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Informativeness of Peer Performance and Analyst Forecasts in Performance Target Setting*

SUN-MOON JUNG**
Dongguk University
Seoul, Korea

SEWON KWON***
Ewha Womans University
Seoul, Korea

JAE YONG SHIN****
Seoul National University
Seoul, Korea

ABSTRACT

Firms consider external information such as peer performance data and analyst forecasts when setting performance targets because this information provides relevant benchmarks about agents' productivity. Using the EPS targets of S&P 1500 firms from the 2006–2014 period, we examine whether firms' reliance on certain benchmarks depends on the relative informativeness of the external information. We find that firms put greater weight on analyst forecasts than on peer performance information because their profitability is less likely to comove with that of their peer firms.

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** First author. Dongguk University-Seoul. Assistant Professor. Email: sunmoonjung@dongguk.edu

*** Co-author. Ewha Womans University. Assistant Professor. Email: k4js1@ewha.ac.kr

**** Corresponding author. Seoul National University. Professor. Email: jshin@snu.ac.kr

We also find that the use of forecasts increases in settings where analyst forecasts are more informative regarding focal firms' profitability.

Keywords: Performance Target; Target Ratcheting; Relative Target Setting; Analyst Forecasts; Peer Performance;

INTRODUCTION

In budget planning, setting appropriate target levels is critical for both corporate planning and executive motivation. The use of past performance information in future target setting ("target ratcheting") may lead to managerial shirking (or "ratchet effect") because it incentivizes managers to ease future targets by reducing current performance (Leone and Rock 2002). Performance targets should be difficult but attainable, reflecting the intrinsic productivity of managers (Merchant and Manzoni 1988; Aranda, Arellano, and Davila 2014). To mitigate managerial shirking, firms may enter into long-term agreements with managers whereby past performance information is not fully used in target revisions (Indjejikian et al. 2014). Alternatively, firms may rely on external information other than their own past performance data when setting performance targets. For instance, firms may rely on peer firms' performance information because it likely reflects permanent productivity at equilibrium (Aranda, Arellano and Davila 2014; Casas-Arce, Holzhacker, Mahlendorf, and Matějka 2018). Analyst forecasts are another useful benchmarking tool from which firms can deduce forward-looking information about future profitability (Choi, Kim, Kwon and Shin 2021). Since future targets are more closely tied to such external benchmarks, they give managers fewer incentives to intentionally reduce (or underreport) their current performance (Aranda et al. 2014).

Using external information is less costly than relying on contractual commitments because it does not necessarily sacrifice the planning function of performance targets. (For planning purposes, performance targets should approximate agents' intrinsic productivity.) Using the vacation divisions of a travel agency, Aranda et al. (2014) find that divisional performance targets reflect other divisions' previous target information, mitigating the use of the divisions' own past performance data. They argue that comparable divisions provide information that helps distinguish intrinsic productivity from transitory performance. In the same vein, Casas-Arce et al. (2018) use government agency data to show that using peer performance information helps rule out common risk components from past performance. Meanwhile, Choi et al. (2021)'s recent analysis of the EPS targets of S&P1500 firms underscores the usefulness of analyst forecasts as a benchmark for forecasting future profitability.

Our paper extends the literature by examining whether firms adjust the relative weights of different types of external information by accounting for the informational costs of using each information type. While prior studies highlight the benefits and informativeness of external information sources, they pay less attention to the cost side. The availability and degree of informativeness of external benchmarks vary for firms in different circumstances. Using less informative benchmarks in performance target setting incurs nontrivial costs such as inefficient use of resources due to inaccurate corporate planning and failure to motivate executives due to inappropriate performance goal levels. Focusing on twotypes of external benchmarks that public firms frequently use in performance target setting (peer performance data and analyst forecasts), we examine whether firms put greater weight on peer performance (analyst forecasts) in settings where benchmarks are more closely correlated with their future profitability.

Analyst forecasts provide richer information about agent-specific productivity than peer performance. While peer performance data elucidates the common components of agents' productivity (Aranda et al. 2014), its relevance in predicting future earnings is limited when focal firms deviate from their peers. Financial analysts make forecasts based on both macroeconomic factors and theplentiful available firm-specific information such as supply chain management, cost advantage, and pricing power data. Analyst forecasts proxy market expectations about future earnings (O'brien 1988). Both markets and managers regard analyst forecasts as important benchmarks of firm productivity, and managers try to avoid earnings that fall short of analyst forecasts (Cheng and Warfield 2005; Bhojraj et al. 2009). A recent study supports the use of analyst forecasts in EPS performance target setting (Choi et al. 2021).

We expect that firms engaged in target revision put greater weight on analyst forecasts than peer performance in settings where they deviate more from peer firms. Using hand-collected EPS performance target data regarding CEOs' annual bonuses in S&P1500 firms for the 2006–2014 period, we find that the use of analyst forecasts in target revision is more pronounced than the use of peer performance information when the firms and their peers function as strategic substitutes and when they undergo non-recurring events (e.g., write-downs, M&As, acquisition of properties, etc.). Our findings indicate that the boards of directors in firms with unique characteristics rely more on external information with richer firm-specific data.

Next, we examine whether the relative weight placed on analyst forecasts increases in settings where forecasts likely provide more relevant information about future profitability. We focus on analyst forecasts in this section because of the scarcity of previous analyses of the usefulness of analyst forecasts in target setting (Choi et al. 2021) relative to peer information (Aranda et al. 2014; Bol and Lill 2014; Casas-arce et al. 2018). We find that the use of analyst forecasts increases in conjunction with information asymmetry in the stock market (measured by the probability of informed trading), suggesting that boards learn from information intermediaries when (sophisticated) outsiders likely have superior forecasting capabilities. The impacts of analyst forecasts also increase with earnings quality (measured by abnormal accruals) and with CEO tenure, implying that analyst forecasts reveal more about future earnings when analysts can better evaluate firms' and incumbent CEOs' performance.

Our paper contributes to the relative target setting literature by suggesting that firms consider both the benefits and costs of using certain information sources in target setting. Our findings reveal that firms determine the weight of each informational source in target revision in a sophisticated manner; specifically, we find that they put more weight on external information with stronger correlations with managers' intrinsic productivity (Meyer and Vickers 1997). While prior studies of relative target setting (Aranda et al. 2014; Casas-Arce et al. 2018) mainly discuss the benefits of using comparable benchmarks, ours is the first to consider the costs of using external information sources. In examining two main sources of external information (peer performance data and analyst forecasts), we expect peer performance data to provide more useful comparable information (CPI) when firm productivity largely consists of common components. Meanwhile, we expect analyst forecasts to be more beneficial when idiosyncratic components explain larger portions of earnings.

We also add to studies of analyst forecasts and executive compensation. While research shows a positive correlation between the likelihood of meeting analyst earnings and the use of stock option compensation (Bauman and Shaw 2006), the relationships between analyst forecasts and other compensation components remain less well understood. In a recent study, Choi et al. (2021) reveal that analyst forecasts are incorporated into performance target setting. We extend the work of that study, documenting how firms selectively adjust their reliance on analyst forecasts in setting bonus targets, depending on the analysts' forecasting capabilities.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Use of External Information in Performance Target Setting

Setting an accurate performance target is extremely important in corporate planning because too-easy or too-difficult performance targets can induce adverse incentive problems. The appropriate performance target level is close to the agent's intrinsic productivity. While principals rely on multiple information sources when setting performance targets, past performance remains the most widely used source. Assuming that observed performance is highly correlated with managerial ability, past performance provides the most relevant information about future performance as well. Furthermore, past performance information is readily available without further acquisition costs.

However, relying solely on past performance data to set future targets may prove inefficient when past performance is less closely related to the agent's intrinsic productivity. Past performance encompasses permanent and transitory performance, and the transitory component is irrelevant to future performance. Consequently, the principals in such cases benefit from considering additional information sources from comparable units (e.g., peer performance) as well as forward-looking information (e.g., analyst forecasts). Prior empirical studies show that firms rely on peer average targets and peer performance as well as analyst forecasts in revising targets (Aranda, Arellano, and Davila 2014; Bol and Lill 2015; Holzhacker et al. 2019; Cacas-Arce et al. 2018; Choi et al. 2021).

The benefits and costs of using external benchmarks hinge on the nature of existing incentive problems and the benchmarks' correlations with agents' intrinsic abilities (Meyer and Vickers 1997). In the relative performance evaluation problem, the use of external benchmarks filters out common noise, improving evaluation efforts based on observed performance (Jensen and Murphy 1990; Albuquerque 2009; Gong, Li, and Shin 2011). In the dynamic target setting problem, on the other hand, external benchmarks help determine agents' productivity at equilibrium, assuming the benchmarks are closely correlated with the agents' abilities (Aranda et al. 2014).

When peer performance is strongly correlated with an agent's intrinsic ability, the future target approaches the agent's intrinsic efficiency by referencing external benchmarks. The use of a benchmark that is closely correlated with ability thus reduces the ratchet effect. By contrast, the use of a benchmark that is strongly correlated with the noise in an agent's past performance rules out the common noise from past performance, making past performance more informative regarding the agent's abilities. In such cases, the principal ends up putting greater weight on past performance, which leads to increased target ratcheting. Placing greater weight on past performance incentivizes agents to reduce current efforts and thereby minimize reported earnings and avoid higher future targets.

Aranda et al. (2014) suggest that comparable units provide information that helps distinguish transitory earnings from permanent earnings in past performance data. Comparable units such as sales divisions at different locations share common input-output functions and productivity. The average performance of comparable units reveals focal agents' productivity at equilibrium. Performance variances exceeding or falling short of the average peer performance, on the other hand, are considered transitory. Incorporating the average peer performance into target revision reduces firms' reliance on agents' past performance in the target revision process, mitigating the potential effect of target ratcheting. Hence, in the ratcheting model, the degree of peer information in target revision manifests in an attenuated target ratcheting coefficient. The fact that future targets are less closely linked to current performance in such cases makes agents less likely to reduce their current efforts.

Placing appropriate weight on each information source and considering their relative informativeness is critical. Relying too much on less informative benchmarks when setting performance targets is very costly because it undermines the efficient use of corporate resources as well as limiting the motivation effect of target-based executive bonuses. For instance, putting too much weight on peer performance when a peer firms' profitability largely deviates from that of the focal firm makes it less likely that the future target actually approximates the focal firm's permanentproductivity. Excessively high (low) performance target levels relativeto permanent productivity result in too much (little) resource allocation to firms and are ineffective in motivating CEOs.

Relative Informativeness of Peer Performance Data and Analyst Forecasts

Analyst forecasts reflect rational expectations regarding future earnings based on sophisticated business analyses (O'brien 1988). Both markets and managers perceive analyst forecasts as an important performance benchmark, and a recent study supports the use of analyst forecasts in performance target setting (Choiet al. 2021). Many analysts incorporate top-down factors such as economic growth rates, currencies, and other macroeconomic factors that influence corporate growth. They use market research reports to understand firms' growth potential and speak to customers, suppliers, and competitors to develop better forecasts. Analysts also estimate sales volume growth and product prices as well as expected changes in production costs.

While peer performance information only captures common shocks, analyst forecasts capture both the common and idiosyncratic components of firm productivity. When a firm's business model deviates from those of peer firms in the same industry, referencing peer performance data does not significantly improve target setting. On the other hand, analyst forecasts regarding EPS performance incorporate all available up-to-date information about firms' future earnings. Hence, analyst forecasts reveal more about firms' productivity than peer performance information when firms' total productivity consists more of idiosyncratic than common components.

When firms and their peers are strategic substitutes (e.g., Cournot competition), the firms' sales change in the opposite direction of those of their peers, indicating that peer performance does not effectively explain focal firms' performance at equilibrium. Under Cournot-type competition, analyst forecasts more clearly distinguish permanent performance from transitory performance because they contain more firm-specific information than peer performance data. The fact that focal firms' performance moves in different directions than the performance of their peers (under Cournot- type competition) makes it unclear whether instances of actual performance exceeding peer performance are purely transitory or not. Instances of actual performance exceeding the forecasted EPS, on the other hand, are highly likely to be transitory. Hence, we expect that firms under Cournot-type competition rely more on analyst forecasts than peer performance when revising performance targets.

When firms and peers are strategic complements (e.g., Bertrand competition), peer performance is highly correlated with focal firms' performance. The fact that focal firms' performance moves in same direction as the performance of their peers (under Bertrand-type competition) means that instances of actual performance exceeding peer performance are likely to be purely transitory. Hence, we expect that firms under Bertrand-type competition put more weight on peer performance data than analyst forecasts. In the ratcheting model, firms' greater (lower) reliance on analyst forecasts (peer performance data) will manifest in the attenuated use of their past performance because analyst forecasts estimate increases (as peer performance increases). More specifically, firms determine the relative weight of each source of information (e.g., past performance data, peer performance data, analyst forecasts), and relatively greater reliance on external information attenuates the use of past performance data in target revision.

> **H1a:** The impact of relying on analyst forecasts over peer performance data in performance target ratcheting is more salient under Cournot-type competition.

When firms undergo special events such as write-downs or business restructuring, their production functions likely deviate from those of industry peers. For firms experiencing nonrecurring events, analyst forecasts based on richer sets of firm-specific information are more informative than peer performance data. Because focal firms' performance moves in different directions than the performance of their peers, analyst forecasts (rather than peer performance) provide more accurate benchmarks for distinguishing between permanent and transitory earnings. Hence, we expectthat firms will put greater weight on analyst forecasts than peer performance data when revising targets, which will result in attenuated ratcheting coefficients on their own past performance as forecasted EPS increases.

> **H1b:** The impact of relying on analyst forecasts over peer performance data in performance target ratcheting is more salient for firms that have experienced non-recurring events during the period under analysis.

Precision of Analyst Forecasts

Because financial analysts rely on various types of information including both firm-specific and macroeconomic information, their forecasting capabilities hinge on the informational environments in which they operate. In our second set of hypotheses, we further examine the settings in which analyst forecasts shed greater light on firms' future productivity. Our discussion highlights the informativeness of an important (but less explored) benchmark in the literature, analyst forecasts (Choi et al. 2021). Because the EPS target for CEO bonus purposes differs from reported EPS (which follows GAAP), we do not directly examine whether reliance on analyst forecasts increases with forecast accuracy (defined as reported EPS – forecasted EPS).

Since analysts evaluate operating performance based on financial disclosures, poor financial reporting quality undermines forecasting capabilities. Relatedly, greater earnings quality and accounting consistency are associated with more accurate analyst forecasts (Salerno 2014; Peterson, Schmardebeck, and Wilks 2015). Hence, we expect that the use of analyst forecasts in target revision will decrease in firms with lower earnings quality. The attenuation of the target ratcheting coefficient (driven by increases in forecasted EPS) will be more salient in the subsample of firms with higher earnings quality.

H2a: The impact of analyst forecasts in performance target ratcheting is more salient for firms with higher earnings quality.

Second, financial analysts with private information provide incrementally useful information (Barron et al. 1998; Botosan and Stanford 2005; Chen and Jiang 2006). Prior studies suggest that what firms “learn” from the stock market and private information regarding prices influences corporate investment decisions (Chen, Goldstein, and Jiang 2007). Moreover, when setting performance targets, boards of directors can learn from analysts who have private information that is not available to firms. Such private information may shed light on the secret projects of competing firms, reveal yet-to-be disclosed tax benefits for certain industries, etc. While boards of directors have superior internal information, analysts arebetter positioned to obtain external information in a timely manner, because analysts have networks with multiple firms. The probability of informed trading serves as a proxy for the relative informational advantage of sophisticated investors, including financial analysts (Brown and Hillegeist 2007). We expect that firms will rely more on analyst forecasts in target setting as information asymmetry in the market increases. The attenuation of the target ratcheting coefficient (driven by the increase in the forecasted EPS) will be more salient in the subsample of firms with a higher probability of engaging informed trading.

H2b: The impact of analyst forecasts in performance target ratcheting is more salient for firms that are more likely to engage in informed trading.

Lastly, analyst forecasts can better evaluate the future earnings of CEOs with longer tenures. Analyst forecast accuracy increases in conjunction with analysts’ firm-specific experience (Clement 1999; Mikhail, Warther, and Willis 1997). The marginal cost of generating accurate forecasts decreases as cumulative experience with a task increases (Mikhail, Warther, and Willis 1997). As long as forecast accuracy increases with analysts’ experience following specific combinations of CEOs and firms, we expect that boards willmake greater use of analyst forecasts in target setting. Althoughthe boards’ internal information improves with CEO tenure, analysts’ abilities to combine firm-executive-specific knowledge with macroeconomic information also grows more robust with CEO tenure, which in turn increases firms' reliance on analyst forecasts.

> **H2c:** The impact of analyst forecasts in performance target ratcheting is more salient as CEO tenure increases.

METHODS

Sample Selection and Data Sources

To examine our hypotheses, we use hand-collected data regarding S&P1500 firms from the 2006–2014 period. Our data encompasses the EPS performance target for CEO annual bonuses as well as firms' actual EPS. We obtain financial statement, stock return, andCEO characteristics data from Compustat, CRSP, and Execucomp, respectively. We begin with 2,554 firm-year observations with EPS performance target information from 2006–2014. We exclude observations with missing data regarding EPS actual performance, analyst forecasts, and peer firms' EPS; this reduces our sample to 1,952 observations. We also exclude observations that lack upcoming year performance target information, because our model requires target revisions over two consecutive years. In addition, we exclude observations missing control variable data. This leaves us with 1,653 firm-year observations for our relative target ratcheting model estimations. To examine the hypotheses, we use observations with cross-sectional variable data. The samples for hypotheses1a and 1b are 1,611 and 1,635, respectively. The samples for hypotheses 2a, 2b, and 2c are 1,556, 622, and 1,425, respectively. Table 1 shows the sample selection procedure.

Table 1. Sample Selection

Sample selection	Number of Observations
S&P 1500 firm-years that provide EPS performance targets for executive annual bonus contracts for the 2006–2014 period:	2,554
Less firm years that lack EPS actual performance information for executive bonus contracts:	(483)

Sample selection	Number of Observations
Sample firm years that have EPS targets and actual EPS performance information:	2,071
Less firm years that lack analyst forecast information or lack peer performance data:	(119)
Sample firm years that have EPS target information and analyst forecast information:	1,952
Less firm years that lack 2 consecutive years of data on EPS targets:	(264)
Sample firm years that have EPS target information, analyst forecast information, and 2 consecutive years of data on targets	1,688
Less firm years that lack data on control variables:	(53)
Final Sample (table 4)	1,635
Sample with the correlation (with peers) of sales change during the past 5 years (table 5)	1,611
Sample with information regarding gains/losses from write-downs and restructuring (table 6)	1,635
Sample with abnormal accruals information (table 7)	1,556
Sample with PIN information (table 8)	622
Sample with CEO tenure information (table 9)	1,425

Empirical Model and Variable Measurement

Because our hypotheses concern the attenuation of reliance on past performance as firms' reliance on external information increases, we utilize the baseline model for relative target ratcheting, following prior studies (Aranda, Arellano, and Davila 2014; Kim and Shin 2017; Choi et al. 2021):

$$\begin{aligned}
\textit{Target Revision}_{i,t+1} = {} & \beta_0 + \beta_1 \textit{Target Deviation}_{i,t} + \beta_2 \textit{Target Deviation}_{i,t} {*} \textit{D_Neg}_{i,t} \\
& + \beta_3 \textit{Target Deviation}_{i,t} {*} \textit{Relative to Forecasts}_{i,t} + \beta_4 \textit{Target Deviation}_{i,t} {*} \\
& \quad \textit{Relative to Peers}_{i,t} \\
& + \beta_5 \textit{Target Deviation}_{i,t} {*} \textit{D_Neg}_{i,t} {*} \textit{Relative to Forecasts}_{i,t} \\
& + \beta_6 \textit{Target Deviation}_{i,t} {*} \textit{D_Neg}_{i,t} {*} \textit{Relative to Peers}_{i,t} \\
& + \beta_7 \textit{D_Neg}_{i,t} {*} \textit{Relative to Forecasts}_{i,t} + \beta_8 \textit{D_Neg}_{i,t} {*} \textit{Relative to Peers}_{i,t} \\
& + \beta_9 \textit{Relative to Forecasts}_{i,t} + \beta_{10} \textit{Relative to Peers}_{i,t} + \beta_{11} \textit{D_Neg}_{i,t}
\end{aligned}$$

$+ \beta_{12} LogAT_{i,t} + \beta_{13} Predicted\ EPS\ Growth_{i,t} + \beta_{14} Returns_{i,t}$
$+ \ Year\ Fixed\ Effects + Industry\ Fixed\ Effects + e_{i,t}$ (1)

The dependent variable, $Target\ Revision_{i,t}$ is defined as $(Target_{i,t+1} - Target_{i,t})/Target_{i,t}$, and measures the percentage revision of the EPS performance target over the year. $Target\ Deviation_{i,t}$ is defined as $(Actual_{i,t} - Target_{i,t})/Target_{i,t}$ and captures the performance variance relative to the target in year t. Based on prior studiesthat document target ratcheting and asymmetric ratcheting (Kim and Shin 2017), we expect that β_1 will be positive and β_2 will be negative. $Relative\ to\ Forecasts_{i,t}$ ($Relative\ to\ Peers_{i,t}$) is defined as $Actual_{i,t} - Forecast\ Consensus_{i,t}$ ($Actual_{i,t} - Average\ Peer\ EPS_{i,t}$). *Relative to Forecast* (*Relative to Peers*) measures the extent to whicha firm's EPS performance is likely to be abnormal relative to analystforecasts (average peer performance). We expect that β_3 and β_5 will be negative, because the use of CPI will attenuate reliance on past performance information. In our model, we further control for firm size ($LogAT_{i,t}$), predicted EPS growth ($Predicted\ EPS\ Growth_{i,t}$), stock returns ($Returns_{i,t}$), and year and industry fixed effects.

To examine our hypotheses, we run equation (1) with subsamples. To test hypothesis 1a, we divide our sample into Cournot versus Bertrand competition, using sales growth's correlation with industry peers ($Corr(\Delta Sales_{i,t}, \Delta Peer\ Sales_{i,t})$). We consider a firm as facing Cournot (Bertrand) competition if its sales change is positively (negatively) correlated with other firms in the same industry during the past 5 years. Hypothesis 1a posits that the use of analyst forecasts (β_3) in target revision is more pronounced than the use of peer performance data (β_4) under Cournot competition, while the use of peer performance data (β_4) is more pronounced than the use of analyst forecasts (β_3) under Bertrand competition.

To test hypothesis 1b, we divide firms experiencing non-recurring events such as write-downs or business restructuring from those not undergoing such events. Hypothesis 1b posits that the use of analyst forecasts (β_3) in target revision will be more pronounced than the use of peer performance data (β_4) for firms experiencing extraordinary events, while the use of peer performance data (β_4) will be more pronounced for firms in ordinary situations.

Next, we examine the second set of hypotheses. Hypothesis 2a posits that the use of analyst forecasts will be more pronounced for firms with higher earnings quality because higher quality accounting information increases forecast accuracy will increase. We expect that the coefficient magnitude of β_3 will greater for the subsample with low abnormal accruals than for the subsample with high abnormal accruals.

Meanwhile, hypothesis 2b posits that analyst forecasts are incrementally more informative when there is more private information in the stock market. Hence, we expect that β_3 will be higher among firms that with a higher probability of informed trading (PIN) than those with lower PIN. Finally, based on hypothesis 2c, we expect that β_3 will be higher for CEOs with longer tenure. The appendix presents the variable definitions.

Descriptive Statistics and Pearson Correlation Coefficients

Table 2 presents the descriptive statistics for the variables. Firms increase their EPS performance targets by $0.18 on average ($Target_{i,t+1} - Target_{i,t}$). In terms of percentage, EPS targets increase by 10% every year on average ($Target\ Revision_{i,t}$). Firms beat their EPS targets by $0.03 ($Actual_{i,t} - Target_{i,t}$) and 1% in percentage terms ($Target\ Deviation_{i,t}$). Firms beat analyst forecasts ($Relative\ to\ Forecasts_{i,t}$) and peer average EPS ($Relative\ to\ Peers_{i,t}$) by $0.04 and

Table 2. Sample Selection

Variables	N	Mean	p25	Median	p75	Min	Max	Std
$Target_{i,t+1} - Target_{i,t}$	1635	0.18	-0.05	0.19	0.47	-2.42	2.31	0.69
$Target\ Revision_{i,t}$	1635	0.10	-0.03	0.09	0.21	-0.90	1.58	0.34
$Actual_{i,t} - Target_{i,t}$	1635	0.03	-0.09	0.06	0.22	-2.50	2.03	0.59
$Target\ Deviation_{i,t}$	1635	0.01	-0.05	0.03	0.11	-1.89	1.24	0.33
$D\_Neg_{i,t}$	1635	0.35	0.00	0.00	1.00	0.00	1.00	0.48
$Relative\ to\ Forecasts_{i,t}$	1635	0.04	-0.02	0.03	0.10	-1.73	1.66	0.40
$Relative\ to\ Peers_{i,t}$	1635	0.72	-0.27	0.58	1.59	-5.20	6.49	1.79
$LogAT_{i,t}$	1635	8.39	7.22	8.34	9.40	5.34	12.36	1.53
$Predicted\ EPS_{i,t}\ Growth_{i,t}$	1635	0.08	-0.37	0.12	0.55	-3.02	3.01	0.99
$Returns_{i,t}$	1635	0.15	-0.07	0.13	0.32	-0.67	1.46	0.37
$Corr(\Delta Sales_{i,t}, \Delta Peer\ Sales_{i,t})$	1611	-0.03	-0.42	-0.04	0.36	-1.00	1.00	0.50
Event	1635	0.48	0.00	0.00	1.00	0.00	1.00	0.50
Abnormal Accruals	1556	-0.01	-0.03	-0.00	0.02	-0.47	0.26	0.05
PIN	622	0.09	0.07	0.08	0.10	0.00	0.24	0.03
Tenure	1425	7.82	3.00	6.00	10.00	0.00	32.00	6.46

Table 3. Pearson Correlation Matrix

	Target Revision$_{i,t}$	*Target Deviation$_{i,t}$*	*Relative to Forecasts$_{i,t}$*	*Relative to Peers$_{i,t}$*	*D_Neg$_{i,t}$*	*Predicted EPS Growth$_{i,t}$*
Target Deviation$_{i,t}$	0.64					
	<.0001					
Relative to Forecasts$_{i,t}$	0.13	0.43				
	<.0001	<.0001				
Relative to Peers$_{i,t}$	0.00	0.25	0.34			
	0.86	<.0001	<.0001			
D_Neg$_{i,t}$	-0.44	-0.55	-0.24	-0.13		
	<.0001	<.0001	<.0001	<.0001		
Predicted EPS Growth$_{i,t}$	0.04	-0.05	-0.03	-0.02	-0.03	
	0.13	0.04	0.23	0.52	0.22	
Return$_{i,t}$	0.30	0.15	0.11	-0.03	-0.20	0.25
	<.0001	<.0001	<.0001	0.19	<.0001	<.0001

$0.72, respectively. On average, 35% of the sample firms fail to meet their EPS targets (*D_Neg$_{i,t}$*). Firms' sales growth correlation with peers (*Corr(ΔSales$_{i,t}$, ΔPeer Sales$_{i,t}$)* is -0.03 on average. Extraordinary gains/losses (*Event*) are incurred for 48% of our sample observations. The average abnormal accrual is -0.01 (*Abnormal Accruals*). The average probability of informed trading (*PIN*) is 0.09. The average CEO tenure is 7.82 (*Tenure*).

Table 3 presents the Pearson correlation coefficients among the main variables. *Target Revision$_{i,t}$* is positively associated with *Target Deviation$_{i,t}$*, *Relative to Forecasts$_{i,t}$*, suggesting that higher performance relative to performance targets and analyst forecasts leads to higher future performance targets.

RESULTS

Table 4 presents the equation (1) OLS estimation results for the full sample. Consistent with the prior studies (Kim and Shin 2017), we find evidence of target ratcheting and asymmetric ratcheting, as the positive coefficient on *Target Deviation$_{i,t}$* (β_1 = 1.2018, p < 0.01) and the negative coefficient on *Target Deviation$_{i,t}$*D_Neg$_{i,t}$* (β_2 = -0.7135, p < 0.01) indicate. In addition, we confirm the use of analyst forecast information (β_3 = -0.3802, p < 0.01) as well as peer

Table 4. OLS Regression Estimation Results – Effect of Peer Performance and Analyst Forecasts on Target Ratcheting (Full Sample)

Independent Variables	Pred.	Dep Var: *Target Revision*$_{i,t+1}$
Constant		**0.1062***
		(1.76)
Target Deviation$_{i,t}$	+	**1.2018*** **
		(24.40)
Target Deviation$_{i,t}$ * *D_Neg*$_{i,t}$	-	**-0.7135*** **
		(-10.21)
Target Deviation$_{i,t}$ * *Relative to Forecasts*$_{i,t}$	-	**-0.3802*** **
		(-3.79)
Target Deviation$_{i,t}$ * *Relative to Peers*$_{i,t}$	-	**-0.0851*** **
		(-3.93)
Target Deviation$_{i,t}$ * *D_Neg*$_{i,t}$* *Relative to Forecasts*$_{i,t}$	+	**0.4944*** **
		(3.66)
Target Deviation$_{i,t}$ * *D_Neg*$_{i,t}$* *Relative to Peers*$_{i,t}$	+	**0.1012*** **
		(3.34)
D_Neg$_{i,t}$* *Relative to Forecasts*$_{i,t}$	?	0.0607
		(1.03)
D_Neg$_{i,t}$* *Relative to Peers*$_{i,t}$	?	**-0.0178** **
		(-2.16)
Relative to Forecasts$_{i,t}$	-	-0.0609
		(-1.27)
Relative to Peers$_{i,t}$	-	-0.0016
		(-0.31)
D_Neg$_{i,t}$	-	-0.0218
		(-1.29)
LogAT$_{i,t}$	?	-0.0017
		(-0.33)
Predicted EPS Growth$_{i,t}$	+	0.0091
		(1.47)
Return$_{i,t}$	+	**0.1946*** **
		(6.70)
Fixed Effects		Year, Industry
Standard Errors Clustered		by Firm
Observations		1,635
Adj. R-squared		0.6024

*, **, *** indicate significance at the 10, 5, and 1 percents levels, respectively, using two-tailed tests. Reported t-statistics and z-statistics are based on heteroscedasticity-robust standard errors clustered by firm in parentheses. See the appendix for variable definitions.

performance information (β_4 = -0.0851, p < 0.01) (Aranda et al. 2014; Choi et al. 2021). Both forms of CPI attenuate the use of past performance information, negatively moderating the relationship between *Target Deviationi,t* and *Target Revisioni,t*. Stock returns are positively correlated with target revisions, suggesting that investors predict the growth in EPS performance.

Relative Informativeness of Analyst Forecasts and Peer Performance

Table 5 presents the subsample results, with firms under Cournot competition in column (1) and those under Bertrand competition in column (2). Consistent with hypothesis 1a, we find that the use of peer performance data is more pronounced for firms facing Bertrand-type competition (insignificant β_4 in column (1); β_4 = -0.1101, p < 0.01 in column (2)). This suggests that, under Bertrand type competition where firms' sales change in the same direction as the sales of their peers, peer performance information is more informative in predicting intrinsic probabilities. Under Cournottype competition, on the other hand, firms' sales change in the opposite direction of their peers' sales. Thus, peer information is less informative regarding focal firms' productivity than under Bertrand competition. Meanwhile, analyst forecasts, which contain morefirm-specific information, are relatively more informative regarding firm productivity. Consistent with this prediction, we find that the use of analyst forecasts is more pronounced than the use of peer information for firms under Cournot competition (β_3 = -0.6139, p < 0.01 and β_4 insignificant in column (1)). Collectively, the results in table 4 support hypothesis 1a.

Table 6 presents the subsample results for firms with and without nonrecurring events (e.g., write downs and restructuring). As column *(1)* shows, firms that undergo nonrecurring events make greater use of analyst forecast information than peer performance information, as evidenced by the significant coefficient on *Target Deviation*$_{i,t}$ * *Relative to Forecasts*$_{i,t}$ (β_3 = -0.4348, p < 0.01) and insignificant coefficient on *Target Deviation*$_{i,t}$ * *Relative to Peers*$_{i,t}$. This supports the idea that peer performance is less relevant about focal firms' productivity when said firms undergo organizational changes. On the other hand, as column (2) shows, for firms that do not undergo extraordinary events, both analyst forecasts and peer performance data significantly affect target ratcheting (β_3 = -0.3100, p < 0.05; β_4

Table 5. OLS Regression Estimation Results– Competition Type, and Relative Weight on Peer Performance and Analyst Forecasts

		Dep Var: *Target Revision$_{i,t+1}$*	
Independent Variables	Pred.	Cournot (Strategic Substitute)	Bertrand (Strategic Complement)
Constant		0.0574	**0.1829****
		(0.56)	(2.19)
Target Deviation$_{i,t}$	+	1.1299***	1.1918***
		(16.88)	(15.39)
*Target Deviation$_{i,t}$ * D_Neg$_{i,t}$*	-	-0.8292***	-0.6550***
		(-9.52)	(-4.41)
*Target Deviation$_{i,t}$ * Relative to Forecasts$_{i,t}$*	-	**-0.6139*****	-0.1727
		(-3.72)	(-1.25)
*Target Deviation$_{i,t}$ * Relative to Peers$_{i,t}$*	-	-0.0185	**-0.1101*****
		(-0.44)	(-3.92)
*Target Deviation$_{i,t}$ * D_Neg$_{i,t}$* Relative to Forecasts$_{i,t}$*	+	**0.7310*****	0.1891
		(3.41)	(1.20)
*Target Deviation$_{i,t}$ * D_Neg$_{i,t}$* Relative to Peers$_{i,t}$*	+	0.0192	**0.1208*****
		(0.39)	(2.74)
D_Neg$_{i,t}$ Relative to Forecasts$_{i,t}$*	?	0.1128	0.0359
		(1.13)	(0.42)
D_Neg$_{i,t}$ Relative to Peers$_{i,t}$*	?	-0.0117	-0.0187
		(-0.99)	(-1.52)
Relative to Forecasts$_{i,t}$	-	-0.0597	-0.0627
		(-0.96)	(-0.84)
Relative to Peers$_{i,t}$	-	-0.0030	-0.0034
		(-0.36)	(-0.48)
D_Neg$_{i,t}$	-	**-0.0666*****	0.0008
		(-2.86)	(0.03)
LogAT$_{i,t}$	?	0.0049	-0.0097
		(0.56)	(-1.33)
Predicted EPS Growth$_{i,t}$	+	**0.0176***	0.0099
		(1.82)	(1.06)
Return$_{i,t}$	+	0.1735***	0.2141***
		(4.46)	(4.95)
Fixed Effects		Year, Industry	Year, Industry
Standard Errors Clustered		By Firm	By Firm
Observations		861	750
Adj. R-squared		0.5885	0.6262

*, **, *** indicate significance at the 10, 5, and 1 percents levels, respectively, using two-tailed tests. Reported t-statistics and z-statistics are based on heteroscedasticity-robust standard errors clustered by firm in parentheses. See the appendix for variable definitions.

TABLE 6. OLS Regression Estimation Results – Nonrecurring Events and Relative Weight on Peer Performance and Analyst Forecasts

		Dep Var: *Target Revision$_{i,t+1}$*	
Independent Variables	Pred.	Events	No Events
Constant		0.1458	-0.2192
		(1.51)	(-2.52)
Target Deviation$_{i,t}$	+	1.1164***	1.1923***
		(17.34)	(16.06)
*Target Deviation$_{i,t}$ * D_Neg$_{i,t}$*	-	-0.7623***	-0.5943***
		(-8.78)	(-4.54)
*Target Deviation$_{i,t}$ * Relative to Forecasts$_{i,t}$*	-	-0.4348**	-0.3100**
		(-2.11)	(-2.08)
*Target Deviation$_{i,t}$ * Relative to Peers$_{i,t}$*	-	-0.0708	**-0.0720*** **
		(-1.34)	(-3.19)
*Target Deviation$_{i,t}$ * D_Neg$_{i,t}$* Relative to Forecasts$_{i,t}$*	+	0.5568**	0.4178**
		(2.48)	(2.38)
*Target Deviation$_{i,t}$ * D_Neg$_{i,t}$* Relative to Peers$_{i,t}$*	+	0.0907	**0.0751** **
		(1.48)	(2.21)
D_Neg$_{i,t}$ Relative to Forecasts$_{i,t}$*	?	0.1128	0.0011
		(1.29)	(0.01)
D_Neg$_{i,t}$ Relative to Peers$_{i,t}$*	?	-0.0157	**-0.0206** **
		(-1.13)	(-1.98)
Relative to Forecasts$_{i,t}$	-	-0.0551	-0.0635
		(-0.77)	(-1.10)
Relative to Peers$_{i,t}$	-	0.0001	-0.0043
		(0.01)	(-0.64)
D_Neg$_{i,t}$	-	-0.0350	-0.0200
		(-1.45)	(-0.97)
LogAT$_{i,t}$	?	-0.0011	0.0011
		(-0.14)	(0.14)
Predicted EPS Growth$_{i,t}$	+	0.0104	0.0106
		(0.96)	(1.36)
Return$_{i,t}$	+	0.2372***	0.1728***
		(5.11)	(5.12)
Fixed Effects		Year, Industry	Year, Industry
Standard Errors Clustered		By Firm	By Firm
Observations		789	846
Adj. R-squared		0.5557	0.6560

*, **, *** indicate significance at the 10, 5, and 1 percents levels, respectively, using two-tailed tests. Reported t-statistics and z-statistics are based on heteroscedasticity-robust standard errors clustered by firm in parentheses. See the appendix for variable definitions.

= -0.0720, $p < 0.01$). This indicates that, in ordinary circumstances, both analysts' expectation and peer performance information are highly correlated with focal firms' productivity. This is because, in equilibrium, individual producers become homogeneous in their production functions and productivity through competition. Furthermore, in situations involving lower levels of uncertainty, analysts can better predict firms' future profitability. Together, the results in table 6 support hypothesis 1b.

Precision of Analyst Forecasts

Now we turn to our hypotheses regarding the signaling precision of analyst forecasts. First, hypothesis 2a predicts that high-quality earnings increase analysts' abilities to predict future earnings because they can better evaluate current performance. The results shown Table 7 align with this prediction. We find that firms with high earnings quality (proxied by below-median abnormal accruals), shown in column (2), exhibit greater reliance on analyst forecasts in target revisions. In particular, the coefficient on $Target\ Deviation_{i,t} * Relative\ to\ Forecasts_{i,t}$ is significant for the firms in column (2) ($\beta_3 = -0.5683$, $p < 0.01$) but insignificant for those with lower quality earnings, shown in column (1). This supports hypothesis 2a, which posits that financial disclosure quality serves as a "bottleneck" for earnings forecasting.

Hypothesis 2b predicts that analyst forecasts are more informative when there is greater information asymmetry in the stock market. Using PIN as the empirical proxy for information asymmetry, we divide the sample into high versus low PIN subsamples. As table 8 shows, analyst forecasts significantly affect the target ratcheting of firms with higher information asymmetry (column (1)), measured by above-median PIN ($\beta_3 = -0.8571$, $p < 0.01$). On the other hand, for firms with lower PIN (column (2)), we find that analyst forecasts have an insignificant effect. These findings are consistent with hypothesis 2b, supporting the idea that boards of directors "learn" from the market, especially through information intermediaries such as financial analysts. Despite having superior internal information, boards of directors can improve target setting by referencing analysts' macroeconomic and industry-wide information-based predictions.

Finally, we examine whether the analyst forecasts are more

Table 7. OLS Regression Estimation Results – Earnings Quality and the Use of Analyst Forecasts

		Dep Var: *Target Revision*$_{i,t+1}$	
Independent Variables	Pred.	High Abnormal Accruals	Low Abnormal Accruals
Constant		0.0692	**0.1512***
		(0.80)	(1.75)
Target Deviation$_{i,t}$	+	1.2314***	1.2435***
		(15.05)	(13.81)
Target Deviation$_{i,t}$ * *D_Neg*$_{i,t}$	-	-0.7207***	-0.7975***
		(-5.34)	(-7.60)
Target Deviation$_{i,t}$ * *Relative to Forecasts*$_{i,t}$	-	-0.1729	**-0.5683*****
		(-1.29)	(-3.39)
Target Deviation$_{i,t}$ * *Relative to Peers*$_{i,t}$	-	-0.0977***	-0.1217**
		(-4.77)	(-2.07)
Target Deviation$_{i,t}$ * *D_Neg*$_{i,t}$* *Relative to Forecasts*$_{i,t}$	+	0.2206	**0.6261*****
		(0.99)	(3.37)
Target Deviation$_{i,t}$ * *D_Neg*$_{i,t}$* *Relative to Peers*$_{i,t}$	+	0.0877*	0.1857**
		(1.81)	(2.54)
D_Neg$_{i,t}$* *Relative to Forecasts*$_{i,t}$	?	0.0613	0.0452
		(0.82)	(0.49)
D_Neg$_{i,t}$* *Relative to Peers*$_{i,t}$	?	**-0.0186***	-0.0121
		(-1.86)	(-0.80)
Relative to Forecasts$_{i,t}$	-	-0.0859	-0.0291
		(-1.36)	(-0.43)
Relative to Peers$_{i,t}$	-	0.0002	-0.0041
		(0.02)	(-0.46)
D_Neg$_{i,t}$	-	-0.0127	-0.0269
		(-0.51)	(-1.02)
LogAT$_{i,t}$	?	0.0000	-0.0048
		(0.00)	(-0.72)
Predicted EPS Growth$_{i,t}$	+	0.0090	0.0059
		(0.89)	(0.59)
Returns$_{i,t}$	+	0.1520***	0.2356***
		(3.60)	(4.89)
Fixed Effects		Year, Industry	Year, Industry
Standard Errors Clustered		By Firm	By Firm
Observations		781	775
Adj. R-squared		0.6269	0.6256

*, **, *** indicate significance at the 10, 5, and 1 percents levels, respectively, using two-tailed tests. Reported t-statistics and z-statistics are based on heteroscedasticity-robust standard errors clustered by firm in parentheses. See the appendix for variable definitions.

Table 8. OLS Regression Estimation Results – Probability of Informed Trading and the Use of Analyst Forecasts

		Dep Var: *Target Revision* $_{i,t+1}$	
Independent Variables	Pred.	High PIN	Low PIN
Constant		0.0367	**-0.3346***
		(0.21)	(-1.78)
Target Deviation $_{i,t}$	+	1.2297***	1.4355***
		(5.88)	(4.43)
Target Deviation $_{i,t}$ * *D_Neg* $_{i,t}$	-	-1.0707***	-0.8914**
		(-4.94)	(-2.00)
Target Deviation $_{i,t}$ * *Relative to Forecasts* $_{i,t}$	-	**-0.8571****	-0.7078
		(-2.08)	(-0.86)
Target Deviation $_{i,t}$ * *Relative to Peers* $_{i,t}$	-	0.0533	-0.0280
		(0.57)	(-1.27)
Target Deviation $_{i,t}$ * *D_Neg* $_{i,t}$* *Relative to Forecasts* $_{i,t}$	+	**0.8593****	1.2504
		(2.08)	(1.48)
Target Deviation $_{i,t}$ * *D_Neg* $_{i,t}$* *Relative to Peers* $_{i,t}$	+	-0.0330	0.0017
		(-0.34)	(0.06)
D_Neg $_{i,t}$* *Relative to Forecasts* $_{i,t}$	?	0.0215	0.2084
		(0.13)	(0.65)
D_Neg $_{i,t}$* *Relative to Peers* $_{i,t}$	?	0.0014	-0.0013
		(0.06)	(-1.54)
Relative to Forecasts $_{i,t}$	-	0.0133	-0.1053
		(0.09)	(-0.60)
Relative to Peers $_{i,t}$	-	-0.0080	0.0003
		(-0.53)	(0.43)
D_Neg $_{i,t}$	-	-0.0253	**-0.1175***
		(-0.61)	(-1.90)
LogAT $_{i,t}$	?	0.0045	0.0140
		(0.32)	(0.83)
Predicted EPS Growth $_{i,t}$	+	-0.0129	-0.0046
		(-1.11)	(-0.22)
Returns $_{i,t}$	+	**0.2786*****	0.0387
		(5.65)	(0.45)
Fixed Effects		Year, Industry	Year, Industry
Standard Errors Clustered		By Firm	By Firm
Observations		313	309
Adj. R-squared		0.5683	0.5853

*, **, *** indicate significance at the 10, 5, and 1 percents levels, respectively, using two-tailed tests. Reported t-statistics and z-statistics are based on heteroscedasticity-robust standard errors clustered by firm in parentheses. See the appendix for variable definitions.

Table 9. OLS Regression Estimation Results – CEO Tenure and the Use of Analyst Forecasts

		Dep Var: *Target Revision*$_{i,t+1}$	
Independent Variables	Pred.	Long Tenure	Short Tenure
Constant		0.0486	**0.2262****
		(0.55)	(2.05)
Target Deviation$_{i,t}$	+	1.1223***	1.1793***
		(12.87)	(14.32)
Target Deviation$_{i,t}$ * *D_Neg*$_{i,t}$	-	-0.6749***	-0.6642***
		(-5.85)	(-4.48)
Target Deviation$_{i,t}$ * *Relative to Forecasts*$_{i,t}$	-	**-0.3907*****	-0.2712
		(-2.92)	(-1.37)
Target Deviation$_{i,t}$ * *Relative to Peers*$_{i,t}$	-	-0.0453	**-0.1212*****
		(-1.18)	(-4.46)
Target Deviation$_{i,t}$ * *D_Neg*$_{i,t}$ * *Relative to Forecasts*$_{i,t}$	+	**0.3529****	0.3885
		(2.21)	(1.38)
Target Deviation$_{i,t}$ * *D_Neg*$_{i,t}$ * *Relative to Peers*$_{i,t}$	+	0.0787*	0.1839**
		(1.77)	(2.20)
D_Neg$_{i,t}$* *Relative to Forecasts*$_{i,t}$	?	0.0523	0.0397
		(0.62)	(0.41)
D_Neg$_{i,t}$* *Relative to Peers*$_{i,t}$	?	-0.0119	**-0.0226***
		(-0.95)	(-1.73)
Relative to Forecasts$_{i,t}$	-	-0.0693	-0.0832
		(-1.11)	(-0.95)
Relative to Peers$_{i,t}$	-	**-0.0117***	0.0044
		(-1.73)	(0.52)
D_Neg$_{i,t}$	-	-0.0337	-0.0325
		(-1.44)	(-1.03)
LogAT$_{i,t}$	?	0.0012	-0.0079
		(0.17)	(-0.82)
Predicted EPS Growth$_{i,t}$	+	**0.0204****	-0.0044
		(2.30)	(-0.36)
Returns$_{i,t}$	+	0.2225***	0.1875***
		(5.14)	(4.03)
Fixed Effects		Year, Industry	Year, Industry
Standard Errors Clustered		By Firm	By Firm
Observations		773	652
Adj. R-squared		0.6294	0.5993

*, **, *** indicate significance at the 10, 5, and 1 percents levels, respectively, using two-tailed tests. Reported t-statistics and z-statistics are based on heteroscedasticity-robust standard errors clustered by firm in parentheses. See the appendix for variable definitions.

relevant when firm CEOs have longer tenures. As the results in table 9 suggest, we find that firms utilize analyst forecasts in target ratcheting when their CEOs have worked for relatively longer tenures (β_3 = -0.3907, $p < 0.01$ in column (1)). On the other hand, firms whose CEOs have shorter tenures (column (2)) do not utilize forecast information at significant levels. This indicates that financial analysts can better predict firms' future earnings when they have a better understanding of CEOs. Since analyst forecasts are more informative in predicting future profits, boards of directors have greater incentives to learn from them. In sum, the results in table 9 support hypothesis 2c.

CONCLUSION

In this paper, we examine the effects of external information (peer performance and analyst forecasts) on performance target ratcheting. Using S&P 1500firms' EPS target for the 2006–2014 period, we first find that firms use peer performance data and analyst forecasts in target revision, consistent with prior studies (Kim and Shin 2017; Choi et al. 2021). We also find that, firms puts greater weight on analyst forecasts than on peer performance (1) when they and their peer firms function as strategic substitutes or (2) when they experience firm-specific extraordinary events. On the other hand, our analysis shows that firms put greater weight on peer performance than on analyst forecasts when they and their peers function as strategic complements. Meanwhile, when firms are in ordinary states, they utilize both forms of CPI. In addition, we findthat the use of analyst forecasts is more pronounced in the settingswhere the forecasts are likely to be more accurate. For instance, the effect of analyst forecasts is more salient for firms with higher disclosure quality, when the information asymmetry in the stock market is higher, and for firms that have CEOs with longer tenures.

Our findings suggest that boards of directors should take into account the relative informativeness of CPI when they use multiple sources of information in target setting. We contribute to the target ratcheting literature that has begun studying multiple sources of information that boards use for target setting by providing evidence of cross-sectional variations in the use of CPI in various settings. Furthermore, we extend studies examining the informativeness of analyst forecasts by suggesting that forecast information has varying degrees of relevance in performance target setting depending on analysts' abilities to predict the future.

Our study has several limitations. First of all, our empirical findings document correlations rather than causal relationships. Even though we control for expected growth and stock returns, we may have omitted other variables that are confounded with peer performance data and analyst forecasts and also affect future target revision. In addition, our empirical model may be underspecified in that firms may use sources of information other than peer performance data and analyst forecasts.

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APPENDIX

Variable Definitions

Variable	Definition
Target $EPS_{i,t}$	Firm *i*'s target EPS used in the firm's executive bonus plan for fiscal year *t*.
Target $Revision_{i,t}$	*(Target* $EPS_{i,t+1}$ – *Target* $EPS_{i,t}$*)* divided by *Target* $EPS_{i,t}$.
$Actual_{i,t}$	Firm *i*'s actual EPS for fiscal year *t*.
Target $Deviation_{i,t}$	*(Actual* $EPS_{i,t}$ – *Target* $EPS_{i,t}$*)* divided by *Target* $EPS_{i,t}$.
Relative to $Forecast_{i,t}$	The difference between *Analyst* $forecast_{i,t}$ and *Actual* $EPS_{i,t}$. *Analyst* $forecast_{i,t}$ is average analyst forecasts for year *t* earnings issued before the announcement of year t earnings. If an analyst issues multiple forecasts during this period, we use only the most recent forecast.
Relative to $Peers_{i,t}$	Firm *i*'s EPS for fiscal year *t* less peer firms' EPS for fiscal year *t*. We construct peer portfolios utilizing the approach used in Albuquerque (2009) as follows. To construct peer portfolios matched on industry and firm size, we first form annual portfolios based on two-digit SIC codes. We use all firms on Compustat to construct portfolios. Second, we sort firms by beginning-of-year market value into size quartiles. Third, we match each firm with an industry-size peer group. Peer performance is the equal-weighted portfolio EPS for an industry-size peer group. When calculating portfolio EPS, we exclude the EPS of the observed firm.
$Tenure_{i,t}$	Tenure of firm *i*'s CEO in year *t*.
$AT_{i,t}$	Asset total of firm i as of the end of fiscal year t-1.

Variable	Definition
EPS Growth Prediction$_{i,t+1}$	The expected EPS growth is estimated using the following model: $$EPS\ growth_{i,t+1} = \alpha_0 + \alpha_1\ Past\ EPS\ growth_{i,t} + \alpha_2\ Size_{i,t} + \alpha_3\ EP_{i,t} + \alpha_4\ Leverage_{i,t} + \alpha_5\ MKT_{i,t} + \alpha_6\ RD_{i,t} + \alpha_7\ CAP_{i,t} + \alpha_8\ BTM_{i,t} + \alpha_9\ Div\ yield_{i,t} + \alpha_{10}\ Past\ RET_{i,t} + Year\ dummy + \varepsilon_{i,t}$$ *Growth*$_{i,t+1}$ is the firm-level expected value of the above cross-sectional model (Kim and Shin 2017). Following previous studies of the factors affecting the growth of accounting earnings and sales, we control for growth in EPS over the previous 3 years (Past EPS growth), firm size (Size), earnings to price ratio (EP), leverage (Leverage), advertising expenses divided by sales (MKT), average of R&D expenses divided by sales over the previous 3 years (RD), average capital expenditures divided by total assets over the previous 3 years (CAP), book-to-market ratio (BTM), dividend yield ratio (Div yield), and stock returns over the previous 12 months (Past RET). We compute leverage (Leverage) as liabilities less cash holdings over total assets less cash holdings. We calculate book-to-market ratio (BTM) as total assets divided by the market value of equity plus long-term liabilities. The dividend yield ratio (Div yield) is ordinary cash dividends divided by net income before extraordinary items. We estimate Equation (2) separately for each fiscal year and two-digit SIC code group.
Return$_{i,t}$	A firm's stock returns over the 12-month period ending 3 months after fiscal year end t.
D_Neg$_{i,t}$	Equals 1 if *Target deviation*$_{i,t}$ is negative, and 0 otherwise.
Cournot (Bertrand) Competition	Equals 1 if a firm's sales change is negatively (positively) correlated with that of the peer firms in the same industry.
Event (No Event)	Equals 1 if a firm incurs (does not incur) extraordinary gains/losses (e.g., write-downs and impairment of investments, or restructuring).
High (Low) Abnormal Accruals	Equals 1 if a firm's abnormal accruals, measured by the residuals from the modified Jones Model (Dechow, Sloan, Sweeney 1995), is above or equal to (less than) the sample median.

Variable	Definition
High (Low) PIN	Equals 1 if Probability of Informed Trading, measured by the fraction of trades in a day that arise from informed traders (Brown and Hillegeist 2007), is above or equal to (less than) the sample median, and 0 otherwise. The PIN data is available until 2010.
Long (Short) Tenure	Equals 1 if a firm's CEO tenure is longer or equal to (less than) the sample median.