This article was downloaded by: [202.66.60.166] On: 22 September 2017, At: 05:25
Publisher: Institute for Operations Research and the Management Sciences (INFORMS)
INFORMS is located in Maryland, USA

Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Management of Reported and Forecast EPS, Investor Responses, and Research Implications

http://orcid.org/0000-0003-3853-4625Foong Soon Cheong, http://orcid.org/0000-0003-4906-4497Jacob Thomas

To cite this article:
http://orcid.org/0000-0003-3853-4625Foong Soon Cheong, http://orcid.org/0000-0003-4906-4497Jacob Thomas (2017) Management of Reported and Forecast EPS, Investor Responses, and Research Implications. Management Science

Published online in Articles in Advance 31 Aug 2017

. https://doi.org/10.1287/mnsc.2017.2832

Full terms and conditions of use: http://pubsonline.informs.org/page/terms-and-conditions

This article may be used only for the purposes of research, teaching, and/or private study. Commercial use or systematic downloading (by robots or other automatic processes) is prohibited without explicit Publisher approval, unless otherwise noted. For more information, contact permissions@informs.org.

The Publisher does not warrant or guarantee the article's accuracy, completeness, merchantability, fitness for a particular purpose, or non-infringement. Descriptions of, or references to, products or publications, or inclusion of an advertisement in this article, neither constitutes nor implies a guarantee, endorsement, or support of claims made of that product, publication, or service.

Copyright © 2017, INFORMS

Please scroll down for article—it is on subsequent pages

INFORMS is the largest professional society in the world for professionals in the fields of operations research, management science, and analytics.
For more information on INFORMS, its publications, membership, or meetings visit http://www.informs.org

MANAGEMENT SCIENCE
Articles in Advance, pp. 1–25
ISSN 0025-1909 (print), ISSN 1526-5501 (online)
http://pubsonline.informs.org/journal/mnsc/

Management of Reported and Forecast EPS, Investor Responses, and Research Implications

Foong Soon Cheong,[a] Jacob Thomas[b]

[a] New York University Shanghai, Shanghai 200122, China; [b] Yale School of Management, Yale University, New Haven, Connecticut 06520

Contact: fscheong@nyu.edu, http://orcid.org/0000-0003-3853-4625 (FSC); jake.thomas@yale.edu, http://orcid.org/0000-0003-4906-4497 (JT)

Received: June 28, 2016
Revised: January 2, 2017; March 27, 2017
Accepted: March 31, 2017
Published Online in Articles in Advance: August 31, 2017

https://doi.org/10.1287/mnsc.2017.2832

Copyright: © 2017 INFORMS

Abstract. We document substantial management of reported and forecast earnings per share (EPS) for analyst-followed U.S. firms, with the extent of management increasing with share price. Managers smooth the volatility of reported EPS by using accruals to offset cash flow shocks. Smoother EPS is easier to forecast, resulting in smaller forecast errors. Managers also differentially guide forecasts to improve accuracy. Whereas *unmanaged* forecast errors are much larger for high-price firms, they are compressed to the point their magnitudes resemble those for low-price firms. Managers also guide analyst forecasts to generate patterns of forecast walkdowns that again vary with share price. Given the remarkable level of management implied by our results, we conduct additional robustness analyses. The strongest evidence is observed in stock price responses: investors recognize efforts to manage reported and forecast EPS and adjust accordingly. We highlight potential biases caused by researchers being unaware of managerial efforts and investor responses, and offer ways to mitigate those biases.

History: Accepted by Shivaram Rajgopal, accounting.
Funding: The authors thank the Yale School of Management for financial support.
Supplemental Material: The online appendix is available at https://doi.org/10.1287/mnsc.2017.2832.

Keywords: EPS forecast errors • earnings management • forecast guidance • scale deflation • earnings response coefficients

1. Introduction

Consistent with intuition, forecast errors are generally unbiased, and their magnitudes increase with scale. That is, first moments (e.g., means) of forecast error distributions are close to zero and second moments (e.g., variances) increase with scale. One notable exception relates to sell-side analysts' forecasts of quarterly earnings per share (EPS) for U.S. firms. (Error for analyst forecasts equals "core" EPS—the recurring portion of reported or GAAP EPS that analysts seek to forecast—minus the consensus of analysts' EPS forecasts available just before earnings announcements.) To understand the nature of the exception, consider the first two items of the findings in Cheong and Thomas (2011), hereafter CT, listed below: first moments of EPS forecast errors are not zero, they are generally positive and increase with scale; whereas second moments do not increase with scale, they are relatively invariant with scale.[1] CT#2 is particularly intriguing because actual and forecast EPS magnitudes increase proportionately with share price and yet magnitudes of the difference—*forecast error measured in cents per share*—do not. The remaining five findings arise from CT's efforts to better understand CT#2.

CT#1. The first moment (means and medians) of EPS forecast error distributions for U.S. firms increases with scale. That is, forecast pessimism (actual EPS beats consensus) increases with scale.

CT#2. The second moment (interquartile ranges and median absolute values) of EPS forecast error distributions for U.S. firms varies little with scale. A similar lack of scale variation is observed for the first moment (median) of forecast dispersion.[2]

CT#3. The second moment of seasonally differenced reported earnings for analyst-followed U.S. firms varies little with scale for price deciles 1–7 but increases with scale for price deciles 8–10.

CT#4. CT#2 and CT#3 are not observed for per share sales and per share cash flow forecasts.

CT#5. Cross-sectional variation in CT#2 is not observed along potential omitted correlated variables, such as analyst following, forecast staleness, and return volatility.

CT#6. U.S. firms not followed by analysts deviate from CT#3: earnings volatility increases with scale.

CT#7. Cross-country variation is observed for CT#2 and #3: some countries exhibit little scale variation (similar to the United States), while others, such as Japan, exhibit more scale variation.

CT propose and investigate three explanations for the puzzling lack of scale variation in CT#2: (a) underlying EPS variability does not increase in nature with share price; or underlying variability increases with share price but that variation is reversed by (b) omitted, correlated variables or (c) analyst effort. Their results

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

reject all three explanations but suggest a fourth one instead: managers play a role. We investigate that possibility and find consistent results. Forecast error magnitudes increase naturally with scale, but managers use a combination of earnings smoothing and forecast guidance to completely reverse that variation.

To investigate CT's conjecture that managers play a role, we undertake a comprehensive investigation of different ways managers can shrink EPS forecast error magnitudes. Our results suggest that forecast errors are differentially compressed mainly by earnings smoothing: using accruals to offset cash flow shocks. Smoother earnings are easier to forecast, resulting in smaller forecast errors. Our measure of smoothing via discretionary accruals—the negative correlation between seasonally differenced cash flow per share (*CPS*) and accruals per share (*APS*)—increases from about −0.5 for price decile 1 to about −0.8 for price decile 7. Increased earnings smoothing, between deciles 1 and 7, offsets entirely any natural increase in EPS volatility. For deciles 8–10, however, smoothing levels remain unchanged—as if they reach a limit at decile 7. Residual scale variation in forecast error magnitudes between deciles 8 and 10 is eliminated by guiding analyst forecasts toward core EPS to increase accuracy.

We observe strong confirmation of managerial intervention when we consider investor responses. If managers of decile 10 firms shrink forecast errors much more than managers of decile 1 firms, rational investors should respond appropriately: price responses per cent of *observed* forecast error—also known as earnings response coefficient or ERC—should be much higher for decile 10 to compensate for greater forecast error compression. Moreover, ERC magnitudes should be much higher than levels anticipated by theory describing the determinants of ERC (e.g., Kormendi and Lipe 1987, Collins and Kothari 1989), because that theory does not anticipate forecast error compression. Our results are remarkably consistent with both predictions. For the 70% of observations with forecast errors in the narrow −5¢ to +5¢ range, ERC varies monotonically between 7 for decile 1 and 50 for decile 10.[3] Given that ERC levels for decile 1 are closer to the levels expected by theory mentioned above, ERCs that are seven times as high for decile 10 suggest that forecast errors in that decile are compressed to *one-seventh* their unmanaged levels.

We also consider falsification tests by investigating two samples that CT#6 and CT#7 suggest are different from analyst-followed U.S. firms: (a) U.S. firms not followed by analysts and (b) analyst-followed firms in Japan. If the increasingly negative cash flow/accrual correlation we document is due to factors other than managerial intervention, we should observe similar patterns of scale variation in accruals/cash flow correlations for other samples, too. Our results, however, indicate very different patterns for both samples: correlations vary little with scale and do not exhibit nonlinearity at price decile 8. Finally, we confirm that investor responses are different in Japan: ERC varies much less with price and ERC levels for high-price firms are much lower, relative to the U.S. sample.

A Stein (1989)-type equilibrium, based on the signal-jamming model used in other contexts by Holmstrom (1982) and Fudenberg and Tirole (1986), might explain why managers differentially compress forecast errors. Managers fear that investors do not adjust for scale; i.e., investors mechanically associate larger forecast error magnitudes with higher risk. In response, managers of high-price firms compress forecast errors to the point that they resemble low-price firms. In equilibrium, investors recognize managerial compression of forecast errors and adjust accordingly. Even though no one is fooled, managers are trapped into compressing forecast errors. Analogous to a prisoner's dilemma, firms that deviate and do not compress forecast errors to expected levels are viewed as being more risky than they actually are.

While the main focus of our study is CT#2, we also probe CT#1—forecast pessimism increases with scale—and our results again suggest that managers play a role. We first confirm the "walk-down" pattern documented in prior research (e.g., Richardson et al. 2004) and then show that walkdowns vary substantially with price[4]: beginning nine months before quarter-end, the walkdown is only about 2¢ per share for share price decile 1 but increases with share price to about 6¢ per share for decile 10. In essence, high-price firms have more optimistic long-horizon forecasts and more pessimistic short-horizon forecasts, relative to low-price firms. Absent managerial involvement, why does the consensus forecast exhibit different walk-down patterns for firms with different share prices, and why are the patterns repeated quarter after quarter? Also, consistent with our findings that investors adjust for differential efforts to compress forecast errors (CT#2), we find that investors adjust for differential pessimism of short-horizon forecasts (CT#1): they rationally expect firms in decile 10 (decile 1) to beat consensus by 2¢ per share (meet consensus). We find that investors respond symmetrically to good- and bad-news forecast errors around these adjusted "no-news" points that vary with share price.

Our first contribution is to provide robust support for the conjecture in CT that managers play a role in the unusual price variation observed for the first and second moments of forecast error distributions. More importantly, the scale and scope of managerial efforts we uncover are remarkable. There is substantial smoothing of reported earnings and guidance of analyst forecasts, especially for high-price firms, and it is

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

sustained over time and widespread across firms. To be sure, alternative explanations exist for some of our results, but they are inconsistent with the portfolio of results documented here and in CT.[5]

Second, we offer new findings to the literature on analyst forecasts and investor responses to forecast errors. We show that the well-known walkdown from optimistic long-horizon forecasts to pessimistic short-horizon forecasts is more acute for high-price firms. We also show that the well-known discontinuity (unusually low frequency) associated with firms just missing consensus by a penny is partly an artifact of combining different samples with differently located forecast error distributions (CT#1).

More importantly, we show that investors recognize and adjust for price variation in pessimism. Contrary to the common wisdom that investors react asymmetrically to good and bad news (very negative response to small misses), we show that responses are symmetric. A perceived asymmetry arises, however, when investor expectations are ignored. Given that investors expect firms in decile 10 to beat consensus by 2¢ per share, missing consensus by a penny is actually falling short by 3¢. In fact, even beating consensus by a penny is bad news for decile-10 firms. As a result, the average negative price reaction to missing by a penny, across low- and high-price firms, is much larger than the average positive price reaction to beating by a penny. Finally, we show that investors recognize and adjust for price variation in compression of forecast errors, offering new insights about levels of and price variation in ERCs.

Third, we contribute to the long literature on earnings smoothing (e.g., Ronen and Sadan 1981, Graham et al. 2005). The motivation to smooth earnings arises here because of a perceived need to compress errors associated with analyst forecasts and is thus conducted in tandem with forecast guidance. Incentives to smooth are greater for analyst-followed firms, and the focus is on the volatility of EPS rather than net income. Moreover, these incentives increase with share price, because high-price firms with higher EPS volatility seek to lower it to levels associated with low-price firms. In addition to identifying a target that firms appear to smooth toward (the volatility of low-price firms), our results suggest a limit to smoothing: whereas the extent of smoothing increases with share price for deciles 1–7, it levels off after that.

Last but not least, we contribute to methodology. Biases might arise if researchers are unaware of the unexpected empirical regularities documented here and in CT. As suggested in CT, measures that should normally vary with scale (e.g., forecast error magnitudes, forecast dispersion, and EPS volatility) are in fact scale invariant. Thus, deflating them induces an unexpected negative correlation with scale that may create biases if other included variables also happen to be related to scale. Similar biases might arise because measures that should not vary normally with scale (e.g., ERCs, earnings smoothing, and forecast optimism/pessimism) exhibit scale variation. Finally, pooling samples that are expected to have similar attributes, but do not in the data, creates a third source of bias. We illustrate how such biases arise by replicating prior studies, and offer ways to detect and mitigate potential bias.

2. Our Predictions

Unlike the testable predictions we generate below to investigate CT#2, our analyses of CT#1 (positive relation between mean/median forecast errors and scale) are descriptive in nature. To determine whether the CT#1 patterns are due to managerial efforts to guide analyst forecasts, we study price variation in median forecast errors associated with time-series forecasts (based on a seasonal random walk model) and consensus analyst forecasts made at different horizons, ranging from nine months before the quarter-end to the most recent consensus available before quarterly earnings announcements. As described in Section 1, our results are consistent with managers guiding analyst forecasts to achieve a positive relation between scale and pessimism of short-horizon forecasts, which results in the observed CT#1 patterns. Details of our evidence and inferences are provided in the online appendix.

2.1. Ways to Alter the Second Moment of Forecast Error Distributions (CT#2)

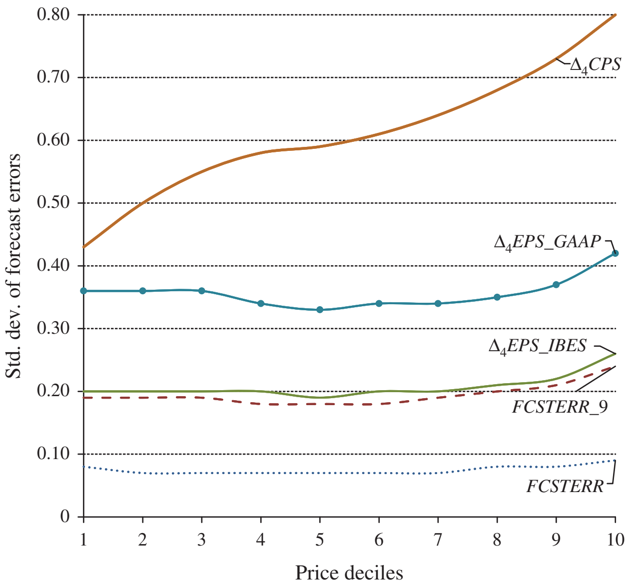
Turning from CT#1 to CT#2, we consider all possible ways to compress forecast errors. We begin with the volatility of shocks to cash flows, represented by seasonal differences ($\Delta_4 CPS$), which we assume is exogenously determined.[6] We investigate the decline in volatility that occurs at each of four stages: (a) *volatility of reported earnings shocks*, represented by seasonal-differences ($\Delta_4 EPS\_GAAP$); (b) *volatility of core earnings shocks*, represented by seasonal differences ($\Delta_4 EPS\_IBES$); (c) *volatility of early forecast errors* (*FCSTERR_9*), based on forecasts made nine months before the quarter-end (*FORECAST_9*); and (d) *volatility of most recent forecast errors* (*FCSTERR*), based on the most recent forecast (*FORECAST*).

Figure 1 describes the decline in volatility—measured as standard deviation—at the different stages, from $\Delta_4 CPS$ (the top line) to *FCSTERR* (the bottom line), for all 10 price deciles. The top line describes CT#4: cash flow volatility increases with share price. The second line from the top describes CT#3: volatility of reported earnings does not increase with share price for deciles 1–7 but increases for deciles 8–10. The third and fourth lines from the top, which run parallel to the second line, describe price variation for the volatilities

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

Figure 1. (Color online) Volatility of Different Variables Across Deciles of Share Price



Notes. This figure describes the path of volatility reduction from unexpected cash flows to analyst forecast errors, through the use of accruals, one-time items, analyst adjustment, and management guidance. We report the standard deviation of different variables across deciles of *BEGPRICE*, which is the beginning-of-quarter share price. Price deciles are computed at the beginning of each calendar quarter for fiscal quarters ending in that quarter, and the lowest (highest) price decile is denoted by 1 (10). *FORECAST* is the most recent consensus (mean) EPS forecast for that firm-quarter, *EPS_IBES* is the actual quarterly EPS as reported by I/B/E/S, and *FCSTERR* is defined as *EPS_IBES* minus *FORECAST*. *FCSTERR_9* is the forecast error corresponding to forecasts made nine months before quarter-end. Earnings per share (*EPS_GAAP*) is the per share quarterly income before extraordinary items, obtained from the cash flow statement. Cash flow per share (*CPS*) is the per share net cash flow from operating activities. $\Delta_4 EPS\_IBES$, $\Delta_4 EPS\_GAAP$, and $\Delta_4 CPS$ are the seasonally differenced value of *EPS_IBES*, *EPS_GAAP*, and *CPS*, respectively. The variables *FCSTERR*, *FCSTERR_9*, $\Delta_4 EPS\_IBES$, $\Delta_4 EPS\_GAAP$, and $\Delta_4 CPS$ are Winsorized at 5% and 95% each year.

of core earnings and early forecast errors, respectively. The bottom line in Figure 1 describes CT#2: volatility of most recent forecast errors does not vary with price.

To investigate managerial involvement in differential forecast error compression, we first derive the determinants of volatility declines at each stage. To do so, we write a relation that links the variable at each stage with the variable above, then take variances of both sides and rearrange terms to describe the decline in variance as a function of two determinants—a variance term and a covariance term. The relations used to link the two variables at each stage are as follows.

(1) $\Delta_4 CPS$ *to* Δ_4 *EPS_GAAP*: we use $\Delta_4 EPS\_GAAP = \Delta_4 CPS + \Delta_4 APS$, where *APS* is accruals per share.

(2) $\Delta_4 EPS\_GAAP$ *to* $\Delta_4 EPS\_IBES$: we use $\Delta_4 EPS\_IBES = \Delta_4 EPS\_GAAP - \Delta_4 ONETIME$, where *ONETIME* refers to one-time items removed from reported EPS to obtain core EPS.

(3) $\Delta_4 EPS\_IBES$ *to FCSTERR_9*: we use $FORECAST\_9 = EPS\_IBES_{t-4} + ANALYADJ$, where *ANALYADJ* reflects the adjustment analysts make to a seasonal random walk forecast (EPS_IBES_{t-4}) when generating their early forecasts.

(4) *FCSTERR_9 to FCSTERR*: we use $FCSTERR = FCSTERR\_9 - REVISION$, where *REVISION* reflects the accuracy improvements that occur in revisions made between early and the most recent forecasts.

Taking variances on both sides of the relations above and rearranging terms generates Equations (1)–(4). The variance declines observed at each stage are on the left-hand side and the corresponding determinants—the variance and covariance terms—are on the right-hand side.

$$\begin{aligned}&\mathrm{Var}(\Delta_4 CPS) - \mathrm{Var}(\Delta_4 EPS\_GAAP)\\&= -\mathrm{Var}(\Delta_4 APS) - 2\mathrm{Corr}(\Delta_4 CPS, \Delta_4 APS)\\&\quad\cdot\sqrt{\mathrm{Var}(\Delta_4 CPS)\mathrm{Var}(\Delta_4 APS)},\end{aligned}\tag{1}$$

$$\begin{aligned}&\mathrm{Var}(\Delta_4 EPS\_GAAP) - \mathrm{Var}(\Delta_4 EPS\_IBES)\\&= \mathrm{Var}(\Delta_4 ONETIME)\\&\quad + 2\mathrm{Corr}(\Delta_4 EPS\_IBES, \Delta_4 ONETIME)\\&\quad\cdot\sqrt{\mathrm{Var}(\Delta_4 EPS\_IBES)\mathrm{Var}(\Delta_4 ONETIME)},\end{aligned}\tag{2}$$

$$\begin{aligned}&\mathrm{Var}(\Delta_4 EPS\_IBES) - \mathrm{Var}(FCSTERR\_9)\\&= -\mathrm{Var}(ANALYADJ) + 2\mathrm{Corr}(\Delta_4 EPS\_IBES, ANALYADJ)\\&\quad\cdot\sqrt{\mathrm{Var}(\Delta_4 EPS\_IBES)\mathrm{Var}(ANALYADJ)},\end{aligned}\tag{3}$$

$$\begin{aligned}&\mathrm{Var}(FCSTERR\_9) - \mathrm{Var}(FCSTERR)\\&= -\mathrm{Var}(REVISION) + 2\mathrm{Corr}(FCSTERR\_9, REVISION)\\&\quad\cdot\sqrt{\mathrm{Var}(FCSTERR\_9)\mathrm{Var}(REVISION)}.\end{aligned}\tag{4}$$

To identify potential managerial intervention, we focus on two nonlinear relations with price created in the four equations above because of CT#2, CT#3, and CT#4. First, the gap between the top two lines in Figure 1, which is the variance decline described in Equation (1), should vary nonlinearly with price because cash flow volatility increases with price (CT#4), whereas reported earnings volatility exhibits a nonlinear relation (CT#3). Second, the gap between the second line from the top and the bottom line in Figure 1—which is the sum of the three variance declines shown in Equations (2)–(4)—should also vary nonlinearly with price because reported earnings volatility exhibits a nonlinear relation (CT#3), but volatility of most recent forecast errors exhibits no scale variation (CT#2). Because visual examination of the three gaps in Figure 1 suggests little variation with price for the variance declines in Equations (2) and (3), we anticipate the gap relating to Equation (4) to be most relevant.

The resulting predictions—P1.1–P1.4 below—are based on the premise that managerial intervention is indicated if nonlinearity in the respective gaps between the lines in Figure 1 is matched *exactly* by

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

nonlinear price variation in just *one* of the determinants (variance/covariance terns) in the corresponding Equations (1)–(4). Additional confirmation is provided if the determinant that exhibits the required nonlinear variation is also more amenable to manipulation. For example, the accruals/cash flow covariance term in Equation (1), which reflects the use of accruals to offset cash flow shocks, is more likely to reflect earnings smoothing than the variance of accruals term.

P1.1. *The variance of Δ_4 APS or the correlation between Δ_4CPS and Δ_4APS should decline for price deciles* 1–7 *and then level off for deciles* 8–10*.*

As mentioned above, the correlation term is more likely to capture managerial intent. A cursory understanding of accounting rules suggests that the correlation between cash flow and accruals surprises should be negative, before any managerial efforts to smooth earnings volatility. For example, a buildup of inventory will cause Δ_4*CPS* to decline and Δ_4*APS* to increase. In addition, any measurement error associated with our measure of cash flow surprise will create an opposite error in accruals surprise, because accruals surprises are obtained by subtracting cash flow surprises from earnings surprises. If differential smoothing plays a role, the correlation between Δ_4*CPS* and Δ_4*APS* should become more negative between deciles 1 and 7 and then remain constant at that high negative level for deciles 8–10.

P1.2. *The variance of Δ_4ONETIME or the correlation between Δ_4ONETIME and Δ_4EPS_IBES should increase more for deciles* 8–10*, relative to deciles* 1–7*.*

The correlation term reflects efforts to reduce volatility of core EPS if managers strategically designate positive (negative) components of reported income as one-time items when reported EPS is unusually high (low). As with the accruals/cash flow correlation in Prediction P1.1, the correlation term is expected to be significant even in the absence of managerial intervention. One-time items are likely to increase the volatility of *EPS_GAAP*, and eliminating those items should reduce the volatility of *EPS_IBES*. However, managerial involvement is indicated if the correlation increases only between price deciles 8 and 10, not between deciles 1 and 7.

P1.3. *The variance of ANALYADJ should decline more or the correlation between ANALYADJ and Δ_4EPS_IBES should increase more for deciles* 8–10*, relative to deciles* 1–7*.*

Prediction P1.3 is based on early analyst forecasts—made soon after earnings are released for quarter $t-4$—being more accurate than forecasts from a seasonal random walk model. Accuracy improvements are due to the arrival of new information, analyst effort, and management guidance. We view management guidance broadly, to include management forecasts, narratives in press releases (e.g., Bonsall et al. 2015), and other soft information provided by managers that cause forecast revisions. Analyst effort and arrival of new information could reasonably increase with share price but are unlikely to increase only between deciles 8 and 10. Management guidance is suggested if accuracy improves only between deciles 8 and 10, not between deciles 1 and 7.

P1.4. *The variance of REVISION should decrease more or the correlation between REVISION and FCSTERR_9 should increase more for deciles* 8–10*, relative to deciles* 1–7*.*

Prediction P1.4 is based on forecast accuracy improving over time, between early and most recent forecasts, with the level of improvement increasing for deciles 8–10. As discussed above for P1.3, observing accuracy improvements only between price deciles 8 and 10 suggests managerial involvement, as it is unlikely to be due to the arrival of new information and analyst effort. Note that systematic biases associated with *FORECAST_9* and *FORECAST*, indicated by positive (negative) means for the corresponding forecast error distributions when forecasts are pessimistic (optimistic), are removed here because we consider variances around those means.

To provide orthogonal evidence on managerial manipulation, we consider price responses to forecast errors. If investors are aware of managerial efforts to differentially compress forecast errors, they should undo that compression and respond to "unmanaged" forecast errors. If so, price responses per cent of *observed* forecast error (or ERC) should be higher for more compressed forecast errors. And ERC should increase with price, provided the correlation between price responses and forecast errors does not vary with scale (see relation (B.1) in Appendix B). This insight generates Prediction P2 below.

P2. *ERC should increase with scale to offset increasing forecast error compression for U.S. firms.*

To provide falsification tests of the managerial intervention hypothesis, we consider three other predictions that arise from CT's results:

P3.1. *Prediction* P1.1 *should be muted for U.S. firms not followed by analysts.*

P3.2. *Predictions* P1.1 *should be muted for analyst-followed firms in Japan.*

P3.3. *Prediction* P2 *should be muted for analyst-followed firms in Japan.*

Predictions P3.1 and P3.2 follow from CT#6 and CT#7, respectively, which show that CT#3 is not observed for nonfollowed firms in the U.S. and analyst-followed firms in Japan. Magnitudes of seasonally differenced earnings increase with scale for both groups.

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

Prediction P3.3 follows from CT#7, which shows that CT#2 is not observed for Japan. If there is less variation in forecast error compression across price deciles, we expect ERCs to also vary less with price in Japan, relative to the United States.

3. Sample Selection and Descriptive Statistics

Our main sample, containing 199,486 firm-quarters, includes all U.S. firms on I/B/E/S with fiscal quarters ending between January 1993 and December 2013. We drop years before 1993 because of concerns about a shift around the early 1990s in the methodology used to compute "actual" EPS as reported by I/B/E/S, which is the core EPS that analysts seek to forecast.[7] We require nonmissing consensus (mean) forecasts (*FORECAST*), actual EPS according to I/B/E/S (*EPS_IBES*), stock price (*BEGPRICE*) from CRSP, and the earnings announcement date from COMPUSTAT.[8] Forecast error (*FCSTERR*) equals *EPS_IBES* minus *FORECAST*. Details of all variables are provided in Appendix A. To exclude less meaningful consensus forecasts, we delete firm-quarters with fewer than three forecasts.[9] We focus on "unadjusted" values—not adjusted for stock splits—because of concerns about rounding in adjusted I/B/E/S data (Diether et al. 2002).

We collect stock prices and daily stock return data from CRSP. Price deciles are formed each calendar quarter based on share prices at the beginning of calendar quarters (*BEGPRICE*) for all fiscal-quarters ending during that calendar quarter. For example, price deciles for firm-quarters ending in October, November, and December of 1999 are based on prices as of October 1, 1999. By using prices as of the same day for all firms, we are able to avoid within-quarter variation due to market-level price movements. To compute a price response associated with each quarterly earnings announcement, we cumulate abnormal returns over a 22-*trading* day window (approximately one month) leading up to the earnings announcement date and multiply that return by the share price at the beginning of the holding period to generate the corresponding price response over the period (*PRICERESP*).

We collect COMPUSTAT quarterly data for our main sample by matching each I/B/E/S observation with a firm-quarter on COMPUSTAT.[10] We estimate reported per share earnings (*EPS_GAAP*) by dividing the net income imputed from quarterly *cash flow* statements by the number of shares underlying the computation of EPS before extraordinary items reported on income statements (*EPS_IS*).[11] While *EPS_GAAP* is generally very close to *EPS_IS*, we prefer to use *EPS_GAAP* to increase comparability with per share operating cash flows (*CPS*) and accruals (*APS*). *CPS* is obtained from cash flow statements, and *APS* is derived as *EPS_GAAP* minus *CPS*.

We use seasonal differences (denoted by Δ_4) for *EPS_GAAP*, *EPS_IBES*, *CPS*, and *APS* to represent surprises for these variables, with surprise magnitudes representing volatility for the corresponding variables. We recognize that seasonal differences are a noisier measure of surprise for reported EPS relative to core EPS because reported EPS includes more nonrecurring items that are transitory. That source of measurement error is likely higher for *CPS* surprise, relative to reported EPS surprise, and higher still for *APS* surprise.[12] We consider sensitivity analyses (results summarized in the next section) to confirm that our main conclusions are not affected by measurement error.

For reasons described next, we Winsorize all variables reported in Figure 1—*FCSTERR*, *FCSTERR_9*, and seasonal difference of *EPS_IBES*, *EPS_GAAP*, and *CPS*—at the 5th and 95th percentiles. (These Winsorized variables are used to derive Δ_4*APS*, Δ_4*ONETIME*, *ANALYADJ*, and *REVISION*.) Prior research focuses on interquartile ranges as the relevant measure of second moments, because the empirical regularities in CT describe the majority of firms in the middle of the relevant distributions, not the subset of firms in the tails. But the relations we derive in Section 2 are stated in terms of variances and covariances. Using a second moment measure that is influenced by observations in the tails, such as variances, alters the profile of scale variation. In particular, it induces a "smile"—second moments increase as we move from decile 5 toward deciles 1 and 10—because extreme values (large positive and negative values) are more likely to be observed for low- and high-price deciles. We searched for relatively unobtrusive ways to transform the underlying distributions to allow us to use variances and covariances and also recover the original patterns observed by CT for interquartile ranges. We find that Winsorizing the distributions of key variables at the 5th and 95th percentiles achieves both objectives.

Panel A of Table 1 provides descriptive statistics for key variables.[13] The distributions of *FORECAST* and *EPS_IBES* are fairly similar, although forecasts tend to be less extreme. The middle of the distribution of *FCSTERR* is slightly to the right of zero, indicated by a median of +1¢, which confirms the prior result that the most recent forecasts are on average pessimistic. Panel B of Table 1 provides medians, computed within price deciles, for the variables in panel A. (Patterns are similar for mean values.) The median values of *BEGPRICE* in row 1 range from about $4 for the lowest price decile to about $67 for the highest price decile. These prices are lower than those reported in CT, possibly because our sample includes the financial crisis period, when prices were substantially lower. As described in CT, the results in rows 2, 3, and 5

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

Table 1. Sample Selection and Descriptive Statistics

Panel A: Univariate statistics for key variables

Row	Variable	*N*	Mean	StdDev	IQR	Min	p25	Median	p75	Max
1	*BEGPRICE*	199,486	27.94	28.98	23.81	0.05	12.41	22.39	36.22	1,080.11
2	*FORECAST*	199,486	0.32	0.56	0.44	−14.96	0.07	0.26	0.51	28.19
3	*EPS_IBES*	199,486	0.32	0.69	0.46	−64.05	0.07	0.27	0.53	30.29
4	*FCSTERR*	199,486	0.01	0.08	0.05	−0.40	−0.01	0.01	0.04	0.25
5	*EPS_GAAP*	199,365	0.25	1.06	0.49	−75.12	0.02	0.24	0.51	78.96
6	*CPS*	188,375	0.58	2.11	0.92	−173.36	0.02	0.38	0.94	115.68
7	*APS*	188,365	−0.35	2.15	0.66	−114.16	−0.61	−0.18	0.05	175.12
8	*ONETIME*	199,365	−0.07	0.80	0.03	−72.24	−0.03	0.00	0.00	77.01
9	*ANALYADJ*	147,086	0.08	0.13	0.09	−1.15	0.03	0.06	0.12	1.43
10	*REVISION*	164,834	−0.08	0.17	0.14	−1.20	−0.13	−0.03	0.01	0.65
11	*PRICERESP*	197,004	0.07	4.87	2.77	−200.70	−1.35	−0.02	1.43	161.84

Panel B: Median values of key variables, by price decile

	Medians for	Price decile									
Row	Variable	1	2	3	4	5	6	7	8	9	10
1	*BEGPRICE*	4.31	8.62	12.88	16.75	20.75	25.25	30.15	36.75	46.04	66.80
2	*FORECAST*	−0.03	0.06	0.14	0.20	0.26	0.33	0.40	0.48	0.59	0.85
3	*EPS_IBES*	−0.04	0.06	0.14	0.20	0.27	0.33	0.41	0.49	0.61	0.87
4	*FCSTERR*	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02
5	*EPS_GAAP*	−0.06	0.03	0.11	0.18	0.24	0.31	0.38	0.46	0.58	0.84
6	*CPS*	−0.01	0.11	0.21	0.30	0.38	0.48	0.58	0.68	0.85	1.21
7	*APS*	−0.08	−0.11	−0.14	−0.17	−0.19	−0.21	−0.24	−0.27	−0.32	−0.40
8	*ONETIME*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9	*ANALYADJ*	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.07	0.08	0.11
10	*REVISION*	−0.05	−0.05	−0.04	−0.04	−0.03	−0.03	−0.03	−0.02	−0.02	−0.01
11	*PRICERESP*	−0.07	−0.08	−0.03	−0.02	0.01	−0.03	0.07	0.06	0.12	0.18

Notes. The sample contains 199,486 firm-quarters derived from U.S. firms on I/B/E/S with nonmissing data, fiscal period end date between January 1993 and December 2013, and at least three EPS forecasts from analysts. Panel A reports the number of observations (*N*), the mean, standard deviation (StdDev), interquartile range (IQR), minimum (min), 25th percentile (p25), median, 75th percentile (p75), and maximum (max) for different variables. Panel B reports the medians of different variables across deciles of *BEGPRICE*, which is the beginning-of-quarter share price. Price deciles are computed at the beginning of each calendar quarter for fiscal quarters ending in that quarter, and the lowest (highest) price decile is denoted by 1 (10). *FORECAST* is the most recent consensus (mean) EPS forecast for that firm-quarter, *EPS_IBES* is the actual quarterly EPS as reported by I/B/E/S, and *FCSTERR* is defined as *EPS_IBES* minus *FORECAST*. Earnings per share (*EPS_GAAP*) is the per share quarterly income before extraordinary items, obtained from the cash flow statement. Cash flow per share (*CPS*) is the per share net cash flow from operating activities. Accrual per share (*APS*) equals *EPS_ GAAP* minus *CPS*. One-time item (*ONETIME*) is defined as *EPS_GAAP* minus *EPS_ IBES*. *ANALYADJ* is the implicit adjustment made by analysts to the actual EPS for quarter $t-4$ (EPS_IBES_{t-4}) to derive the forecast made nine months before the quarter-end (*FORECAST_9*). *REVISION* is the EPS forecast revision from nine months before quarter-end to the most recent forecast before earnings announcement. *PRICERESP* is the price response over 22 trading days, adjusted for market movements. *FCSTERR* is Winsorized at 5% and 95% each year, and *ANALYADJ* (= $\Delta_4 EPS\_IBES - FCSTERR\_9$) and *REVISION* (= $FCSTERR\_9 - FCSTERR$) are derived from Winsorized variables. All variables are denominated in dollars and are described in more detail in Appendix A.

confirm that consensus forecasts as well as reported and core *EPS* increase approximately proportionately with share price. The remaining rows are provided for reference.

4. Managerial Efforts to Compress Forecast Errors

The first four rows in panel A of Table 2 describe variation with price for four key volatilities already described in Figure 1. Consistent with CT#2, standard deviations and interquartile ranges (IQR) for *FCSTERR* exhibit little variation with price.[14] Consistent with CT#3, standard deviations for $\Delta_4 EPS\_GAAP$ are relatively similar across deciles 1–7 and increase across deciles 8–10. Consistent with CT#4, standard deviations for $\Delta_4 CPS$ increase with scale.

4.1. Prediction P1.1: Differential Reduction of Volatility from Δ_4*CPS* to Δ_4*EPS_GAAP*

We begin with Prediction P1.1, which describes the variance and covariance terms that determine the gap in Figure 1 between the standard deviation of $\Delta_4 CPS$ and $\Delta_4 EPS\_GAAP$. Managerial involvement is suggested if price variation in that gap is explained by the correlation between $\Delta_4 CPS$ and $\Delta_4 APS$ becoming more negative with price between deciles 1 and 7, but holding constant after that. Row 5 in panel A of Table 2

RIGHTSLINK

Table 2. Predictions P1.1 and P3.1: Use of Accruals to Reverse Cash Flow Shocks

Panel A: Volatilities of forecast error (*FCSTERR*), unexpected per share earnings (*EPS*), cash flows (*CPS*), and accruals (*APS*), and the correlation between unexpected *APS* and *CPS*, estimated using pooled samples for each price decile; 172,674 firm-quarter observations

		Price decile									
Row	Statistic and variable	1	2	3	4	5	6	7	8	9	10
1	StdDev *FCSTERR*	0.08	0.07	0.07	0.07	0.07	0.07	0.07	0.08	0.08	0.09
2	IQR *FCSTERR*	0.05	0.06	0.05	0.05	0.04	0.05	0.05	0.06	0.07	0.08
3	StdDev $\Delta_4 EPS\_GAAP$	0.36	0.36	0.36	0.35	0.34	0.34	0.35	0.35	0.38	0.43
4	StdDev $\Delta_4 CPS$	0.43	0.50	0.55	0.58	0.59	0.61	0.64	0.68	0.73	0.81
5	StdDev $\Delta_4 APS$	0.52	0.57	0.62	0.64	0.64	0.65	0.67	0.71	0.75	0.82
6	Pearson Corr ($\Delta_4 CPS$, $\Delta_4 APS$)	−0.72	−0.78	−0.81	−0.84	−0.85	−0.85	−0.86	−0.87	−0.87	−0.86
7	Spearman Corr ($\Delta_4 CPS$, $\Delta_4 APS$)	−0.62	−0.73	−0.78	−0.82	−0.83	−0.84	−0.85	−0.87	−0.88	−0.88

Panel B: Repeat panel A by firm—The statistics are estimated in time series for each firm, and the means (across firms) and the number of firms in each price decile are reported below

	Means of	Price decile									
Row	Statistic and variable	1	2	3	4	5	6	7	8	9	10
1	StdDev *FCSTERR*	0.06	0.06	0.06	0.07	0.06	0.06	0.07	0.07	0.08	0.08
2	IQR *FCSTERR*	0.06	0.07	0.06	0.08	0.07	0.07	0.08	0.08	0.09	0.10
3	StdDev ($\Delta_4 EPS\_GAAP$)	0.26	0.28	0.27	0.30	0.27	0.28	0.32	0.32	0.34	0.40
4	StdDev ($\Delta_4 CPS$)	0.30	0.41	0.46	0.55	0.52	0.54	0.61	0.64	0.68	0.74
5	StdDev ($\Delta_4 APS$)	0.37	0.48	0.51	0.60	0.57	0.58	0.66	0.68	0.71	0.76
6	Pearson Corr ($\Delta_4 CPS$, $\Delta_4 APS$)	−0.54	−0.71	−0.77	−0.79	−0.82	−0.82	−0.83	−0.86	−0.85	−0.82
7	Spearman Corr ($\Delta_4 CPS$, $\Delta_4 APS$)	−0.54	−0.69	−0.76	−0.78	−0.81	−0.81	−0.82	−0.84	−0.84	−0.82
8	Number of firms	659	554	456	376	332	323	291	301	320	330

suggests that the first determinant in Equation (1)—represented by the standard deviation of $\Delta_4 APS$—increases with share price, which is inconsistent with Prediction P1.1. The bottom two rows, which describe the second determinant in Equation (1), suggest managerial involvement: both Spearman and Pearson correlations become more negative from decile 1 to 7 and then level off. The net effect is driven by the second determinant, as it has a bigger impact than the first determinant because the correlation magnitudes exceed 0.5 and that term is multiplied by 2 (the variances of $\Delta_4 APS$ and $\Delta_4 CPS$ are similar).

To provide more reliable evidence, we estimate the correlations separately for each firm, using time-series data. Firms are assigned to price deciles based on their modal price decile across sample years. Untabulated results confirm that most firms move across price deciles over time, mainly because of normal price volatility, especially among the middle price deciles. To obtain a meaningful share price decile classification for each firm, we require (a) sufficient time-series data (more than 10 quarters) and (b) reasonably stable price levels (price decile equals, or is adjacent to, the modal decile for more than half the available quarters). The first requirement reduces our sample from 8,320 to 5,036 firms and the second requirement reduces it further to 3,942 firms. The number of firms retained in different price deciles, reported in the bottom row of panel B in Table 2, suggests that there is more stability of price levels over time for low-price firms. Our main finding is that inferences from the cross-sectional results in panel A are confirmed in panel B. Consistent with managerial involvement, the mean correlations become more negative for deciles 1–7 and level off thereafter.

To provide a more direct test of P1.1, we regress the firm-specific Pearson and Spearman correlations reported in panel B on price decile (*PRCDEC*). To estimate potential nonlinearity, we allow for a separate slope and intercept for firms in deciles 8–10, indicated by the dummy *HIPRC*. We also include controls for three variables—analyst coverage (*CVRGE*), forecast dispersion (*DISP*), and prior sales growth (*SLSGR*)—that might separately affect, or proxy for variables that affect, correlation between $\Delta_4 CPS$ and $\Delta_4 APS$. The regression we estimate is given in Equation (5):

$$\begin{aligned}\mathrm{Corr}(\Delta_4 CPS, \Delta_4 APS) &= \beta_0 + \beta_1 HIPRC + \beta_2 PRCDEC + \beta_3 HIPRC \times PRCDEC \\ &\quad + \beta_4 CVRGE + \beta_5 DISP + \beta_6 SLSGR. \qquad (5)\end{aligned}$$

Our results reported in panel C of Table 2 are again consistent with P1.1. The coefficient on *PRCDEC* of about −0.05, representing the per decile decrease in the correlation between deciles 1 and 7, is economically and statistically significant. In contrast, the coefficient

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

Table 2. (Continued)

Panel C: Regression of firm-specific correlations ($\Delta_4 CPS$, $\Delta_4 APS$) on price deciles (*PRCDEC*), with separate slope and intercept for price deciles 8–10 (*HIPRC*) (see Equation (5)); the control variables included are analyst coverage (*CVRGE*), forecast dispersion (*DISP*), and sales growth (*SLSGR*)

($\Delta_4 CPS$, $\Delta_4 APS$) correlation	Intercept	*HIPRC*	*PRCDEC*	*HIPRC* × *PRCDEC*	*CVRGE*	*DISP*	*SLSGR*	Obs.	R^2
Pearson	−0.606***	−0.326***	−0.049***	0.050***	0.006***	0.129	0.000	3,929	0.14
	(−57.93)	(−3.66)	(−21.48)	(5.01)	(6.62)	(1.27)	(1.10)		
Spearman	−0.603***	−0.267***	−0.049***	0.043***	0.006***	0.412***	0.000	3,929	0.16
	(−62.12)	(−3.23)	(−23.01)	(4.65)	(6.70)	(4.36)	(1.13)		

Panel D: Repeat panel B for firms not followed by analysts—The statistics are estimated in time series for each firm, and the means (across firms) and the number of firms in each price decile are reported below; price deciles are formed using *BEGPRICE* for the analyst-followed sample

	Means of	Price decile									
Row	Statistic and variable	1	2	3	4	5	6	7	8	9	10
1	StdDev ($\Delta_4 EPS\_GAAP$)	0.17	0.23	0.14	0.16	0.28	0.25	0.27	0.24	0.38	0.47
2	StdDev ($\Delta_4 CPS$)	0.27	0.43	0.32	0.56	0.51	0.53	0.74	0.55	0.66	0.84
3	StdDev ($\Delta_4 APS$)	0.30	0.45	0.34	0.59	0.56	0.55	0.74	0.58	0.62	0.88
4	Pearson Corr ($\Delta_4 CPS$, $\Delta_4 APS$)	−0.69	−0.81	−0.81	−0.91	−0.73	−0.81	−0.87	−0.90	−0.85	−0.85
5	Spearman Corr ($\Delta_4 CPS$, $\Delta_4 APS$)	−0.66	−0.79	−0.79	−0.89	−0.68	−0.79	−0.87	−0.89	−0.84	−0.81
6	Number of firms	629	52	50	27	5	9	6	5	6	5

Notes. EPS smoothing should increase the magnitude of the normally negative correlation between unexpected per share cash flows (CPS) and accruals (APS). Panels A–C refer to Prediction P1.1, and panel D refers to Prediction P3.1. We use seasonal differences of EPS, CPS, and APS, represented by $\Delta_4 EPS\_GAAP$, $\Delta_4 CPS$, and $\Delta_4 APS$, respectively, to proxy for the corresponding unexpected components. The variables $\Delta_4 EPS\_GAAP$ and $\Delta_4 CPS$ are Winsorized at 5% and 95% each year, and $\Delta_4 APS$ is derived from $\Delta_4 EPS\_GAAP - \Delta_4 CPS$. We investigate patterns of EPS smoothing across deciles of *BEGPRICE*, the beginning-of-quarter share price. Price deciles are computed at the beginning of each calendar quarter for fiscal quarters ending in that quarter, and the lowest (highest) price decile is denoted by 1 (10). In panel A, using the pooled sample in each price decile, we report the volatilities of $\Delta_4 EPS\_GAAP$, $\Delta_4 CPS$, and $\Delta_4 APS$, measured by their standard deviations, and the correlation between $\Delta_4 CPS$ and $\Delta_4 APS$. For the firm-specific results in panel B, we assign each firm to its modal price decile if (a) more than 10 quarters of data are available, and (b) the price decile for more than half of the quarters equals, or is adjacent to, the modal price decile. We report the mean volatilities of $\Delta_4 EPS\_GAAP$, $\Delta_4 CPS$, and $\Delta_4 APS$, and correlations between $\Delta_4 CPS$ and $\Delta_4 APS$. In panel C, we report a regression analysis of the firm-specific correlations on price deciles. The t-statistics are reported in parentheses below each coefficient estimate. In panel D, we repeat the analysis in panel B using firms not followed by analysts. All variables are denominated in dollars and are described in more detail in Appendix A.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

on *PRCDEC* × *HIPRC*, representing the incremental slope for deciles 8–10 is positive and of equal magnitude. As the sum of the two coefficients is close to zero, correlations vary little for deciles 8–10. Untabulated results show that the coefficients on *PRCDEC* and *PRCDEC* × *HIPRC* are relatively unaffected when we drop the three control variables or add a fourth control variable for firm-age. That is, even though the control variables explain cross-sectional variation in cash flow/accrual correlations, they are unrelated to price variation in that correlation.

We conduct robustness analyses to investigate the extent to which the seasonal random walk process we assume for *APS* and *CPS* approximate the underlying time-series processes. Our concern is that measurement error in *APS* and *CPS* surprise varies across price deciles in such a way that it induces the observed pattern of correlation between $\Delta_4 APS$ and $\Delta_4 CPS$. We examine autocorrelations and partial autocorrelations at the first four lags for $\Delta_4 APS$ and $\Delta_4 CPS$ for firms with sufficient time-series data (more than 10 quarters) and reasonably stable price levels over time. While our results indicate nonzero autocorrelations, especially at the fourth lag, we note that the levels of these autocorrelations are similar across price deciles.[15] Overall, we conclude that measurement error in *APS* and *CPS* biases the *levels* of correlations reported in Table 2, but that bias is unlikely to become more negative with price up to decile 7 and hold constant after that. We do not estimate discretionary accruals to measure smoothing, because the accruals used to smooth cash flow shocks are mainly captured in *nondiscretionary* accruals when smoothing is sustained through time (e.g., Lang et al. 2012).[16]

The main finding in panels A–C of Table 2 is evidence consistent with substantial and widespread earnings smoothing using accruals to offset cash flow shocks. The extent of smoothing is particularly high for high-price firms. Any natural variation in forecast error magnitudes between deciles 1 and 7 is eliminated by such smoothing. Observing a nonlinearity in the level of smoothing after decile 7 suggests that firms reach a limit beyond which additional smoothing

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

is not the preferred way to further compress forecast errors.

4.2. Prediction P1.2: Differential Reduction of Volatility from $\Delta_4 EPS\_GAAP$ to $\Delta_4 EPS\_IBES$

The second way to compress forecast errors is to selectively classify components of reported earnings as one-time items (*ONETIME)* and exclude them from core EPS. According to Prediction P1.2, managerial involvement is likely if the variance of Δ_4*ONETIME* or the correlation between Δ_4*ONETIME* and Δ_4*EPS_IBES* increases with price between deciles 8 and 10, but not between deciles 1 and 7. As mentioned earlier, the results in Figure 1 suggest that Prediction P1.2 is unlikely to explain *differential* earnings smoothing. There is clear evidence that removing one-time items from reported EPS substantially reduces the volatility of core EPS: both the gap between the lines for Δ_4*EPS_GAAP* and Δ_4*EPS_IBES* in Figure 1 and the difference between the volatility levels reported in rows 1 and 2 in panel A of Table 3 are substantial. But there is no indication of larger volatility declines between deciles 8 and 10.

The results in the bottom two rows of panel A of Table 3 confirm this expectation. The standard deviation of Δ_4*ONETIME* reported in row 3 exhibits a slight increase for deciles 8–10, which is consistent with P1.2. However the results reported in row 4, indicate an offsetting decline in the correlation terms, which is inconsistent with the increasing pattern predicted by P1.2. Overall, the results suggest that managers do not use one-time items to differentially smooth core EPS.

4.3. Prediction P1.3: Accuracy of Early Forecasts vs. *EPS_IBES* from Quarter $t-4$

The third approach we consider to compress forecast errors is to selectively guide the early forecasts of analysts (*FORECAST_9*) to improve their accuracy as share price increases between deciles 8 and 10, but not between deciles 1 and 7. According to Prediction P1.3, this selective approach should be reflected as a reduction in the variance of *ANALYADJ* or an increase in the correlation between Δ_4*EPS_IBES* and *ANALYADJ* between deciles 8 and 10.

As discussed earlier, we do not anticipate support for Prediction P1.3. Not only is there little price variation in the gap between Δ_4*EPS_IBES* and *FCSTERR_9* in Figure 1, there is little evidence of guidance because that gap is quite small. Early analyst forecasts, made nine months before the quarter-end, are only marginally more accurate than *EPS_IBES* from quarter $t-4$. The first two rows in panel B of Table 3 confirm the results noted in Figure 1: the standard deviations of Δ_4*EPS_IBES* and *FCSTERR_9* are close to each other and both exhibit a similar increase between deciles 8 and 10.

Returning to Prediction P1.3, the variance of *ANALYADJ* reported in row 3 of panel B increases slightly from decile 8 to decile 10, which is contrary to the decline predicted by P1.3. Row 4 of panel B indicates a slight increase in correlation from decile 8 to decile 10, which is consistent with P1.3. Overall, the results do not support P1.3: managers do not appear to use guidance to differentially improve the accuracy of early forecasts.

4.4. Prediction P1.4: Accuracy Improvement Between Early and More Recent Forecasts

The final approach we consider to compress forecast errors is to selectively guide analysts to improve the accuracy of their most recent forecasts as share price increases between deciles 8 and 10, but not between deciles 1 and 7. According to Prediction P1.4, this selective managerial guidance should be reflected in a decrease in the variance of *REVISION* or an increase in the correlation between *FCSTERR_9* and *REVISION* between deciles 8 and 10.

The large gap between *FCSTERR_9* and *FCSTERR* in Figure 1 suggests that most recent forecasts (*FORECAST*) are considerably more accurate than early forecasts (*FORECAST_9*). More important, that gap increases between deciles 8 and 10, which suggests that P1.4 is relevant. The first two rows in panel C of Table 3 confirm the results noted in Figure 1: the standard deviations of *FCSTERR* are considerably lower than those of *FCSTERR_9* and that gap increases from decile 8 to decile 10.

Row 3 in panel C of Table 3 shows that the variance of *REVISON* increases from decile 8 to decile 10, which is inconsistent with the decrease predicted by P1.4. Row 4 indicates only a slight increase in correlation from decile 8 to decile 10, which is marginally consistent with P1.4. Inspection of Equation (4) reveals, however, that an increase in the variance of *REVISON* has a second, indirect effect: it also increases the covariance term. More important, its effect on the covariance term offsets its direct effect, for two reasons: (a) because the variance of *REVISION* is less than one, the square root of the variance of *REVISION* grows faster than the variance; and (b) the covariance term is multiplied by two. As a result, increases in the variance of *REVISION* for deciles 8–10 explain the differential improvement in accuracy between early and recent forecasts in that range. Analyst forecasts are revised by larger amounts as scale increases between deciles 8 and 10, and those larger revisions compress forecast errors by bringing recent forecasts closer to *EPS_IBES*.

Panel D of Table 3 confirms the inferences from panel C using a regression analysis. We use the nonlinear relation with scale proposed in Equation (5), and replace $\mathrm{Corr}(\Delta_4 CPS, \Delta_4 APS)$ with the standard deviation of *REVISION*. The standard deviation is estimated annually for all price deciles. The coefficient on

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

Table 3. Predictions P1.2, P1.3, and P1.4: Use of One-Time Items and Managerial Guidance to Compress EPS Forecast Error

Panel A: Prediction P1.2—Analysis of one-time items, estimated in the cross section, across price deciles; sample has 163,582 firm-quarter observations

		Price decile									
Row	Statistic and variable	1	2	3	4	5	6	7	8	9	10
1	StdDev (Δ_4*EPS_GAAP*)	0.39	0.38	0.37	0.35	0.34	0.34	0.35	0.35	0.37	0.42
2	StdDev (Δ_4*EPS_IBES*)	0.20	0.20	0.20	0.20	0.19	0.20	0.20	0.21	0.22	0.26
3	StdDev (Δ_4*ONETIME*)	0.30	0.29	0.28	0.27	0.25	0.26	0.25	0.25	0.27	0.30
4	Corr (Δ_4*EPS_IBES*, Δ_4*ONETIME*)	0.16	0.17	0.18	0.14	0.14	0.14	0.14	0.13	0.11	0.12

Panel B: Prediction P1.3—Analysis of analyst adjustment, estimated in the cross section, across price deciles; sample has 147,086 firm-quarter observations

		Price decile									
Row	Statistic and variable	1	2	3	4	5	6	7	8	9	10
1	StdDev (*FCSTERR_9*)	0.19	0.19	0.19	0.18	0.18	0.19	0.19	0.20	0.21	0.24
2	StdDev (Δ_4*EPS_IBES*)	0.20	0.20	0.20	0.20	0.19	0.20	0.20	0.21	0.22	0.26
3	StdDev (*ANALYADJ*)	0.14	0.13	0.13	0.12	0.12	0.12	0.12	0.13	0.14	0.15
4	Corr (Δ_4*EPS_IBES*, *ANALYADJ*)	0.42	0.40	0.41	0.41	0.41	0.39	0.41	0.43	0.42	0.44

Panel C: Prediction P1.4–Analysis of revisions between early and more recent forecasts, estimated in the cross section, across price deciles; sample has 164,834 firm-quarter observations

		Price decile									
Row	Statistic and variable	1	2	3	4	5	6	7	8	9	10
1	StdDev (*FCSTERR_9*)	0.19	0.19	0.19	0.18	0.18	0.18	0.19	0.20	0.21	0.24
2	StdDev (*FCSTERR*)	0.08	0.07	0.07	0.07	0.07	0.07	0.07	0.08	0.08	0.09
3	StdDev (*REVISION*)	0.15	0.15	0.15	0.15	0.15	0.16	0.16	0.17	0.18	0.21
4	Corr (*FCSTERR_9*, *REVISION*)	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.93

Panel D: Prediction P1.4—Regression of the standard deviation of forecast revision (calculated in each year and price decile) on price decile (*PRCDEC*), with separate slope and intercept for price deciles 8–10 (*HIPRC*)

	Intercept	*HIPRC*	*PRCDEC*	*HIPRC* × *PRCDEC*	Obs.	R^2
StdDev *REVISION*	0.137***	−0.128***	0.002	0.017***	210	0.20
	(21.35)	(−2.61)	(1.30)	(3.01)		

Notes. This table investigates the extent to which one-time items and managerial guidance are used to compress EPS forecast error across price deciles. For example, analysts may selectively reclassify large spikes in reported EPS (*EPS_GAAP*) as one-time items to reduce the volatility of core EPS (*EPS_IBES*), thereby reducing the volatility or compressing forecast errors. We report the statistics of different variables across deciles of *BEGPRICE*, which is the beginning-of-quarter share price. Price deciles are computed at the beginning of each calendar quarter for fiscal quarters ending in that quarter, and the lowest (highest) price decile is denoted by 1 (10). *EPS_IBES* is the actual quarterly EPS as reported by I/B/E/S. Earnings per share (*EPS_GAAP*) is the per share quarterly income before extraordinary items, obtained from the cash flow statement. One-time item (*ONETIME*) is defined as *EPS_GAAP* minus *EPS_IBES*. Δ_4*EPS_IBES* and Δ_4*EPS_GAAP* are seasonal differences of *EPS_IBES* and *EPS_GAAP* respectively. The variables Δ_4*EPS_IBES*, Δ_4*EPS_GAAP*, *FCSTERR*, *FCSTERR_9*, and Δ_4*EPS_IBES* are Winsorized at 5% and 95% each year. Δ_4*ONETIME* (= Δ_4*EPS_GAAP* − Δ_4*EPS_IBES*), *ANALYADJ* (= Δ_4*EPS_IBES* − *FCSTERR_9*), and *REVISION* (= *FCSTERR_9* − *FCSTERR*) are derived from those Winsorized variables. In the regression analysis, t-statistics are reported in parentheses below each coefficient estimate. All variables are denominated in dollars and are described in more detail in Appendix A.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

PRCDEC, which is insignificant, indicates little scale variation in the accuracy improvement from forecast revisions for deciles 1–7. However, the coefficient on *HIPRC* × *PRCDEC*, which indicates the incremental scale variation in accuracy for deciles 8–10, is positive and significant. The results in panels C and D suggest that managers guide analyst forecasts to be differentially more accurate for deciles 8–10. If managers are not involved, why would accuracy improvements be similar for deciles 1–7, but increase with scale only for deciles 8–10?

The results so far suggest that natural scale variation in error magnitudes for analysts' EPS forecasts is suppressed by managers in two ways. First, all the natural scale variation between price deciles 1 and 7 and much of the natural scale variation between deciles 8 and 10 is suppressed by increased earnings smoothing, using accruals to offset cash flow shocks. Second, any

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

residual scale variation between deciles 8 and 10 is suppressed by increased management guidance designed to improve forecast accuracy.

The extent of managerial efforts to alter reported and forecast EPS, especially for high-price firms, is so substantial and so widespread—across firms and over time—that skeptical readers may remain unconvinced. Perhaps the patterns of price variation we document for correlations between cash flow and accrual shocks (P1.1) and variances of forecast revisions (P1.4) are due to alternative explanations other than managerial intervention. To investigate this possibility, we consider two strategies. First, we investigate investor responses to provide an orthogonal perspective (P2). Second, we turn to falsification tests (P3.1, P3.2, and P3.3) to determine whether the results described above are observed for two samples that should resemble U.S. analyst-followed firms under alternative explanations.

4.5. Prediction P2: Do Investors Adjust for Differential Compression of Forecast Errors?

This prediction is based on a simple premise: if investors recognize managerial efforts to compress forecast errors, they should adjust observed forecast errors to recover uncompressed forecast errors. That is, the ERC—price response (*PRICERESP*) per cent of observed forecast error—should increase with compression levels. Investigating ERCs offers a powerful test of the managerial intervention hypothesis. First, there should be substantial price variation in ERC. Second, the magnitude of ERC for high-price firms needs to be many times higher than that anticipated by theory. Panel A of Table 4 provides initial confirmation of P2: the standard deviation of *PRICERESP*, which reflects the magnitudes of price responses, increases substantially with scale. The standard deviation for decile 10, reported in row 2, is about 10 times as high for decile 1. Row 1 of panel A, which shows little price variation in the correlation between *PRICERESP* and *FCSTERR*, confirms that scale variation in *PRICERESP* magnitudes will be reflected in corresponding scale variation in ERC (see relation (B.1) in Appendix B).

To provide a more granular view of scale variation in price responses, we analyze them at the level of each cent of forecast error. We begin with a detailed view of scale variation in forecast errors before moving to price responses. Panel A of Figure 2 reports the distribution of forecast errors for three representative price deciles: deciles 1, 5, and 10. We show frequencies for each cent of *FCSTERR* between −10¢ and +10¢. Observations outside of that range are consolidated in the two extreme bins. Consistent with the results reported in panel A of CT's Figure 2, forecast error distributions are relatively similar across price. There are, however, important findings relating to discontinuities and location of the distributions that we return to in Section 5.

Panel B of Figure 2 reports mean *PRICERESP* for the same three price deciles and *FCSTERR* bins. The slope of a hypothetical line that connects the midpoints of the tops of the vertical bars represents the incremental price response per cent of forecast error, or ERC, in each subpanel. Consistent with P2, we see that the slope increases sharply with share price, especially for the majority of observations that are clustered within the narrow [−5¢ to +5¢] range. Note that the y axis scale for decile 5 (10) in the middle (right) column is four (10) times that for decile 1. Observing similar slopes from left to right suggests that the slope for decile 5 (10) is about four (10) times that for decile 1. While not as evident in Figure 2, that slope is relatively flat for larger forecast error magnitudes outside of the [−5¢ to +5¢] range.

Panel C of Figure 2 describes our estimates of ERC—slopes from regressions of *PRICERESP* on *FCSTERR*—for three partitions: (a) large negative *FCSTERR* (<−5¢), (b) small *FCSTERR* (≤−5¢ to ≥+5¢), and large positive *FCSTERR* (>+5¢). These estimates are also reported in panel B of Table 4. The middle group contains about 70% of our sample, and the two groups on each side contain about 15% each. Consistent with the results in panel B of Figure 2 ERC varies widely across different partitions. While ERC is generally close to zero for most price deciles in the large negative and large positive forecast error groups, it is much higher for the small forecast error partition in the middle.[17] More relevant to P2, those ERC values increase sharply with price, from 7.3 for decile 1 to 51.6 for decile 10.

The results in panel C of Table 4 describe scale variation in ERC based on a regression analysis. ERC estimated annually within each price decile is regressed on price deciles, separately for the three forecast error groups. Consistent with the results in panel B of Table 4, ERC varies considerably with scale for the small forecast error group (coefficient of 3.975 on *PRCDEC*) but exhibits significantly lower scale variation for the large negative and large positive forecast error groups, indicated by similarly large coefficients of the opposite sign on the interactions between *PRCDEC* and *LARGE NEGATIVE* and *LARGE POSITIVE* (−3.883 and −3.657), respectively.

4.6. Falsification Tests Based on U.S. Firms Not Followed by Analysts and Analyst-Followed Firms in Japan

Prediction 3.1 investigates whether price variation in earnings smoothing we document for analyst-followed U.S. firms is also observed for firms not followed by analysts. If scale variation in the correlation between $\Delta_4 CPS$ and $\Delta_4 APS$ observed for analyst-followed firms is due to some factor other than managerial intervention—such as omitted correlated variables or opposite measurement error in $\Delta_4 CPS$ and $\Delta_4 APS$—we

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

Table 4. Prediction 2: Variation in ERC Across Price Deciles, and the Effects of Pooling and Deflation

Panel A: Correlation and standard deviation of price response

Row	Statistic and variable	Price decile 1	2	3	4	5	6	7	8	9	10
1	Corr (*FCSTERR*, *PRICERESP*)	0.18	0.21	0.23	0.23	0.25	0.22	0.22	0.21	0.18	0.16
2	StdDev *PRICERESP*	1.26	1.68	2.15	2.59	2.91	3.52	4.01	4.92	6.11	11.14

Panel B: ERC slope coefficient from a regression of undeflated 22-day price response (*PRICERESP*) on forecast error, estimated separately for each price decile, each partition of forecast error, and each year. The mean coefficient (across all years) is reported below. The bottom row combines observations across all three forecast error ranges, and the rightmost column combines observations across all price deciles.

	Price decile 1	2	3	4	5	6	7	8	9	10	All
FCSTERR < −5¢	0.1	0.1	0.1	0.2	0.8	0.9	0.0	0.8	0.9	0.8	0.3
FCSTERR = [−5¢, +5¢]	7.3	12.7	17.4	19.8	23.1	26.7	26.6	31.7	35.7	51.6	23.3
FCSTERR > 5¢	0.1	0.1	0.3	1.4	1.0	1.2	0.4	1.5	2.5	3.6	1.5
All	0.7	1.1	1.8	2.9	3.7	4.5	4.1	5.0	5.2	3.5	2.2

Panel C: Regression of undeflated ERC slope coefficients on price deciles (*PRCDEC*), with separate slope and intercept for the sample with large negative (*FCSTERR* < −5¢) and large positive (*FCSTERR* > 5¢) forecast errors

	Intercept	*LARGE NEGATIVE*	*LARGE POSITIVE*	*PRCDEC*	*LARGE NEGATIVE* × *PRCDEC*	*LARGE POSITIVE* × *PRCDEC*	Obs.	R^2
ERC	3.411***	−3.429**	−3.928**	3.975***	−3.883***	−3.657***	630	0.73
	(2.85)	(−2.03)	(−2.32)	(20.60)	(−14.23)	(−13.40)		

Panel D: ERC slope coefficient from a regression of price response (*CAR*) on forecast error, both deflated by lagged share price. ERC is estimated separately for each price decile, each partition of forecast error, and each year. The mean coefficient (across all years) is reported below. The bottom row combines observations across all three forecast error ranges, and the rightmost column combines observations across all price deciles.

	Price decile 1	2	3	4	5	6	7	8	9	10	All
FCSTERR < −5¢	0.1	0.1	0.0	0.3	1.0	1.3	0.1	0.8	1.6	−0.8	0.1
FCSTERR = [−5¢, +5¢]	4.7	11.7	16.7	19.3	22.6	26.3	27.5	32.0	38.2	50.7	7.6
FCSTERR > 5¢	0.4	−0.1	0.7	1.5	0.9	1.1	0.1	1.3	1.6	1.8	0.6
All	0.4	1.0	1.8	3.0	3.8	4.7	4.1	5.2	5.4	3.9	0.6

Notes. This table describes how ERC varies with share price and magnitude of forecast errors. We also examine the impact of pooling subgroups of firms with different ERC. Our I/B/E/S sample of 197,004 firm-quarters with available data is split into price deciles based on beginning-of-quarter share price (*BEGPRICE*). The sample is also split into three subgroups based on forecast error ranges: (a) large negative (<−5¢); (b) small (between −5¢ and +5¢); and (c) large positive (>+5¢). In the regression analysis, *t*-statistics are reported in parentheses below each coefficient estimate. All variables are denominated in dollars and are described in more detail in Appendix A.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

should observe similar scale variation for not-followed firms.

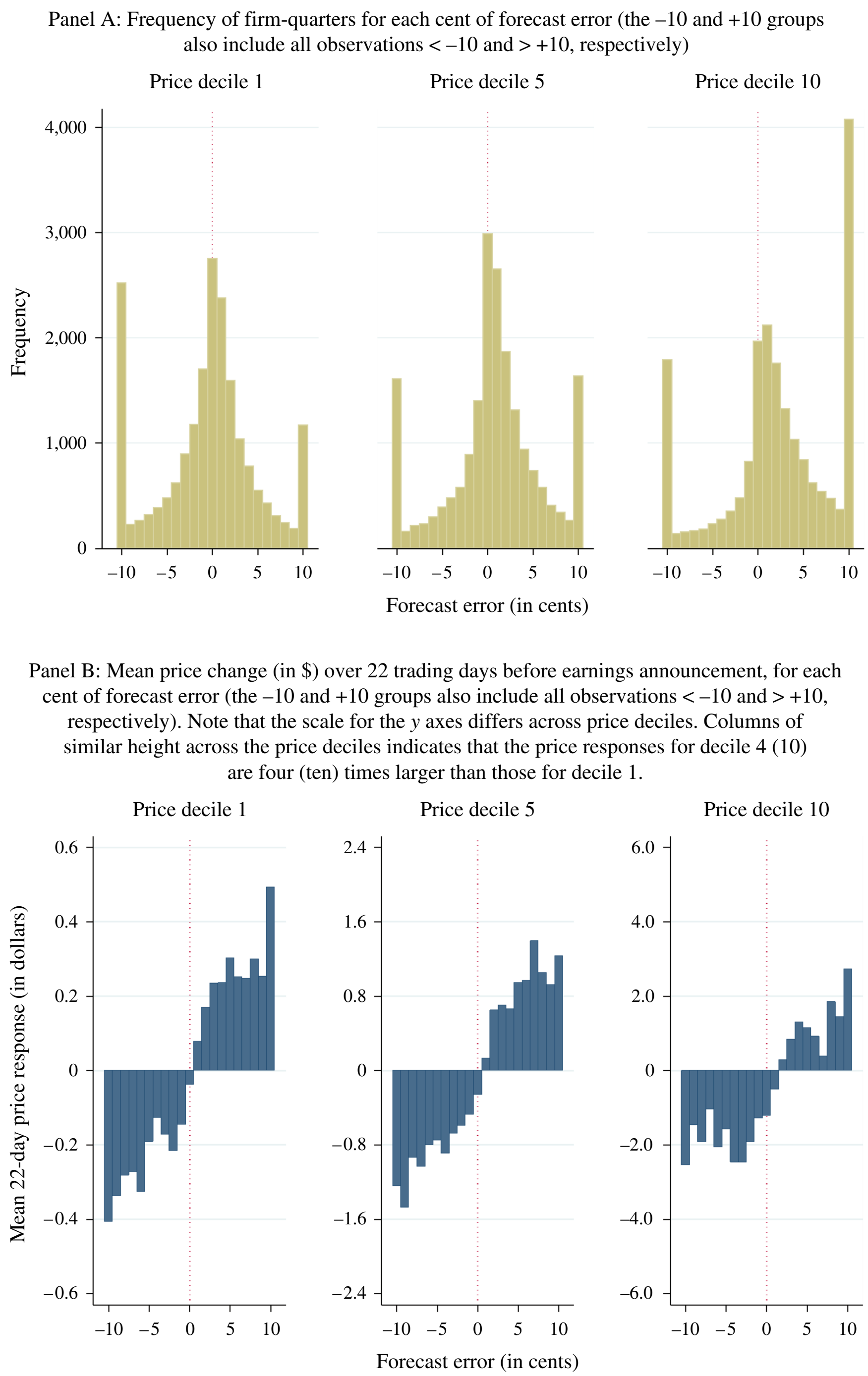
Our results are reported in panel D of Table 2. As described in CT, most not-followed firms are in price decile 1. The additional conditions required to estimate firm-specific cash flow/accruals correlations results in only a handful of firms in the remaining deciles. Regardless, we find a relatively flat profile in panel D, quite different from the increasing negative pattern reported in panel B for analyst-followed firms.[18] This flat profile is consistent with P3.1 and suggests that scale variation observed for analyst-followed firms is due to differential earnings smoothing. We note that the levels of correlations observed in panel D of Table 2 are substantially negative, suggesting very high levels of smoothing for all not-followed firms. As mentioned earlier, base levels of observed cash flow/accrual correlations—before any smoothing occurs—are expected to be negative, because of accounting rules and opposite errors in our cash flow and accruals measures. Perhaps, that base level is higher for not-followed firms; i.e., correlations levels are not comparable across panels D and B.

Our second falsification test, based on P3.2, investigates whether the earnings smoothing documented for analyst-followed firms in the United States is also

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

Figure 2. (Color online) Variation Across Price Deciles in Price Response to Forecast Errors

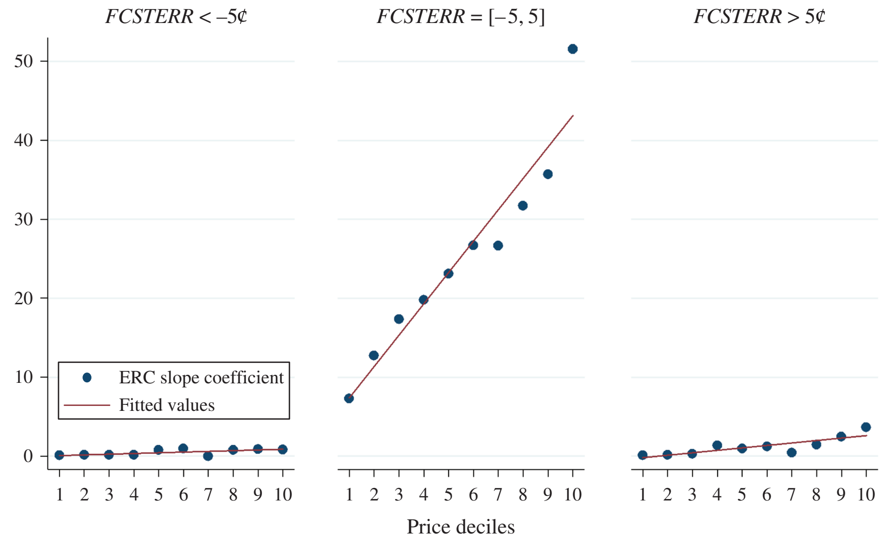


observed in Japan. (Lack of sufficient data prevents us from considering three other markets that resemble Japan: Brazil, Italy, and Switzerland.) As with Prediction P3.1, if price variation in the correlation between $\Delta_4 CPS$ and $\Delta_4 APS$ observed for U.S. firms is due to some factor other than managerial intervention, we should observe similar price variation in Japan. For brevity, we report in the next two paragraphs a summary of those results. Additional details of the samples and results are provided in Table A1 of the online appendix.

First, even though the correlation between $\Delta_4 CPS$ and $\Delta_4 APS$ for Japanese firms becomes more negative with scale, the rate of decline is much lower than that for the United States. The coefficient on *PRCDEC* is about −0.01 in Japan, approximately one-fifth of the corresponding coefficient in panel C of Table 2 for U.S. firms. Second, there is no evidence of a nonlinearity in that correlation pattern around price decile 7. Finally, to confirm that our results for Japan are not due to the sample selection process employed, we collect a sample

Figure 2. (Continued)

Panel C: ERC or slope of regression of 22-day price change on forecast error, estimated separately for each price decile, over three forecast error ranges.



Notes. Our I/B/E/S sample of 199,486 firm-quarters with available data is split into price deciles based on beginning-of-quarter share price. Price deciles are computed at the beginning of each calendar quarter for fiscal quarters ending in that quarter, and the lowest (highest) price decile is denoted by 1 (10). The histograms in panel A provide the number of firm-quarters with forecast errors that lie within each cent between −10 and +10¢. All observations with forecast errors ≤−10¢ (≥10¢) are included in the leftmost (rightmost) group in each plot. Panel B provides the mean price response (in $) over the 22-trading-day period prior to earnings announcements for the forecast error subgroups. For brevity, we provide plots for only three price deciles (deciles 1, 5, and 10) for panels A and B. Panel C provides the ERC (slope from regression of 22-day price response on forecast error), estimated separately for each price decile over three forecast error ranges: <−5¢, between −5 and +5¢, and >+5¢.

of U.S. firms using the same process. The results for this smaller U.S. sample are similar to those reported for our full U.S. sample—coefficient on *PRCDEC* of −0.036 versus −0.049 in panel B of Table 2—and the smaller U.S. sample remains significantly different than the Japanese sample.

Our third falsification test, based on P3.3, compares price variation in ERC between analyst-followed firms in the United States and Japan. Finding that ERC in Japan increases substantially with price, as it does for U.S. firms, suggests that factors other than differential forecast error compression play a role. Our results for P3.3 are again inconsistent with alternative explanations and suggest managerial intervention in the United States. The main finding is that there is relatively little scale variation in ERC for the small forecast error group (defined as for the U.S. sample to exclude 15% of our Japan sample with large forecast errors in the left and right tails). The coefficient on *PRCDEC* is insignificant for Japan, and the Japanese sample is significantly different than both our full U.S. sample as well as the smaller U.S. sample collected using the same process as that we used for Japan.

4.7. Summary of Evidence About Managers Differentially Compressing Forecast Errors

Price variation in the negative correlation between $\Delta_4 CPS$ and $\Delta_4 APS$ for U.S. firms followed by analysts is quite different from the corresponding variation observed for U.S. firms not followed by analysts and for analyst-followed firms in Japan. Only U.S. analyst-followed firms exhibit the pattern predicted by P1.1: the correlation becomes more negative with price through decile 7 and flattens out thereafter. Not observing the same pattern for both falsification tests (P3.1 and P3.2) is inconsistent with alternative explanations. Similarly, finding that revisions made between early and late forecasts increase accuracy only for deciles 8–10 (Prediction P1.4), and by amounts that are just sufficient to eliminate any residual price variation in forecast errors magnitudes is also inconsistent with alternative explanations. In combination, the evidence suggests that managers of U.S. analyst-followed firms engage in systematic earnings smoothing and forecast guidance to suppress natural scale variation in EPS forecast errors.

Our investigation of investor responses, relating to Predictions P2 and P3.3, provides the strongest support for the hypothesis that managers intervene to suppress scale variation in forecast errors. Absent differential compression, we cannot explain why ERC varies so much across price deciles for U.S. analyst-followed firms. And it is harder still to explain why ERC is so high for higher-price deciles. Theory describing the determinants of ERC (e.g., Kormendi and Lipe

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

1987, Collins and Kothari 1989) has identified persistence, risk, and growth. Predicted levels of ERC, once low persistence earnings components are removed, are expected to be in the neighborhood of 10, representing the inverse of an average assumed discount rate of 10%. ERCs are of course expected to be higher for high-growth firms and should approach the high P/E ratios associated with high-growth firms (e.g., Burgstahler and Chuk 2010). Untabulated results show that growth, measured as past growth in sales, is reasonably similar across deciles (median sales growth is 4% in decile 2, 5% in decile 3, and increases slightly to 7% in decile 9 and 8% in decile 10). Therefore, *average* ERCs as high as those we observe for high-price firms are not predicted by theory. They are, however, explained by forecast error compression.

While very high ERCs—higher than those predicted by theory—have been noted before for small forecast errors, no alternative explanation is offered for why high-price firms are associated with very high ERC. Abarbanell and Park (2016) show ERC increasing from about 3 to about 21 across quintiles of PPB, an indicator of firms' propensity to exhibit positive forecast error bias (i.e., beat consensus estimates). These ERC levels are assumed, however, to be exogenously determined, and PPB is the endogenous firm response that is consistent with the model in Fischer and Verrecchia (2000).

Burgstahler and Chuk (2010) also document high ERCs, with ERCs rising toward 30 as they narrow the range of forecast errors to ±0.25% of share price. Their focus is on cross-sectional variation in ERC, which they attribute to variation in signal precision, and do not comment on the high ERC levels as they believe it is consistent with high-growth firms that have P/E ratios of about 30. While we agree that high-growth firms might be associated with high ERC, firms in higher-price deciles with very high ERC are not high-growth firms. One unusual aspect of their findings is that ERCs increase as the forecast error range narrows, whereas our results in panel B of Figure 2 indicate little variation with forecast error magnitudes once the large forecast errors on either side are eliminated. This seeming difference arises because they deflate forecast errors by price, while we do not. Narrowing the range of deflated forecast errors increases the proportion of high-price firms included (as magnitudes of *undeflated* forecast errors vary little with price), which we show are the firms associated with very high ERCs.[19]

In sum, our results in combination with those in CT are strongly consistent with managers of U.S. analyst-followed firms engaging in substantial and pervasive compression of forecast errors, designed to eliminate scale variation in forecast error magnitudes. Alternative explanations—typically based on omitted, correlated variables—exist for individual results, but they are unlikely to explain the portfolio of results.

5. Implications of Managerial/Investor Behavior for Research

We turn next to the implications of our results for studies that use variables derived from actual/forecast EPS and associated investor responses. Inferences from those studies might be biased if researchers are unaware of the unintuitive empirical regularities documented here and in CT. Regardless of why the regularities arise, their existence is sufficient to generate potential biases. We see three general sources of bias: (a) variables that are expected to vary with scale but do not in the data; (b) variables that are not expected to vary with scale but do so in the data; and (c) pooling samples that are expected to have similar attributes but do not in the data. We provide a brief description of the nature of potential biases and ways to mitigate them. We then illustrate those points as they relate to (a) and (b) by replicating two earlier studies—Thomas (2002) and Ng et al. (2008).[20] When replicating the studies, our scope is limited to showing how bias arises for specific coefficient estimates, and the impact of using alternative specifications that mitigate such bias. We do not conduct a full replication of those studies.

5.1. Variables That Are Expected to Vary with Scale But Do Not in the Data

CT note that researchers tend to deflate certain variables—such as forecast error magnitudes, forecast dispersion, and volatility of seasonally differenced earnings—not realizing that deflation actually induces a negative relation with scale.[21] At the same time, various firm attributes used as dependent or independent variables are also unexpectedly related to scale. As discussed in CT, this common relation with scale might create spurious relations between firm attributes and the deflated variables mentioned above. Our recommendations to mitigate potential bias are as follows. First, examine the relations between different variables and scale at the *share* level, separate from any relation with scale at the firm level. Caution is called for if a dependent and at least one independent variable are related to share price. Second, deflate variables that do not in fact vary with scale only if theory calls for it. If not, avoid deflation to avoid the negative relation with scale induced by deflation. Third, include share price (or the inverse of share price) as an additional control if scale is correlated with variables in the specification used.

We explore this source of bias and the impact of our recommendations by reexamining Thomas (2002), which tests hypotheses that link the degree of firm diversification across different lines of business with information asymmetry between managers and investors/analysts. Two of many measures of information asymmetry considered in Thomas (2002) are absolute forecast error ($|FCSTERR|$) and forecast dispersion

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

(*DISPERSION*), both deflated by share price. Diversification is measured by the Herfindahl index (*HERF*) computed for each firm-year based on segment assets.

We selected this study for replication because *HERF* is associated with a positive coefficient in all regressions, except for a final specification that includes *RESIDVOL*—the standard deviation of market model residuals—as an additional control variable: the coefficient on *HERF* swings to significant negative values. We conjecture that the positive coefficient on *HERF* is because it as well as the dependent variables are related to scale. Introducing *RESIDVOL*, which is strongly negatively related to share price, alters the coefficient on *HERF* because it soaks up some of the effect caused by the relation between HERF and scale.

After documenting that scale is related to the deflated dependent variables and *HERF*, we consider three alternative specifications to investigate our recommendations above: (a) *INVPRICE* is included as a control variable to the original deflated specifications; (b) |*FCSTERR*| and *DISPERSION* are not deflated by price; and (c) price is added as an additional regressor to the undeflated specifications. We obtain similar findings for |*FCSTERR*| and *DISPERSION*. For brevity, we report only the results for |*FCSTERR*| in Table 5 and provide separately the results for *DISPERSION* in Table A2 of the online appendix.

Panel A of Table 5 contains Pearson and Spearman correlations for key variables from Thomas (2002) as well as two other variables we create from the underlying data: undeflated absolute forecast errors (|*FCSTERR*|) and the inverse of share price (*INVPRICE*). The dependent variable is |*DEFLFE*|, which is absolute forecast error deflated by share price five days before the annual earnings announcement (*BEGPRICE*). Both HERF and |*DEFLFE*| are strongly related to share price, which creates the potential for the coefficient on *HERF* to be biased.

Panel B of Table 5 contains the results of extending the analyses in Table 3 of Thomas (2002). The other variables considered in Thomas (2002) are included in our regressions but not reported in Table 5. The row labeled specification I refers to the original results, and columns (1)–(5) refer to the corresponding models estimated in Thomas (2002). We are able to replicate the main findings in Thomas (2002): the coefficient on *HERF* is positive and significant in Equations (1)–(4), but that relation switches to a negative and significant coefficient in Equation (5), when *RESIDVOL* is introduced.

Specification II introduces the inverse of share price as an additional regressor. This inclusion is appropriate if theory calls for forecast error magnitudes to be scaled by share price. Introducing the inverse of share price offers a direct way to mitigate the spurious relation with HERF. In effect, it plays the role of *RESIDVOL* in Equation (5). The main finding in specification II is that the significant positive coefficients on *HERF* observed in the original results for Equations (1)–(4) are no longer significantly positive.

Specification III is similar to the original specification, except the dependent variables are undeflated. As with specification II, no significant *positive* coefficients are observed on *HERF*. Specification IV adds share price as an additional regressor to specification III to control for the small positive relations between share price and undeflated measures of |*FCSTERR*| and *DISPERSION* observed in panel A of Table 5. Again, no significant positive coefficients are observed for *HERF*.

The results in Table 5 suggest that the positive coefficient on *HERF* observed in Equations (1)–(4) of specification I is likely spurious. Finding that scale is correlated with both the dependent variable and *HERF* points to the source of bias. Avoiding deflation and including scale as an additional control variable mitigate that bias.[22]

5.2. Variables That Are Not Expected to Vary with Scale But Do So in the Data

There are many examples of variables that unexpectedly vary with scale. First, as shown earlier, ERCs and measures of earnings smoothing increase with scale. Second, CT show that forecast pessimism—observed at short horizons—increases with scale (CT#1). Third, results in Table A3 and Figure A1 of the online appendix indicate that forecast *optimism* for longer horizons also increases with scale. As a byproduct, the walkdown from optimistic early forecasts to pessimistic recent forecasts is positively related to scale. Researchers unaware of these relations with scale face the same potential for biased inferences mentioned above if these variables are used in regressions where other variables also happen to be related to scale. Our recommendations are similar to those for the first case above: check if scale is correlated with the dependent and at least one independent variable; and include scale as an additional regressor.

We illustrate these points by reexamining Table 2 of Ng et al. (2008). That study documents a strong negative relation between ERC and transactions costs. They consider three measures of transaction costs: *ESPREAD*, *QSPREAD*, and *LDV*. Even though these proxies for transactions costs increase with share price, scaling by price creates "overdeflation," which induces a negative relation with scale. This negative relation creates the potential for bias in the observed relation between ERC and transaction cost because both variables are related to scale. To investigate possible bias, we also control for share price.

We select the specification in their study that is closest to that considered here; i.e., regressions of abnormal returns around earnings announcements (*CAR*) on analysts' forecast errors (*DEFLFE*), defined as the

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

Table 5. Extension of Analyses in Table 3 of Thomas (2002) to Show Price Deflation Effect

Panel A: Pearson (Spearman) correlations below (above) the main diagonal

	|FCSTERR|	*|DEFLFE|*	*BEGPRICE*	*INVPRICE*	*HERF*	*RESIDVOL*
|FCSTERR|		0.89	−0.13	0.13	−0.10	0.12
|DEFLFE|	0.56		−0.54	0.54	0.03	0.39
BEGPRICE	0.10	−0.26		−1.00	−0.29	−0.69
INVPRICE	0.04	0.58	−0.48		0.29	0.69
HERF	−0.09	0.06	−0.26	0.18		0.40
RESIDVOL	0.05	0.42	−0.47	0.64	0.34	

Panel B: Selected coefficients from regressions based on Table 3 of Thomas (2002)

Specification		Equation				
Dep. var.	Variable	(1)	(2)	(3)	(4)	(5)
I	*HERF*	2.55	0.91	0.95	0.86	−1.02
|DEFLFE|		(8.65)***	(2.73)***	(2.88)***	(2.49)**	(3.14)***
	RESIDVOL					4.37
						(22.82)***
II	*HERF*	−1.40	0.45	0.47	0.35	−0.36
|DEFLFE|		(5.13)***	(1.59)	(1.65)*	(1.19)	(1.20)
	INVPRICE	67.01	71.55	70.38	70.27	56.28
		(24.11)***	(22.73)***	(22.09)***	(22.05)***	(17.11)***
	RESIDVOL					1.89
						(11.46)***
III	*HERF*	−0.2701	0.0139	0.0154	−0.0021	−0.0861
|FCSTERR|		(7.10)***	(0.30)	(0.33)	(0.04)	(1.84)*
	RESIDVOL					0.1955
						(18.52)***
IV	*HERF*	−0.1954	0.0159	0.0209	0.0049	−0.0737
|FCSTERR|		(4.35)***	(0.33)	(0.43)	(0.10)	(1.56)
	BEGPRICE	0.0031	0.0004	0.0011	0.0013	0.0038
		(3.10)***	(0.36)	(0.97)	(1.16)	(3.32)***
	RESIDVOL					0.2151
						(16.98)***

Notes. Panel A reports the Pearson (Spearman) correlation of selected variables from Thomas (2002) below (above) the main diagonal. Panel B reports a partial view of the regression results in Table 3 of Thomas (2002), which investigates the relation between forecast error magnitudes (|*FCSTERR*|) and diversification (*HERF*). *FCSTERR* is measured as actual EPS less consensus EPS forecast. |*FCSTERR*| scaled by *BEGPRICE*, share price five days before the annual earnings announcement, is denoted as |*DEFLFE*|. *HERF* is the Herfindahl index, based on assets reported for different segments. Lower *HERF* represents more diversification. *RESIDVOL*, the standard deviation of market model residuals 210 to 11 days before the earnings announcement date, is a control variable that is included in Equation (5) in panel B. See Thomas (2002) for more details. Specification I refers to the regressions estimated in the original study. Specification II includes the inverse of *BEGPRICE* (*INVPRICE*) as an additional regressor. Specification III returns to specification I but considers undeflated values of the dependent variable. Specification IV adds price as an additional regressor to specification III. All variables considered in the original analyses in Thomas (2002) are included in our regressions even though they are not reported. Associated White (1980) t-statistics are reported in parentheses below each coefficient estimate.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

actual EPS according to I/B/E/S minus the most recent consensus forecast, deflated by share price at the end of the fiscal quarter (*BEGPRICE*). Regressions (7)–(9) in that study investigate the coefficient on the interaction between *DEFLFE* and *ESPREAD*, *QSPREAD*, and *LDV*, respectively. All three measures of transactions costs have been transformed into quintiles and scaled to range between 0 and 1. The share price variable we include (*PRCDEC*) is based on deciles of *BEGPRICE*, also scaled to range between 0 and 1.

Panel A of Table 6 reports pairwise correlations for selected variables from Ng et al. (2008). As we expect, all three measures of transactions costs are overdeflated and are strongly negatively related to share price. Panel B reports the original regressions in Table 2 of Ng et al. (2008), which we refer to as specification I. Panel B also reports results for our specification II, which includes price decile (*PRCDEC*) as an additional variable that is interacted with *DEFLFE*.

The results reported in panel B of Table 6 confirm that the significant, negative coefficients on the interaction between forecast errors and all three measures of transactions costs observed in specification I turn insignificant in specification II. These results suggest

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

Table 6. Extension of Analyses in Table 2 of Ng et al. (2008) to Show Price Effect on ERC

Panel A: Pearson (lower diagonal) and Spearman (upper diagonal) correlation

	CAR	*DEFLFE*	*ESPREAD*	*LDV*	*PRICEDEC*	*QSPREAD*
CAR		0.25	−0.04	−0.02	0.03	−0.04
DEFLFE	0.10		−0.12	−0.07	0.12	−0.12
ESPREAD	−0.02	−0.16		0.72	−0.83	0.92
LDV	−0.00	−0.15	0.72		−0.78	0.72
PRICEDEC	0.01	0.17	−0.83	−0.78		−0.84
QSPREAD	−0.03	−0.16	0.92	0.72	−0.84	

Panel B: Selected coefficients from regressions based on Table 2 of Ng et al. (2008).
Variables included in the regression but not shown below are (i) Intercept; (ii) Interaction terms between *DEFLFE* and (a) Beta, (b) LogSize, (c) Book-to-Market; and (iii) Main effect for Beta, LogSize, Book-to-Market, and Transaction Cost.

	Regression specification I			Regression specification II		
	(7)	(8)	(9)	(7)	(8)	(9)
DEFLFE	2.60 (6.35)***	2.23 (7.11)***	2.04 (8.76)***	1.08 (2.20)**	0.62 (1.77)*	0.80 (3.14)***
DEFLFE × *ESPREAD*	−1.68 (−4.56)***			−0.27 (−0.62)		
DEFLFE × *QSPREAD*		−1.27 (−4.77)***			0.18 (0.59)	
DEFLFE × *LDV*			−1.11 (−6.18)***			0.01 (0.02)
DEFLFE × *PRICEDEC*				1.97 (6.19)***	2.25 (6.46)***	2.07 (6.60)***

Notes. Ng et al. (2008) hypothesize that "firms with higher transaction costs have lower earnings response coefficients because transaction costs prevent informed trades required for the price adjustment to earnings news" (p. 676). This table examines how their result is affected by the positive relation between ERC and share price, induced by differential smoothing of EPS forecast errors. Panel A reports pairwise correlations for selected variables from Ng et al. (2008). Panel B reports the regressions in Table 2 of Ng et al. (2008) based on three-day announcement window abnormal returns (*CAR*) on price-deflated analyst forecast errors (*DEFLFE*). These regressions investigate the relation between ERC and three measures of transaction costs: *ESPREAD*, *QSPREAD*, and *LDV*. *ESPREAD* (*QSPREAD*) is the average daily effective (quoted) spread plus commissions in the announcement month. *LDV* is a measure of transaction costs developed by Lesmond et al. (1999). All three variables have been transformed into quintiles and scaled to range between 0 and 1. Forecast error equals actual EPS according to I/B/E/S less the most recent monthly consensus forecast deflated by share price at the end of the fiscal quarter (*BEGPRICE*). See Ng et al. (2008) for details. Specification I refers to the original specification in Ng et al. (2008), whereas specification II includes price decile (*PRICEDEC*) as an additional variable that is interacted with *DEFLFE*. *PRICEDEC* is scaled so that it ranges from 0 to 1. Fama–Macbeth t-statistics are reported in parentheses below each coefficient estimate.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

that the negative relation between ERC and transactions costs documented in Ng et al. (2008) is explained by two joint effects: (a) the positive relation between ERC and share price described in Section 4, and (b) the negative relation between deflated transactions costs and share price described in panel A of Table 6.

5.3. Pooling Samples That Are Expected to be Similar But Are in Fact Dissimilar in the Data

The various regularities described here and in CT suggest that key attributes vary unexpectedly across different subsamples. Pooling together different subsamples might bias inferences for a variety of reasons. Related to this issue, deflation, truncation, or Winsorization that affects one subsample more than others can have unexpected effects on pooled data. The key is to recognize that subsamples might differ. If they do, the subsamples should be separately analyzed or allowed to have separate coefficients if they are pooled. We consider first how pooled ERCs substantially overweight and underweight the ERCs of different subsamples, and then provide examples of other instances where pooling might create biases.

Appendix B derives the general relation for ERCs when two subsamples are pooled, which is a function of the separate ERCs, separate forecast error variances, the proportions of each subsample in the pooled sample, and two terms are that are relevant if forecasts are systematically optimistic or pessimistic in the subsamples. Even though forecast pessimism varies across price deciles (CT#1), we assume as a first approximation that forecasts are unbiased. That allows us to state the pooled ERC as a weighted average of the two separate ERCs, where the weight is the product of the proportion represented in the pooled sample and variance

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

of forecast errors (relation (B.7) in Appendix B). Teets and Wasley (1996) offer a related expression.

Even though the majority of our sample that lies in the small forecast error group is associated with relatively high ERCs, adding the few observations with large positive/negative forecast errors pulls the pooled ERC down dramatically. This is because the low ERCs of observations with large forecast errors, and therefore very large forecast error variances, have a disproportionate impact on the pooled ERC. The results reported in the bottom row of panel B of Table 4 describe the extent to which the pooled ERC is pulled toward zero. In contrast, pooling across price deciles within the three forecast error groups in panel B results in an ERC reported in the rightmost column ("All") that is a simple average of the 10 ERCs. This is because the variances of forecast errors do not vary much across the 10 price deciles.

Unlike the ERCs discussed so far, which are based on regressions of undeflated price responses on earnings surprises, prior research has estimated these regressions after deflating both variables, typically by price per share.[23] Comparing panel D of Table 4, based on deflated regressions, with panel B reveals that the ERC estimates within each cell are relatively unaffected by deflation. The ERC estimates in the bottom row are also similar in panels B and D, suggesting that the disproportionate impact of including large forecast errors is unaffected by deflation. However, pooling the ERCs across price deciles within rows results in much lower ERCs reported in the "All" column in panel D. This is because deflation of forecast errors that do not vary with scale results in deflated forecast errors that are much larger for low-price firms. As a result, the pooled ERCs in the rightmost column reflect disproportionately the low ERC of low-price firms. The low ERC of 0.6, reported in the last entry in panel D, for the overall sample, reflects the joint effects of more weight being given to large forecast errors and low-price firms (when forecast errors are deflated).

The typical response in the literature to low observed values of ERC is to truncate or Winsorize forecast errors to mitigate the impact of extreme forecast errors. Truncation based on deflated forecast error increases substantially the pooled ERC because it reduces the proportion of large forecast errors with low prices, which are associated with the lowest ERCs. Winsorization reduces the variance of observations with large forecast errors and low prices, which again raises the pooled ERC, though to a lesser extent than truncation. Overall, pooled ERCs estimated in the prior literature based on deflated forecast errors are (a) unrepresentative because they overweight the few observations with low prices and large forecast errors, and (b) sensitive to seemingly innocuous choices that reduce the impact of these observations.

We turn next to other instances of potential biases created by pooling dissimilar samples. First, as described in panel A of Figure 2, forecast pessimism varies across price deciles: actual EPS is expected to meet consensus forecast for price decile 0 but beat it by 1¢ (2¢) for decile 5 (10). Relatedly, there is price variation in discontinuities in forecast error distributions between −1 and 0¢, and between 0 and +1¢. Untabulated results indicate that these findings also vary with forecast dispersion.[24] Pooling across groups with dissimilar distributions can either blur existing discontinuities or create discontinuities where none exist. Similarly, scaling variables before pooling can create discontinuities or blur discontinuities that exist in the separate groups.

Second, as suggested by the results in panel B of Figure 2, investors adjust rationally not only to differential compression of forecast errors, but also to differences in forecast pessimism across price deciles. For example, a forecast error of 0 (2¢) is considered no news for decile 0 (10). Another key finding in panel B is the absence of sharp discontinuities in price responses around zero forecast error, within the ±5¢ range. Again, ignoring such variation and pooling price responses across dissimilar samples can lead to unrepresentative inferences (see Abarbanell and Park 2016 for a more detailed investigation). For example, a commonly held view is that firms that miss forecast by a penny are associated with a disproportionately large negative price response (see the "torpedo" effect in Skinner and Sloan 2002 and the opposite view of Payne and Thomas 2011). Our results suggest that pooling can create the perception of a discontinuity, even if there are no discontinuities in the distributions for separate subgroups. Specifically, while a forecast error of −1¢ represents missing forecast by just a penny for price decile 1, it is really bad news for firms in decile 10, which are expected on average to beat forecast by 2¢.

A final possible case of bias created by pooling arises in studies that pool analyst-followed firms with firms not covered by analysts. Given that the two groups of firms, with and without analyst following, exhibit different relations between scale and different variables noted here and in CT, pooling the two groups may affect inferences if levels of the explanatory variables differ across the groups. Overall, our main recommendation is that researchers be aware of the substantial potential for cross-sectional variation in different attributes based on scale at the share level. Researchers could separately analyze different subgroups or explicitly allow for separate variation if pooling is called for.

6. Conclusion

CT propose an intriguing possible explanation for the lack of scale variation observed for EPS forecast error magnitudes for analyst-followed U.S. firms

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

(Degeorge et al. 1999): forecast error magnitudes naturally increase with scale, but managers offset that variation by differentially compressing forecast errors. That is, the level of compression increases with share price to completely offset natural scale variation in forecast error magnitudes. CT also document a second result that may similarly be due to managerial intervention: forecast pessimism increases with scale. That is, managers of higher-price firms face incentives to beat consensus forecasts by larger amounts.

If so, three interrelated questions arise. First, how do managers compress forecast errors and create forecast pessimism? Second, do investors recognize and adjust for such managerial efforts? Finally, how should researchers incorporate the behavior of managers and investors when conducting studies? Our investigation of these questions suggests the following conclusions.

Managers compress forecast errors in two ways. Mainly, they smooth reported earnings, thereby making earnings easier to forecast. Differential smoothing eliminates scale variation in forecast error magnitudes between price deciles 1 and 7. Residual variation between deciles 8 and 10 is eliminated by managers guiding analysts to make more accurate forecasts. Substantial amounts of compression are required, especially for higher-price firms, to completely reverse natural scale variation in forecast error magnitudes. And these levels of compression have to be undertaken by most firms in most quarters. Even though the scale and scope of smoothing and guidance that is required casts doubt on whether this strategy is employed, additional tests confirm that our conclusion is robust.

Turning from forecast error compression to pessimism of short-horizon forecasts, we find that the walkdown of consensus forecasts, from optimism at long horizons to pessimism at short horizons, increases with share price. It seems unlikely that analysts would have different walkdowns for high and low share prices unless managers are involved. Managers of high-price firms must guide analysts, directly or indirectly, to make more optimistic long-horizon and more pessimistic short-horizon forecasts, relative to low price firms.

Investors recognize these managerial efforts and adjust accordingly. They unwind managerial efforts and respond to forecast errors they estimate would have been observed absent smoothing and guidance. As a result, price responses to *observed* forecast errors, which have been differentially compressed and guided, vary with share price. Finding that investor responses are more closely tied to forecast errors before compression and guidance, relative to observed forecast errors, strongly supports managerial involvement.

Our conclusions regarding the first two questions have important implications for research. Biases might arise if researchers are unaware that reported and forecast EPS are managed in systematic ways to alter forecast error distributions, and that investors recognize and adjust for such managerial intervention. Many dependent and independent variables exhibit unexpected relations with share price. Some variables that should intuitively increase with scale do not in the data. Conversely, other variables that should not increase with scale do in fact vary with scale. Also, pooling samples that appear to be similar but are in fact quite different can result in unrepresentative inferences.

Implications for Policy and Practice

Managers fear that investors misinterpret financial numbers in different ways and seek to correct potential errors. One set of concerns relates to investors of analyst-followed firms not adjusting for differences in scale. Consider two firms with very different share prices: firm H has a high share price and firm L has a low share price. The reported and forecast earnings per share (EPS) for firm H are both proportionately larger than those for firm L. Forecast errors—reported EPS minus forecast—for firm H should also be proportionately larger than those for firm L. Our evidence suggests that firm H's managers fear that investors do not adjust for its larger size and would misinterpret the larger forecast errors. In particular, investors would underprice firm H because they overstate its risk or view it as being "not in control." In response, firm H's managers smooth reported earnings and guide analyst forecasts (toward the number they expect to report) to compress forecast errors to the point where they resemble those for firm L. The extent of smoothing and guidance we document is remarkable: firms in the top decile (10%) of share price compress forecast errors on average to *one-seventh* their original magnitudes.

Firm H's managers also fear that investors expect higher growth than that for firm L, and would respond negatively if reported growth is similar. In response, they create the perception of higher growth. They first guide long-horizon analyst forecasts upward to suggest a brighter future than that for firm L. They then proceed to walk down those forecasts as horizon decreases to the point where they fall below reported numbers, allowing firm H to beat the forecast. Again, the extent of guidance is remarkable. Firms in the top decile of share price walk down forecasts by 6¢ on average over the nine months preceding the quarter end, and beat consensus forecast by 2¢. Firms in the bottom decile walk down forecasts only by 2¢ on average and meet forecast.

Both concerns about investor naiveté are misplaced. Not only do investors recognize that firm H's managers compress forecast errors and guide forecasts down to beatable levels, they undo earnings smoothing and forecast guidance and respond to premanaged numbers. For example, investors of firms in the top price decile view beating forecast by 1¢ as *bad* news, because they expect reported EPS to beat forecast by 2¢. And the price response per cent of compressed forecast error is seven times as high because forecast errors are compressed to one-seventh their unmanaged levels. The implications for managers is that investors are capable of adjusting for scale difference. The implications for media and other observers is that earnings smoothing and forecast guidance is widespread, and these managerial efforts increase with share price.

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

Acknowledgments
The paper benefited from comments provided by anonymous reviewers, Ryan Ball, Sudipta Basu, Sanjeev Bhojraj, Shuping Chen, Jonathan Glover, Adam Koch, S.P. Kothari, Christian Leuz, Nathan Marshall, Krish Menon, Barry Nalebuff, Shiva Rajgopal, Eddie Riedl, K. Sivaramakrishnan, Jeremy Stein, and seminar participants at American Accounting Association annual meetings, Financial Accounting and Reporting Section midyear meetings, Baruch College, Boston University, University of California at Berkeley, Erasmus University, University of Illinois at Chicago, Indian School of Business, University of Indiana, Rice University, Rutgers University, Singapore Management University, Tel Aviv University, Temple University, University of Virginia, the Wharton School, and Yale University. The authors thank Ian Gow for suggesting the ERC implication and Ed Kaplan for deriving the relation for pooled ERCs.

Appendix A. Variable Definitions and Sources

Label	Description	Source
APS (in \$)	Accruals per share	= *EPS_GAAP* – *CPS*
ANALYADJ (in \$)	Amount by which analysts adjust core EPS for quarter $t-4$, when making forecast nine months before quarter-end for quarter t	= *FORECAST_9* – EPS_IBES_{t-4} = Δ_4*EPS_IBES* – *FCSTERR_9*
BEGPRICE[a] (in \$)	Share price of firm at the beginning of calendar quarter that includes the fiscal quarter-end date	Share price from CRSP (WRDS filename is crsp.msf)
CAR[a]	Cumulative abnormal stock returns over 22 trading days leading up to and including the earnings announcement	Cumulative stock returns from trading day −20 to day +1, minus cumulative market returns over the same period (WRDS filename is crsp.dsf)
CPS[b] (in \$)	Cash flow per share	Quarterly net cash flow from operating activities (data item #oancfy from WRDS filename comp.fundq), divided by number of common shares used by COMPUSTAT to calculate basic/diluted EPS (data item #cshprq or #cshfdq), depending on whether *FORECAST* is made on a basic/diluted basis
CVRGE	Number of estimates that constitute *FORECAST*	I/B/E/S unadjusted summary data (WRDS file name is ibes statsumu_epsus)
DISP	Standard deviation of the individual analyst's forecasts that constitute *FORECAST*	See description provided for *FORECAST*
EPS_GAAP (in \$)	Actual quarterly earnings per share before extraordinary items, as derived from the cash flow statement[b]	Quarterly income from cash flow statement (data item #ibcy from WRDS filename comp.fundq), divided by number of common shares used by COMPUSTAT to calculate basic/diluted EPS (data item #cshprq or #cshfdq), depending on whether *FORECAST* is made on a basic/diluted basis; if *EPS_GAAP* is missing, we substitute it with data item #epspxq or #epsfxq from COMPUSTAT, depending on whether *FORECAST* is made on a basic/diluted basis
EPS_IBES (in \$)	Actual quarterly EPS, as reported by I/B/E/S, after I/B/E/S has adjusted it "for comparability with estimates"	Actual quarterly EPS is obtained from I/B/E/S (WRDS filename is ibes.actu_ epsus), which is unadjusted for stock splits
FCSTERR (in \$)	EPS forecast error, relative to the most recent consensus forecast before earnings is announced	= *EPS_IBES* – *FORECAST*
FORECAST[a] (in \$)	Most recent consensus (mean) estimate of *EPS_IBES* for the firm-quarter	I/B/E/S summary file (WRDS filename is ibes.statsumu_epsus), which is unadjusted for stock splits
FORECAST_n (in \$)	The consensus (mean) estimate of *EPS_IBES* made n months before quarter-end ($n = 0$ corresponds to the last month of the quarter)	I/B/E/S summary file (WRDS filename is ibes.statsumu_epsus), which is unadjusted for stock splits
HIPRC	Dummy for high-price deciles that equals 1 for price deciles 8–10, and 0 otherwise	= 1, if *PRCDEC* = 8, 9, or 10; = 0, otherwise
ONETIME (in \$)	One-time items	= *EPS_GAAP* – *EPS_IBES*
PRCDEC	Price deciles are computed at the beginning of each calendar quarter for fiscal quarters ending in that quarter, and the lowest (highest) price decile is denoted by 1 (10)	
PRICERESP (in \$)	Price response over 22 trading days, adjusted for market movement	Cumulative abnormal stock returns (*CAR*) multiplied by the closing stock price 21 trading days prior to earnings announcement (WRDS filename is crsp.dsf)

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

Appendix A. (Continued)

Label	Description	Source
REVISION (in \$)	EPS forecast revision from nine months before quarter-end to most recent forecast before earnings announcement	EPS forecast is obtained from the I/B/E/S summary file (WRDS filename is ibes.statsumu_epsus), which is unadjusted for stock splits
REV (in \$)	EPS forecast revision from the last month of the quarter to the month with the most recent consensus before earnings announcement	$REV = FORECAST\_0 - FORECAST$
SLSGR	Sales growth = $\Delta_4 Sales_t / Sales_t$	Compustat Fundamentals Quarterly (comp.fundq)
Δ_4	Operator to denote seasonal difference.	$\Delta_4 X_t = X_t - X_{t-4}$

[a] *BEGPRICE* refers to the share price five days before the earnings announcement for Thomas (2002) and price at the end of the fiscal quarter for Ng et al. (2008). In our analysis of Ng et al. (2008), *CAR* is based on the three-day announcement window. In our analyses of Thomas (2002) and Ng et al. (2008), *FORECAST* refers to the *median* consensus forecast.

[b] As the values on 10-Q cash flow statements (and on COMPUSTAT) are cumulative, from the beginning of the fiscal year, we impute quarterly values for all quarters other than the first fiscal quarter by subtracting the cumulative values from the prior quarter.

Appendix B. Derivation of Relevant Relationships

B.1. Implication for Earnings Response Coefficient

Given that the variance of forecast errors is relatively constant across price deciles, and given that price responses (*PRICERESP*) to those forecast errors vary proportionately with price, we consider next how these two patterns affect variation across price deciles in the ERC, or earnings response coefficient, which is the slope of a regression of price response on forecast errors.

(a) *Undeflated regression*. We consider first the case where both variables are undeflated. The slope from this regression is

$$\begin{aligned} ERC &= \frac{\mathrm{Cov}(FCSTERR, PRICERESP)}{\mathrm{Var}(FCSTERR)} \\ &= \mathrm{Corr}(FCSTERR, PRICERESP) \\ &\quad \cdot \frac{\sqrt{\mathrm{Var}(PRICERESP)\mathrm{Var}(FCSTERR)}}{\mathrm{Var}(FCSTERR)}. \end{aligned} \tag{B.1}$$

If the correlation between *FCSTERR* and *PRICERESP* does not vary much with price, *ERC* should increase with price because *PRICERESP* increases with price.

(b) *Price-deflated regression*. The corresponding slope (*ERC*) from a price-deflated regression, where both per share price responses and forecast errors are deflected by lagged share price (*LPRICE*)

$$\begin{aligned} ERC &= \mathrm{Corr}(FCSTERR/LPRICE, PRICERESP/LPRICE) \\ &\quad \cdot \frac{\sqrt{\mathrm{Var}(PRICERESP/LPRICE)\mathrm{Var}(FCSTERR/LPRICE)}}{\mathrm{Var}(FCSTERR/LPRICE)}. \end{aligned} \tag{B.2}$$

When price-deflated regressions are estimated within price deciles, for which price is approximately a constant, *LPRICE* cancels out between the numerator and denominator. If so, the expression in (B.2) reverts to the expression in (B.1) for *undeflated* regressions. That is, as long as the correlation term is relatively constant across price deciles, *ERC* should increase with price.

B.2. Impact of Pooling Samples with Different ERC

Consider two samples, 1 and 2, that are drawn from different populations. Assume that the slope for the first (second) sample is β_1 (β_2), and it equals $(\mathrm{cov}(x_1, y_1)/\mathrm{var}(x_1)) \cdot (\mathrm{cov}(x_2, y_2)/\mathrm{var}(x_2))$.

When pooling together the two samples, we allow for the proportion of observations from sample 1 (p) to differ from that for sample 2 ($1-p$). The slope for the pooled sample is β, and it equals $\mathrm{cov}(x, y)/\mathrm{var}(x)$. Manipulating terms, we can show that

$$\begin{aligned} \mathrm{Cov}(x, y) &= p\beta_1 \cdot \mathrm{var}(x_1) + (1-p)\beta_2 \cdot \mathrm{var}(x_2) \\ &\quad + p(1-p)\{\mathrm{E}[x_1 - x_2] \cdot \mathrm{E}[y_1 - y_2]\}, \end{aligned} \tag{B.3}$$

$$\begin{aligned} \mathrm{Var}(x) &= p\,\mathrm{var}(x_1) + (1-p)\mathrm{var}(x_2) \\ &\quad + p(1-p)\{\mathrm{E}[x_1 - x_2] \cdot \mathrm{E}[x_1 - x_2]\}. \end{aligned} \tag{B.4}$$

If the means of x_1 and x_2 are approximately zero (because forecast errors should be centered on zero), the expressions (B.3) and (B.4) simplify as follows:

$$\mathrm{Cov}(x, y) = p\beta_1 \cdot \mathrm{var}(x_1) + (1-p)\beta_2 \cdot \mathrm{var}(x_2), \tag{B.5}$$

$$\mathrm{Var}(x) = p\,\mathrm{var}(x_1) + (1-p)\mathrm{var}(x_2). \tag{B.6}$$

The pooled slope for this special case is given by

$$\beta = \frac{\beta_1 \cdot p \cdot \mathrm{var}(x_1) + \beta_2 \cdot (1-p) \cdot \mathrm{var}(x_2)}{p\,\mathrm{var}(x_1) + (1-p)\mathrm{var}(x_2)}. \tag{B.7}$$

As a result, the pooled slope is a weighted average of the separate slopes for the two samples, where the weights are the product of the fractions of the pooled sample for each sample times the variance of the regressors for each sample; i.e., $p\,\mathrm{var}(x_1)$ and $(1-p)\mathrm{var}(x_2)$.

Endnotes

[1] These results are only observed when scale is measured at the share level, not the firm level. This focus on share-level earnings is consistent with sell-side analyst practice (e.g., Hermann and Thomas 2005).

[2] Degeorge et al. (1999) document CT#3 and the first part of CT#2, but make no mention of their unusual nature or behavioral implications.

[3] We show later why including the small fraction of remaining observations (about 15% in each tail with forecast error magnitudes greater than 5¢) shrinks ERC toward the much lower levels reported in prior work. Two recent studies—Burgstahler and Chuk (2010) and Abarbanell and Park (2016)—also document ERCs as high as 30 for small forecast errors. See Section 4 for a discussion of their findings and proposed explanations.

[4] Long-horizon forecasts are quite optimistic, but optimism declines with horizon as if analyst forecasts are "walked down" to the point

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

where forecasts become slightly pessimistic before the earnings announcement date.

[5] To illustrate the difficulty that alternative explanations face, consider as an initial hurdle our findings regarding scale variation in accruals/cash flow correlation and forecast accuracy. While one can conceive of alternative explanations for why correlations become more negative and accuracy increases with share price, it is hard to explain why (a) the correlations increase only from decile 1 to decile 7, (b) forecast accuracy increases only from decile 8 to decile 10; and (c) the combination causes forecast error magnitudes to be the *same* in all 10 deciles.

[6] To the extent managers smooth using real earnings management (e.g., altering maintenance and advertising), cash flows have also been managed to smooth earnings volatility. That is, our evidence based on accruals understates managerial smoothing designed to compress forecast errors.

[7] Cohen et al. (2007, p. 272) states that "prior to the early 1990s, I/B/E/S did not always adjust actual earnings to exclude items not forecasted by analysts, thereby creating a mismatch between its actual (realized) and forecasted (expected) earnings." Despite this mismatch, we find similar lack of scale variation before 1993.

[8] The most recent forecast is typically from the same month as the month of earnings announcement, or the prior month if the earnings announcement has already been made before I/B/E/S' cutoff date for that month. In a few cases, we go back up to 90 days before the earnings announcement to find an available consensus forecast.

[9] This requirement is also observed in practice; e.g., Standard and Poor's use the same filter to implement their fundamental valuation model (Kaye 2003).

[10] We use the IBES-CRSP linking program provided on the Wharton Research Data Services (WRDS) in combination with the CRSP-COMPUSTAT Merged Database. See https://wrds-web.wharton.upenn.edu/wrds/ds/ibes/index.cfm (last accessed August 26, 2017).

[11] Because net income and cash flows reported on 10-Q reports (and on COMPUSTAT) are cumulative, from the beginning of the fiscal year, we impute quarterly net income and cash flows for all quarters other than the first fiscal quarter by subtracting the corresponding cumulative amounts reported in the prior quarter.

[12] Despite its apparent inadequacies, the seasonal random walk expectation model outperforms other models that use more information for out-of-sample predictions (see Francis and Olsen 2011).

[13] Three variables—*FCSTERR*, *ANALYADJ*, and *REVISION*—are affected by the Winsorization previously discussed.

[14] There is some evidence of a slight increase in magnitudes of *FCSTERR* for the higher-price decile, whereas the results reported in CT, which are based on a sample period that ends in 2006, exhibits almost no variation with price. Year-by-year analysis reveals a slight increase for high-price deciles after 2006. Given that there are other prior years where the opposite pattern is observed, we are unable to judge whether the results for the post-2006 period represent a change in regime or normal variation over time.

[15] The high autocorrelations observed at the fourth lag are consistent with a large transitory component in both *APS* and *CPS* surprises, suggesting that both variables follow ARIMA $(0, 1, 1)$ processes. If so, the estimated correlations between seasonally differenced *APS* and *CPS* we report in Table 2 are a function of the true correlation between shocks in *APS* and *CPS* and the moving average parameters for *APS* and *CPS*.

[16] We estimate discretionary accruals using different models offered in the literature for nondiscretionary accruals. The coefficients on *PRCDEC* decline by 80%, relative to those reported in panel C of Table 2 consistent with systematic smoothing being excluded from discretionary accruals. Those correlations remain significant for models that do not adjust for contemporaneous performance but become insignificant when performance is controlled for, consistent with the view that smoothing is designed to offset contemporaneous performance.

[17] Lower ERC levels, close to zero, for large magnitudes of forecast error and higher ERCs for small forecast errors is well documented in the prior literature (e.g., Freeman and Tse 1992).

[18] The correlations for price decile 1 are clearly less negative than the other nine deciles. Further investigation reveals that this decile for not-followed firms includes many penny stocks (with prices below $1) that are associated with low and even positive correlations between $\Delta_4 CPS$ and $\Delta_4 APS$.

[19] We confirm in untabulated results the finding in Burgstahler and Chuk (2010) that ERCs are higher for low-dispersion firms. ERC for our sample of firms in the highest price decile increases to over 90 when we include only firms with dispersion less than the median of 2¢.

[20] We thank Shawn Thomas and Jeff Ng for generously sharing their data and patiently assisting us with replication.

[21] There are many studies that deflate such variables, too many for us to provide a comprehensive list here. For example, Appendix B of CT lists numerous studies that use two of those variables—forecast error magnitudes and dispersion—as dependent or independent variables, and both variables are deflated in the primary analyses in all of the studies investigated. In some cases, footnotes indicated that similar results were obtained with undeflated proxies for these two variables; examples include Barron et al. (1999, Footnote 13) and Barron (1995, Footnote 13).

[22] While our suggestions appear similar to recommendations in econometrics texts and in prior accounting literature investigating effects of scaling (e.g., Christie 1987, Barth and Kallapur 1996), the context and motivation here are quite different. In that general setting, the questions of interest are whether: (a) both dependent and independent variables should be scaled, (b) scaling reduces heteroscedasticity, and (c) scaling by a variable other than the unobservable true scale variable induces bias in estimated coefficients. We, on the other hand, are concerned with scaling just one variable, either the dependent or an independent variable, and our focus is on bias induced by researchers not incorporating the behavior of managers and investors.

[23] In some studies (e.g., Beaver et al. 1980), earnings surprises are scaled by the level or absolute level of earnings. Similar results are observed when deflators other than share price are used.

[24] These untabulated results suggest different incentives are at play for the different subgroups. For example, explanations of the sharp discontinuity observed for firms that just miss forecast (e.g., Brown and Caylor 2005) must also explain why no discontinuity is observed for low- and mid-price firms among the high dispersion group.

References

Abarbanell J, Park H (2016) Do bright-line earnings surprises really affect stock price reactions? *Management Sci.* 63(4):1063–1084.

Barron O (1995) Trading volume and belief revisions that differ among individual analysts. *Accounting Rev.* 70(4):581–597.

Barron OE, Kile CO, O'Keefe TB (1999) MD&A quality as measured by the SEC and analysts' earnings forecasts. *Contemporary Accounting Res.* 16(1):75–109.

Barth ME, Kallapur S (1996) The effects of cross-sectional scale differences on regression results in empirical accounting research. *Contemporary Accounting Res.* 13(2):527–567.

Beaver W, Lambert R, Morse D (1980) The information content of security prices. *J. Accounting Econom.* 2(1):3–28.

Brown L, Caylor M (2005) A temporal analysis of quarterly earnings thresholds: Propensities and valuation consequences. *Accounting Rev.* 67(4):423–440.

RIGHTSLINK

Downloaded from informs.org by [202.66.60.166] on 22 September 2017, at 05:25 . For personal use only, all rights reserved.

Bonsall SB, Bozanic Z, Merkley KJ (2015) Managers' use of forward and non-forward-looking narratives in earnings press releases. Working paper, Pennsylvania State University, State College.

Burgstahler D, Chuk E (2010) Earnings precision and the relation between earnings and returns. Working paper, University of Washington, Seattle. http://ssrn.com/abstract=1119400.

Cheong FS, Thomas J (2011) Why do EPS forecast error and dispersion not vary with scale? Implications for analyst and managerial behavior. *J. Accounting Res.* 49(2):359–401.

Christie A (1987) On cross-sectional analysis in accounting research. *J. Accounting Econom.* 9(3):231–258.

Cohen D, Hann RR, Ogneva M (2007) Another look at GAAP versus the Street: An empirical assessment of measurement error bias. *Rev. Accounting Stud.* 12(2):271–303.

Collins D, Kothari SP (1989) An analysis of intertemporal and cross-sectional determinants of earnings response coefficients. *J. Accounting Econom.* 11(2–3):143–181.

Degeorge F, Patel J, Zeckhauser R (1999) Earnings management to exceed thresholds. *J. Bus.* 72(1):1–33.

Diether K, Malloy C, Scherbina A (2002) Differences of opinion and the cross section of stock returns. *J. Finance* 57(5): 2113–2141.

Fischer PE, Verrecchia RE (2000) Reporting bias. *Accounting Rev.* 75(2):229–245.

Francis RN, Olsen J (2011) The out-of-sample prediction of annual operating cash flow: A comparison of regression and naïve forecast models. Working paper, University of Texas at El Paso, El Paso. http://ssrn.com/abstract=2025224.

Freeman R, Tse S (1992) A nonlinear model of security price responses to unexpected earnings. *J. Accounting Res.* 30(2):185–209.

Fudenberg D, Tirole J (1986) A "signal jamming" theory of predation. *RAND J. Econom.* 17(3):366–376.

Graham JR, Harvey CR, Rajgopal S (2005) The economic implications of corporate financial reporting. *J. Accounting Econom.* 40(1–3): 3–73.

Hermann D, Thomas W (2005) Rounding of analyst forecasts. *Accounting Rev.* 80(3):805–823.

Holmstrom B (1982) Moral hazard in teams. *Bell J. Econom.* 13: 324–340.

Kaye M (2003) Stocks worth twice the price? *Bloomberg* (October 3), https://www.bloomberg.com/news/articles/2003-10-02/stocks-worth-twice-the-price.

Kormendi R, Lipe R (1987) Earnings innovations, earnings persistence, and stock returns. *J. Bus.* 60(3):323–345.

Lang M, Lins K, Maffett M (2012) Transparency, liquidity, and valuation: International evidence on when transparency matters most. *J. Accounting Res.* 50(3):729–774.

Lesmond DA, Ogden JP, Trzcinka CA (1999) A new estimate of transaction costs. *Rev. Financial Stud.* 12(5):1113–1141.

Ng J, Rusticus TO, Verdi RS (2008) Implications of transaction costs for the post-earnings announcement drift. *J. Accounting Res.* 46(3):661–696.

Payne J, Thomas W (2011) The torpedo effect: Myth or reality? *J. Accounting Auditing Finance* 26(2):255–278.

Richardson S, Teoh SH, Wysocki PD (2004) The walk-down to beatable analyst forecasts: The role of equity issuance and insider trading incentives. *Contemporary Accounting Res.* 21(4):885–924.

Ronen J, Sadan S (1981) *Smoothing Income Numbers: Objectives, Means, and Implication* (Addison Wesley, Boston).

Skinner D, Sloan R (2002) Earnings surprises, growth expectations, and stock returns, or don't let an earnings torpedo sink your portfolio. *Rev. Accounting Stud.* 7(2):289–312.

Stein JC (1989) Efficient capital markets, inefficient firms: A model of myopic corporate behavior. *Quart. J. Econom.* 104(4): 655–669.

Teets W, Wasley C (1996) Estimating earnings response coefficients: Pooled versus firm-specific models. *J. Accounting Econom.* 21(3):279–295.

Thomas S (2002) Firm diversification and asymmetric information: Evidence from analysts' forecasts and earnings announcements. *J. Financial Econom.* 64(3):373–396.

White H (1980) A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* 48(4):817–838.

RIGHTSLINK
Copyright Clearance Center