Costs of including accounting performance goals in executive compensation*

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Abstract

How is firm performance related to executive compensation goals? We study this question using a large dataset of performance goals employed in executive incentive contracts. A disproportionately large number of firms exceed their goals by a small margin as compared to the number that fall short of the goal by a similar margin. This asymmetry is particularly acute when compensation is contingent on a single goal or if there is a discontinuous jump in compensation earned for meeting the goal and for short-term goals. Firms that just exceed their EPS goals have higher abnormal accruals and lower Research and Development (R&D) expenditure, firms that just exceed their sales goals have higher Sales General and Administrative (SG&A) expenditure and firms that just exceed their profit goals have lower SG&A expenditure as compared to firms that just miss their EPS, sales and profit goals respectively. Overall our results highlight some unintended costs of linking executive compensation to specific performance goals, which suggests boards need to actively monitor the chosen performance metrics.

JEL Classification: G30, J33

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“Charlie and I believe that those entrusted with handling the funds of others should establish performance goals at the onset of their stewardship. Lacking such standards, managements are tempted to shoot the arrow of performance and then paint the bull’s-eye around wherever it lands.”

Warren Buffett

Introduction

The extent to which managerial pay varies with underlying firm performance has been of great interest both for researchers and for the popular press (see Jensen and Murphy (1990); Hall and Liebman (1998)). In their ongoing effort to achieve an optimal link between pay and performance, firms have increasingly resorted to tying annual bonus grants and long-term stock and option grants to achieving explicit performance goals. As noted in the quote above, investors like Warren Buffett have been major proponents of assessing management against specific performance goals. A typical cash or stock grant linked to firm performance identifies a threshold, target and maximum value for one or more accounting or stock price-based metrics. The payout from the grant or the vesting schedule of the grant is then tied to the firm achieving these particular performance goals. For example, a manager may receive no payout if performance is below the threshold, and her payout may increase if she exceeds the target performance.\(^1\) Performance linked grants often result in a discontinuous change in managerial pay with firm performance around some “kink points”, thereby providing management strong incentives to achieve the performance goals. This practice certainly has a bright side, especially when the goals are challenging, but it may also have a dark side. If actual performance is close to but short of the goal, managers may be tempted to take actions – with possible negative long-term consequences – to push reported performance past the goal. In other words, managerial myopia may be exacerbated around the “kink points”. In this paper, we use a comprehensive dataset containing information on the performance goals employed in pay contracts to investigate the extent to which reported

\(^1\)See Appendix A for the description of a few bonus and stock grants linked to firm performance.
financial performance is “managed” to achieve compensation performance goals.

We focus on absolute accounting based performance goals and analyze the distribution of reported performance around the goal. If reported accounting performance is managed, then a disproportionate number of firms will just exceed the goal as compared to the number that just miss it. In other words, the distribution of reported performance will exhibit a discontinuity around the goal (Burgstahler and Dichev (1997) and Bollen and Pool (2009)). McCrary (2008) develops a test to identify if a probability density has a statistically significant discontinuity at a given point. We employ this methodology, along with those in Bollen and Pool (2009) and bootstrapping techniques to test for the presence of discontinuities.

To the extent managerial pay discretely increases at the goal, a discontinuity in reported performance at the goal may also be consistent with managers working “very hard” when actual performance is close to the goal. We call this the “effort channel”. Since we don’t observe managerial effort, it is very difficult to distinguish the effort channel from the performance management channel. We compare firms that just beat and just miss benchmarks on a number of observable dimensions to understand how firms beat performance goals. Our evidence from these tests is consistent with managers increasing accounting accruals and changing discretionary expenditure such as research and development (R&D) and Sales General and Administrative expenses (SG&A) to meet performance goals. In sum, our findings reveal a dark side to the intended benefits extolled by Buffett.

Managers can ensure that they achieve the performance goals by manipulating either the ex ante goals or the ex post reported performance. They can influence the goal setting process to ensure easy goals, a practice known as “sandbagging” (Morse et al. (2011)), or change real activities or accounting accruals to alter reported performance (Dechow et al. (2003); Roychowdhury (2006a)). As we explain below, our evidence is consistent with both sandbagging and ex post performance management enabling firms beat performance benchmarks.

We obtain the data on performance goals from a dataset collected from firm’s proxy statements by Incentive Lab (IL). We have information on all the cash, stock and option
grants awarded to a top five highest paid executive for the 750 largest firms by market capitalization over the time period 1998-2012. We have information on the metric(s) the grant is tied to, the nature of the relationship, i.e., whether the payout or vesting schedule is tied to the metric(s), and the nature (absolute versus relative) and specific value of the performance goal. Given our interest in understanding how executives manage reported accounting performance to achieve goals, for most of the paper we focus on grants linked to an absolute accounting based metric that we can match with actual performance as reported in Compustat. This limits the grants to those that are tied to the level or the growth of one of the following metrics: Earnings, EPS, Sales, EBIT, EBITDA, Operating Income and FFO. This results in a sample of 29,591 grants awarded by 974 firms to 7,933 executives. Among the accounting metrics employed, EPS is the most popular with around 40% of the grants linked to a EPS goal. Cash and stock are the most popular modes of payout for the grants in our sample, with over 74% (25%) of the grants involving some cash (stock) payout.

We begin our empirical analysis by comparing the target performance in the pay contract to the firm’s reported performance. We conduct this test separately on earnings (Earnings and EPS), sales (Sales) and profit (EBIT, EBITDA, Operating Income and FFO) based grants because the underlying distribution of these metrics are quite different and combining them in the same test will make the density estimation very noisy. We construct three variables to help us identify discontinuity at the performance goal. Actual less target EPS is the difference between actual EPS as reported in Compustat and the target EPS as identified in the pay contract. Similarly Actual less target sales (Actual less target profit) is the difference between actual sales (profit) and targeted sales (profits) normalized by the book value of total assets. We find that the density of both Actual less target EPS and Actual less target profit exhibit a significant discontinuity at zero, that is, at the target value specified in the grant. A disproportionately large number of firms exceed the performance target by a small margin as compared to the number of firms that fail to meet the performance target by a small margin. Interestingly, we do not find a corresponding discontinuity at zero for

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2 We also design placebo tests on grants linked to relative performance goals, for which we include grants tied to relative stock and accounting performance.
Actual less target sales.

We confirm these results with our bootstrapping test, wherein we draw multiple random samples of the underlying variable and compare the number of observations that fall just to the right and just to the left of zero. We find a similar pattern when we compare the actual performance to the threshold performance mentioned in the pay contract. Overall there is robust evidence of firms disproportionately beating performance goals by a small margin as compared to falling short by a small margin. This is consistent with both the performance management and the effort channels.

To the extent influencing a single metric is easier than influencing multiple metrics, grants contingent on a single metric may provide greater incentives for managers to influence the accounting values that are tied to their performance contracts, compared to those contingent on multiple metrics. Consistent with this, when we divide or sample into executives that obtain grants contingent on single versus multiple metrics, we find that the discontinuity at the performance target is larger for executives who obtain grants contingent on a single metric. Since the methodology in McCrary (2008) does not allow for a statistical comparison of the size of two discontinuities, we employ the bootstrapping methodology to statistically compare the size of the discontinuities. Presently we also introduce a regression based test that allows us to statistically compare the size of discontinuities.

Some grants involve interpolation of the payout between the threshold and target performance. That is, the payout varies continuously with firm performance between the threshold and target performance. Such grants do not involve a discontinuous jump in pay at the target performance, and hence may not provide incentives to manage reported accounting performance. Consistent with this, we find the discontinuity at the target to be larger for executives who receive grants that do not involve interpolation between the threshold and target markers.\footnote{In unreported tests, using bootstrapping methodology we find the size of the discontinuity to be larger around performance thresholds as compared to around performance targets.}

\footnote{Since disclosure requirements for the grant features is not standardized, firms may not always disclose if a grant involves interpolation or not. For our analysis, we classify all grants that do not disclose information about interpolation as not involving interpolation. Thus some of the grants that we classify as not involving interpolation, may actually involve interpolation. This is likely to bias downwards any difference we find between the two subsamples.}
To distinguish between performance management and sandbagging, we compare the extent of discontinuity at the goal for short-term and long-term grants. Since managers will be better able to anticipate short-term performance as compared to long-term performance, setting performance goals close to anticipated performance (sandbagging) is more likely for short-term grants than for long-term grants. When we divide the grants into short-term and long-term grants, we find a significant discontinuity for both sets of grants, especially in the case of EPS and profit goals. We interpret this to be consistent with the presence of both sandbagging and performance management.

To cross-sectionally compare the size of the discontinuities, for the first time, we introduce a regression based test. Similar to the test in McCrary (2008), the regression involves comparing the actual number of firms whose performance falls within a bin to an expected number. That is, for any metric, such as say EPS, we use the bin size as recommended by McCrary (2008) and divide all our sample firms into bins based on reported EPS. The dependent variable in the regression is \textit{Number of firms}, the logarithm of one plus the number of firms in each bin. We do a similar exercise for sales and profit measures as well. Our main independent variable is \textit{Number of goals} which is defined as the logarithm of one plus the number of firms with the target or threshold performance in a particular bin. If firms manage reported performance so as to exceed a goal, then we expect their reported performance to fall near (within the same bin as) the performance goal. We model the expected number of firms in each bin in a flexible manner by including a fourth order polynomial of the mid-point of the bin.

In comparison to McCrary (2008), the regression analysis has three advantages and two disadvantages. The first advantage is that we can combine all the metrics in the same test. We can estimate the metric-specific distribution within the same model by including an interaction term between metric fixed effects and the fourth order polynomial. Second, the regression allows us to test for discontinuities at multiple points in the density. We can include both the threshold and target goals to construct the \textit{Number of goals}. Third, the regression also allows us to perform cross-sectional tests. We can do this by splitting our grants say, based on the number of metrics involved and constructing two versions of the
**Number of goals.** By comparing the coefficients on the two variables we can compare the size of the discontinuity. The first disadvantage of the regression approach is that it will not be able to tell if the firm actually exceeded the goal or fell short of the goal as we only test to see if the actual performance is close to the goal. To overcome this, we rely on our prior analysis which clearly shows that whenever firm performance is close to a goal, it is more likely to be greater than the goal. The second disadvantage of the regression approach is that since we only model the total number of firms in a bin as a function of the number of goals in a bin, we will not know if the same firm has its performance and goal in the same bin. In comparison to the bootstrapping tests, which only compare the number of firms in the bins to the right and left of zero, the regression based approach models the entire distribution. We see these two as complementing each other in helping us form our conclusions.

Our results from the regression analysis is broadly consistent with our earlier results. We find that the presence of a performance goal in a bin increases the probability of an additional firm’s performance falling in the bin by 30%. We also find that this effect is greater if the grant does not involve interpolation of the payout between the threshold and target performance. We also find that the actual performance clusters around the goal, both for single and multiple metric based grants and for long-term and short-term goals.

If firms meet performance goals by managing reported performance, then the tendency to just meet goals should be weaker for relative-performance goals. We find that is indeed the case. When we compare relative performance goals to the firm’s actual relative performance, we do not find a tendency for firms to just beat their performance goals.

To distinguish between the performance management and the effort channels, and to understand how firms meet their accounting performance goals, in our final set of tests we compare firms that just exceed a goal to those that just miss a goal on a number of dimensions. We compare the level of Accruals, Change R&D/TA, Change SG&A/Sales and Repurchase for firms that just exceed the goal, i.e., the firms that fall in the first bin above the performance goal (either target or threshold) and the firms that just miss the goal – that is, firms whose performance is in the two bins below the performance goal – to identify
if there are any systematic differences.\textsuperscript{5} Since firms deliberately pick performance goals and may take deliberate action to meet those goals, firms that meet and miss goals are not likely to be randomly selected. To this extent our evidence should not be interpreted as causal in nature.

We find that firms that exceed the EPS goal by a small margin have much higher abnormal accruals and smaller changes in R&D expenditure as compared to firms that miss the goal by a small margin. Firms that exceed sales goal by a small margin have greater increase in SG&A expenditure as compared to firms that miss the goal while firms that exceed the profit goal have significantly lower SG&A expense as compared to firms that miss the goal by a small margin. Thus overall our evidence is consistent with firms using both accruals and cuts to discretionary expenditures to meet EPS and profit goals, respectively and increasing SG&A expense to meet sales goals (see also Graham et al. (2005a); Roychowdhury (2006a)).

The rest of the paper is organized as follows. Section 1 discusses the related literature. Section 2 describes our empirical methodology. Section 3 discusses the hypothesis we test while Section 4 describes our data and provides the summary statistics. Section 5 discusses the results of our empirical tests while Section 6 concludes. Definitions of empirical variables are in Appendix A.

\section{Related Literature}

Our paper is most closely related to the papers that highlight the exercise of CEO power over her pay. Bebchuk and Fried (2004) and Adams et al. (2005) argue that CEO power over the pay process can explain much of the contemporary landscape of executive compensation. More managerial power leads to pay that is less sensitive to performance (what they call “compensation camouflage”). Morse et al. (2011) argue that a powerful CEO may

\textsuperscript{5}Note that these bins are identified in an “optimal” manner using the procedure in McCrary (2008). Since there is a disproportionately large number of firms in the bin above the performance goal as compared to the bin below the performance goal, we include firms in the two bins below the performance goal to ensure a relatively equal number of firms that exceed and miss the goal.
opportunistically change performance benchmarks to increase her pay. In comparison, our paper highlights the effects of having explicit performance goals when executives exercise power over both the goal setting process and the reported performance.

Our paper is related to the prior literature that studies other performance goals that managers try to meet. These include the zero EPS goal (Burgstahler and Dichev (1997)) and the consensus analyst estimates (Bartov et al. (2002)). Our study differs from these in two important respects. In our setting, we know the monetary penalty managers face for not meeting a performance goal. This allows us to design sharper cross-sectional tests. Our analysis also helps highlight a dark side to the increasing use of accounting and stock based metrics to design pay contracts and the important role performance goals can play in predicting actual firm performance.

Our research is also related to the theoretical moral hazard and adverse selection literature. More specifically applicable is a strand of theoretical research on contracting settings where the agent can manipulate the observable performance measure. The main finding in Crocker and Slemrod (2008) is that compensation contracts that are written in terms of reported earnings cannot provide managers with incentives to maximize profits and at the same time provide managers with incentives to report those profits truthfully. Maggi and Rodríguez-Clare (1995) study a principal-agent setting in which the agent is privately informed about his marginal cost of production. In their paper, costly information distortion emerges as an equilibrium behavior. Additionally, Guttman et al. (2006) find that there exist equilibria in which kinks and discontinuities emerge endogenously in the distribution of reported earnings.

A large literature in accounting and finance documents how executives manipulate reported performance to achieve performance goals. Cheng et al. (2010) find that firms may repurchase shares to manipulate EPS to achieve bonus targets. Roychowdhury (2006b) and Dechow et al. (2003) find that firms may reduce discretionary expenditures, such as R&D and SG&A, to improve reported margins and avoid reporting a loss. Additionally, Graham et al. (2005b) show that when surveyed, a majority of CEOs admit to sacrificing long-term value to smooth earnings. Bergstresser and Philippon (2006) provide evidence that the
use of discretionary accruals to manipulate reported earnings is related to the amount of stock-based pay. In comparison, we find that firms increase accruals and cut discretionary spending to meet highly specific performance goals explicitly embedded in compensation contracts.

Our paper is also related to the recent literature that studies the use of performance provisions in executive compensation. Bettis et al. (2010, 2013) explore the usage, determinants and implications of performance-vesting provisions in executive stock and option grants, and find that firms with such provisions have better subsequent operating performance. Gong et al. (2011) study grants that are tied to relative performance and find a weak relationship between the relative performance targets and future peer group performance. Kuang and Qin (2009) find that performance-vesting stock options plans are associated with better executive incentives among non-financial UK firms. Unlike these papers, we focus on the role of performance provisions in providing incentives to manage reported performance to meet managers own performance targets.

Our paper is also related to the literature that highlights the costs and benefits of alternate metrics to evaluate executive performance. Holmstrom (1979) argues for the use of metrics that are most informative about CEO effort. More recently, Matějka et al. (2009) hypothesize that metrics are chosen in response to past poor performance, while Gao et al. (2012) hypothesize that good past performance is indicative of the importance of a given metric. In comparison, our paper highlights the costs of picking metrics that can be more readily managed by the executive.

In addition to the intended contribution to the literature, our paper may also further stir up the already active, policy-oriented, executive compensation debate. As revealed in the opening quote from Warren Buffett, large investors are in favor of evaluating managers against specific performance goals. There is also increasing pressure from proxy advisory firms such as ISS and Glass Lewis for the use of explicit performance goals in executive compensation. Our paper highlights that the effective use of such provisions also requires greater board oversight on firm performance to minimize executives gaming of reported performance to meet the goals.
2 Empirical methodology

In this section, we describe the three tests that we perform to identify manipulation of firm performance to meet goals. All three tests look for discrepancies in the distribution of reported performance.

The first test we implement is the one described in McCrary (2008) that is designed to test for the presence of a discontinuity at a point in a density. To implement this test, we construct variables that measure the difference between actual performance and the stated goal, and test for discontinuity at zero, i.e., at the performance goal. The test involves two steps. In the first step, one obtains a "finely-gridded histogram" of the underlying variable. The bins are carefully defined such that no bin includes points both to the left and right of zero. In the second step, one smooths the histogram by estimating a weighted regression separately on either side of zero. The midpoints of the histogram bins are treated as the regressor and the normalized counts of the number of observations falling within each bin are treated as the outcome variable. The weighing function is a triangular kernel that gives most weight to the bins nearest to where one is trying to estimate the density. The test for discontinuity is then implemented as a Wald test of the null hypothesis that the discontinuity is zero. We implement the test using the “DCdensity” function in STATA. The output of this function includes both the first-step histogram and the second step smoother along with 95% confidence intervals (CI) of the second step density.

The critical parameters in the test are the bin-size for the first-step histogram and the bandwidth used in the second stage estimation. For our analysis we use the default bin-size and bandwidth as recommended by the DCdensity function. The default bin size \( b \) equals \( 2\sigma n^{-1/2} \), where \( \sigma \) is the sample standard deviation and \( n \) is the number of observations. To estimate the default bandwidth, the “DCdensity” function estimates the weighted regression described above and for each side, it computes \( 3.348[\sigma^2(b - a)/\Sigma \tilde{f}(X_j)^2]^{1/5} \), and sets the bandwidth equal to the average of the two quantities. In this formula \( \sigma^2 \) is the mean-squared error of the regression, \( b - a \) equals \( X_j \) for the right-hand regression and \( -X_j \) for the left-hand regression, where \( X_j \) is the bin-size and \( \tilde{f}(X_j)^2 \) is the estimated second
derivative implied by the global polynomial model.

The second test that we conduct to detect performance manipulation is from Bollen and Pool (2009). This test not only serves as a robustness check on the test in McCrary (2008) but also allows us to test for discontinuities all through the density. This test is similar to McCrary (2008) and involves dividing the data into bins, estimating a smooth density, and comparing the actual number of observations to those predicted by the smooth density. The bin-size for the first-stage histogram is estimated to minimize the mean square error and is equal to $1.0585 \times \min\{\sigma, \frac{Q}{1.34}\} \times n^{\frac{1}{2}}$ where $\sigma$ is the standard deviation, $Q$ the interquartile range and $n$ the number of observations.

In the second stage, the test uses the Gaussian kernel and estimates the smooth density. The bandwidth for the second stage estimation is set equal to the bin size from the first stage. The test then uses an estimate of sampling variation in the histogram to determine whether the actual number of observations in a given bin is significantly different from the expected number under the null hypothesis of a smooth underlying distribution. If $p$ denotes the probability that an observation lies in a bin (estimated by integrating the kernel density along the boundary of each bin) then according to the Demoivre-Laplace theorem the actual number of observations in a bin is asymptotically normally distributed with mean $np$ and standard deviation $np \sqrt{1-p}$, where $n$ is the total number of observations. This is used to design the test for discontinuity all along the density.

An important limitation of the tests described above is that they do not allow one to compare the size of the discontinuities at two points in the density or across densities. To do this, we do a bootstrapping exercise and a regression based analysis to complement the above two tests. In our bootstrapping exercise we draw a random sample from the variable of interest and count the number of observations that lie in the first bin to the right of zero and the number of observations that lie in the first bin to the left of zero. We repeat this 1,000 times and compare the means. To do cross-sectional tests we do the sampling separately, say for single and multiple metric based grants, and compare the size of the differences. We describe our regression based tests in greater detail in Section 5.3.
3 Hypothesis

In this section, we outline the hypothesis that have predictions relevant for our setting. If managers realize that actual performance is likely to be close to but short of the goal and take actions to push reported performance past the goal, then the distribution of reported performance will exhibit a discontinuity around the goal (Burgstahler and Dichev (1997) and Bollen and Pool (2009)). The actions managers take can either be in terms of managing the reported performance (by increasing accounting accruals or by cutting discretionary expenses), or in terms of exerting more effort. In the rest of the discussion we refer to these as actions managers take to “influence” performance. Irrespective of the channel employed, we expect the reported performance of a disproportionate number of firms to exceed the goal by a small margin as compared to fall short by a small margin. This forms our first prediction.

We expect managers to be more likely to influence performance to meet a goal if (a) it is relatively easy to influence the performance and (b) if there is a large and discontinuous increase in pay around the goal. To the extent influencing a single metric is easier than influencing multiple metrics, grants contingent on a single metric may provide greater incentives for managers to find ways to achieve the financial performance embedded in their compensation contracts. Thus, for our second prediction, we expect a larger discontinuity in the underlying performance for executives that obtain grants that depend on a single metric as compared to executives that obtain grants contingent on multiple metrics.

As described in Appendix A, a grant typically has both a target and threshold performance goal. If the firm performance falls between the threshold and target performance, some grants interpolate the payout, whereas others do not. Without interpolation, pay jumps discontinuously when firm performance exceeds the target. For grants that involve interpolation, there is no discontinuous increase in pay when the performance exceeds the target. To the extent a discontinuous increase in pay provides greater incentives to meet a goal, we expect managers that obtain grants that do not involve interpolation to influence reported results to a greater extent as compared to managers that obtain grants that
involve interpolation. Hence we expect a larger discontinuity at zero for executives that obtain grants that do not involve interpolation. This forms our third prediction.

Managers can exceed target performance by their discretionary control over reported financial performance, but they can also accomplish this by lowering the ex ante goal. That is, managers can set a goal below and close to the anticipated performance so that they achieve it with a high probability and small margin. This is often referred to as sandbagging. Since managers will be better able to anticipate short-term performance as compared to long-term performance, management of the accounting values associated with the performance goal is more likely for short-term grants than for long-term grants. We compare the level of discontinuity for short-term and long-term grants to understand the extent to which ex ante goals and ex post reported performances are managed.

Depending on the metric involved, managers can employ a variety of means to meet a goal. In the case of EPS goals, managers can increase abnormal accruals, cut discretionary expenditures such as R&D and SG&A, and repurchase shares to meet a goal. Managers can meet their sales goals by increasing SG&A and accounts receivables. Managers can meet profit goals by cutting discretionary expenditures. We compare the level of Accruals, Change R&D/TA, Change SG&A/Sales and Repurchase for firms that exceed the goal by a small margin to the firms that miss the goal by a small margin to test these predictions. These tests help estimate the extent to which our results are due to management of reported performance.

4 Data

Our data come from four sources: Incentive Lab, ExecuComp, the Center for Research in Security Prices (CRSP), and Compustat.

1. Data on the metrics used to design stock and bonus awards are from Incentive Lab (hereafter IL). Similar to S&P (provider of ExecuComp), IL collects grant data from firms’ proxy statements. We obtain details of all the stock, option and cash grants to
all named executives of the 750 largest firms by market capitalization for the years 1998-2012. Since SEC standardized disclosure requirements for grants of plan based awards after 2006, for some of our analysis, we confine the sample to the time period 2006-2012. Since the identity of the set of largest firms changes from year to year, IL backfill and forward fill data to yield a total sample of 1,166 firms for the period 2006-2012. Of these firms, 1,025 tie some of their grants to a performance metric, that is, they award “performance-based grants”. For our analysis, we use information on the performance metrics employed in the grant and the specific threshold, target and maximum performance goals specified in the award.

2. We obtain data on other components of executive pay, such as salary and bonus, from ExecuComp. We carefully hand-match IL and ExecuComp using firm tickers and executive names. Since prior studies on executive compensation predominantly use ExecuComp, we ensure comparability of IL and ExecuComp in terms of the total number of stock and options awarded during the year.

3. We complement the compensation data with stock returns from CRSP and firm and segment financial data from Compustat.

Given our interest in understanding how reported accounting performance is managed to achieve managerial performance goals, except for in Section 5.4, we focus on grants linked to an absolute accounting performance metric that we can match with actual performance as reported in Compustat. This limits the grants to those that are linked to the level or the growth of one of the following metrics: EPS, Earnings, Sales, EBIT, EBITDA, Operating Income and FFO. This results in a final sample of 974 firms and 7,933 executives covered by both IL and ExecuComp for the time period 2006-2012. For most of our analysis, we group the performance metrics into earnings (EPS and earnings), sales (Sales), and profit (EBIT, EBITDA, Operating Income and FFO) based metrics.

Panel A of Table 1 provides the summary characteristics of the grants that we analyze. We have a total of 29,591 grants in our sample. As can be seen, EPS is the most popular metric with around 40% of the grants in our sample (11,691 out of 29,591) linking some of
the payout to an EPS goal. This is followed by sales, with about 30.5% of the grants (9,017 out of 29,591) partly tied to a sales goal. Note that the classification of grants based on the metric employed is not mutually exclusive because a single grant can be (and typically is) tied to multiple metrics. Grants can involve a cash, stock or option payout. In the next three rows, we break up the grants in our sample based on the nature of the payout involved. Cash is by far the most popular payout, with 21,910 of the 29,591 grants involving some cash payout. Stock is the next most popular form of payout, while very few grants involve an option payout. Grants can also involve more than one form of payout and hence, the sum of grants involving cash, stock and option payouts will exceed the total number of grants in our sample.

We classify a grant as *long* if its final vesting occurs 11 or more months after the grant date; 11 months is the median time between grant date and final vesting date for the grants in our sample. About 17.6% of the grants in our sample are classified as long. The fraction of the grants that we classify as long is less than 50% because a large number of grants award their final payout 11 months after the grant date. We find that grants that tie their payout to EPS are more likely to be long term as compared to grants that tie their payout to other metrics. *Interpolated* identifies grants for which the payout varies in a continuous manner with firm performance between the threshold and target performance. That is, for grants with *Interpolated* = 0, the payout discontinuously jumps when the firm performance exceeds the target performance. Since all firms do not disclose whether the payout is interpolated or not, in case of missing information, we assume the grants do not involve interpolation. We find that about 32% of the grants in our sample are *Interpolated*. We classify a grant as being tied to multiple metrics if more than 50% of the grant is tied to more than one metric. We find that about 20% of the grants in our sample are tied to multiple metrics. We find that sales and EBT are more likely to be used in combination with other metrics in designing performance grants.

In the next panel, we provide the summary statistics for the key variables we employ in our analysis. In this panel, we convert our dataset to have one observation per executive-year. To do this, we combine all grants to an executive linked to the same metric (i.e., EPS
for 2006) into one observation. Given our interest in understanding if firms try to exceed performance goals, if more than one grant is tied to the same accounting metric and if the goals mentioned are different, then we pick the goal that is closest to the actual performance. Actual less target EPS is the difference between the reported EPS (from Compustat) and the goal identified as the target EPS in a grant to an executive of the firm. Compustat provides four different EPS estimates for the firm, (epspi, epspx, epsfi, epsfx) that vary based on whether they are fully diluted or not and whether they include extraordinary items or not. Firms do not typically provide information on which EPS the grant is tied to. Hence in constructing Actual less target EPS, we pick the actual EPS that is closest to the target EPS specified in the grant. Note that while this is likely to concentrate the distribution of Actual less target EPS around zero, it is not likely to bias our tests that compare the number of firms that just exceed the goal with the number that just miss the goal. Given our interest in estimating an empirical density of the variable around zero, we truncate Actual less target EPS at the 5th and 95th percentiles.

We find that while the average firm performance is just short of the targeted EPS (mean value of Actual less target EPS is -0.118), the median performance is very close to the targeted EPS (median value of Actual less target EPS is 0). Actual less threshold EPS is the difference between the reported EPS (from Compustat) and the goal identified as the threshold EPS in a grant to an executive of the firm. We construct this in the same manner as we construct Actual less target EPS. We find that actual firm performance is, on average, greater than the threshold performance. Both the mean and median values of Actual less threshold EPS is positive. The Actual less target sales is the difference between the actual sales and sales target mentioned in the pay contract normalized by the book value of total assets. We find that firms, on average, exceed the sales target as seen from the positive mean value of Actual less target sales. Not surprisingly, as compared to the target sales, firms exceed the threshold sales by a larger margin. We have information about threshold performance for fewer grants because not all grants mention a threshold performance. On the other hand, for the purpose of calculating a fair value, all performance-linked grants

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6See Wall Street Journal article from June 26, 2014 entitled “Some Companies Alter the Bonus Playbook” for instances of firms using non-GAAP measures to design executive compensation.
mention a target performance. Finally, we find that the average firm’s reported profits are higher than both the target and threshold profit mentioned in the pay contract, as can be seen from the mean value of Actual less target profit (Actual less threshold profit). We now discuss the empirical tests of our hypothesis.

Table 2 provides summary statistics of the firm level variables used in our analysis. We have a total of 6,846 firm-year observations and our sample is tilted towards the larger firms in Compustat. The average Log(Total assets) of our sample firms is 8.733 and this translates into a mean book value of total assets of about $6.2 Billion. Our sample firms have growth opportunities as seen from the average market to book ratio of 1.812. The average annual stock return of our sample firms is 11.5% while the average volatility is 0.208. The average bid-ask spread of 0.105 also highlights the skew of our sample towards the larger firms in Compustat.

5 Empirical tests

5.1 Fullsample analysis

In panel (a) of Figure (1), we plot the histogram of Actual less target EPS along with a smooth density. The bin width for this histogram is 0.0125, the default suggested by the “DCdensity” procedure in STATA. The histogram is bunched around zero with a larger number of observations to the right of zero as compared to the left. Actual less target EPS appears to be left skewed and because of this, the smooth density estimated by STATA has a mode to the left of zero. In panel (b), we present the results of the test proposed in McCrary (2008) that tests for the presence of a discontinuity in the empirical density at zero. This is the output from the “DCdensity” function in STATA with the default bin width. Panel (b) of Figure 1 plots the empirical density along with the 95% confidence intervals (CIs). Given the small standard errors, the CIs are difficult to visually distinguish from the density plot. From the figure, we find significant evidence for a discontinuity at zero. A disproportionately large number of firms have reported performance that just exceeds the
target performance as compared to the number of firms whose reported performance falls short of the target performance. One of the critical parameters that may affect the test results is the bin width. A small bin width will result in a noisy (and volatile) empirical density and lead to identifying discontinuities where there are none, whereas a large bin width will smooth the density and result in false negatives. We find that the discontinuity at zero for Actual less target EPS is not very sensitive to the bin width. The discontinuity is present and significant when we vary the bin width from 0.01 to 0.05.

We also do a bootstrapping exercise to test if there are more observations to the right of zero as compared to the left of zero. Specifically, we draw a random sample of 50 observations of Actual less target EPS and count the number of observations that lie in the first bin to the right of zero (i.e. between 0 and 0.0125) and the number of observations that lie in the first bin to the left of zero (i.e. between -0.0125 and 0). We repeat this 1,000 times and compare the means. We find that on average, in a sample of 50, there are 1.31 more observations just to the right of zero as compared to the number of observations just to the left of zero. We find this is statistically very significant with a t-value of 22.721.

In panel (c) of Figure 1, we present the result of a test that provides a t-statistic for the presence of a discontinuity in the density at points other than at zero. Specifically, we plot the t-statistic for the test of the difference between the actual number of observations in a bin and the number of observations that is expected based on the empirical density. The tests are similar to the ones in Bollen and Pool (2009). Similar to Bollen and Pool (2009), we pick the bin size for these tests as 0.7764 × 1.364 × min(σ, Q_{1.34} n^{-\frac{1}{2}}) where σ is the empirical standard deviation, Q is the empirical interquartile range and n is the number of observations. This results in a bin size of 0.0537 for Actual less target EPS. The green line plots the t-values and the blue lines identify the cutoff t-values for 99% significance. As we see, there is again a significant discontinuity at zero. The t-values are significantly large (small) to the right (left) of zero. This is consistent with the presence of a disproportionately large (small) number of observations to the right (left) of zero.

Interestingly, the graph in panel (c) also identifies discontinuities at places other than at zero. There are two possible reasons for this. First is the noise in our estimate of Actual
less target EPS. As mentioned before, Compustat provides four different EPS numbers as reported by the firm. Unfortunately, pay contracts do not typically specify the exact EPS the contract is based on. A comparison of the target performance with the wrong EPS (say fully diluted EPS instead of undiluted EPS) is likely to introduce noise in Actual less target EPS. This can result in discontinuities at places other than zero. The second reason is that the pay contract often involves a discontinuous change in managerial payoff at more than one place (see Appendix A). Specifically, the manager’s payoff may jump not only at the target value, but also plateau off when the firm performance exceeds the max value. Our tests in Figure 1 only test for the presence of a discontinuity at the target performance. If firm performance is closer to the max, then the high t-values may capture the clustering of firm performance at the max performance. This is because the manager may have no incentives to report a performance that exceeds the max performance. This is likely to happen at positive values of Actual less target EPS because max values are more than target values. Thus, an issue with the test in panel (b) of Figure 1 is its inability to accommodate and test for discontinuities at more than one place in the density.

In Figure 2, we test for discontinuities at zero for Actual less target sales. Note that we perform our analysis separately for the earnings, sales and profit metrics because their distributions are very different and combining them will make our empirical density noisy. The tests in Figure 2 are similar to the ones in Figure 1. From panel (a), we find that the histogram is clustered around zero, but the distribution is positively skewed with a few large positive values. The bin width for the histogram is 0.0029. From panel (b), we find that there is no significant discontinuity at zero at the 95% CI when we employ the default bin width of 0.0029. Thus there does not appear to be a disproportionately large number of firms that beat sales goals.

Interestingly, when we do the bootstrapping exercise, we do find that there are more observations to the right of zero as compared to the left of zero. Specifically, the difference in the number of observations just to the right and left of zero is .44 and it is statistically significant with a t-value of 4.94. Note that the bootstrapping exercise does not model the entire density and in this sense, is not strictly comparable to the test in Panel B.
The contrasting results from the two tests does indicate the fact that the discontinuity at zero is not very large. Finally, from the last panel we find that while the t-values indicate a significant discontinuity at zero, there are significant discontinuities at points other than zero as well. Here again, we believe that these are partly due to the presence of discontinuities at the max value.

Finally in Figure 3, we test for discontinuities at zero for Actual less target profit. From panel (a), we find that the histogram is clustered around zero, but the distribution is positively skewed with a few large positive values. The bin width for the histogram is 0.0006. From panel (b), we find that there is a significant discontinuity at zero at the 95% CI when we employ the default bin width of 0.0006. We find that the discontinuity is again not dependent on the bin width when we vary the bin width from .0001 to .001. Here again, when we perform the bootstrapping exercise, we find that there are more observations to the right of zero as compared to the left of zero. Specifically, the difference in the number of observations just to the right and left of zero is .115 and it is statistically significant at the 10% level with a t-value of 1.9. Finally, from the last panel we find that while the t-values indicate a significant discontinuity at zero, they also indicate discontinuities at places other than zero.

In unreported tests, we repeat our analysis with Actual less threshold EPS, Actual less threshold sales and Actual less threshold profit and find a statistically significant discontinuity at zero for Actual less threshold EPS and Actual less threshold profit. Thus a disproportionate number of firms have performance just above threshold performance as compared to the number of firms with performance just below the threshold performance.

5.2 Subsample analysis

An important advantage of our empirical setting is that we know the exact amount of pay at stake for a manager when she beats a goal. If the discontinuity at zero documented in Figures 1-3 is because of the manager either altering the reported performance or exerting more effort to exceed the goal and obtain a higher pay, then we expect the discontinuity to
be larger if the pay involved in exceeding the goal is greater. We test this in Figures 4-6. Specifically, we divide our sample into two subsamples based on a proxy for the manager’s incentive to exceed the goal and test for discontinuities within the subsamples. As mentioned before, the methodology in McCrary (2008) does not allow for a statistical comparison of the size of the discontinuities. Hence in this section we use bootstrapping to compare the size of the discontinuities. In the next section, we introduce a regression-based test that allows us to statistically compare the size of the discontinuity.

In Figure 4, we focus on Actual less target EPS, and in panels (a) and (b) we divide our sample into subsamples based on whether the grant involves a single metric or multiple metrics. We expect managers are more likely to alter reported EPS if that is the only metric that affects a majority of the payout from the grant. Thus, we expect the size of discontinuity to be larger in panel (a) as compared to in panel (b). Consistent with this, we find that, visually at least, the size of the discontinuity appears larger in the former subsample. In panels (c) and (d), we focus on Actual less target sales and find that the discontinuity at zero is insignificant both for grants involving a single metric and for grants involving multiple metrics. Finally in panels (e) and (f), we focus on Actual less target profit and find that similar to Actual less target EPS, the discontinuity at zero is larger for firms that award grants that include profit as the only metric. The discontinuity when profit is used along with other metrics is much smaller.

To statistically compare the discontinuities across the subsamples, we perform a bootstrapping exercise. We pool the values of Actual less target EPS, Actual less target sales, and Actual less target profit for all grants in our sample and draw two samples of 100 observations each from grants involving single and multiple metrics respectively. In these samples we count the number of observations that lie just to the right of zero and the number that lies just to the left of zero. In doing this, we take care to use the same bin size as in Figure 4. That is we use different bin sizes for the different metrics and for single and multiple metric based grants. We repeat this 1000 times and compare the difference in the number of observations to the right and left of zero across single versus multiple metric based grants. Consistent with the results in Figure 4, we find that the discontinuity is larger for grants
based on a single metric. On average, there are 1.843 more observations just to the right of zero as compared to the number just to the left of zero for single-metric based grants as compared to for multiple metric based grants. We find this is statistically very significant with a t-value of 20.97.

In Figure 5, we perform cross-sectional tests focusing on whether the grant involves interpolation between the target and threshold values. Grants that do not involve interpolation will involve a discontinuous jump in the payoff at the target value and may provide incentives for the manager to alter firm performance to exceed the target. This in turn would imply that the size of discontinuity should be greater among such grants. Note that in these tests we classify grants with missing information on interpolation as not involving interpolation. In panels (a) and (b) of Figure 5, we divide our sample into grants that involve interpolation and those that do not and test for a discontinuity at zero for Actual less target EPS. We find that the discontinuity at zero appears to be larger among grants that do not involve interpolation. In panels (c) and (d), we repeat our analysis with Actual less target sales and find that there is no discontinuity at zero for either set of grants. Finally in panels (e) and (f), we focus on Actual less target profit and again find that the discontinuity at zero is much larger for grants that do not involve interpolation. Overall the evidence in Figure 5 is consistent with a bigger discontinuity at zero for grants that do not involve interpolation.

Here again we perform a bootstrapping exercise to statistically compare the size of the discontinuity. Our procedure is similar to the one that we perform to compare single versus multiple-metric based grants. Interestingly, when we combine all three metrics, our bootstrapping exercise shows that there is no significant difference in the size of the discontinuity for interpolated and non-interpolated grants. On the other hand, when we perform the bootstrapping exercise on just Actual less target EPS, and Actual less target profit consistent with the evidence in Figure 5 we find that the discontinuity is larger for grants that do not involve interpolation as compared to those that involve interpolation. On average, there are 0.266 more observations just to the right of zero as compared to the number just to the left of zero for non-interpolated grants as compared to for interpolated
grants. We find this is statistically significant with a t-value of 2.9715.

In Figure 6, we divide our sample into short-term and long-term grants and test for a discontinuity at zero in each of the two subsamples. As mentioned before, to the extent it is difficult to anticipate long-term performance as compared to short-term performance, any discontinuity at zero for long-term grants is likely to be due to managers managing ex post accounting performance as opposed to the ex ante goal. On the other hand, the discontinuity at zero for short-term grants can arise both due to setting lower goals and managing ex post accounting values. In panels (a) and (b), we focus on Actual less target EPS and find that the discontinuity at zero is present for both short-term and long-term grants. Recall that we classify all grants with a final payout beyond 11 months after the grant date as long-term. In panels (c) and (d), we focus on Actual less target sales and find that the discontinuity at zero is not present for either short-term or long-term grants. Finally in panels (e) and (f), we focus on Actual less target profit and find that while the discontinuity at zero is present for both long-term and short-term grants, it appears larger for short-term grants. Overall, the evidence in Figure 7 indicates that while the discontinuity is more pronounced for short-term grants especially if they are based on an earnings or profit metric, there is some discontinuity at zero even for long-term grants. The latter evidence is consistent with ex post management of accounting values to meet compensation performance goals.

When we perform the bootstrapping exercise to statistically compare the size of the discontinuities, we find that the discontinuity is present for both short-term and long-term grants. Specifically, for long-term grants we find that there are 1.88 more observations in the bin to the right of zero as compared to the bin immediately to the left of zero while the corresponding number is 1.1 for short-term grants. Thus, interestingly the bootstrapping exercise indicates that the size of discontinuity is actually greater for long-term as compared to for short-term grants.
5.3 Regression analysis

Note that in addition to the bootstrapping exercise, to statistically compare the size of the discontinuities and also to accommodate for discontinuities at multiple points in the density we perform a regression analysis. That is we estimate the following model:

\[
\text{Number of firms} = \alpha + \beta_0 \text{Metric} \times \text{Mid-point} + \beta_1 \text{Metric} \times \text{Mid-point}^2 + \beta_2 \text{Metric} \times \text{Mid-point}^3 \\
+ \beta_3 \text{Metric} \times \text{Mid-point}^4 + \beta_4 \text{Number of goal} + Y
\]  

(1)

where the dependent variable, \textit{Number of firms} is the logarithm of one plus the number of firms whose reported performance falls in a particular bin. That is, for any metric, such as say EPS, we use the bin size as recommended by McCrary (2008) and divide the firms into bins based on reported EPS. In this test, we combine the metrics so \textit{Number of firms} also counts the number of firms whose reported sales falls within a sales-bin and the number of firms whose profit falls within a profit-bin. The bin sizes vary for the different metrics. The number of observations for this test for each year is the sum of the number of bins of EPS, sales and profit. Note that the number of bins each year depends on the bin size (which is the same across years), the maximum and the minimum values of the metric. Our main independent variable is \textit{Number of goals}, which is the logarithm of one plus the number of firms whose target or threshold performance is in a particular bin. If firms manage reported performance so as to exceed a goal, then we expect their reported performance to fall near (within the same bin) as the performance goal. This would imply a positive \( \beta_4 \). We model the expected number of firms in each bin in a flexible manner by including a fourth order polynomial of the mid point of the bin – the first four terms in the above model. Also we allow this model to vary across the earnings, sales and profit metric groups by including an interaction term between \textit{Metric}, a set of dummy variables that identify the metric group and the fourth order polynomial in \textit{Mid-point}. In this specification, we also include year fixed effects to control for time-series effects and cluster the standard errors at the bin level.

Note that the spirit of the test in (1) is similar to the graphical test in that it statistically compares the number of firms whose actual performance falls near the goal to some expected
number. In comparison to the graphical test, the regression analysis has three advantages and two disadvantages. The first advantage is that we can combine all the metrics in the same test. We can account for differences in the distribution of the metrics by including the interaction term between Metric and the fourth order polynomial in Mid-point. The regression also allows us to test for discontinuities at multiple points in the density. We include both the threshold and target goals to construct Number of goals. For example, if a firm has an EPS-based grant with a threshold EPS of 0.9 and a target EPS of 1.1, then Number of goals will increment in both the bins that include 0.9 and 1.1. Thus, $\beta_4$ will capture firms whose managers appear to alter reported performance to exceed either the target or the threshold value. The regression also allows us to perform cross-sectional tests. To test if the discontinuity is greater in cases where the grant only depends on one metric as compared to when the grant depends on multiple metrics, we divide Number of goals into two variables Number of goals - single metric and Number of goals - multiple metrics and repeat our estimation. Number of goals - single metric (Number of goals - multiple metric) counts the number of firms that offer a grant with a single (multiple) metric and whose performance goal falls within a bin. By comparing the size of the coefficient on the two variables, we can compare the marginal incentive for firms to exceed these goals.

The first of two disadvantages of this regression approach is that it will not be able to identify if the firm actually exceeds the goal or falls short of the goal as we only test to see if the actual performance is close to the goal. To overcome this, we rely on our graphical analysis that clearly shows that whenever firm performance is close to a goal, it is more likely to be greater than the goal. The second disadvantage of the approach is that since we only model the total number of firms in a bin as a function of the number of goals in a bin, it does not tell us if the same firm has its performance and goal in the same bin.

In Table 3, we present the results of our analysis. The positive and significant coefficient on Number of goals in column (1) shows that, consistent with the graphical analysis, a disproportionate number of firms have their actual performance close to the performance goal mentioned in the pay contract. The size of the coefficient indicates that the presence of a performance goal within a bin increases the probability of an additional firm having
its reported performance in that bin by 30%. Note that we include all the control variables mentioned in (1), but for brevity we do not report their coefficients. The $R^2$ of 0.66 highlights that the fourth order polynomial does a reasonable job of fitting the empirical density.

In column (2), we repeat our tests after splitting Number of goals into two variables, Number of goals- single metric and Number of goals- multiple metrics, and find that while the coefficient on both the variables is positive and significant, and the one on Number of goals- single metric is observationally smaller than the one on Number of goals- multiple metrics, from the row titled ∆Coefficient we find that this difference is not statistically significant. In column (3) we include two variables, Number of goals- interpolation and Number of goals- non-interpolation, and repeat our tests. Number of goals- interpolation (Number of goals- non-interpolation) counts the number of firms that offer a grant that involves interpolation (no interpolation) between the threshold and target values and whose performance goal falls within a bin. The results in column (3) shows that only the coefficient on Number of goals- non-interpolation is positive and significant. This is consistent with non-interpolated awards providing greater incentives for firms to manage reported performance to exceed performance goals. From the row titled ∆Coefficient we find that the coefficient on Number of goals- non-interpolation is statistically larger than that on Number of goals- interpolation.

Finally in column (4), we compare long-term and short-term goals by including two terms, Number of goals-short term and Number of goals-long term, and surprisingly we find that while the coefficient on Number of goals-long term is positive and significant, the coefficient on Number of goals-short-term is not significant. We also find that the coefficient on the former is statistically larger than that on the latter (row titled ∆Coefficient). Our results are consistent with our bootstrapping exercise but counter to the observational evidence in Figure 6. Since these tests make different assumptions in modelling the density – the validity of each of which is difficult to establish – and in the case of the bootstrapping exercise, only focus on the bins around the goal, we do not pick one result over the other. Overall we interpret the evidence as being consistent with the existence of a discontinuity.
around both short-term and long-term goals, consistent with the presence of performance management.

In additional robustness tests, instead of a fourth-order polynomial in *Mid-point*, we include bin fixed effects and repeat our tests. We find our results are robust to this alternate specification.

### 5.4 Relative performance based awards

In Figure 7 we focus on relative performance based awards to test if firms have a tendency to just meet these targets as compared to just miss them. Not only do these tests inform us about firms’ tendency to beat relative performance goals but also serve as an additional (falsification) test of our hypothesis. If firms beat performance goals by managing reported performance, then that tendency should be less prevalent for grants tied to relative performance as it is difficult to manage the performance of the peer group. To see if this is the case in Figure 7 we compare the relative performance targets to the firm’s actual relative-performance. Relative performance based awards typically specify the target performance in terms of a relative rank or a percentile with respect to the peer group performance. We convert the targets into ranks and compare them to the firm’s actual rank. Panel a of Figure 7 plots the histogram of the difference between the actual rank and the target rank. Since ranks typically take on integer values, the bin size for this histogram is 1 and we confine the histogram to values between -20 and +20. As can be seen, there is no tendency for firms to just beat their performance target. There are more firms that just miss the target as compared to firms that just meet the target. In Panel B we perform the test in McCrary (2008) to test for discontinuity at zero and do not find any statistically significant discontinuity at zero. Here again, the bin size is 1. Thus when performance benchmarks are based on relative performance, firms do not have a tendency to just meet the target. On the other hand our prior evidence indicates that when targets are given in terms of absolute performance, firms do have a greater tendency to just meet the target as compared to just miss it. In conjunction, these two pieces of evidence are consistent with firms managing reported performance to meet the performance targets.
5.5 How do firms exceed performance goals?

In our next set of tests, we compare firms that just exceed a manager’s compensation goal and those that just miss a goal on a number of dimensions to understand how firms exceed performance goals. These tests help us understand the extent to which firms manage accruals and discretionary expenditure to manage reported performance. Depending on the metric involved, managers can employ a variety of means to meet a performance goal. In the case of EPS goals, managers can use abnormal accruals, cut discretionary expenditures such as R&D and SG&A, as well as repurchase shares to meet the goal. Similarly managers can meet their sales goals by increasing SG&A and accounts receivables. In these tests, we compare firms that just exceed their goal, that is, the firms that fall in the first bin above the performance goal (either target or threshold) and the firms that just miss their goal that is, firms whose performance is in the two bins below the performance goal. We include two bins to the left of the performance goal because there are very few firms in the bin just below the performance goal. We separately look at EPS, sales and profit goals because the sample of firms that exceed and miss the goals are different. In Table 4, we compare firms that exceed and those that miss their performance goal. Definitions of all the variables we compare in this table are provided in Appendix B.

In panel (a) we focus on EPS goals. We find that firms that exceed the EPS goal are very similar to firms that miss their EPS goal on most observable characteristics. The two significant differences between the two sets of firms are that firms that exceed their EPS goal repurchase less shares and have smaller changes in R&D expenditure. The first result is rather surprising because if one expects firms to strategically repurchase stock to meet EPS goals then one would expect to find greater share repurchase among firms that just beat their EPS goals. In the second panel, we compare firms that just exceed and just miss their sales goal. Apart from a higher sales growth rate for the former set of firms, we do not find any other significant difference between the two sets of firms. Finally, in the last panel we focus on profit goals and find that firms that exceed their profit goals are larger, have higher ROA, lower sales growth and smaller changes in SG&A as compared to firms that miss their profit goals. The smaller change in SG&A for the firms that just exceed their profit goals
as compared to firms that miss their profit goals is consistent with Roychowdhury (2006b) and Dechow et al. (2003) who find that firms often decrease discretionary spending, in an effort to increase short term earnings. We now present some multivariate evidence.

In Table 5 we perform multivariate tests that compare firms that exceed and miss their performance goals. We do this by estimating variants of the following model:

$$y_i = \alpha + \beta_0 \times \text{Exceed EPS/Sales/Profit} + \beta_1 \times \text{Size} + \beta_2 \times \text{Market to book} + \gamma_j + \epsilon_i$$

where the dependent variable is one of Accruals, Change R&D/TA, Change SG&A/Sales or Repurchase. The main independent variable is one of Exceed EPS, Exceed sales, or Exceed profit. These variables take a value one for firms whose performance is in the bin just above the performance goal, and zero for firms whose performance is in the two bins below the performance goal. In all the regressions, we control for firm size, Size and Market to book. In addition, for the regressions with Accruals as the dependent variable, we also include the standard deviation of sales growth and standard deviation of profitability as additional controls. We suppress their coefficient to conserve space. All the regressions include year and industry fixed effects, the latter at the two digit SIC code level, and the standard errors are clustered at the firm level. Since managers at firms are typically involved in selecting performance goals and may take deliberate actions to meet those goals, firms that meet and miss goals are not likely to be randomly selected. To this extent, our evidence should not be interpreted as being causal in nature. On the other hand, our univariate evidence did not indicate systematic differences between the two sets of firms on observable characteristics.

In panel (a) we focus on firms that exceed EPS goals. From column (1) we find that the coefficient on Exceed EPS is positive and significant. This indicates that firms that exceed EPS goals have higher abnormal accruals as compared to firms that miss EPS goals. We also find that firms that exceed EPS goals have lower R&D expenditure. This is consistent with such firms lowering R&D expenditure more than firms that miss EPS goals. In panel (b), we compare firms that exceed sales goals to firms that just miss sales goal. Interestingly here we find the firms that exceed their performance goals have higher SG&A expenditures.
This is consistent with such firms spending more on sales promotion to increase sales growth to meet their goals. Finally in panel (c), we compare firms that miss profit goals to firms that exceed profit goals and find that the latter set of firms reduce SG&A (column (4)) expense more than firms that just miss their profit goal. In summary, the evidence in Table 9 offers evidence consistent with managers using accruals and discretionary expenses to meet their incentive compensation EPS goals, increasing SG&A to meet sales goals and reducing discretionary expenditure to meet their profit goals.

6 Conclusion

In this paper, we use a comprehensive dataset containing information on the performance goals employed in 29,591 stock and cash grants awarded by 974 firms to 7,933 executives to investigate the extent to which they influence reported financial performance to meet their own compensation-related performance goals. Executives can influence the reported performance either by exerting more effort or by managing reported performance. We identify this effect by testing for discontinuities in reported performance around the goals (McCrary (2008)).

We find evidence consistent with executives managing the reported accounting performance to achieve compensation goals. A disproportionately large number of firms just exceed the goals as compared to the number of firms that just fail to meet the goals. This effect is present for EPS, and profit based goals, and is stronger among executives who receive grants contingent on a single metric as opposed to grants contingent on multiple metrics. This effect is stronger among executives whose grants involve a discontinuous increase in pay around the goal, and is present both for short-term and long-term goals. We do not find a corresponding tendency for firms to beat relative performance goals. Firms that just exceed their EPS goals have higher abnormal accruals and lower R&D expenditure as compared to firms that just miss their EPS goal. Firms that just exceed their sales goals have higher SG&A expenditure while firms that exceed their profit goals have lower SG&A expenses as compared to firms that miss their goals.
In their ongoing effort to achieve an optimal link between pay and performance, firms have increasingly resorted to linking annual bonus grants and long-term stock and option grants to achieving explicit performance goals. Our paper highlights an important cost to awarding such performance-contingent grants. Our results highlight that the discontinuous increase in pay associated with achieving the performance targets may result in incentivizing management to manage the reported performance so that they can maximize their own compensation. We believe that, at a minimum, our results suggest that it is better to include performance provisions in pay contracts in a way that they provide a more continuous link between pay and performance.
Appendix A - Variable Definitions

The variables used in the empirical analysis are defined as follows:

- **Abnormal-1 yr. (Abnormal-3 yr.)** is the abnormal return on the firm’s stock over the next one (three) fiscal year(s). We calculate abnormal return as the difference between realized return and expected return and employ the Fama-French four-factor model to estimate expected returns.

- **Accruals** is signed abnormal accruals. We calculate this measure following the procedure outlined in Jones (1991).

- **Actual less target/threshold EPS** if the difference between actual EPS as reported in Compustat and the target/threshold EPS as identified in the compensation contract.

- **Actual less target/threshold profit** is the difference between the actual profit and the target or threshold profit mentioned in the compensation contract normalized by the book value of total assets.

- **Actual less target/threshold sales** is the difference between the actual sales and the target or threshold sales mentioned in the compensation contract normalized by the book value of total assets.

- **Change R&D** is the percentage change in R&D/Total assets with respect to the previous fiscal year.

- **Change SG&A** is the percentage change in SG&A/Sales with respect to the previous fiscal year.

- **Debt/Total Assets** (or Leverage) is the ratio of the sum of long-term and short-term debt (Compustat items: dltt and dlc) to the book value of total assets.

- **Exceed EPS/sale/profit** take a value one for firms whose performance is in the bin just above the performance goal and zero for firms whose performance is in the two bins below the performance goal.
- *Fraction contingent* is the percentage of grants tied to a particular metric.

- *Ind. adjusted-1 yr (Ind. adjusted-3 yr)* is the industry-adjusted abnormal return on the firm’s stock over the next one (three) fiscal year(s). We calculate industry-adjusted abnormal return as the difference between realized return on the firm’s stock and average return of all firms in the same three-digit SIC code industry.

- *Market to book* is the ratio of market value of total assets to book value of total assets.

- *Number of firms* is one plus the natural logarithm of number of firms whose actual performance (EPS, sales, EBIT, EBITDA, FFO or Operating Income) falls within a bin.

- *Number of goals* is one plus the natural logarithm of number of firms whose compensation contract goals (EPS, sales, EBIT, EBITDA, FFO or Operating Income) fall within a bin.

- *Number of goals - Single metric (Number of goals - Multiple metrics)* is one plus the natural logarithm of number of firms whose compensation contract goals (EPS, sales, EBIT, EBITDA, FFO or Operating Income) that are in grants involving a single (multiple) metric fall within a bin.

- *Number of goals - Interpolated (Number of goals - Not-interpolated)* is one plus the natural logarithm of number of firms whose compensation contract goals (EPS, sales, EBIT, EBITDA, FFO or Operating Income) that are in grants involving interpolation (no interpolation) fall within a bin.

- *Number of goals - Long-term (Number of goals - Short-term)* is one plus the natural logarithm of number of firms whose compensation contract goals (EPS, sales, EBIT, EBITDA, FFO or Operating Income) that are in short-term (long-term) grants fall within a bin.

- *Number of metrics* is the number of different metrics (such as EPS, sales, ROA, etc) that the particular grant is tied to.
• *Option* is a dummy variable that takes a value of one if a grant payout is in the form of stock options and zero otherwise.

• *R&D/Total Assets* is the ratio of research and development expenditure over book value of total assets. We code missing values of research and development expenditure as zero.

• *Repurchase* is the percentage change in shares outstanding with respect to the previous fiscal year.

• *ROA* is return on assets calculated as the ratio of net income to total assets.

• *Sales growth* is the percentage change in revenue with respect to the the previous fiscal year.

• *Spread* is the average daily stock bid-ask spread during the previous year.

• *Stock* is a dummy variable that takes a value of one if a grant payout is in the form of stock and zero otherwise.

• *Stock Return* is the one-year percentage return for the firm’s stock over the previous fiscal year.

• *Tangibility* is the ratio of tangible assets to total assets.

• *Total assets* is the book value of total assets; *Log(Total assets)* (or *Size*) is the natural logarithm of Total assets.

• *Volatility* is the stock return volatility calculated as the annualized volatility of daily stock returns during the previous year.
Appendix B - Examples of performance linked grants

Example - 1 Barnes & Noble in fiscal year 2012

This is a cash award without interpolation. The proxy reads: “Set forth below is a chart showing the payout scale on which the consolidated Adjusted EBITDA portion of incentive compensation was based.”

Table A.1: Barnes and Nobel payout levels

<table>
<thead>
<tr>
<th>Level of Achievement of Consolidated Adjusted EBITDA Target</th>
<th>% of Target Payout</th>
</tr>
</thead>
<tbody>
<tr>
<td>0% - less than 50%</td>
<td>0</td>
</tr>
<tr>
<td>50% - less than 75%</td>
<td>0.25</td>
</tr>
<tr>
<td>75% - less than 100%</td>
<td>0.625</td>
</tr>
<tr>
<td>100% - less than 112.5%</td>
<td>1</td>
</tr>
<tr>
<td>112.5% - less than 125%</td>
<td>1.085</td>
</tr>
<tr>
<td>125% or more</td>
<td>1.17</td>
</tr>
</tbody>
</table>

Subsequently in the proxy statement for fiscal year 2013, the company mentions the actual payout from the award as follows: “For Fiscal 2013, the Company’s actual consolidated Adjusted EBITDA was less than the minimum performance level of 50% of the consolidated Adjusted EBITDA target. Accordingly, actual consolidated Adjusted EBITDA performance resulted in a payout for this portion of the executives’ annual incentive compensation of 0% of target.”

Example - 2 HealthNet in fiscal year 2006

Our next example is a cash/stock award that involves interpolation The proxy reads: “The performance share unit awards were granted pursuant to our 2006 Long-Term Incentive Plan (the “2006 LTIP”). The grants cliff vest as soon as practicable following the third anniversary of the date of grant based on achievement of minimum levels of pre-tax income and pre-tax income margin (pre-tax income as a percent of total revenues). For the Chief Executive Officer, no shares vest upon achievement of the target level of pre-tax income and pre-tax income margin, 100% of the shares vest upon achievement of the median level and 200% of the shares vest upon achievement of the maximum level (with linear interpolations for performance between the target and maximum levels), and for all other named executive officers, 50% of the shares vest upon achievement of the threshold level of pre-tax income and pre-tax income margin, 100% of the shares vest upon achievement of
the target level, 150% of the shares vest upon achievement of the median level and 200% vest upon achievement of the maximum level (with linear interpolations for performance between the threshold and maximum levels). In addition, the Chief Executive Officer’s award can be settled in (i) shares of Common Stock, (ii) a cash payment equal to the fair market value of the shares earned as of the vesting date, or (iii) a combination of stock and cash.”

**Example - 3 Quanta in fiscal year 2012**

This is a cash award that involves interpolation. The proxy reads: “Based upon the sliding performance/payout scale adopted by the Compensation Committee, NEOs could earn cash awards under the annual incentive plan for 2012 as follows (when the attainment of the performance goal falls between the designated percentages in the table below, the cash awards are determined by interpolation).”

<table>
<thead>
<tr>
<th>Percentage of Operating Income Goal Attained</th>
<th>Payout as a Percentage of AIP Target Incentive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than 75%</td>
<td>0</td>
</tr>
<tr>
<td>0.75</td>
<td>0.25</td>
</tr>
<tr>
<td>0.8</td>
<td>0.4</td>
</tr>
<tr>
<td>0.85</td>
<td>0.55</td>
</tr>
<tr>
<td>0.9</td>
<td>0.7</td>
</tr>
<tr>
<td>0.95</td>
<td>0.85</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1.1</td>
<td>1.3</td>
</tr>
<tr>
<td>1.2</td>
<td>1.75</td>
</tr>
<tr>
<td>1.3</td>
<td>1.85</td>
</tr>
<tr>
<td>1.4</td>
<td>1.95</td>
</tr>
<tr>
<td>150% or greater</td>
<td>2</td>
</tr>
</tbody>
</table>

**Example 4 Sunoco in fiscal year 2006**

This is an example of a performance based award with multiple metrics, each with its own weight, threshold, target, and maximum levels. The proxy reads: “Set forth below are the performance elements, and their respective weightings as a percentage of annual incentive compensation, the Committee used to arrive at actual 2006 bonus awards. It is the Committee’s philosophy that annual incentive plan elements should be limited to three or fewer to maximize concentration on those most critical to the success of our business in the forthcoming year. Base earnings per share,
revenue growth and working capital management are all considered to be key performance variables essential to maximizing shareholder value. Base earnings per share are defined as earnings per share excluding the impact of restructuring charges and certain non-recurring, infrequent or unusual items and are used to place primary focus on year over year operating results. Revenue growth excludes revenue from acquisitions completed during the year. We believe that in most years, base earnings per share will be the most critical measure in driving share price and, in turn, shareholder value. Consequently, the Committee felt that a 60% weighting on this element was appropriate. Revenue growth was weighted at 20%. This is an important Company objective, but profitable revenue growth is of greater importance, hence the lower weighting than that for base earnings per share. The Committee added working capital improvement as a performance element in 2006 because it believed there was an opportunity to increase cash flow through reduction in our working capital requirements.”

Table A.3: Sunoco performance elements and weights

<table>
<thead>
<tr>
<th>Incentive Plan Elements</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Earnings per share</td>
<td>0.6</td>
</tr>
<tr>
<td>Revenue growth</td>
<td>0.2</td>
</tr>
<tr>
<td>Working capital improvement</td>
<td>0.2</td>
</tr>
</tbody>
</table>

The proxy then gives the levels required for each metric.

Table A.4: Sunco payout levels

<table>
<thead>
<tr>
<th></th>
<th>Threshold</th>
<th>Target</th>
<th>Maximum</th>
<th>Actual 2006 Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Earnings per Share</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amount</td>
<td>1.89</td>
<td>1.98</td>
<td>2.12</td>
<td>2.13</td>
</tr>
<tr>
<td>Percent of Prior Year</td>
<td>1</td>
<td>1.048</td>
<td>1.122</td>
<td>1.127</td>
</tr>
<tr>
<td>Revenue (Excluding Acquisitions)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amount (millions)</td>
<td>3528.6</td>
<td>3652.1</td>
<td>3705.3</td>
<td>3648.4</td>
</tr>
<tr>
<td>Percent of Prior Year</td>
<td>1</td>
<td>1.035</td>
<td>1.05</td>
<td>1.034</td>
</tr>
<tr>
<td></td>
<td>Working capital - cash gap days</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reduction from Prior Year</td>
<td>0</td>
<td>3.25 days</td>
<td>6.5 days</td>
<td>7.2 days</td>
</tr>
</tbody>
</table>
Table 1: Summary characteristics

This table reports the summary statistics of the key variables used in our analysis. Panel (a) reports the summary characteristics of grants broken down based on the metric employed. Panel (b) reports the summary statistics of the variables that compare actual performance outcomes to corresponding performance goals in the compensation contract. All variables are defined in detail in appendix A. The data covers the period 2006-2012. The compensation data is from Incentive Lab (IL), Compustat, CRSP and ExecuComp.

(a) Summary grant characteristics

<table>
<thead>
<tr>
<th>Variable</th>
<th>EPS</th>
<th>Earnings</th>
<th>Sales</th>
<th>EBIT</th>
<th>EBITDA</th>
<th>EBT</th>
<th>FFO</th>
<th>Operating Income</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of firms</td>
<td>492</td>
<td>291</td>
<td>456</td>
<td>106</td>
<td>224</td>
<td>135</td>
<td>35</td>
<td>399</td>
<td>974</td>
</tr>
<tr>
<td>Number of executives</td>
<td>3,551</td>
<td>1,670</td>
<td>3,153</td>
<td>598</td>
<td>1,415</td>
<td>741</td>
<td>221</td>
<td>2,617</td>
<td>7,933</td>
</tr>
<tr>
<td>Number of grants</td>
<td>11,691</td>
<td>4,275</td>
<td>9,017</td>
<td>1,446</td>
<td>3,762</td>
<td>1,788</td>
<td>725</td>
<td>7,221</td>
<td>29,591</td>
</tr>
</tbody>
</table>

Number of grants that involve

| Cash payout       | 8,165 | 3,374 | 7,012 | 1,210 | 3,059 | 1,462 | 585 | 5,842 | 21,910 |
| Stock payout      | 3,347 | 872   | 1,935 | 202   | 645   | 323   | 139 | 1,368 | 7,343  |
| Option payout     | 179   | 29    | 70    | 34    | 58    | 3     | 1   | 11    | 338    |
| Long-term vesting | .235  | .111  | .140  | .107  | .110  | .099  | .092 | .126  | .176   |
| Interpolation      | .320  | .236  | .331  | .304  | .334  | .335  | .453 | .323  | .317   |
| Multiple           | .199  | .265  | .350  | .172  | .206  | .258  | .126 | .261  | .213   |

(b) performance goals and actual performance

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual less target EPS</td>
<td>10,959</td>
<td>-0.118</td>
<td>0.633</td>
<td>-0.287</td>
<td>0.000</td>
<td>0.150</td>
</tr>
<tr>
<td>Actual less threshold EPS</td>
<td>7,466</td>
<td>0.100</td>
<td>0.690</td>
<td>-0.120</td>
<td>0.100</td>
<td>0.420</td>
</tr>
<tr>
<td>Actual less target sales</td>
<td>6,830</td>
<td>0.034</td>
<td>0.122</td>
<td>-0.019</td>
<td>0.006</td>
<td>0.047</td>
</tr>
<tr>
<td>Actual less threshold sales</td>
<td>4,391</td>
<td>0.085</td>
<td>0.139</td>
<td>0.009</td>
<td>0.047</td>
<td>0.118</td>
</tr>
<tr>
<td>Actual less target profit</td>
<td>9,566</td>
<td>0.007</td>
<td>0.029</td>
<td>-0.008</td>
<td>0.003</td>
<td>0.017</td>
</tr>
<tr>
<td>Actual less threshold profit</td>
<td>6,498</td>
<td>0.017</td>
<td>0.029</td>
<td>-0.001</td>
<td>0.011</td>
<td>0.032</td>
</tr>
</tbody>
</table>
Table 2: **Summary firm characteristics**

Table A.6 reports firm characteristics for our sample. All variables are defined in detail in appendix A. The data covers the period 2006-2012. The compensation data is from Incentive Lab (IL), Compustat, CRSP and ExecuComp.

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Total assets)</td>
<td>6846</td>
<td>8.733</td>
<td>1.517</td>
<td>7.705</td>
<td>8.579</td>
<td>9.655</td>
</tr>
<tr>
<td>Market to book</td>
<td>6844</td>
<td>1.812</td>
<td>1.064</td>
<td>1.127</td>
<td>1.464</td>
<td>2.077</td>
</tr>
<tr>
<td>Stock return</td>
<td>6588</td>
<td>0.115</td>
<td>0.419</td>
<td>-0.124</td>
<td>0.086</td>
<td>0.301</td>
</tr>
<tr>
<td>Volatility</td>
<td>6747</td>
<td>0.208</td>
<td>0.256</td>
<td>0.065</td>
<td>0.12</td>
<td>0.238</td>
</tr>
<tr>
<td>Debt/Total assets</td>
<td>6821</td>
<td>0.248</td>
<td>0.193</td>
<td>0.099</td>
<td>0.223</td>
<td>0.358</td>
</tr>
<tr>
<td>Spread</td>
<td>6846</td>
<td>0.105</td>
<td>0.105</td>
<td>0.046</td>
<td>0.08</td>
<td>0.125</td>
</tr>
</tbody>
</table>
Figure 1: Difference between actual and target EPS

This figure tests for discontinuity in the density of Actual less target EPS. In Figure (a) we present the histogram of Actual less target EPS along with a smooth density. The bin width for this histogram is 0.0118. Figure (b) presents the results of McCrary (2008) test for the presence of a discontinuity in the empirical density at zero. Figure (c) presents the result of a test for the presence of a discontinuity in the density at points other than zero. These tests are similar to those in Bollen and Pool (2009).

(a) Histogram of difference between actual and target EPS

(b) Test of discontinuity at zero

(c) Results of t-test of difference between actual and estimated density
Figure 2: Difference between actual and target sales

This figure tests for discontinuity in the density of Actual less target sales. In Figure (a) we present the histogram of Actual less target sales along with a smooth density. The bin width for this histogram is 0.0028. Figure (b) presents the results of McCrary (2008) test for the presence of a discontinuity in the empirical density at zero. Figure (c) presents the result of a test for the presence of a discontinuity in the density at points other than zero. These tests are similar to those in Bollen and Pool (2009).

(a) Histogram of difference between actual and target sales growth

(b) Test of discontinuity at zero

(c) Results of t-test of difference between actual and estimated density
Figure 3: Difference between actual and target profit

This figure tests for discontinuity in the density of Actual less target profit. In Figure (a) we present the histogram of Actual less target profit along with a smooth density. The bin width for this histogram is 0.0006. Figure (b) presents the results of McCrary (2008) test for the presence of a discontinuity in the empirical density at zero. Figure (c) presents the result of a test for the presence of a discontinuity in the density at points other than zero. These tests are similar to those in Bollen and Pool (2009).

(a) Histogram of difference between actual and target sales growth

(b) Test of discontinuity at zero

(c) Results of t-test of difference between actual and estimated density
Figure 4: Actual performance and targets: Single versus multiple metrics

This figure presents the results of a test for a discontinuity at zero in the density of Actual less target EPS (panels (a-b)), Actual less target sales (panels (c-d)) and Actual less target profit (panels (e-f)). In the left-hand-side panel we focus on grants that involve a single metric while in the right-hand-side panel we focus on grants that involve multiple metrics.

(a) Actual versus target EPS: Single metric
(b) Actual versus target EPS: Multiple metrics
(c) Actual versus target Sales: Single metric
(d) Actual versus target Sales: Multiple metrics
(e) Actual versus target Profit: Single metric
(f) Actual versus target EPS: Short grants
Figure 5: Actual performance and targets: Interpolated versus non-interpolated grants

This figure presents the results of a test for a discontinuity at zero in the density of Actual less target $EPS$ (panels (a-b)), Actual less target sales (panels (c-d)) and Actual less target profit (panels (e-f)). In the left-hand-side panel we focus on grants that involve interpolation between the threshold and target value while in the right-hand-side panel we focus on grants that do not involve interpolation.

(a) Actual versus target EPS: Interpolated grants  (b) Actual versus target EPS: Non-interpolated grants

(c) Actual versus target Sales: Interpolated payoffs  (d) Actual versus target Sales: Non-interpolated payoffs

(e) Actual versus target Profit: Interpolated grants  (f) Actual versus target Profit: Non-interpolated grants
This figure presents the results of a test for a discontinuity at zero in the density of Actual less target EPS (panels (a-b)), Actual less target sales (panels (c-d)) and Actual less target profit (panels (e-f)). In the left-hand-side panel we focus on long-term grants while in the right-hand-side panel we focus on short-term grants. We classify any grant with a final vesting longer than 11 months as long-term.

(a) Actual versus target EPS: Long grants
(b) Actual versus target EPS: Short grants
(c) Actual versus target Sales: Long grants
(d) Actual versus target Sales: Short grants
(e) Actual versus target Profit: Long grants
(f) Actual versus target Profit: Short grants
Figure 7: Difference between actual and target ranks for relative performance grants

This figure tests for discontinuity in the density of Actual less target rank. In Figure (a) we present the histogram of Actual less target rank along with a smooth density. The bin width for this histogram is 1. Figure (b) presents the results of McCrary (2008) test for the presence of a discontinuity in the empirical density at zero. Figure (c) presents the histogram of Actual less threshold rank along with a smooth density. The bin width for this histogram is 1.

(a) Histogram of difference between actual and target rank

(b) Test of discontinuity at zero of the difference between actual and target rank
Table 3: Reported performance and earnings based pay targets

Table 3 reports the results of an OLS regression relating number of firms whose performance (earnings, sales or profit) falls within a bin to the bin mid-pint and the number of firms with a performance goal in the same bin. Standard errors reported in parentheses are robust to heteroskedasticity and are clustered at the bin level. All variables are defined in detail in appendix A. The data covers the period 2006-2012. The compensation data is from Incentive Lab (IL), Compustat, CRSP and ExecuComp. (***) ; (**); (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

<table>
<thead>
<tr>
<th>Number of Firms</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of goals</td>
<td>.299</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.065)***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of goals - Single metric</td>
<td>.173</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.057)***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of goals - Multiple metrics</td>
<td>.305</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.088)***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of goals - Interpolated</td>
<td>.074</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.079)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of goals - Not-interpolated</td>
<td>.303</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.071)***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of goals - Long-term</td>
<td>.531</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.101)***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of goals - Short-term</td>
<td>-.012</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.044)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Const.</td>
<td>2.810</td>
<td>2.830</td>
<td>2.818</td>
<td>2.834</td>
</tr>
<tr>
<td></td>
<td>(.107)***</td>
<td>(.107)***</td>
<td>(.107)***</td>
<td>(.106)***</td>
</tr>
<tr>
<td>Obs.</td>
<td>8970</td>
<td>8970</td>
<td>8970</td>
<td>8970</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.66</td>
<td>.66</td>
<td>.66</td>
<td>.663</td>
</tr>
<tr>
<td>$\Delta$ Coefficient</td>
<td>.132</td>
<td>-.229</td>
<td>.543</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.097)</td>
<td>(.111)***</td>
<td>(.119)***</td>
<td></td>
</tr>
</tbody>
</table>
Table 4: Univariate comparison of firms that exceed and miss performance goals

This table compares the mean values of the key variables across the subsamples of firms that just exceed and just miss their performance goals. Performance metrics investigated are EPS, sales and profit. The data covers the period 2006-2012. The compensation data is from Incentive Lab (IL), Compustat, CRSP and ExecuComp. (***); (**) ; (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

<table>
<thead>
<tr>
<th>Exceed EPS goals</th>
<th>Miss EPS goal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
</tr>
<tr>
<td>Size</td>
<td>231</td>
</tr>
<tr>
<td>ROA</td>
<td>231</td>
</tr>
<tr>
<td>Market to book</td>
<td>231</td>
</tr>
<tr>
<td>Leverage</td>
<td>230</td>
</tr>
<tr>
<td>Sales growth</td>
<td>229</td>
</tr>
<tr>
<td>Accruals</td>
<td>195</td>
</tr>
<tr>
<td>Repurchase</td>
<td>231</td>
</tr>
<tr>
<td>Change R&amp;D</td>
<td>231</td>
</tr>
<tr>
<td>Change SG&amp;A</td>
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<table>
<thead>
<tr>
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<th>Miss sales goal</th>
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<tr>
<td></td>
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</tr>
<tr>
<td>Size</td>
<td>190</td>
</tr>
<tr>
<td>ROA</td>
<td>190</td>
</tr>
<tr>
<td>Market to book</td>
<td>185</td>
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<td>Leverage</td>
<td>187</td>
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<td>Sales growth</td>
<td>190</td>
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<td>Accruals</td>
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<td>190</td>
</tr>
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<td>190</td>
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<td>121</td>
</tr>
<tr>
<td>Change SG&amp;A</td>
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</table>
Table 5: Multivariate difference between firms that exceed and miss performance goals

This table reports the results of multivariate tests that compare firms that exceed and miss their performance goals. The dependent variables are *Accruals, Repurchase, Change in R&D, Change in SG&A*. The main independent variables are *Exceed EPS* (panel (a)), *Exceed sales* (panel (b)), and *Exceed profit* (panel (c)). These variables take a value one for firms whose performance is in the bin just above the performance goal and zero for firms whose performance is in the two bins below the performance goal. Details on the definition of the variables in this table are provided in the Appendix A. Standard errors reported in parentheses are robust to heteroskedasticity and are clustered at the two-digit SIC industry level. The data covers the period 2006-2012. The compensation data is from Incentive Lab (IL), Compustat, CRSP and ExecuComp. (**); (***); (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

(a) Exceed EPS goal and firm performance

<table>
<thead>
<tr>
<th></th>
<th>Accruals</th>
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<th>ΔR&amp;D</th>
<th>ΔSG&amp;A</th>
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</thead>
<tbody>
<tr>
<td>Exceed EPS</td>
<td>.011</td>
<td>-.913</td>
<td>-.1356</td>
<td>.130</td>
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<td>Size</td>
<td>.0009</td>
<td>1.221</td>
<td>-.091</td>
<td>-.926</td>
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<tr>
<td>Market to book</td>
<td>-.0001</td>
<td>7.991</td>
<td>2.801</td>
<td>12.479</td>
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<tr>
<td>Const.</td>
<td>-.002</td>
<td>-15.020</td>
<td>-2.249</td>
<td>1.866</td>
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<tr>
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<td>870</td>
<td>1084</td>
<td>1084</td>
<td>1084</td>
</tr>
<tr>
<td>R²</td>
<td>.153</td>
<td>.194</td>
<td>.078</td>
<td>.237</td>
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</table>

(b) Exceed sales goal and firm performance

<table>
<thead>
<tr>
<th></th>
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<th>Repurchase</th>
<th>ΔR&amp;D</th>
<th>ΔSG&amp;A</th>
</tr>
</thead>
<tbody>
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<td>Exceed sale</td>
<td>-.007</td>
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<td>-.109</td>
<td>-1.011</td>
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<tr>
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<td>870</td>
<td>1084</td>
<td>1084</td>
<td>1084</td>
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<tr>
<td>R²</td>
<td>.15</td>
<td>.195</td>
<td>.079</td>
<td>.239</td>
</tr>
</tbody>
</table>

(c) Exceed profit goal and firm performance

<table>
<thead>
<tr>
<th></th>
<th>Accruals</th>
<th>Repurchase</th>
<th>ΔR&amp;D</th>
<th>ΔSG&amp;A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exceed profit</td>
<td>-.003</td>
<td>-.461</td>
<td>-6.038</td>
<td></td>
</tr>
<tr>
<td>Size</td>
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<td>1.234</td>
<td>-.072</td>
<td>-.924</td>
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<td>1084</td>
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<tr>
<td>R²</td>
<td>.147</td>
<td>.194</td>
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References


