenets of the goal-setting theory is that specific, challenging, but achievable targets lead to higher levels of performance than no targets or easy targets (Locke and Latham 1990). Similar insight arises from analytical models of target-based compensation and its incentive effects, where higher targets increase performance up to a point where they become too difficult to achieve and lose their incentive effects (Ray 2007; Matějka and Ray 2017). Many prior studies provide experimental evidence consistent with these insights (Wood, Mento, and Locke 1987). There are also some field and survey studies providing evidence on the association between target difficulty and performance (Latham and Yukl 1975; Chowdhury 1993; Indjejikian et al. 2014b; Arnold and Artz 2015). However, there is hardly any evidence on how target difficulty affects performance of large public companies where executives have to manage not only performance relative to internal targets but also performance relative to analyst forecasts and stock market expectations.

Some studies at least highlight the importance of performance target choices in executive compensation. Murphy (2000) examines annual bonus plans of large firms and shows that internal performance targets can give rise to income smoothing that is largely absent when performance is evaluated relative to external benchmarks. Bennett et al. (2017) find that missing internal targets increases the likelihood of a forced CEO turnover, a disproportionately large number of firms exceeds their targets by a small margin (relative to the number of firms that falls short of their target by a small margin), and exceeding earnings targets by a small margin is associated with higher discretionary accruals and lower discretionary expenses. Armstrong et al. (2020) argue that internal earnings targets are often similar to analyst forecasts and, if they are different, CEOs have stronger incentives to achieve market expectations than internal earnings targets.

Guay et al. (2019) use data on bonus payouts at different levels of performance goals, often referred as the threshold, target, and maximum (Merchant, Stringer, and Shantapriyan 2018), and estimate pay-performance sensitivities implied by annual bonus plans. They find much higher incentive strength estimates than prior studies but do not estimate difficulty of targets or their performance effects. Chen et al. (2021) define ex ante earnings target difficulty as the difference between internal targets and analyst forecasts and examine how it affects corporate risk-taking. They find evidence of greater risk-taking when earnings thresholds are relatively easy and earnings maximums relatively difficult to achieve.

Finally, there is literature on how firms revise their performance targets over time (Indjejikian et al. 2014a). Prior studies show that exceeding a target in one period is followed by a target revision upward (Kim and Shin 2017), in part because exceeding a target is informative about favorable shocks to performance that are likely to persist into the future (Leone and Rock 2002). It is also well understood that revising targets based on prior-period performance too aggressively gives rise to perverse implicit incentives to withhold effort, also referred to as the ratchet effect (Weitzman 1980; Bouwens and Kroos

2011). In other words, disregarding past performance of well-performing managers may result into targets that are too easy to achieve. In contrast, relying too much on their past performance when revising targets effectively penalizes effort with more difficult future targets. This implies that target revisions, and the extent to which they are based on past performance and other forward-looking indicators of performance, are informative about target difficulty. Nevertheless, we are aware of no prior study that would use publicly available data to empirically distinguish between increases in target levels and increases in target difficulty (Matějka, Mahlendorf, and Schäffer 2020).

Theory and Hypotheses

We define ex ante target difficulty as the (inverse of the) likelihood of meeting a target conditional on all information available before the choice of an action. We describe our empirical measures in the next section. Below, we discuss the theory and present several hypotheses about the economic determinants and consequences of ex ante target difficulty.

There are two main economic forces that can explain why some companies choose more (or less) difficult performance targets than others. First, easy-to-achieve targets may be manifestations of information rents or optimal contracting in the presence of information asymmetry between the board and corporate executives. If the board wants to incentivize the CEO to truthfully reveal private information, they have to commit to rewarding good news with higher expected compensation (Baron and Myerson 1982). In equilibrium, high-ability, well-performing CEOs will have nominally higher targets that partly incorporate the good news revealed in past performance, but those targets will also be easier to achieve (conditional on past performance and ability) and consequently translate into higher expected compensation as a reward (Indjejikian and Matějka 2006; Indjejikian et al. 2014a). In other words, commitment to low target difficulty for well-performing managers can eliminate or at least alleviate the information asymmetry between the board and the CEO.[1]

[1] We assume that such commitment and the resulting information sharing assures that both the board and the CEO have the same performance expectation at the beginning of the year when targets are set. This also implies that the board's and the CEO's perceptions of ex ante target difficulty are the same. We acknowledge that this assumption may not always hold in practice.

Second, target difficulty can also be an incentive design choice used by the board to address moral hazard issues and improve risk sharing in settings where incentive compensation is contingent on performance relative to target. Although a performance target does not have direct incentive effects in the standard model (Holmström 1979; Murphy 2000), it does affect the participation constraint—increasing target difficulty lowers expected compensation and therefore has essentially the same effect as reducing salary. Given that the participation constraint is always binding, greater risk exposure has to be offset by weaker incentives, higher salary, or lower ex ante target difficulty. To the extent the salaries are sticky, boards may prefer annual adjustments to target difficulty rather than to salaries (Matějka and Ray 2017).

The economic forces discussed above can motivate at least two empirically testable predictions about the determinants of ex ante target difficulty. First, assuming that information asymmetry and risk exposure are greater in more volatile or uncertain environments, we expect that target difficulty is negatively associated with uncertainty, which is consistent with evidence from the field (Bol, Keune, Matsumura, and Shin 2010; Bol and Lill 2015).

H1: *Uncertainty is negatively associated with ex ante target difficulty*.

Second, the theory also predicts that greater concerns about CEO retention due to tighter labor markets have to be offset by higher expected compensation, which can again be implemented as an increase in salary or a reduction in ex ante target difficulty. This is consistent with recent empirical studies suggesting that retention concerns are an important determinant of executive compensation (Bizjak, Lemmon, and Naveen 2008; Cadman and Carter 2014; Cadman et al. 2021).

H2: *CEO retention concerns are negatively associated with ex ante target difficulty*.

Third, executive compensation may not only be driven by optimal contracting considerations. It may also reflect CEO power, entrenchment, and self-serving incentive design choices (Conyon and Peck 1998; Bebchuk, Fried, and Walker 2002). Public compensation disclosures and other regulatory requirements put constraints on the extent to which executives can increase their salary and other compensation components (Vafeas and Afxentiou 1998; Matsumura and Shin 2005; Ertimur, Ferri, and

Oesch 2013). Entrenched CEO may therefore favor less transparent ways to increase their expected compensation, such as negotiating relatively easy performance targets.

H3: *CEO entrenchment is negatively associated with ex ante target difficulty.*

Our last two hypotheses are about the consequences of performance target difficulty. Our theoretical definition of ex ante target difficulty implies that, holding effort and other incentive design choices constant, higher target difficulty reduces end-of-year performance relative to target and expected bonuses. This does not mean that greater beginning-of-year target difficulty always translates into lower end-of-year bonuses. First, as discussed below, greater target difficulty can either increase or reduce effort and the compensation-reducing effect of target difficulty can sometimes be fully offset by more effort. Second, unforeseen events can make beginning-of-year targets outdated (Arnold and Artz 2015) and sometimes result in high end-of-year bonuses despite what were initially meant to be challenging targets. Nevertheless, we expect that slack targets often translate into generous bonuses and, conversely, challenging targets are often not met which leads to reduced or no bonuses.

H4: *Ex ante target difficulty is negatively associated with CEO compensation.*

It has long been established that ex ante target difficulty does have consequences for effort and performance (Locke and Latham 1990). Matějka and Ray (2017) find that target difficulty has an inverted U-shaped effect on effort. Making easy-to-achieve targets more challenging increases the sensitivity of expected compensation to managerial effort, which in turn strengthens incentives and effort. However, once targets become sufficiently challenging, increasing them further has the opposite effect on effort because managers rationally give up on targets that are unlikely to be achieved regardless of effort. Matějka and Ray (2017) also show that the incentive effects of targets depend on uncertainty about end-of-year performance. At the beginning of the year, when there is a lot of uncertainty, different target levels imply only small differences in optimal effort. In contrast, toward the end of the year, when much of the initial uncertainty is resolved, even small differences in target levels can have strong incentive effects. It follows that the performance consequences of challenging targets should be most pronounced in the last fiscal quarter. Relatedly, in the last fiscal quarter, managers can respond to challenging targets not only with changes to value-enhancing activities but also with window dressing such as real and accrual earnings management that reverses in the next period (Roychowdhury 2006). Thus, we expect that moderately high (challenging but achievable) targets affect short-term performance but we make no predictions about long-term performance.

H5: *Moderately high ex ante target difficulty strengthens incentives to manage short-term performance.*

III. RESEARCH DESIGN

Beginning-of-year target difficulty

Targets are typically calibrated at the beginning of the fiscal year based on all information available at that time. A common way of setting targets is to use prior-year target or actual performance as a starting point and to adjust it for anticipated future changes (Milgrom and Roberts 1992; Murphy 2000; Aranda, Arellano, and Davila 2019). Target difficulty can therefore be defined as the difference between the target and expected performance:

$$TD_{t+1} = T_{t+1} - E_t[A_{t+1}], \tag{1}$$

$$E_t[A_{t+1}] = \beta_0 + \beta_1 A_t + \beta_2 T_t + \sum_k \beta_k Forward_{k,t} , \tag{2}$$

where TD_{t+1} is difficulty of year t + 1 target, T_{t+1} is year t + 1 target, A_{t+1} is year t + 1 actual performance, $Forward_{k,t}$ is a forward-looking signal about year t + 1 performance, and E_t[.] is the performance expectation based on all information available at the end of year t or the beginning of year t + 1.[2] Combining (1) and (2) shows that target difficulty can be viewed as a target level unexplained by past performance and forward-looking information, i.e., as the residual from the following model:

$$T_{t+1} = \beta_0 + \beta_1 A_t + \beta_2 T_t + \sum_k \beta_k Forward_{k,t} + TD_{t+1} . \tag{3}$$

[2] An alternative approach is to set performance expectations equal to analyst forecasts (Armstrong et al. 2020; Chen et al. 2021). However, the difference between beginning-of-period internal targets and IBES analyst forecasts captures not only target difficulty but also differences in internal versus external definitions of earnings. Appendix A shows that this can introduce noise and bias into this alternative measure of ex ante target difficulty, whereas our approach described above is less susceptible to this confounding issue.

Model (3) is closely related to the target ratcheting model used in prior studies (Leone and Rock 2002; Bouwens and Kroos 2011). The commonly estimated target ratcheting model imposes the constraint $\beta_2 = 1 - \beta_1$ (as well as $\beta_k = 0$ because it does not control for all available forward-looking information). Moreover, the target ratcheting model also allows for asymmetric ratcheting in the sense that targets can be updated differently depending on whether year *t* performance met or failed to meet the target (the latter represented as $Fail_t = 1$ below):

$$T_{t+1} - T_t = \beta_0 + \beta_1(A_t - T_t) + \beta_3 Fail_t + \beta_4 Fail_t(A_t - T_t) + TD_{t+1}. \tag{4}$$

Our main measure of beginning-of-year target difficulty combines features of both models above. We start with model (3) which is directly based on the definition of target difficulty in (1). We add the constraint $\beta_2 = 1 - \beta_1$ as in the target ratcheting model and also allow for the asymmetry in target updating. Our validation tests discussed later provide evidence that both of these specification choices improve the fit of our main model:

$$RevTarget_{i,t+1} = \beta_0 + \beta_1 DevTarget_{i,t} + \beta_3 Fail_{i,t} + \beta_4 Fail_{i,t} \cdot DevTarget_{i,t} + \sum_{k=5}^{K} \beta_k Forward_{k,i,t} + \varepsilon_{i,t+1}, \tag{5}$$

where $RevTarget_{i,t+1}$ is earnings target revision ($T_{t+1} - T_t$) of firm *i* and $DevTarget_{i,t}$ is performance relative to target ($A_t - T_t$). Table 1 lists all the forward-looking variables ($Forward_{k,i,t}$) used in our empirical analysis including, for example, analyst forecasts, accruals, dividends, sales growth, peer performance, and changes in compensation.

[Insert Table 1]

In summary, model (5) shows that beginning-of-year target difficulty can be estimated as abnormal changes in targets conditional on past performance and all other information predicting future performance, as long as the constraint $\beta_2 = 1 - \beta_1$ fits the data. Therefore, in what follows, we refer to the error term in model (5) as beginning-of-year target difficulty, $TargetDiff_{t+1}$. Positive (negative) values reflect a low (high) likelihood that year $t + 1$ target will be met based on the expectations at the end of year *t* or the beginning of year $t + 1$.

Incentives to manage short-term performance

A test of H5 calls for a measure of short-term performance management that comprehensively reflects managers' impact on earnings through both value-enhancing and window-dressing activities. Our main measure described below is based on abnormal patterns in quarterly performance. Specifically, we use quarterly earnings percentages (*QEPs*) calculated as earnings of firm *i* in quarter *q* of year *t* divided by annual earnings of firm *i* in year *t* (epsfxq / epsfx in Compustat). For all firm-year observations with at least one quarterly loss, we add the absolute value of the largest loss to all quarterly earnings, so that the lowest *QEP* equals zero.[3] We define abnormal quarterly earnings percentage (*AQEP*) as the deviation from the firm-specific mean for a given quarter *q*, i.e., $AQEP_{i,t,q} = QEP_{i,t,q} - \sum_{t=1}^{y} QEP_{i,t,q} / y$, where *y* is the number of years with non-missing data on *QEP*s.[4] This definition implies that using *AQEP* as a dependent variable is equivalent to using *QEP* in a model with firm-quarter fixed effects, which control for seasonality in quarterly performance.

AQEP is negatively autocorrelated because *QEP*s sum up to one in any given fiscal year and an abnormally high quarterly earnings percentage in one quarter mechanically leads to abnormally low earnings percentages in other quarters. In the absence of incentives to manage quarterly performance, this negative autocorrelation should be the same for all quarters (except for the first quarter which spans two different fiscal years). This implies that unusual patterns in quarterly performance can be identified in the following empirical model:

$$AQEP_{i,t,q} = \gamma_0 + \gamma_1 AQEP_{i,t,q-1} + \gamma_2 AQEP_{i,t,q-1} \cdot Q4_i + \gamma_3 Loss_{i,t} + \sum_{d=1}^{23} \delta_d QD_d + \omega_{i,t,q}, \tag{6}$$

where QD_d are quarter fixed effects, $Q4_i$ is an indicator for the last fiscal quarter,[5] and *Loss* is an indicator

[3] Panel B of Table 2 shows that 22% of our sample observations report losses in at least one quarter. We obtain qualitatively similar results in our hypotheses tests if we exclude these observations.

[4] For example, suppose that firm *i* has five years of data (*y* = 5) on quarterly earnings and fourth-quarter $QEP_{i,t,q=4}$ in those years are: 0.20, 0.24, 0.30, 0.25, and 0.26. The firm-specific mean of fourth-quarter *QEP* is 0.25 and the abnormal quarterly earnings percentages are: -0.05, -0.01, 0.05, 0.00, and 0.01.

[5] The sum of all $AQEP_{i,t,q}$ observations for any firm *i* and any quarter *q=2,3,4* across all years *t* is zero by construction, which implies no need to include the main effect $Q4_i$ in model (6). QD_d represents 23 non-redundant indicator variables for three

for one or more quarterly losses in a fiscal year *t*. Abnormal reversals in fourth-quarter performance should manifest as $\gamma_2 < 0$, regardless of whether executives manage performance upward following poor third-quarter performance or downward following abnormally high third-quarter performance. In supplementary tests, we examine whether abnormal reversals depend on the sign of abnormal Q3 earnings using *AQEP_POS*, an indicator variable for *AQEP* > 0.[6]

Data

Our primary source of data is proxy statement disclosures of S&P 1500 firms during 2006–2014. We hand collect data on earnings per share (EPS) targets used in CEO annual cash incentive plans as well as data on actual performance as disclosed in the proxy statements. If firms disclose multiple performance goals, we use the target which is typically the middle goal between the threshold and the maximum goal. We find 2,492 firm-year observations with non-missing data on both actual and targeted EPS. Some firms do not use EPS targets but other types of earnings-based targets such as net income, operating income, pre-tax income, etc. We identify additional 626 firm-year observations with data available on such earnings-based targets and actual performance. This yields our initial sample of 3,118 firm-year observations representing 709 unique firms with actual and targeted earnings data available at least in some years.[7] We augment this data set with additional information from Compustat annual and quarterly files, IBES, CRSP, and Execucomp.

[Insert Table 2]

quarters in each of the eight years in our main sample. First-quarter observations are excluded because the autocorrelation coefficient in the first quarter spans two different fiscal years, involves *QEP*s that do not sum up to one, and therefore cannot be used as a benchmark for autocorrelation in the last fiscal quarter.

[6] In untabulated analyses (available upon request), we estimate model (6) using the full Compustat population and find very similar results as in our main sample. We further find that the abnormal reversals in fourth-quarter performance are not primarily driven by the integral approach to accounting (the reconciliation of accrual estimation errors) because they are strongly pronounced not only in earnings but also in sales and cash-flows. They are also distinct from income smoothing, measured as in Black, Pierce, and Thomas (2021), in that firms engaging in income smoothing are less likely to report abnormal reversals in fourth-quarter performance. Finally, we find that abnormal reversals are only weakly related to discretionary accrual choices, measured as in Tucker and Zarowin (2006).

[7] We acknowledge that this limits generalizability of our findings because firms that do not disclose their performance targets or choices of performance measures drop out of our sample. In an untabulated analysis, we find that firms with all required disclosures are larger, more profitable, and experience slower sales growth than the S&P 1500 population.

Panel A of Table 2 shows how we obtain our main estimation sample. First, we exclude 748 firm-year observations without data on next-year's earnings target, required to calculate target revisions. Second, we further exclude 113 firm-year observations with missing data on analyst forecasts or other forward-looking variables used in our model predicting target difficulty (presented in Table 4). This yields our main estimation sample of 2,257 firm-year observations on 630 unique firms for which we can estimate target difficulty. Missing data on our proxies for market uncertainty, retention concerns, entrenchment, compensation, and performance can further reduce the sample size available to test our hypotheses.

The sample of 2,257 firm-year observations includes a total of 9,028 firm-year-quarters. Panel B of Table 2 describes exclusions from this total to obtain our quarterly data sample. First, we remove all first-quarter observations because they are not used in any of our tests. Second, we exclude six quarterly observations from two unique firms with missing data on first-quarter earnings, for which we cannot estimate (6) in the second quarter. In some of our robustness checks, we also exclude all observations in any fiscal year with at least one quarterly loss (*Loss* = 1).

Variable measurement

In what follows, we discuss the measures used in our empirical analysis. We first describe all variables used in the model of ex ante target difficulty, i.e., model (5). Subsequently, we discuss an alternative measure of target difficulty based on quarterly data and all other variables used in our analysis.

Variables used in the model of ex ante target difficulty

Model (5) uses several variables based on actual and targeted earnings. To improve comparability of EPS targets and actuals across firms with different share prices, we rescale earnings-based variables to reflect return on assets, i.e., we multiply EPS by the number of shares (cshpri) and divide it by total assets (at). Target revision (*RevTarget*) is the rescaled earnings target for year $t + 1$ minus the rescaled target for year t. Performance relative to target (*DevTarget*) is defined as rescaled actual earnings in year t minus the rescaled target for year t reported in the proxy statement. Failure to meet earnings target (*Fail*) is an indicator for *DevTarget* < 0.

We use several forward-looking variables when estimating the ex ante target difficulty model (5). First, analyst forecasts are often highly informative about expected earnings and target revisions (Chen et al. 2021). We use analyst earnings forecast revision, *RevAFE*, defined as the difference between one-year-ahead earnings forecast for year $t + 1$ and IBES actual earnings in year t, scaled by total assets in year t. One-year-ahead earnings forecast is the median analyst EPS forecast (multiplied by the number of shares) issued during the first fiscal quarter of year $t + 1$ after year t earnings announcement. If the same analyst makes multiple earnings forecasts during the quarter, we only use the most recent one. We construct analyst sales forecast revision, *RevAFS*, in a similar way as the difference between one-year-ahead sales forecasts for year $t + 1$ and IBES actual sales in year t, scaled by sales in year t.

Second, past own and peer performance can predict future earnings. We measure peer performance, *PeerROA*, as the median of industry-size peer earnings in year t scaled by total assets. Industry-size peers are defined as in Albuquerque (2009), based on two-digit SIC codes and size. To better predict future earnings, we separately measure current earnings, accruals, and dividends (Hou, van Dijk, and Zhang 2012; Easton, Kapons, Kelly, and Neuhierl 2020). *Earnings* is defined as income before extraordinary items in year t scaled by total assets, *Accrual* is income before extraordinary items minus operating cash flow in year t scaled by total assets, and *Dividend* is total dividends scaled by total assets.

Third, board members may have private information about future earnings. To the extent that they use such private information when determining compensation awards, increases (decreases) in executive compensation unexplained by past performance may reflect good (bad) news about future performance (Hayes and Schaefer 2000). We calculate *ChgComp* as a change in CEO cash compensation (salary plus cash bonuses) between years t and $t - 1$ scaled by cash compensation in year $t - 1$.[8]

[8] We consider alternative proxies for private information. First, we measure directors' and CEO's net share purchases as a percentage of total shares outstanding. Second, we use various indicators for CEO (and other executives) trading in opposite directions than non-executive directors to proxy for information asymmetry between directors and corporate executives. Third, we collect data on analysts following and dispersion in analyst forecasts (Cao, Dhaliwal, Li, and Yang 2015), business segment complexity, geographic complexity, timeliness of earnings (Bushman, Chen, Engel, and Smith 2004), and board busyness (Chen and Guay 2020). However, none of these additional variables has significant explanatory power in our alternative estimations of model (5).

Fourth, stock returns are likely to be informative about future earnings. We calculate *OwnReturn* as fiscal year *t* stock returns and *PeerReturn* as the median of industry-size-peer stock returns over the same period. Finally, firm size and prior-year sales growth may also be informative about earnings growth (Abernethy et al. 2015). As proxies for firm size, we use *MktValue,* calculated as the natural logarithm of total market value of equity at the end of year *t*, or *Assets*, calculated similarly using total assets. *Growth* is the change in sales between years *t* and *t* - 1 scaled by sales in year *t* - 1.

Ex ante target difficulty (*TargetDiff*) is then defined as the residuals from the regression of *RevTarget* on the variables discussed above, as specified by model (5). All variables included in the model and all other continuous variables used in our empirical analysis are winsorized at the top and bottom 1% levels.[9] Large positive residuals reflect high target difficulty because they capture abnormally large increases in performance targets.

Fourth-quarter target difficulty

In our tests of H5, we also use a measure of target difficulty at the beginning of the fourth quarter, i.e., the (inverse of the) likelihood that the annual target will be met based on information available at the end of the third quarter. First, we divide the sum of quarterly earnings in the first three quarters by the annual earnings target to obtain the percentage of annual earnings targets met before the fourth quarter. If the sum of the three quarterly earnings exceeds the annual target (the target has already been met), the percentage is capped at 100% to represent the likelihood of meeting the annual target. One minus the percentage calculated as just described is then the percentage of the annual target still to be met in the fourth quarter. Second, we use the firm-specific mean of *QEP* in the fourth quarter, $\sum_{t=1}^{y} QEP_{i,t,q=4} / y$, as a measure of normal fourth-quarter performance. Third, we divide the percentage of the annual target still to be met in the fourth quarter by normal fourth-quarter performance to obtain fourth-quarter target difficulty:

[9] Using robust MM-estimators to minimize the impact of outliers on our hypotheses test does not change our inferences (Leone, Minutti-Meza, and Wasley 2019; Jann 2021).

$$Q4TargetDiff_{i,t} = \left(1 - \min(1, \frac{\sum_{q=1}^{3} QEarnings_{i,t,q}}{T_t})\right) \Big/ \sum_{t=1}^{y} QEP_{i,t,q=4} \, / \, y \, , \tag{7}$$

where $QEarnings_{i,t,q}$ stands for Q1–Q3 IBES actual earnings of year t and T_t for the annual earnings target in year t.[10] A limitation of the measure in (7) is that public data on quarterly earnings need not be based on the same definition of earnings as the annual target, given that the latter can reflect various non-GAAP adjustments (Kim and Shin 2019; Curtis, Li, and Patrick 2021). This introduces measurement error when calculating the percentage of the annual target still to be met in the fourth quarter.[11]

To proxy for earnings targets that are neither too easy nor too difficult to achieve at the beginning of the fourth quarter, we use the indicator *Q4MediumTD* which equals one for the middle three quintiles of fourth-quarter target difficulty (*Q4TargetDiff*) and zero for the lowest and highest quintiles as well as for *Loss* = 1 observations that have very difficult targets. Similarly, we use an indicator *MediumTD* which equals one for the middle three quintiles of beginning-of-year target difficulty (*TargetDiff*) and zero for the lowest and highest quintiles as well as for *Loss* = 1 observations.

Other variables

We measure market uncertainty, *Uncertain,* as the standard deviation of monthly returns of the S&P 500 index during the 12-month period through the first fiscal quarter of year $t + 1$.[12] In untabulated robustness tests, we also use various alternative proxies for market uncertainty including the monthly averages of Economic Policy Uncertainty (Baker, Bloom, and Davis 2016), the VIX index (Whaley 2009), and

[10] For example, suppose normal fourth-quarter performance is 0.25 as calculated in footnote 4. If 70% of the annual target is met after the first three quarters, *Q4TargetDiff* = 0.30 / 0.25 = 1.2, which represents a relatively difficult target because the percentage still to be met (30%) exceeds normal fourth-quarter performance (25%). If 100% or more of the annual target is met after the first three quarters, *Q4TargetDiff* = 0.

[11] We take several steps to alleviate concerns about this measurement issue. First, we use non-GAAP quarterly earnings from IBES, which are often the same as managers' non-GAAP earnings disclosures and thus are likely to be similar to earnings definitions used in internal targets (Bentley, Christensen, Gee, and Whipple 2018). Second, we check that using quarterly GAAP earnings from Compustat rather than IBES earnings leaves our main results qualitatively unchanged. Third, in untabulated tests, we find that our main results are not sensitive to a separate estimation in two subsamples with low vs. high non-GAAP adjustments to annual earnings used for internal performance evaluation (split at the median).

[12] We also consider measures of idiosyncratic risk such as the standard deviation of monthly firm stock returns or the residuals from a regression of firm-level stock returns on industry stock returns (two-digit SIC) estimated over the previous 36 months (Nam 2020). However, none of these measures has a significant explanatory power in our alternative estimations of model (5).

macroeconomic uncertainty (Jurado, Ludvigson, and Ng 2015). We find qualitatively similar results using each of these alternative proxies.

We use two measures of CEO retention concerns from Cadman et al. (2021). *RetnNonenf* is the state-level noncompetition enforceability index (Garmaise 2011) normalized to range between zero and one, so that high values reflect a low level of enforcement. A lack of state-level enforcement of non-compete agreements may increase the mobility of executives and retention concerns. *RetnDist* is based on proximity to peer headquarter, calculated as the average distance in thousands of miles between headquarters of firm *i* and industry (two-digit SIC) peers. Large distance to peer headquarters may limit the supply of potential CEO candidates and increase CEO retention concerns.[13]

We use several measures reflecting CEO entrenchment, power, and influence over compensation design choices. *EntrIndex,* is the entrenchment index of Bebchuk, Cohen, and Ferrell (2009) using six corporate governance provisions tracked by the Investor Responsibility Research Center (IRRC), normalized to range between zero and one so that high values reflect a high level of CEO entrenchment. *EntrDual*, is an indicator variable that equals one if a firm's CEO is also the chair of the board.[14] *EntrTenure* is the natural logarithm of CEO tenure measured in months. *EntrAge* is an indicator variable for CEO older than 65 years. *EntrOwner* is the percentage of shares owned by the CEO. The latter two variables may proxy for CEO focus on short-term targets (proximity to retirement) versus long-term value creation (wealth tied to firm value).

Finally, we measure two components of CEO compensation. *CashComp* is the sum of salary and annual bonuses and *OtherComp* is all other annual (primarily equity-based) compensation, calculated as the difference between total compensation (tdc1) and *CashComp*. See Table 1 for more details on these measures.

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[13] We collect data on three other potential proxies for retention concerns as in Cadman et al. (2021): (i) the number of times that the sample firm is the compensation peer of other firms in the same fiscal year, (ii) the Herfindahl index of industry peer group in year *t* based on the sum of squared market shares (in terms of total assets) of all peers with the same two-digit SIC, and (iii) the industry (two-digit SIC) average percentage of insider CEO hires. Using these additional proxies reduces our sample size considerably due to missing values but does not yield any significant results in our model of ex ante target difficulty.

[14] Separately including an indicator variable for CEO serving on the compensation committee reduces our sample size due to missing values but does not yield any significant results in our model of ex ante target difficulty.

IV. RESULTS

Descriptive evidence

Table 3 presents descriptive statistics for our main estimation sample during 2006–2014 and we selectively discuss some of them. The mean of *RevTarget* implies that earnings target increases annually by 0.6% of total assets. The descriptives for *DevTarget* suggest that targets are typically met or slightly exceeded (median earnings exceed target by 0.1% of assets). About 37.1% of our sample observations fail to meet target, which is similar to findings in prior work (Guay et al. 2019).

[Insert Table 3]

The next set of variables captures forward-looking information about performance in year $t + 1$ that is available at the beginning of the year. The mean of *RevAFE* suggests that analysts revise their forecasts upward during the first fiscal quarter—year $t + 1$ earnings forecast exceeds prior-year earnings by 0.5% of total assets on average, which is similar to the mean of *RevTarget*. The mean of *RevAFS* shows that the average sales forecast revision during the first fiscal quarter is an increase by 5.6% of sales. Average peer performance in year t as measured by ROA (*PeerROA*) is 4.6%. Average own performance in terms of ROA (*Earnings*) is 5.7%. The means of *Accrual* and *Dividend* in year t are -4.8% and 1.4% of assets, respectively. Average CEO cash compensation is $2.5 million with median annual growth of 4.0% (the mean is much higher due to a small number of large increases); the average of all other compensation is $3.8 million. Average stock returns as reflected in *OwnReturn* and *PeerReturn* are 14.3% and 9.1%, respectively. Finally, average market value, exp(*MktValue*), is $3.5 billion, average assets, exp(*Assets*), is $4.3 billion, and average *Growth* in sales is 6.3%.

Estimation of ex ante target difficulty

We measure ex ante target difficulty as abnormal target increases conditional on past performance and forward-looking information available at the beginning of the year, i.e., as in model (5). As discussed earlier, this model imposes the constraint $\beta_2 = 1 - \beta_1$. As a specification test, we estimate model (5) without imposing this constraint, i.e., estimate a model similar to (3). We find that the constraint fits our data well in that the empirical estimate of $\beta_1 + \beta_2 = 1.004$ is not significantly different from one ($p = .841$). In what follows, we therefore use this empirically valid constraint and discuss the results of estimating model (5) as presented in the first column of Table 4.

[Insert Table 4]

Consistent with prior studies on target ratcheting (Leone and Rock 2002; Bouwens and Kroos 2011), we find that targets are revised upward if performance exceeds prior-period target. The marginal effect of *DevTarget* when *Fail* equals zero is 0.782 ($p < .001$). We also find evidence of a target ratcheting asymmetry in that targets update less when prior-period performance falls below target. The marginal effect of *DevTarget* when *Fail* equals one is lower by 0.287 ($p < .001$). This may reflect lower persistence of unfavorable shocks to performance or long-term contractual commitments to penalize poor performance with more difficult targets and lower compensation in the future (Acharya, John, and Sundaram 2000; Indjejikian et al. 2014b). We further find significant positive effects of many of the forward-looking variables including analyst earnings forecast revisions, sales forecast revisions, prior-year own and peer earnings, change in prior-year cash compensation, own stock returns (the effect of peer stock returns is weakly negative), and sales growth.

Model (5) explains about 66% of the variance in target revisions, which is similar to or higher than in prior studies using proxy statement data to estimate target revision models (Kim and Shin 2017; Choi, Kim, Kwon, and Shin 2020). The remaining unexplained variance is captured by the residuals which can be interpreted as abnormal target revisions given all available information. We use these residuals as our main measure of beginning-of-year difficulty, *TargetDiff*. Appendix A provides additional evidence validating this measure. In particular, we provide evidence that our measure of high beginning-of-year target difficulty (*TargetDiff*) has a strong predictive power in a model of end-of-year performance relative to target. We also show that the predictive power is higher than for other measures of target difficulty used in prior work and that our measure is less susceptible to biases arising when companies use non-GAAP earnings and targets for internal performance evaluation.

Test of H1–H3: Determinants of ex ante target difficulty

Our first three hypotheses make predictions about the determinants of ex ante target difficulty. To avoid a two-step regression that could unnecessarily bias our coefficient estimates and standard errors (Chen, Hribar, and Melessa 2018), we test our hypotheses by including our measures of market uncertainty, retention concerns, and CEO entrenchment directly into model (5). This single-step approach estimates the effect of the measures of interest on abnormal target revisions and is therefore similar to regressing *TargetDiff* on the measures and all explanatory variables in model (5).

The remaining two columns of Table 4 present our findings. The second column includes industry and year fixed effects as well as all measures of market uncertainty, retention concerns, and CEO entrenchment into model (5), which reduces the sample size considerably due to missing values on the additional variables. The third column increases the sample size by 19.8% by excluding *EntrIndex*, which has the highest number of missing values. We interpret the findings as follows.

First, we find strong support for H1 in that market uncertainty is negatively associated with ex ante target difficulty (p = .018 and p = .007 in the second and third columns, respectively). This is consistent with the theory that greater information asymmetry and risk exposure in uncertain environments justify a compensation risk premium or an information rent in the form of less difficult performance targets. There is also support for H2 predicting that concerns about CEO retention reduce ex ante target difficulty. In particular, we find that distance to peer headquarters (*RetnDist*) is negatively associated with ex ante target difficulty (p = .019 and p = .008). This finding suggests that firms far away from their industry peers (e.g., firms headquartered outside of major metropolitan areas) increase expected compensation by lowering performance target difficulty, which facilitates attraction and retention of top executives. Finally, we find some support for H3 predicting that CEO entrenchment reduces ex ante target difficulty. The second column of Table 4 shows that the entrenchment index (*EntrIndex*) is negatively associated with ex ante target difficulty (p = .021) and the third column shows that the negative effect of CEO proximity to retirement (*EntrAge*) becomes significant (p = 0.044) after excluding *EntrIndex*.[15]

Combined, our findings in Table 4 are broadly consistent with our theoretical predictions. This provides not only support for economic theory about the determinants of ex ante target difficulty but also support for the validity of our measure of ex ante target difficulty.

Test of H4: Ex ante target difficulty and CEO compensation

H4 predicts that higher ex ante target difficulty lowers CEO compensation. Given that we use data on performance targets in annual cash bonus plans, we expect this effect to be particularly strong for cash compensation. Nevertheless, we also test for the association between ex ante target difficulty and other (equity-based) compensation because annual targets are typically derived from long-term strategic plans, and therefore, success or failure to meet annual performance targets is likely to be associated with performance relative to multi-year targets that determine equity grants.

In Table 5, we model CEO compensation ($CashComp_{t+1}$) as a function of past performance, size, growth, industry and year fixed effects as well as the market uncertainty, retention, and entrenchment variables from the last column of Table 4. The first column of Table 5 adds to this model our measure of target difficulty at the beginning of year t+1 ($TargetDiff_{t+1}$). Consistent with H4, we find a significantly negative association between target difficulty and cash compensation (p = .034).[16] Further, as expected, we find that CEO cash compensation is positively associated with past performance as reflected in accounting returns, stock returns, and the book value of total assets. We also find a negative association with peer accounting and stock returns, which is consistent with relative performance evaluation. Finally, we find that CEO cash compensation is higher when retention concerns are greater and when the CEO is the chair of the board, has longer tenure, or has a lower ownership stake.

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[15] As a robustness check, we reestimate the second column of Table 4 in the subsample of 1,698 observations with CEO tenure of at least three years. We find qualitatively similar results, which suggests that learning about CEO ability does not drive our main findings (Pan, Wang, and Weisbach 2015).

[16] $TargetDiff_{t+1}$ is a generated regressor which means that reported standard errors, that do not account for the measurement error in our measure of target difficulty, are somewhat understated (Chen, Hribar, and Melessa 2020). As a robustness check, we use a bootstrapping procedure that includes both parts of the estimation (the measurement part from Table 4 and the first column of Table 5) for every bootstrap sample. Our inferences remain unchanged.

[Insert Table 5]

The second column of Table 5 includes indicator variables for the quintiles of $TargetDiff_{t+1}$ to assess the economic significance of the effect of ex ante target difficulty on CEO cash compensation and to allow for non-linear effects. The indicator for the lowest quintile representing easy targets is the excluded baseline category. We separately include an indicator for losses (*Loss* = 1), which typically go together with very high target difficulty (Indjejikian et al. 2014b). We also include indicator variables for failure to meet the performance target in the current year ($Fail_{t+1}$) and in the previous year ($Fail_t$). We find that, on average, failure to meet the annual target reduces same-year cash compensation by $714,000 ($p < .001$) and next-year cash compensation by $155,000 ($p = .022$). Once failure to meet the annual target is controlled for, the $TargetDiff_{t+1}$ quintiles have little incremental explanatory power, which implies that the effect of ex ante target difficulty on CEO cash compensation is largely mediated by failure to meet the annual target.

The third column of Table 5 estimates the same model as the second column, except that the dependent variable is other non-cash CEO compensation ($OtherComp_{t+1}$), i.e., primarily restricted stock and stock option grants. We find that it is positively associated with past performance as measured by accounting returns but not with past own stock returns, peer performance, market uncertainty, retention concerns, or most of the proxies for entrenchment. However, we find that failure to meet the earnings performance target in annual bonus plans is associated with an average decrease in same-year equity grants by $300,000 ($p = .053$) and a decrease in next-year grants by $339,000 ($p = .016$). Finally, we find that moderately difficult annual targets (the third quintile in particular) are associated with a decrease in other compensation and difficult earnings targets during *Loss* years with an increase in other compensation. In an untabulated test, we find no significant association between $TargetDiff_{t+1}$ and other compensation.

Combined, the findings in Table 5 provide evidence that ex ante target difficulty is an economically important incentive design choice. Making earnings targets in annual bonus plans more difficult to achieve increases the likelihood of ex post failure, which reduces cash compensation on average by $869,000 over two years. In addition, failure to meet annual bonus plan targets is associated with an average reduction in other compensation by $639,000 over two years.

Test of H5: Ex ante target difficulty and incentives to manage short-term performance

H5 predicts that challenging but achievable targets strengthen incentives to manage short-term performance. Section III discusses abnormal reversals in fourth-quarter performance as our measure of short-term performance management that captures both value-enhancing and window-dressing actions. Panel B of Table 2 describes how we construct our sample of 6,765 firm-quarter observations. Before we discuss our main tests examining abnormal reversals in fourth-quarter performance for different levels of ex ante target difficulty, we present additional descriptive statistics for our quarterly sample.

Table 6 shows that, by construction, the mean of *QEP* is close to 0.250, the mean of *AQEP* is close to zero, about one half of the observations have positive abnormal *QEP* (*AQEP_POS* = 1), and one third of the Q2–Q4 observations are from the fourth quarter (given that Q1 observations are dropped from the sample). The mean of *Fail* implies 38.9% likelihood of failure to meet annual targets. About 22% of observations are from years with one or more quarterly losses. *TargetDiff* is the same measure of ex ante target difficulty as in the annual analysis and its mean equals zero by construction. The mean of *MediumTD* is 47.0%, which reflects the three middle quintiles of *TargetDiff* after removing *Loss* = 0 observations, i.e., $(1 - 0.215)/5 \cdot 3$. *Q4TargetDiff* is a ratio of the percentage of annual earnings target still to be met at the beginning of the fourth quarter and the average *QEP* in the fourth quarter, as defined in (7). The mean of 1.235 and median of 1.024 imply that the annual target often remains challenging at the beginning of the fourth quarter because the performance required to meet the annual target slightly exceeds the typical performance in the fourth quarter. *Q4MediumTD* has the same mean as *MediumTD* because it is constructed from *Q4TargetDiff* in the same way.

[Insert Table 6]

Panel B of Table 6 shows how our measures of ex ante target difficulty (*TargetDiff* and *Q4TargetDiff*) are associated with ex post failure to meet the annual target (*Fail*). In particular, it shows the conditional likelihood of failure in the following subsamples: (i) low refers to the lowest quintile of a target difficulty measure within the *Loss* = 0 sample, (ii) medium refers to the middle three quintiles, (iii) high refers to the highest quintile, and (iv) loss refers to the remaining observations with at least one quarterly loss (*Loss* = 1). We find that the lowest quintile of beginning-of-year target difficulty (*TargetDiff*) has a 29.3% likelihood of failure as compared to 46.4% in the highest quintile and 58.4% among *Loss* = 1 observations. The differences are even more pronounced for our measure of fourth-quarter target difficulty (*Q4TargetDiff*), for which the lowest quintile has a likelihood of failure of only 4.5% as compared to 68.8% in the highest quintile.

Table 7 presents our main tests of H5 about the effect of ex ante target difficulty on short-term performance management. As discussed in Section III, our baseline specification is model (6) where the interaction term $AQEP_{q-1} \cdot Q4$ reflects abnormal reversals in fourth-quarter performance. Panel A of Table 7 reestimates model (6) after including the three-way interaction term $AQEP_{q-1} \cdot Q4 \cdot Medium$ (and all non-redundant lower level effects), where *Medium* refers to our proxies for challenging but achievable targets, *MediumTD* or *Q4MediumTD*. H5 predicts that abnormal reversals in fourth-quarter performance are more pronounced for moderately high targets.

[Insert Table 7]

Panel A of Table 7 shows that when beginning-of-year targets are challenging but achievable (*MediumTD* = 1), the marginal effect representing abnormal performance reversals in the fourth quarter is -0.350 ($p < .001$). In contrast, when beginning-of-year targets are either very easy or very difficult to achieve (*MediumTD* = 0), this marginal effect is -0.162 ($p = .001$). The difference between these two marginal effects, which equals the coefficient on the three-way interaction effect, is significant ($p = .014$). We find very similar results when using *Q4MediumTD*, the indicator variable for challenging but achievable targets at the beginning of the fourth quarter.

Panel B of Table 7 presents a descriptive analysis examining whether this evidence in support of H5 is driven by increases or reductions in fourth-quarter performance. It extends the analysis in Panel A by including the four-way interaction term $AQEP_{q-1} \cdot Q4 \cdot MediumTD \cdot AQEP\_POS_{q-1}$, where the last term is the indicator variable for favorable abnormal performance in the third quarter. Although the results have to be interpreted with caution due to the inclusion of a higher-order interaction, it is descriptively interesting that the abnormal reversals documented in Panel A are mainly driven by reversals from high Q3 earnings to abnormally low Q4 earnings. For example, the marginal effect of $AQEP_{q-1} \cdot Q4$ when *Q4MediumTD* = 1 and Q3 earnings are abnormally high (-0.478, $p < .001$) is almost twice the size of the marginal effect estimate when *Q4MediumTD* = 1 and Q3 earnings are abnormally low (-0.257, $p = .014$).

In untabulated tests, we further examine the non-monotonic effect of target difficulty predicted by H5. Specifically, we separately estimate model (6) within each of the quintiles of our target difficulty measures and within the subsample of loss observations. As predicted, we find evidence of an inverted U-shaped relation between *TargetDiff* and the magnitude of abnormal performance reversals. In particular, the fourth-quarter reversal magnitudes in the lowest quintile of *TargetDiff* through the highest quintile and in the loss subsample are: -0.223, -0.293, -0.393, -0.357, -0.214, and -0.110. These estimates imply that the abnormal performance reversals are most pronounced for moderately difficult beginning-of-year targets and least pronounced when target difficulty is either very high (which includes loss observations) or very low. We find a similar inverted U-shaped relation for the effect of *Q4TargetDiff* on abnormal performance reversals, which is consistent with H5 predicting that moderately difficult targets strengthen incentives to manage short-term performance.

Additional evidence on incentives to manage short-term and long-term performance

In our last set of tests, we use an alternative measure of short-term performance management as well as measures of longer-term performance. Specifically, we define abnormal annual earnings (*AAE*) as the difference between actual earnings and earnings expectations at the beginning of the year, $AAE_{t+1} = A_{t+1} - E_t[A_{t+1}]$. Equations (2)–(5) imply that $E_t[A_{t+1}]$ equals prior-year target T_t plus expected target revision as measured by the predicted values from model (5). Note that AAE_{t+1} is different from performance relative to target ($A_{t+1} - T_{t+1}$). The latter is mechanically associated with T_{t+1} and therefore also with target difficulty. In contrast, AAE_{t+1} measures earnings relative to beginning-of-year expectations, regardless of whether T_{t+1} was set at, above, or below those expectations. The limitation of this measure is that income-increasing short-term actions in some firms could be offset by income-decreasing actions in other firms, which would reduce the power of our tests of H5. An advantage of using *AAE* is that it allows us to examine the effect of ex ante target difficulty ($TargetDiff_{t+1}$) on same-year (AAE_{t+1}) as well as next-year (AAE_{t+2}) abnormal annual performance.

We estimate a model of abnormal annual earnings (AAE_{t+1}) as a function of same-year peer earnings ($PeerROA_{t+1}$), peer returns ($PeerReturn_{t+1}$), and ex ante target difficulty ($TargetDiff_{t+1}$). We control for prior-year market uncertainty, retention concerns, entrenchment, assets, sales growth, industry and year fixed effects. Given that $TargetDiff_{t+1}$ is estimated in a first-stage model (presented in Table 4) we also include all other right-hand side variables from that model as additional controls. In our model of next-year abnormal annual earnings (AAE_{t+2}), we use same-year peer earnings and returns ($PeerROA_{t+2}$ and $PeerReturn_{t+2}$) but all other variables including ex ante target difficulty ($TargetDiff_{t+1}$) remain unchanged. Alternative models with own stock returns as the dependent variable ($OwnReturn_{t+1}$ or $OwnReturn_{t+2}$) are specified in a similar way, except that we also include same-year earnings as an additional explanatory variable.

[Insert Table 8]

Table 8 presents the results of our estimations.[17] The first two columns show that ex ante target difficulty ($TargetDiff_{t+1}$) is positively associated (p = .001) with same-year abnormal annual earnings (AAE_{t+1}) but negatively associated (p < .001) with next-year abnormal annual earnings (AAE_{t+2}). Further, we find little or no association (p = .449) between earnings target difficulty and same-year stock returns but a significantly negative association with next-year stock returns (p = .009). We interpret these findings as evidence that challenging targets increase short-term performance but some of this increase comes at the expense of future performance.

[17] We use the same bootstrapping procedure as discussed in footnote 15 to make sure that our inferences are unaffected by the measurement error inherent in the generated regressor $TargetDiff_{t+1}$ (Chen et al. 2020).

V. CONCLUSIONS

Many prior studies provide theory and evidence that target difficulty is an important compensation design choice. However, empirical evidence on the determinants and consequences of challenging performance targets mainly comes from settings where target difficulty can be experimentally manipulated and from field or survey studies examining performance targets of workers and lower-level managers. Given the challenges of measuring target difficulty with publicly available data, there is hardly any evidence on the determinants and performance consequences of target difficulty in incentive plans of top executives in large public companies.

In this study, we construct a new measure of ex ante target difficulty based on abnormal revisions, i.e., target increases exceeding revisions justified by past performance and forward-looking information available at the beginning of the year. We validate our measure of beginning-of-year target difficulty by showing that it is highly predictive of end-of-year performance relative to target, which is not the case for unadjusted target revisions and for other estimation approaches used in prior work. We also provide evidence consistent with the theory that target difficulty is negatively associated with uncertainty, CEO retention concerns, and entrenchment.

To shed some light on the economic significance of ex ante target difficulty as an incentive design choice, we examine its consequences for CEO compensation. More difficult targets increase the likelihood of a failure to meet them, which reduces cash compensation by $714,000 on average. Moreover, failure to meet annual bonus plan targets is associated with significantly lower equity grants, as reflected in an estimated decrease in other compensation by $639,000 over two years. Given the magnitude of these effects, it is hardly a surprise that CEOs manage short-term performance to avoid failure to meet earnings targets in their annual bonus plans. We examine the performance consequences of challenging targets and find strong evidence to reject the null hypothesis that ex ante target difficulty has no effect on performance.

First, we document the prevalence of abnormal earnings reversals in the fourth quarter and show that such reversals are more pronounced for moderately difficult targets and less pronounced for very easy- or very difficult-to-achieve targets. Second, we show that challenging earnings targets are also associated with higher abnormal annual earnings. Third, we find some evidence suggesting that such performance improvements driven by challenging annual bonus targets are short-lived and largely reverse in the next year. Combined, these findings suggest that ex ante target difficulty is an important incentive design choice that can boost short-term performance but it is unlikely to be effective in increasing firm value.

A limitation of our measure of ex ante target difficulty is that it assumes that all relevant forward-looking information is publicly available. Our estimates of abnormal target revisions will be inaccurate to the extent that boards incorporate into targets additional private information that we cannot control for. Although this may increase measurement error and reduce the power of our tests, we do not think it systematically biases our findings. Finding additional proxies for boards' private information with high predictive power in our target-setting model is a worthwhile opportunity for future research. Another limitation is that we can only measure ex ante target difficulty in firms that provide sufficiently detailed disclosures of their internal performance evaluation and compensation policies. S&P 1500 firms that do not disclose performance targets or do not specify their choice of performance measures in annual bonus plans drop out of our sample. We acknowledge that this limits the generalizability of our findings which therefore apply primarily to large and mature firms with more detailed proxy statement disclosures.

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APPENDIX A

Our measure of ex ante target difficulty is based on the model of expected performance from equation (2): $E_t[A_{t+1}] = \beta_0 + \beta_1 A_t + \beta_2 T_t + \sum_k \beta_k Forward_{k,t}$, where $Forward_t$ is a vector of forward-looking variables that also includes analyst earnings and sales forecast revisions (*RevAFE* and *RevAFS*). In what follows, we consider alternative models of expected performance and focus in particular on the model used in several prior studies that sets $E_t[A_{t+1}]$ equal to beginning-of-year average analyst forecasts (Armstrong et al. 2020; Chen et al. 2021).

A valid measure of beginning-of-year target difficulty should predict end-of-year performance relative to target. We know from prior work that target increases at the beginning of year t+1 ($RevTarget_{t+1}$) need not reduce ex post performance relative to target ($DevTarget_{t+1}$). In particular, t +1 target may increase as a result of an update for persistent favorable shocks from year t or in response to new favorable information about year t +1 performance, which we refer to as predictable target increases (Indjejikian et al. 2014b; Matějka et al. 2020). We do not expect predictably higher targets to be associated with lower ex post performance relative to target. In contrast, once persistent favorable shocks are controlled for, abnormal target increases ($TargetDiff_{t+1}$) should make targets more difficult to achieve and reduce ex post performance relative to target.

[Insert Table A1]

Our validation analysis presented in Table A1 decomposes a target revision into two components—a predictable target revision ($RevTargetPred_{t+1} = RevTarget_{t+1} - TargetDiff_{t+1}$) and target difficulty ($TargetDiff_{t+1}$)—and examines the extent to which each of the components predicts future performance relative to target. Specifically, Table A1 estimates an OLS model of $DevTarget_{t+1}$ as function of $RevTargetPred_{t+1}$, $TargetDiff_{t+1}$, and prior-period performance relative to target ($DevTarget_t$). The latter is motivated by prior studies showing that performance relative to target is autocorrelated (Indjejikian and Nanda 2002; Kim and Shin 2017). The differences in estimates across the four columns of Table A1 are due to different definitions of beginning-of-year target difficulty, as discussed next.

The first column of Table A1 uses our main definition from model (5) and provides evidence consistent with the validity of $TargetDiff_{t+1}$ as a measure of beginning-of-year target difficulty. As expected, we find that predictable target revisions and target difficulty have a very different effect on year t +1 performance relative target. $RevTargetPred_{t+1}$ has a strong positive effect (p < .001), which implies that favorable past performance and forward-looking information that increase $RevTargetPred_{t+1}$ are also positively associated with future performance relative to target. This is consistent with the notion that targets do not fully adjust for all available information (Indjejikian et al. 2014a). In contrast, $TargetDiff_{t+1}$ has a strong negative effect on year t +1 performance relative to target (p < .001), which implies that abnormally high target revisions indeed make targets more difficult to achieve.

The second column of Table A1 uses a similar model as the first column, except that it does not impose the constraint $\beta_2 = 1 - \beta_1$.[18] Although the findings are similar, the coefficient of $TargetDiff_{t+1}$ in the first column is significantly more negative than the coefficient of $TargetDiffAlt_{t+1}$ (p = .001) and the adjusted R^2 of 0.162 in the first column is weakly greater than 0.154 in the second column. Thus, imposing the extra constraint slightly improves the predictive power of our main measure of target difficulty. The third column of Table A1 is based on the standard target ratcheting model in (5) after excluding all forward-looking variables except for *MktValue*. The predictive power of the residuals from this model ($TargetDiffAlt2_{t+1}$) is much lower than in the first column, which underscores the importance of including multiple forward-looking variables when estimating ex ante target difficulty.

Finally, the fourth column of Table A1 defines beginning-of-year target difficulty as the difference between the earnings target and the average analyst earnings forecast ($TargetDiff\_AF_{t+1}$).[19] We find that $TargetDiff\_AF_{t+1}$ is negatively associated with future performance relative to target (p < .001) but the coefficient estimate is significantly less negative (p < .001) than the coefficient of $TargetDiff_{t+1}$

[18] The estimation in the second column does allow for asymmetric effects of both past actual performance and targets, i.e., it includes both $A_t \cdot Fail_t$ and $T_t \cdot Fail_t$ as separate interaction effects.

[19] We use the same analyst forecasts as in *RevAFE*, i.e., one-year-ahead earnings forecasts for year t+1 issued during the first fiscal quarter of year t+1 after year t earnings announcement. Both the earnings target and the average analyst forecast are multiplied by the number of shares and divided by total assets, as other earnings-based variables.

and the adjusted R^2 is also lower than in the first column. In what follows, we conduct an additional analysis to better understand why our measure of ex ante target difficulty ($TargetDiff_{t+1}$) outperforms the alternative measure using only analyst forecasts as a benchmark of expected performance ($TargetDiff\_AF_{t+1}$).

The key issue arising when using consensus analyst forecasts from IBES as a benchmark for internal performance targets is that the definition of earnings used by boards to set targets and evaluate executives is often different than the definition of earnings implied in analyst forecasts (Bentley et al. 2018; Jang, Urcan, and Yoon 2019; Black, Black, Christensen, and Gee 2021; Curtis et al. 2021). This means that the difference between beginning-of-period internal targets and IBES analyst forecasts captures not only target difficulty but also boards' choices of performance measures and the resulting differences in earnings definitions. The performance expectation model in (2), underlying our main measure of target difficulty, avoids this confounding effect by using analyst forecast *revisions* as a determinant of future targets (and thus holding the definition of earnings constant).

To examine how this issue affects the measure of target difficulty based on analyst forecasts, we construct an indicator variable for firm-year observations with relatively low non-GAAP adjustments to earnings used for internal evaluation purposes (and reported in proxy statements together with earnings targets). Specifically, *GAAP* = 1 for observations with below-sample-median adjustments, defined as the absolute value of the difference between GAAP EPS (epsfx) and earnings used for internal evaluation purposes, both rescaled as return on assets (multiplied by cshpri / at).[20] To examine how *GAAP* affects the ability of beginning-of-year analyst forecasts to predict future earnings, we use three other variables. $AROA\_AF_t$ is the average analyst earnings forecast issued after the earnings announcement in the first quarter of year t+1. $IBROA_{t+1}$ is IBES actual earnings in year t+1 and $AROA_{t+1}$ is actual earnings used for internal evaluation purposes in year t+1. All three variables are rescaled as return on assets.

[Insert Table A2]

[20] For *GAAP* = 0 observations, the median adjustment (the absolute value of the difference between GAAP and internal earnings) is 2.13 percent of return on assets. For *GAAP* = 1 observations, the median adjustment is 0.01 percent of return on assets.

The first column of Table A2 shows that analyst forecasts are a good predictor of IBES earnings ($IBROA_{t+1}$) regardless of whether firms adjust GAAP earnings for internal performance evaluation purposes. The coefficient of $AROA\_AF_t$ is not significantly different from one, the intercept and the interaction term ($GAAP \cdot AROA\_AF_t$) are not significantly different from zero, and the adjusted R-squared is 90%. The second column shows that analyst forecasts are noisier when it comes to predicting internal earnings ($AROA_{t+1}$) because the adjusted R-squared drops to 76%. Although analyst forecasts are a still a relatively good predictor of internal earnings in *GAAP* = 1 firms, they are systematically biased downward in firms that make substantial adjustments to GAAP earnings (the intercept is significantly positive, $p < .001$), possibly because analysts do not fully predict the extent to which *GAAP* = 0 firms exclude expenses from GAAP and IBES definitions of earnings (Bentley et al. 2018; Jang et al. 2019).

If analysts use a different definition of earnings than firms do for internal performance evaluation, then the difference between year t+1 targets and analyst forecasts at the beginning of the year ($TargetDiff\_AF_{t+1}$) captures both target difficulty and GAAP adjustments. This adds noise but potentially also an upward bias for *GAAP* = 0 firms. A simple way of quantifying the magnitude of this bias is to examine the correlation between *GAAP* and each of our measures of target difficulty. We find that the (biserial) correlation between *GAAP* and $TargetDiff\_AF_{t+1}$ is -0.421 as compared to the -0.012 correlation between *GAAP* and our main measure of target difficulty ($TargetDiff_{t+1}$), which suggests that $TargetDiff\_AF_{t+1}$ overestimates target difficulty for firms that make adjustments to GAAP earnings.

[Insert Table A3]

Another way of quantifying potential biases due to GAAP adjustments is to reestimate the validation models from Table A1 and allow the main coefficients of interest to vary with *GAAP*. The first column of Table A3 reestimates the fourth column of Table A1 after including the interaction between *GAAP* and $TargetDiff\_AF_{t+1}$. As expected, we find that the predictive power of $TargetDiff\_AF_{t+1}$ is much weaker for *GAAP* = 0 firms ($p < .001$). The second column of Table A3 estimates a similar model after including the interaction with our main measure of target difficulty $GAAP \cdot TargetDiff_{t+1}$. We find

$TargetDiff_{t+1}$ has strong predictive power regardless of *GAAP* ($p < .001$). This provides additional evidence that our main measure of target difficulty is less susceptible to biases due to different earnings definitions than the measure of target difficulty based on analyst forecasts.

We recognize that using beginning-of-year analyst forecasts as a proxy for expected performance has practical advantages because it can easily be constructed from publicly available data. We show that this comes at the cost of introducing noise and bias into the measure of target difficulty. Our validation analyses in Tables A1 and A3 also show that such noise and bias can be alleviated by hand-collecting data on actual performance (as measured for internal performance evaluation purposes) and estimating a comprehensive model of expected performance and target difficulty as described in equations (2)–(5).

TABLE 1. Variable definitions

Variable	Definition
Variables used in abnormal quarterly performance models	
QEP	quarterly earnings percentage calculated as epsfxq / epsfx, i.e., EPS in quarter *q* of year *t* scaled by annual EPS in year *t*.
AQEP	abnormal quarterly earnings percentage defined as the deviation from firm-quarter-specific mean of *QEP*.
AQEP_POS	an indicator variable for positive *AQEP*.
Q4	an indicator variable for the fourth quarter of a fiscal year.
Loss	an indicator variable for one or more quarterly losses in a given fiscal year.
Variables used in the model of ex ante target difficulty	
$RevTarget_{t+1}$	target revision, defined as the difference between earnings target for year $t + 1$ and the target for year *t*, scaled by total assets in year *t*.
DevTarget	performance relative to target, defined as the difference between actual earnings in year *t* and earnings target for year *t* as disclosed in the proxy statement, scaled by total assets in year *t*.
Fail	failure to meet target, i.e., an indicator variable for *DevTarget* < 0.
RevAFE	analyst earnings forecast revision, defined as the difference between IBES median analyst earnings forecast for year $t + 1$ and year *t* IBES actual earnings multiplied by year *t* common shares / total assets.
RevAFS	analyst sales forecast revision, defined as the difference between IBES median analyst sales forecast for year $t + 1$ and IBES actual sales in year *t*, scaled by sales in year *t*.
PeerROA	peer performance, defined as the median of industry-size peer earnings in year *t*, scaled by total assets in year *t*.
Earnings	actual earnings, defined as income before extraordinary items in year *t*, scaled by total assets in year *t*.
Accrual	accruals, defined as income before extraordinary items minus operating cash flow in year *t*, scaled by total assets in year *t*.
Dividend	total dividends scaled by total assets in year *t*.
ChgComp	change in CEO cash compensation, defined as the difference between cash compensation (salary + bonus + noneq_incent) in year *t* and $t – 1$, scaled by cash compensation in year $t – 1$.
OwnReturn	fiscal year *t* stock return.
PeerReturn	median fiscal year *t* stock return of industry-size peers.
MktValue	the natural logarithm of market value of equity at the end of year *t*.
Growth	sales growth, defined as the difference between sales in year *t* and $t – 1$, scaled by sales in year $t – 1$.

Measures of ex ante target difficulty

TargetDiff$_{t+1}$	ex ante target difficulty, calculated as the residual from regressing *RevTarget*$_{t+1}$ on the variables listed above as described in model (5).
TargetDiff_AF$_{t+1}$	the difference between an earnings target for year t + 1 and one-year-ahead mean analyst earnings forecast available at the beginning of year t + 1.
MediumTD	an indicator variable equal to zero for all observations with at least one quarterly loss and, among the remaining observations, zero for the lowest and highest quintiles of ex ante target difficulty (*TargetDiff*) and one for the three quintiles reflecting medium target difficulty.
Q4TargetDiff	target difficulty at the beginning of the fourth quarter, calculated as one minus the percentage of annual earnings target met after Q3 divided by firm-specific mean of *QEP* in the fourth quarter.
Q4MediumTD	an indicator variable equal to zero for all observations with at least one quarterly loss and, among the remaining observations, zero for the lowest and highest quintiles of ex ante target difficulty (*Q4TargetDiff*) and one for the three quintiles reflecting medium target difficulty.

Other variables used in hypotheses tests

Uncertain	monthly return volatility of the S&P 500 index over the same fiscal year period as in *OwnReturn*.
RetnNonenf	low enforcement of non-compete agreements, calculated as the state-level noncompetition enforceability index, normalized to range between zero and one.
RetnDist	distance to peer headquarters, calculated as the average distance in thousands of miles between headquarters of firm *i* and industry peers.
EntrIndex	entrenchment index using six corporate governance provisions tracked by the IRRC, normalized to range between zero and one.
EntrDual	an indicator variable equal to one if CEO is also the chair of the board.
EntrTenure	the natural logarithm of CEO tenure measured in months.
EntrAge	an indicator variable for CEO older than 65 years.
EntrOwner	percentage of shares owned by the CEO (shrown_excl_opts / shrout).
CashComp	CEO cash compensation (salary + bonus + noneq_incent) in $ millions.
OthComp	CEO other compensation (tdc1 – salary – bonus – noneq_incent) in $ millions.
Assets	the natural logarithm of total assets at the end of year *t*.
AAE$_{t+1}$	abnormal annual earnings, i.e., the difference between actual earnings in year $t+1$ (used for internal performance evaluation as disclosed in proxy statements) and earnings expectations at the beginning of year $t+1$ calculated as the target for year *t* plus predicted values from model (5).

Variables used in Appendix A

AROA	earnings used for internal performance evaluation purposes, i.e., actual earnings in year *t* as disclosed in the proxy statement divided by total assets in year *t*.
IBROA	IBES actual EPS multiplied by prior-year common shares / total assets.
AROA_AF	one-year-ahead earnings as reflected in the average analyst forecast at the beginning of the year (multiplied by prior-year common shares / total assets).
GAAP	an indicator variable equal to one for firm-years with low (below-median) non-GAAP adjustments to earnings used for internal evaluation purposes.

TABLE 2. Sample

Panel A. Sample selection (annual data)	No. of firm-years	No. of unique firms
Initial sample with hand-collected data on actual and targeted earnings in CEO cash incentive plans (2006–2014)	3,118	709
Less : Observations without next year's earnings target	(748)	(66)
Observations with two consecutive earnings targets	2,370	643
Less : Observations with missing data on variables used in the model predicting target difficulty (Table 4)	(113)	(13)
Main sample used to estimate target difficulty	**2,257**	**630**

Panel B. Sample selection (quarterly data)	No. of quarters	No. of firm-years	No. of unique firms
Main sample (annual data)	9,028	2,257	630
Less : Observations from Q1	(2,257)		
Q2–Q4 observations	6,771	2,257	630
Less : Observations from firm-years with Q1 EPS missing	(6)	(2)	
Main sample for quarterly data analysis	**6,765**	**2,255**	**630**
Less : Observations with at least one quarterly loss	(1,473)	(491)	(104)
Subsample with positive EPS in all quarters	**5,292**	**1,764**	**526**

TABLE 3. Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	25th Pct.	Median	75th Pct.
$RevTarget_{t+1}$	2,257	0.006	0.024	-0.001	0.005	0.016
DevTarget	2,257	0.000	0.020	-0.003	0.001	0.007
Fail	2,257	0.371	0.483	0.000	0.000	1.000
RevAFE	2,257	0.005	0.015	0.000	0.005	0.012
RevAFS	2,257	0.056	0.107	0.013	0.050	0.097
PeerROA	2,257	0.046	0.032	0.028	0.048	0.067
Earnings	2,257	0.057	0.055	0.027	0.053	0.084
Accrual	2,257	-0.048	0.051	-0.069	-0.042	-0.018
Dividend	2,257	0.014	0.017	0.000	0.010	0.022
ChgComp	2,257	0.163	0.599	-0.146	0.040	0.286
OwnReturn	2,257	0.143	0.361	-0.071	0.124	0.324
PeerReturn	2,257	0.091	0.266	-0.052	0.127	0.240
MktValue	2,257	8.161	1.454	7.066	8.089	9.228
Assets	2,257	8.374	1.585	7.190	8.337	9.423
Growth	2,257	0.063	0.150	-0.013	0.055	0.125
Uncertain	2,257	0.045	0.016	0.030	0.046	0.056
RetnNonenf	2,111	-4.189	1.936	-5.000	-5.000	-3.000
RetnDist	2,122	1.036	0.294	0.826	1.014	1.168
EntrIndex	1,787	0.601	0.196	0.500	0.667	0.667
EntrDual	2,248	0.613	0.487	0.000	1.000	1.000
EntrTenure	2,173	4.141	0.875	3.584	4.248	4.754
EntrAge	2,253	0.059	0.235	0.000	0.000	0.000
EntrOwner	2,245	0.010	0.024	0.001	0.002	0.007
CashComp	2,257	2.460	1.846	1.235	2.013	3.115
OtherComp	2,256	3.787	3.598	1.215	2.727	5.301
AAE	2,156	-0.008	0.025	-0.014	-0.003	0.003

See Table 1 for variable definitions.

TABLE 4. Estimation of ex ante target difficulty and Tests of H1–H3

	Dependent variable: *RevTarget* $_{t+1}$		
	Coeff. (*p* -value)	Coeff. (*p* -value)	Coeff. (*p* -value)
Uncertain		-0.154 **	-0.159 ***
		(0.018)	(0.007)
RetnNonenf		-0.002	-0.001
		(0.321)	(0.660)
RetnDist		-0.003 **	-0.003 ***
		(0.019)	(0.008)
EntrIndex		-0.004 **	
		(0.021)	
EntrDual		0.000	-0.001
		(0.891)	(0.470)
EntrTenure		-0.001 **	-0.001
		(0.033)	(0.149)
EntrAge		-0.001	-0.002 **
		(0.283)	(0.044)
EntrOwner		0.028	0.023
		(0.202)	(0.191)
DevTarget	0.782 ***	0.799 ***	0.813 ***
	(0.000)	(0.000)	(0.000)
Fail	-0.002 **	-0.001	-0.002 **
	(0.020)	(0.253)	(0.050)
DevTarget · *Fail*	-0.287 ***	-0.282 ***	-0.358 ***
	(0.000)	(0.007)	(0.000)
RevAFE	0.641 ***	0.634 ***	0.641 ***
	(0.000)	(0.000)	(0.000)
RevAFS	0.008 **	0.005	0.009 **
	(0.028)	(0.198)	(0.016)
PeerROA	0.018 *	-0.014	-0.004
	(0.073)	(0.406)	(0.796)
Earnings	0.021 **	0.017	0.016 *
	(0.017)	(0.125)	(0.098)
Accrual	0.000	-0.007	-0.003
	(0.973)	(0.428)	(0.659)

Continued on the next page.

TABLE 4. Continued

Dividend	-0.008	-0.058 *	-0.013
	(0.744)	(0.076)	(0.675)
ChgComp	0.001 **	0.001 *	0.001 **
	(0.025)	(0.085)	(0.027)
OwnReturn	0.005 ***	0.005 ***	0.004 ***
	(0.001)	(0.001)	(0.009)
PeerReturn	-0.003 *	-0.004	-0.003
	(0.083)	(0.138)	(0.183)
MktValue	0.000	0.000	0.000
	(0.123)	(0.162)	(0.713)
Growth	0.006 **	0.009 ***	0.006 **
	(0.013)	(0.003)	(0.029)
Industry fixed effects	No	Yes	Yes
Year fixed effects	No	Yes	Yes
Adjusted R^2	0.656	0.689	0.658
Observations	2,257	1,675	2,007

***, **, * represent significance at the 0.01, 0.05, and 0.1 level, respectively. Standard errors are clustered at the firm level. The first column presents OLS estimates of the model of target difficulty in (5). It does not include industry and year fixed effects because ex ante target difficulty (defined as the residual from the model) may vary across industries and over time. The other two columns add the fixed effects and additional explanatory variables into model (5). The sample size is lower because of missing values on some of the additional explanatory variables. See Table 1 for variable definitions.

TABLE 5. Ex ante target difficulty and CEO compensation (Test of H4)

	Dependent variable		
	CashComp $_{t+1}$	*CashComp* $_{t+1}$	*OtherComp* $_{t+1}$
	Coeff. (*p* -value)	Coeff. (*p* -value)	Coeff. (*p* -value)
TargetDiff $_{t+1}$	-4.564 **		
	(0.034)		
TargetDiff $_{t+1}$, *qnt*= 2 (Medium)		0.129	-0.307
		(0.231)	(0.173)
TargetDiff $_{t+1}$, *qnt*= 3 (Medium)		-0.178 *	-0.595 ***
		(0.061)	(0.006)
TargetDiff $_{t+1}$, *qnt*= 4 (Medium)		-0.099	-0.337
		(0.362)	(0.130)
TargetDiff $_{t+1}$, *qnt*= 5 (High)		0.017	0.078
		(0.862)	(0.735)
TargetDiff $_{t+1,}$ *Loss* = 1		-0.020	0.639 **
		(0.864)	(0.012)
Fail $_{t+1}$		-0.714 ***	-0.300 *
		(0.000)	(0.053)
Fail $_{t}$		-0.155 **	-0.339 **
		(0.022)	(0.016)
Earnings $_{t+1}$	4.622 ***	3.597 ***	8.077 ***
	(0.000)	(0.000)	(0.000)
PeerROA $_{t+1}$	-2.931 **	-3.998 ***	0.921
	(0.046)	(0.008)	(0.753)
OwnReturn $_{t+1}$	0.668 ***	0.281 ***	-0.012
	(0.000)	(0.008)	(0.961)
PeerReturn $_{t+1}$	-0.291 *	-0.118	-0.093
	(0.067)	(0.453)	(0.787)
Uncertain $_{t+1}$	-0.268	-1.084	-6.799
	(0.947)	(0.786)	(0.498)
RetnNonenf $_{t+1}$	0.602 **	0.605 **	0.324
	(0.030)	(0.034)	(0.534)
RetnDist $_{t+1}$	0.649 **	0.530 *	0.824
	(0.030)	(0.079)	(0.110)

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TABLE 5. Continued

EntrDual $_{t+1}$	0.209 **	0.159 *	0.236
	(0.023)	(0.082)	(0.216)
EntrTenure $_{t+1}$	0.168 ***	0.167 ***	0.149
	(0.001)	(0.001)	(0.168)
EntrAge $_{t+1}$	0.136	0.178	0.328
	(0.350)	(0.259)	(0.378)
EntrOwner $_{t+1}$	-4.880 **	-4.530 *	-8.317 *
	(0.038)	(0.081)	(0.075)
Assets $_{t+1}$	0.815 ***	0.814 ***	1.529 ***
	(0.000)	(0.000)	(0.000)
Growth $_{t+1}$	0.281	-0.006	-0.195
	(0.272)	(0.983)	(0.686)
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Adjusted R^2	0.531	0.563	0.497
Observations	2,017	1,874	1,874

***, **, * represent significance at the 0.01, 0.05, and 0.1 level, respectively. Table 5 estimates an OLS model of CEO compensation (*CashComp* or *OthComp*) as a function of beginning-of-year target difficulty (*TargetDiff*). In the last two columns, the effect of ex ante target difficulty is modelled with six indicator variables representing the subsample of observations with a quarterly loss (*Loss* = 1) and the remaining subsample divided into five quintiles based on *TargetDiff*. Standard errors are clustered at the firm level. The estimation sample is the same as in Table 4 except for missing values on some of the additional variables. See Table 1 for variable definitions.

TABLE 6. Descriptive statistics on quarterly sample

Panel A. Quarterly earnings data

Variable	Obs.	Mean	Std. Dev.	25th Pct.	Median	75th Pct.
QEP	6,765	0.252	0.112	0.208	0.258	0.311
AQEP	6,765	-0.001	0.079	-0.031	0.003	0.037
AQEP_POS	6,765	0.535	0.499	0.000	1.000	1.000
Q4	6,765	0.333	0.471	0.000	0.000	1.000
Fail	6,462	0.389	0.488	0.000	0.000	1.000
Loss	6,765	0.215	0.411	0.000	0.000	0.000
TargetDiff	6,765	0.000	0.014	-0.003	0.000	0.004
MediumTD	6,765	0.470	0.499	0.000	0.000	1.000
Q4TargetDiff	6,738	1.235	0.895	0.715	1.024	1.498
Q4MediumTD	6,738	0.470	0.499	0.000	0.000	1.000

Panel B. Ex ante target difficulty and ex post failure to meet targets

Groups based on	*Fail*				*Fail*	
TargetDiff	Fail = 0	Fail = 1		*Q4TargetDiff*	Fail = 0	Fail = 1
Low	717	297		Low	966	45
	70.7%	29.3%			95.6%	4.5%
Medium	2,115	948		Medium	2,079	969
	69.1%	31.0%			68.2%	31.8%
High	552	477		High	321	708
	53.6%	46.4%			31.2%	68.8%
Loss	564	792		Loss	561	786
	41.6%	58.4%			41.7%	58.4%
Total	3,948	2,514		Total	3,927	2,508
	61.1%	38.9%			61.0%	39.0%

Panel A shows descriptive statistics for variables used in our quarterly data analysis. The sample of 6,765 quarterly observations is derived from the sample of annual observation as described in Table 2. Panel B describes ex post failure to meet annual earnings targets (*Fail*) as a function of *Loss* and ex ante target difficulty, using either the beginning-of-year measure (*TargetDiff*) or the beginning-of-fourth-quarter measure (*Q4TargetDiff*). “Loss” refers to the subsample of observations with at least one quarterly loss during the fiscal year, i.e., *Loss* = 1. In the remaining subsample of observations with positive earnings in all quarters, “Low” (“High”) refers to the lowest (highest) quintile of *TargetDiff* (or *Q4TargetDiff*) and “Medium” refers to the three medium quintiles, i.e., *MediumTD* = 1 (*Q4MediumTD* = 1). See Table 1 for other variable definitions.

TABLE 7. Ex ante target difficulty and short-term performance management (Test of H5)

Panel A. Target difficulty and Q4 performance reversals

Medium defined as	*MediumTD*	*Q4MediumTD*
	Dependent variable: $AQEP_q$	Dependent variable: $AQEP_q$
The effect of	Marginal effect (*p*-value)	Marginal effect (*p*-value)
$AQEP_{q-1} \cdot Q4, Medium = 0$	-0.162 ***	-0.152 ***
	(0.001)	(0.001)
$AQEP_{q-1} \cdot Q4, Medium = 1$	-0.350 ***	-0.373 ***
	(0.000)	(0.000)
Difference	-0.187 **	-0.221 ***
	(0.014)	(0.002)
Quarter fixed effects	Yes	Yes
Adjusted R^2	0.077	0.078
Observations	6,765	6,738

Panel B. Favorable vs. unfavorable Q3 performance

Medium defined as	*MediumTD*	*Q4MediumTD*
	Dependent variable: $AQEP_q$	Dependent variable: $AQEP_q$
The effect of	Marginal effect (*p*-value)	Marginal effect (*p*-value)
Unfavorable Q3 ($AQEP\_POS_{q-1} = 0$)		
$AQEP_{q-1} \cdot Q4, Medium = 0$	-0.055	-0.075
	(0.449)	(0.317)
$AQEP_{q-1} \cdot Q4, Medium = 1$	-0.286 **	-0.257 **
	(0.010)	(0.014)
Difference	-0.231 *	-0.182
	(0.077)	(0.148)
Favorable Q3 ($AQEP\_POS_{q-1} = 1$)		
$AQEP_{q-1} \cdot Q4, Medium = 0$	-0.127	-0.113
	(0.149)	(0.184)
$AQEP_{q-1} \cdot Q4, Medium = 1$	-0.406 ***	-0.478 ***
	(0.000)	(0.000)
Difference	-0.279 **	-0.365 ***
	(0.033)	(0.004)
Quarter fixed effects	Yes	Yes
Adjusted R^2	0.079	0.078
Observations	6,765	6,738

***, **, * represent significance at the 0.01, 0.05, and 0.1 level, respectively. Standard errors are clustered at the firm level. Table 7 examines whether abnormal reversals in fourth-quarter performance (γ_2 in equation (6)) are associated with moderately difficult targets as measured at the beginning of the year (*MediumTD*) or at the beginning of the fourth quarter (*Q4MediumTD*). Specifically, Panel A extends equation (6) to include a three-way interaction term with *Medium* (one of the two indicators for moderately difficult targets) and an indicator for losses:

$$AQEP_{i,t,q} = \gamma_0 + \gamma_1 AQEP_{i,t,q-1} + \gamma_2 AQEP_{i,t,q-1} \cdot Q4_i + \gamma_3 Medium_{i,t} + \gamma_4 AQEP_{i,t,q-1} \cdot Medium_{i,t} + \gamma_5 Q4_i \cdot Medium_{i,t}$$
$$+\gamma_6 AQEP_{i,t,q-1} \cdot Q4_i \cdot Medium_{i,t} + \gamma_7 Loss_{i,t} + \sum_{d=1}^{23} \delta_d QD_d + \omega_{i,t,q}.$$

For brevity, Panel A of Table 7 only presents OLS estimates of the marginal effects of interest, i.e., $AQEP_{q-1} \cdot Q4$ (conditional on *MediumTD* = 0), $AQEP_{q-1} \cdot Q4$ (conditional on *MediumTD* = 1), and their difference equal to γ_6 (the effect of the three-way interaction). Panel B further extends the model by adding a four-way interaction term $AQEP_{q-1} \cdot Q4 \cdot Medium \cdot AQEP\_POS_{q-1}$ (and all lower-level interaction effects). See Table 1 for variable definitions.

TABLE 8. Ex ante target difficulty and abnormal annual performance

	Dependent variable			
	AAE_{t+1}	AAE_{t+2}	$OwnReturn_{t+1}$	$OwnReturn_{t+2}$
	Coeff. (*p* -value)	Coeff. (*p* -value)	Coeff. (*p* -value)	Coeff. (*p* -value)
$Earnings_T$			1.829 ***	1.303 ***
			(0.000)	(0.000)
$PeerROA_T$	0.088 **	0.055	-0.338	-0.139
	(0.010)	(0.158)	(0.331)	(0.678)
$PeerReturn_T$	0.004	0.003	0.582 ***	0.595 ***
	(0.317)	(0.654)	(0.000)	(0.000)
$TargetDiff_{t+1}$	0.271 ***	-0.276 ***	0.361	-1.698 ***
	(0.001)	(0.000)	(0.449)	(0.009)
$Uncertain_t$	0.351 ***	-0.086	-0.636	-0.743
	(0.001)	(0.523)	(0.523)	(0.523)
$RetnNonenf_t$	0.002	0.001	-0.009	-0.003
	(0.633)	(0.777)	(0.794)	(0.947)
$RetnDist_t$	0.003	0.000	0.047 *	-0.006
	(0.105)	(0.912)	(0.078)	(0.860)
$EntrDual_t$	0.000	0.001	-0.001	-0.009
	(0.819)	(0.366)	(0.949)	(0.557)
$EntrTenure_t$	-0.001 *	-0.001	-0.005	-0.013
	(0.089)	(0.218)	(0.530)	(0.131)
$EntrAge_t$	0.000	0.000	-0.049 *	0.001
	(0.983)	(0.858)	(0.073)	(0.957)
$EntrOwner_t$	0.092 ***	0.027	0.639 *	0.027
	(0.001)	(0.370)	(0.089)	(0.939)
$Assets_t$	0.005 ***	0.000	0.116 ***	0.030
	(0.006)	(0.910)	(0.000)	(0.118)
$Growth_t$	-0.006	-0.011 **	-0.068	0.030
	(0.189)	(0.034)	(0.155)	(0.661)
Other variables	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.205	0.170	0.458	0.396
Observations	1,892	1,307	1,975	1,461

***, **, * represent significance at the 0.01, 0.05, and 0.1 level, respectively. Standard errors are clustered at the firm level. Table 8 presents OLS estimates of the associations between beginning-of-year target difficulty ($TargetDiff_{t+1}$) and (i) same-year abnormal annual earnings (AAE_{t+1}), (ii) next-period abnormal annual earnings (AAE_{t+2}), (iii) same-year stock returns ($OwnReturn_{t+1}$), and (iv) next-year stock returns ($OwnReturn_{t+2}$). Subscript *T* represents the same year as the dependent variable, either *t*+1 or *t*+2. See Table 1 for other variable definitions.

TABLE A1. Validation of ex ante target difficulty

	Dependent variable: *DevTarget* $_{t+1}$			
	Coeff. (*p*-value)	Coeff. (*p*-value)	Coeff. (*p*-value)	Coeff. (*p*-value)
Intercept	-0.005 ***	-0.005 ***	-0.003 **	-0.001 *
	(0.000)	(0.000)	(0.019)	(0.071)
DevTarget $_t$	-0.140 *	-0.055	0.134	0.179 ***
	(0.056)	(0.435)	(0.467)	(0.007)
RevTargetPred $_{t+1}$	0.480 ***			
	(0.000)			
TargetDiff $_{t+1}$	-0.384 ***			
	(0.000)			
RevTargetPredAlt $_{t+1}$		0.378 ***		
		(0.000)		
TargetDiffAlt $_{t+1}$		-0.288 ***		
		(0.000)		
RevTargetPredAlt2 $_{t+1}$			0.130	
			(0.549)	
TargetDiffAlt2 $_{t+1}$			-0.048	
			(0.348)	
RevTarget $_{t+1}$				0.038
				(0.452)
TargetDiff_AF $_{t+1}$				-0.209 ***
				(0.000)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No
Adjusted R^2	0.162	0.154	0.056	0.102
Observations	2,156	2,156	2,156	2,156

***, **, * represent significance at the 0.01, 0.05, and 0.1 level, respectively. Standard errors are clustered at the firm level. The estimation sample is the same as in the first column of Table 4 except for 101 observations with missing values on year $t + 1$ earnings (used to measure performance relative to target). Each column presents a model forecasting next-period performance relative to target ($DevTarget_{t+1}$) as a function of prior-period performance relative to target ($DevTarget_t$) and target revision ($RevTarget_{t+1}$) decomposed into (i) predicted revision ($RevTargetPred_{t+1}$) and (ii) target difficulty defined as unexplained revision ($TargetDiff_{t+1}$), so that $RevTarget_{t+1} = RevTargetPred_{t+1} + TargetDiff_{t+1}$. Each column uses a different definition of target difficulty. $TargetDiff_{t+1}$ is the main measure used in our analysis and based on model (5). $TargetDiffAlt_{t+1}$ is based on model (3). $TargetDiffAlt2_{t+1}$ is based on model (5) after excluding all forward-looking variables except for *MktValue*. $TargetDiff\_AF_{t+1}$ is the difference between earnings targets and average analyst earnings forecasts. We do not include year fixed effects because end-of-year effects are unknown at the time of forecasting. We find qualitatively similar results if we include both industry and year fixed effects or if we exclude both types of fixed effects.

TABLE A2. Predicting future performance using analyst forecasts

	Dependent variable: $IBROA_{t+1}$	Dependent variable: $AROA_{t+1}$
	Coeff.	Coeff.
	(p -value)	(p -value)
Intercept	-0.001	0.013 ***
	(0.616)	(0.000)
$AROA\_AF_t$	1.003 ***	1.006 ***
	(0.000)	(0.000)
$GAAP$	-0.001	-0.015 ***
	(0.652)	(0.000)
$GAAP \cdot AROA\_AF_t$	0.006	0.011
	(0.781)	(0.781)
Industry fixed effects	Yes	Yes
Year fixed effects	No	No
Adjusted R^2	0.904	0.759
Observations	2,257	2,156

***, **, * represent significance at the 0.01, 0.05, and 0.1 level, respectively. Standard errors are clustered at the firm level. The estimation sample is the same as in Table 4. We do not include year fixed effects because end-of-year effects are unknown at the time of forecasting. We find qualitatively similar results if we include both industry and year fixed effects or if we exclude both types of fixed effects. See Table 1 for variable definitions.

TABLE A3. Predicting future perfromance relative to target

	Dependent variable: $DevTarget_{t+1}$			
	Coeff.		Coeff.	
	(p-value)		(p-value)	
Intercept	0.000		0.000	***
	(0.970)		(0.000)	
$DevTarget_{t}$	0.114		-0.126	*
	(0.104)		(0.072)	
$RevTarget_{t+1}$	0.066		0.404	***
	(0.203)		(0.000)	
$TargetDiff\_AF_{t+1}$	-0.167	***	-0.106	***
	(0.000)		(0.000)	
$GAAP$	-0.003	***	-0.002	**
	(0.009)		(0.039)	
$GAAP \cdot TargetDiff\_AF_{t+1}$	-0.674	***	-0.460	***
	(0.000)		(0.003)	
$TargetDiff_{t+1}$			-0.614	***
			(0.000)	
$GAAP \cdot TargetDiff_{t+1}$			-0.030	
			(0.840)	
Industry fixed effects	Yes		Yes	
Year fixed effects	No		No	
Adjusted R^2	0.154		0.198	
Observations	2,156		2,156	

***, **, * represent significance at the 0.01, 0.05, and 0.1 level, respectively. Standard errors are clustered at the firm level. The estimation sample is the same as in Table 4. We do not include year fixed effects because future year effects are unknown at the time of forecasting. We find qualitatively similar results if we include both industry and year fixed effects or if we exclude both types of fixed effects. See Table 1 for variable definitions.