Management of actual and forecast EPS and the extent to which investors adjust

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Abstract

We document substantial and pervasive management of actual and forecast earnings per share (EPS) for analyst-followed firms, with the level of management increasing with share price. Much of the effort is designed to smooth the volatility of GAAP EPS by using accruals to offset cash flow shocks. High price shares with higher levels of *unmanaged* EPS volatility compress EPS volatility so much that it resembles the volatility of low price shares. There is also differential downward guidance of forecasts, such that high price firms beat forecasts by larger amounts than low price firms. We find that investors recognize these managerial efforts and adjust for differential earnings smoothing and forecast guidance. For example, each cent of observed forecast error for high price firms is associated with very high price responses, because investors recognize the substantial extent to which forecast errors are compressed. And high price firms that beat forecast by a penny are associated with *negative* price responses, because investors recognize that forecasts are guided down even more.

Keywords: Earnings management; Forecast guidance; and EPS forecast errors.

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1. Introduction

Intuitively, forecast error distributions should have zero means and standard deviations or forecast error magnitudes that increase with scale. However, results of prior research suggest that distributions of forecast errors based on sell-side analysts' forecasts of quarterly earnings per share (EPS) deviate considerably from this intuition. Mean forecast errors are positive and increase with scale (Cheong and Thomas, 2011), whereas standard deviations do not (e.g., Degeorge et al., 1999)[1]. Further investigation—based on comparing US versus non-US firms, analyst-followed firms versus those not followed by analysts, and earnings versus sales and cash flows—suggests that US managers/analysts differentially shrink EPS forecast error magnitudes and bias forecasts, with the extent of forecast error compression and forecast pessimism increasing with scale. We investigate here whether earnings management and forecast guidance play a role, and the extent to which investors adjust for any such intervention.

We consider three ways for managers to shrink magnitudes of EPS forecast error, where forecast error 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. First, managers make discretionary accruals to offset cash flow surprises, resulting in smoother *reported* EPS. Second, they strategically designate large deviations in reported EPS as non-recurring, resulting in smoother *core* EPS. Both methods shrink forecast errors by smoothing the underlying core EPS that analysts forecast. Third, accuracy is increased by managers guiding analyst forecasts toward the core EPS they expect to announce.

Our results suggest that the first approach plays a major role in differential compression of forecast error magnitudes. That is, the use of accruals by managers to smooth the volatility of

[1] We focus on scale at the share-level, rather than firm-level, because prior research (e.g., Hermann and Thomas, 2005) indicates that sell-side analysts focus on share-level earnings. We use share price to represent scale.

reported EPS is both widespread and substantial, especially for high price firms. The negative correlation between seasonally-differenced cash flow per share (*CPS*) and accruals per share (*APS*), our primary measure of smoothing via discretionary accruals, increases from a mean of –0.55 for firms in price decile 1 to –0.84 for price decile 7, and holds constant at that level for higher price deciles. As scale increases between deciles 1 and 7, increased earnings smoothing offsets entirely any natural increase in EPS volatility that would have been observed absent earnings management. Because high price firms (deciles 8, 9, and 10) do not shrink EPS volatility *further*, some of the natural increase in EPS volatility remains. It appears as if there is a ceiling up to which firms smooth reported EPS. Any remaining scale-variation in forecast error magnitudes among high price firms is eliminated by the third approach: we observe incremental improvements in forecast accuracy as scale increases, consistent with increased guidance by managers.[2]

We find that differential forecast guidance is also responsible for the positive relation between forecast pessimism and price observed in Cheong and Thomas (2011): median forecast error increases from 0¢ for decile 1 (unbiased forecasts) to +2¢ for decile 10 (pessimistic forecasts). Given that actual median growth in EPS is +3¢ for decile 1 and +1¢ for decile 10, analysts forecast EPS growth of +3¢ for decile 1 but forecast a decline of –1¢ for decile 10. To determine whether this differential pattern is induced by managers, we investigate analyst forecasts made 9 months prior to quarter-end—before the incentives to meet/beat benchmarks based on the most recent forecasts are operative—to determine whether analysts anticipated lower growth for higher price deciles. We find that forecasts made 9 months earlier project the same EPS growth of +5¢ for all deciles. In effect, as forecast horizon declines analyst growth forecasts decline from +5¢ to +3¢ for decile 1 but exhibit a greater decline from +5¢ to –1¢ for decile 10. This evidence suggests that

[2] We are surprised that managers do not use the second approach. While core EPS is smoother than reported EPS, because one-time items are deleted, we find no evidence of differential smoothing across price deciles.

managers induce analysts to engage in a differential "walk-down" of forecasts during the year. While the average walk-down of forecasts noted in prior research (e.g., Richardson et al., 2004) does not require managerial involvement, a differential walk-down—larger (smaller) walk-downs for high (low) price firms—suggests that managers play a role.

Turning to investor responses to management of reported and forecast EPS, we find that investors recognize and adjust appropriately for differential compression of forecast errors because they respond to the *projected* forecast errors that would obtain if errors had not been compressed. The price response per each additional cent of *observed* forecast error, or ERC, is as high as 90¢ for the highest price decile, ten times that for the lowest price decile. While an ERC as high as 90 has neither been recorded before nor predicted by theory (e.g., Kormendi and Lipe, 1987, and Collins and Kothari, 1989), it is rational given that a cent of highly compressed forecast error for decile 10 corresponds to 10¢ of forecast error for decile 1.[3] Such abnormally high price responses confirm that forecast errors for high price firms have been compressed substantially.[4]

We find that investors also adjust appropriately for differential forecast pessimism. They recognize that the differential walk-down of analyst forecasts leads to variation across price in the implications of just missing, meeting, and just beating consensus forecast—forecast errors of −1¢, 0¢, and +1¢, respectively. Just missing, meeting, and just beating the consensus forecast elicits negative, zero, and positive price responses, respectively, for price decile 1, which is appropriate given that forecasts are unbiased for low price firms. In contrast, the corresponding price responses for decile 10 are all *negative*. If investors expect forecasts to be guided down for decile 10, such that the expected forecast error is +2¢, meeting and even beating forecast by +1¢ is bad news.[5]

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3 ERC can be stated as a function of the standard deviations of price response and forecast error as well as their correlation (see Appendix B). Given that the standard deviation of forecast error and the correlation term do not vary with scale, ERC increases with the standard deviation of price response, which increases with scale.

4 These results are observed for the majority of our sample that lies within a narrow range of forecast errors: between −5¢ and +5¢. The remainder of our sample (about 15 percent in each tail) is associated with ERCs close to zero.

5 The popular press describes the large negative response to just missing forecast for some firms as a "torpedo effect", based on the implicit assumption that investors expect those firms to meet forecasts on average. If,

We contribute in the following ways to the long-standing literature on management of earnings and forecasts (e.g., Healy and Wahlen, 1999) and the more recent literature on investor responses to such management (e.g., Keung et al., 2010, and Doyle et al., 2013). First, we document new evidence of management of earnings and forecasts that is both widespread and substantial. Second, much of this management relates to smoothing the underlying volatility of reported earnings, an objective of earnings management that has received less attention of late. Third, we document considerable variation in management of earnings and forecasts across scale at the share level. Given that scale at the share level is seemingly arbitrary, as it can be altered simply by stock splits and stock dividends, prior research did not anticipate or examine variation in management along this dimension. Finally, we document that investors recognize and adjust for differential compression of forecast errors and forecast pessimism.

We limit the scope of this study to documenting our findings, as the analyses required to do so already result in a lengthy manuscript. We leave to follow-up studies the task of offering rationales for the puzzling managerial behavior we document and conducting statistical tests to discriminate among alternative hypotheses. One potential hypothesis is that managers fear that investors do not adjust forecast error magnitudes for scale; i.e. investors view forecast errors in cents per share and therefore overestimate the risk of high price firms. While that may explain why forecast error magnitudes for high price firms are compressed to levels observed for low price firms, it does not explain why the same naïve investors are not confused when they observe high price firms associated with larger sales and cash flow forecast errors, larger earnings forecast errors in some countries, and greater EPS volatility for firms not followed by analysts. It also does not explain differential forecast guidance designed to create greater forecast pessimism for high price firms. Another puzzling finding is that firms do *not* use one-time items to differentially smooth

however, those firms are high price firms, with an expected forecast error of +2¢, just missing forecast is indeed very bad news, and should elicit a large negative response.

core earnings volatility. Finally, if investors recognize and adjust for differential earnings and forecast management, why do firms continue to engage in it?

The remainder of our study is organized as follows. Section 2 describes our sample selection procedure and Section 3 considers ways in which managers and analysts alter the distribution of EPS forecast errors. Section 4 investigates investor responses to observed forecast error distributions, and Section 5 concludes.

2. Sample selection and descriptive statistics.

For our main sample, containing 184,227 firm-quarters, we include all U.S. firms on I/B/E/S with fiscal quarters ending between January 1993 and December 2011. We drop years before 1993 because of concerns about a shift around the early 1990's 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.[6] We require non-missing consensus forecasts (*FORECAST*), measured as the mean of individual forecasts, actual EPS according to I/B/E/S (*EPS_IBES*), stock price (*BEGPRICE*) from CRSP, and the earnings announcement date from COMPUSTAT.[7] To increase the likelihood of obtaining an accurate measure of forecast error, we delete firm-quarters with fewer than three forecasts.[8] 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).[9] We measure forecast error (*FCSTERR*), or the earnings surprise associated with earnings announcements, as *EPS_IBES* minus *FORECAST*. Our measure of the volatility of core EPS is the standard deviation of seasonally-differenced *EPS_IBES*.

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[6] 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.

[7] 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.

[8] This requirement is also observed in practice; e.g., Standard & Poor's use the same filter to implement their fundamental valuation model (http://www.businessweek.com/stories/2003-10-02/stocks-worth-twice-the-price)

[9] One firm, Berkshire Hathaway (I/B/E/S ticker BKHT), is deleted from our sample because it had an unusually large forecast error for the quarter ending December 2006 (the forecast error of $406.64 per share arises from an *EPS_IBES* of $1859 versus a *FORECAST* of $1452.36). This error is so large that it skews some of our descriptive statistics (the next highest forecast error magnitude in our sample is below $60).

We assume that core quarterly EPS follows a seasonal random walk process, and seasonal differences represent shocks to that process or earnings surprises.

We collect stock prices and daily stock return data from CRSP. Price (*BEGPRICE*) deciles are formed each calendar quarter based on share prices at the beginning of the quarter for all firm-quarters ending during that calendar quarter. For example, prices as of October 1, 1999 are used to form price deciles for firm-quarters ending in October, November, and December of 1999. By using prices as of the same day for all firms, we are able to avoid within-quarter price variation. 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*), obtained from cash flow statements, and per share accruals (*APS*), which equal *EPS_GAAP* minus *CPS*.

As with surprises for core EPS, we use seasonal differences (denoted by Δ_4) for *EPS_GAAP*, *CPS*, and *APS* to represent surprises for these variables. We recognize that seasonal differences are a noisier measure of surprise for reported EPS relative to core EPS because reported EPS

[10] We use the IBES-CRSP linking program provided on WRDS in combination with the CRSP-COMPUSTAT Merged Database. See https://wrds-web.wharton.upenn.edu/wrds/ds/ibes/index.cfm.

[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.

includes more non-recurring items that are transitory. That source of measurement error is likely to increase for *CPS* surprise, and is higher still for *APS* surprise.[12] We consider sensitivity analyses (results summarized in Section 3) to confirm that our main conclusions are not affected by such measurement error. Again, the magnitudes of these surprises represent our measure of volatility of the corresponding variables. Details of all variables are provided in Appendix A.

For the analysis in Section 3, we Winsorize forecast error (*FCSTERR*) and surprises based on seasonal difference of *EPS_IBES*, *EPS_GAAP*, and *CPS* at the 5th and 95th percentiles. (Appendix B describes how surprises of accruals, onetime items, analyst adjustment, and revision are derived from these Winsorized variables.) We do so to retain the pattern of forecast error scale-invariance documented in prior research. The literature (e.g., DeGeorge et al., 1999) has typically used the interquartile range of forecast error distributions as a measure of the magnitudes of forecast errors. However, we switch from interquartile ranges to variances to allow the decomposition described in Appendix B.[13] Before Winsorization, we observe a U-shaped pattern across price deciles for variances of forecast error distributions, rather than the flat pattern observed for interquartile ranges, because extreme forecast errors are more likely for low and high price deciles. We find that a 5/95 percentile Winsorization mitigates sufficiently the effects of extreme forecast errors observed for low and high price deciles and provides a relatively flat pattern of forecast error variances across the price deciles.

Table 1, Panel A, provides descriptive statistics for different variables for our sample, after the Winsorization discussed above.[14] The distribution of *BEGPRICE* suggests concentration

[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] Our approach in Appendix B is to cast different variables as the sum or difference of two variables to allow us to state the variance of the first variable as a function of the variances and covariance of the other two variables. We are unable to state these relations in terms of interquartile ranges.

[14] Before Winsorization of forecast errors and seasonal differences, four of the statistics—mean, minimum, maximum, and standard deviation—are different from those reported in Panel A for the affected variables. Winsorization at 5%/95% does not affect the other statistics. The remaining variables are not Winsorized.

around the middle of the distribution, which is expected if firms tend to split (reverse-split) stocks when share prices are above (below) desirable trading ranges. As a result, we expect attributes predicted to be related to share price to vary more for extreme price deciles. 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 that forecasts are on average slightly pessimistic.

Panel B of Table 1 describes variation across price deciles in the first moment of distributions for key variables, mainly for EPS forecast errors at different horizons and seasonal differences for core and reported *EPS*. The distributions are obtained by pooling across quarters. For brevity, we report only medians; the patterns are similar for mean values. The median values of *BEGPRICE* in row 1 range from about $5 for the lowest price decile to about $65 for the highest price decile. As described in Cheong and Thomas (2011), the results in rows 2, 3, and 4 confirm that consensus forecasts as well as reported and core *EPS* increase proportionately with share price. We defer until Section 3 a discussion of the remaining rows in Panel B.

Panel C of Table 1 describes variation across price deciles in the second moment of distributions of forecast errors and seasonal differences. We use mainly the standard deviation (StdDev) of the distributions to describe the magnitudes of forecast errors and surprises for (or volatilities of) per share earnings, cash flows, and accruals. Again, we defer until Section 3 a more detailed discussion of these results. At this stage we confirm the results reported in DeGeorge et al. (1999) and Cheong and Thomas (2011): the magnitudes of EPS forecast error (StdDev and IQR of *FCSTERR*), volatility of reported and core EPS (StdDev of Δ_4*EPS_GAAP* and Δ_4*EPS_IBES*) do not vary much with share price.[15].

[15] There is some evidence of a slight increase in magnitudes of *FCSTERR* for the higher price decile, whereas the results reported in Cheong and Thomas (2011), which are based on a sample period that ends in 2006, exhibits almost no variation with price. Similarly, increased variation observed for the highest price decile for core EPS volatility is more than that reported in Figure 4 of DeGeorge et al. (1999). Year-by-year analysis reveals a slight

To provide more reliable evidence on patterns of scale invariance for forecast error magnitudes we turn from the cross-sectional distributions reported in Panel C to standard deviations of forecast errors computed separately for each firm's time-series of forecast errors, reported in Panel D. One reason why the pattern observed for time-series estimates might deviate from that observed for the cross-section is that across-firm variation in mean forecast errors might be systematically different across different price deciles.

Firms are assigned to price deciles based on their modal price decile. Untabulated results confirm that most firms move across price deciles over time. Whereas much of that movement occurs because of normal price volatility, especially among the middle price deciles, some of it is due to stock splits and reverse splits. 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 8,014 to 4,876 firms and the second requirement reduces it further to 3,912 firms. The number of firms retained in different price deciles, reported in the bottom row of Panel D in Table 1, suggests that there is more stability of price levels over time for low price firms.

Our main finding from Table 1, Panel D is that the magnitudes of mean and median firm-specific standard deviations of forecast errors reported in the first two rows and the relatively flat pattern observed across price deciles resemble the corresponding magnitudes and pattern reported for the cross-section in row 2 of Panel C.

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increase for high price deciles during the years 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.

3. Efforts by analysts and managers to influence the distribution of forecast errors.

In this section we investigate ways in which managers and analysts might alter the distribution of EPS forecast errors such that the observed distributions exhibit pessimism and compressed forecast error magnitudes, both of which increase with share price. To investigate ways in which the first moment is altered, we use the following procedure: a) document price-variation in observed EPS growth; b) determine whether analysts recognize that variation based on forecasts made early in the year; and c) track how analyst forecasts change over the year to produce the positive relation between forecast pessimism and price observed at year-end. To investigate ways in which the second moment is altered by compressing forecast errors, we investigate the following three approaches: a) use of accruals to smooth *reported* EPS volatility; b) use of one-time items to smooth *core* EPS volatility and c) guidance of analyst forecasts to improve forecast accuracy.

3.1. Efforts to manage the first moment of the forecast error distribution

Results in row 5 in Panel B of Table 1, which describes median seasonally-differenced reported EPS ($\Delta_4 EPS\_GAAP$) for the different price deciles, suggest that quarterly earnings growth increases with scale. Whereas quarterly earnings experience no growth for decile 1, they increase by 9¢ for decile 10. These results should be interpreted with caution, however, because they reflect an induced positive relation between seasonally-differenced EPS and share price: Firms that performed badly (well) after quarter *t-4* will both have lower (higher) seasonally-differenced EPS and be overrepresented in the lower (higher) deciles of *BEGPRICE*. Sorting on price in quarter *t* creates a bias as it contains information that is released in quarter *t* but not available in quarter *t-4*.

To investigate the magnitude of this induced effect, we repeat the analysis in Panel B for price deciles formed 9 months before the beginning of the calendar quarter (*PRICE_9*), close to the date EPS is announced for quarter *t-4*. Those results are reported in Figure 1 and in rows 2 through 7 of Table 2. (The median values of *PRICE_9* reported in row 1 are similar to those reported in Table 1 for *BEGPRICE*.) The median values of seasonally-differenced reported EPS (Δ_4*EPS_GAAP*) reported in row 2 suggest that earnings growth is relatively constant—about 2¢—across all price deciles.[16] Apparently, the positive relation between growth in reported EPS and price observed in row 5 in Panel B of Table 1 is induced entirely by the effect mentioned above.

The same effect explains why the strong positive relation between *BEGPRICE* and seasonally-differenced core EPS (Δ_4*EPS_IBES*) observed in row 6 of Table 1, Panel B, is eliminated in row 3 of Table 2, when we replace *BEGPRICE* with *PRICE_9*. Observing similar results in rows 2 and 3 of Table 2 suggest that the one-time items excluded in core EPS have little effect on median growth (the means for Winsorized growth in reported and core EPS are also similar to the medians reported here).[17]

To investigate whether managerial guidance plays a role in explaining why forecast pessimism increases with share price, we examine variation with share price in errors associated with forecasts made 9 months before the quarter end (*FCSTERR_9*), soon after earnings is announced for quarter *t-4*. Prior evidence suggests that forecasts are generally optimistic at that early stage, unaffected by the incentives to meet or beat forecast that are potentially important for the most recent forecast. If so, we do not expect the relation between *FCSTERR_9* and share price to resemble the positive relation observed between *FCSTERR* and share price. Alternatively, if the positive relation observed between *FCSTERR* and share price is due to systematic analyst error,

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[16] Because the medians in Figure 1 are based on EPS and forecast numbers that are rounded to the nearest cent, smooth variations across price deciles will appear as discrete jumps across full cent amounts.

[17] We note that the medians reported in row 7 of Table 2, based on deciles of *PRICE_9*, are identical to the medians reported in row 10 of Table 1, Panel B, which are based on deciles of *BEGPRICE*. Even though the arrival of news between the two pricing dates causes firms to move across price deciles, causing changes in membership within the different deciles, the median levels of forecast error remain unchanged. While these changes in membership affect the patterns observed for error associated with earlier forecasts, they do not affect the patterns observed for errors associated with the most recent forecasts.

not induced by managerial incentives, we expect the same positive relation to be also observed between *FCSTERR_9* and share price.

The negative values for *FCSTERR_9* reported in in row 4 of Table 2 confirm the general optimism in long horizon forecasts noted in prior work (e.g., Richardson et al., 2004). More relevant to this analysis, the negative relation between *FCSTERR_9* and share price is the opposite of the positive relation observed between *FCSTERR* and share price. That is, forecasts for high price shares exhibit greater optimism than that for low price shares at long horizons, which contrasts with the greater pessimism exhibited at short horizons. This switch between long and short horizon results suggests that managerial guidance plays a role in the observed relation between price and pessimism in short horizon forecasts.

Comparing the relation between forecast growth and price at long and short horizons suggests that a systematic relation between error in analyst growth forecasts and share price does not play a role. The negative relation between *FCSTERR_9* and share price in row 4 resembles that between Δ_4*EPS_GAAP* and share price reported in row 2. This similarity suggests that long horizon forecasts imply the same EPS growth of 5¢ for all price deciles, indicated by the uniform downward shift of 5¢ from Δ_4*EPS_GAAP* to *FCSTERR_9* that is clearly visible in Figure 1. (Growth over EPS in quarter t–4 implied by the forecast n months before quarter-end equals Δ_4*EPS_GAAP* minus *FCSTERR_n*.) In contrast, subtracting the numbers in row 7 from the corresponding values in row 2 suggests that short horizon forecasts imply EPS growth that declines with share price: growth of 3¢ for decile 1, but a decline of –1¢ for decile 10.

Results in rows 5 and 6 of Table 2 provide median errors associated with forecasts made 6 months before the quarter-end (*FCSTERR_6*) and 3 months before the quarter-end (*FCSTERR_3*). These results describe the trend over time as the general optimism observed in early forecasts turns to pessimism over the period leading up to the announcement of earnings for quarter t. Again, this "walk-down" pattern for forecasts, which is reflected as an upward movement for median forecast error in Figure 1 as horizon decreases, has been described in prior research (e.g., Richardson et al., 2004): forecasts become less optimistic over time and turn into pessimistic or "beatable" forecasts by the earnings announcement date. Our contribution is to document variation across price in the extent of walk-down during the year: whereas the slope for *FCSTERR_9* is clearly negative, it becomes less negative for *FCSTERR_6*, turns positive for *FCSTERR_3*, and is clearly positive for *FCSTERR*. In essence, the amount of walk-down increases with share price: whereas price decile 1 is associated with an increase over the horizon in median forecast error of 2¢ (from –2¢ in row 4 to 0¢ in row 7), the increase for price decile 10 is 6¢ (from –4¢ to +2¢).

Overall, we do not see how the evidence in Table 2 and Figure 1, which shows increasing optimism with price for early forecasts but increasing pessimism with price for more recent forecasts, is consistent with explanations that do not involve managerial intervention. Not only are these results inconsistent with systematic analyst error they are inconsistent with scale variation in the arrival of news or analyst effort. While increased news arrival or analyst effort increases the precision of analyst forecasts, it does not explain the variation in bias. Instead, our results suggest that managers differentially guide analyst forecasts down (or signal to analysts their preferred level of forecasts, and analysts cooperate). More evidence consistent with this view is described later in Section 3.2.3, where guidance is used to differentially compress forecast errors for high price firms.

3.2. Efforts to manage the second moment of the forecast error distribution

A convenient way to view the efforts undertaken by managers to differentially suppress natural scale variation in the magnitude of EPS forecast errors is to consider the step-by-step decline in scale variation described in Figure 2, from cash flow surprise (the upward sloping line at the top) to forecast errors (the flat line at the bottom). As documented in Cheong and Thomas (2011), much of the upward slope for cash flow surprise volatility ($\Delta_4 CPS$) is eliminated in the volatility of reported earnings surprise ($\Delta_4 EPS\_GAAP$). Some increase in volatility remains, however, between price deciles 8 and 10.[18] There is little differential decline in volatilities in the next step when we consider the volatility of core earnings ($\Delta_4 EPS\_IBES$). These volatilities of seasonally-differenced earnings represent magnitudes of errors associated with time-series forecasts based on a seasonal random walk process.

Switching from time-series forecasts to analysts' forecasts, there is little change in forecast error magnitudes when we consider errors relative to early forecasts made 9 months before the end of the current quarter (*FCSTERR_9*). That is, analyst forecasts made soon after earnings is announced for quarter *t-4* are about as accurate as seasonal-random walk forecasts (adjusting for the optimism biases discussed in Section 3.1). As forecast horizon declines, however, not only do analyst forecasts get more accurate, there is incremental improvement among price deciles 8 through 10. Most of the evidence of scale variation is eliminated by the last step, when we consider the volatility of errors relative to the most recent forecast (*FCSTERR*).

Appendix B derives a variance decomposition for each step, by representing the variance of the variable at each step as the sum of the variances of two component variables and a covariance term. Investigating variation across price deciles in those variances and covariances allows us to determine the source of forecast error compression occurring at each step.

We confirm in rows 8 through 13 of Table 2 that the results in Figure 2 based on deciles formed using *BEGPRICE* are also observed when we form deciles using *PRICE_9*. As described in Section 3.1, there is potential for a spurious relation between price and forecast errors because of new information in *BEGPRICE* that is not available for forecasts (including those based on seasonal random walk processes) made before the date used to collect *BEGPRICE*. We find similar

[18] There is also some evidence of very low price firms exhibiting levels of volatility that are slightly higher than low and mid-price firms. As mentioned in Section 2, this slight U-shape is due to volatilities being measured by standard deviations here, rather than the interquartile ranges used in Cheong and Thomas (2011).

results for the two sets of price deciles, suggesting that the bias induced for first moments does not appear in the second moments of the corresponding forecast error distributions.

3.2.1 Using discretionary accruals to offset cash flow shocks.

The first way to compress forecast errors, described by relation B2, is to select discretionary accruals that offset cash flow shocks. In effect, forecasts become more accurate if managers smooth the volatility of *reported* EPS. The variance of reported EPS surprises equals the sum of the variances of cash flow and accruals surprises plus a covariance term which reflects the correlation between cash flow and accruals surprises.

Given that the volatilities of cash flow and accruals surprises increase with scale (see rows 5 and 6 of Table 1, Panel C) managerial efforts to suppress scale variation in reported EPS surprises will be reflected in the covariance term being negative and becoming increasingly negative with scale. That is, the correlation between cash flow and accruals surprises should become more negative as scale increases, and that correlation should be sufficiently negative for the impact of the covariance term to be large enough in magnitude to offset the positive impact of the two variance terms increasing with scale.

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 build-up of inventory or a decision to grant more credit to customers will cause *CPS* to decline and *APS* to increase unexpectedly, even though *EPS_GAAP* remains unaffected. In addition to such operational reasons to expect a negative correlation, measurement errors associated with our measure of cash flow surprise will create a negative bias in our correlation estimates. Because accruals surprises are obtained by subtracting cash flow surprises from earnings surprises, measurement errors associated with cash flow surprise induce opposite measurement errors in accrual surprise. Although these reasons predict a negative correlation between cash flow and accruals surprises, we see no reason to expect this correlation to become more negative with scale.

The results in Table 3 provide evidence on the extent to which this first approach is used by managers. The first three rows in Panel A repeat the results already reported in rows 4, 5, and 6, respectively, in Panel C of Table 1.[19] Whereas the volatilities of cash flow and accruals surprises increase with scale, the volatility of surprise for reported EPS varies little with scale (except for the small increase with scale for deciles 9 and 10). This difference in scale variation patterns is explained by observed variation for Pearson and Spearman correlations between cash flow and accruals surprises described in rows 4 and 5, respectively, of Table 3, Panel A. Those correlations are negative, become more negative as scale increases, and then flatten out after price decile 8.

As with Table 1, we believe that firm-by-firm analyses are more reliable than the cross-sectional analyses reported in Panel A, because they control for differences across firms (mainly growth). Also, at the firm level we are able to consider a second measure of the extent to which managers offset cash flows shocks with discretionary accruals: the ratio of firm-specific standard deviation of surprises in reported per share earnings to the corresponding standard deviation for cash flows (*RATIO*). If managers of high priced firms offset cash flow shocks to a greater extent with discretionary accruals, such earnings management should cause *RATIO* to decline with scale. We follow the same procedure described for Panel D of Table 1 and assign firms to price deciles based on the modal price decile associated with that firm.

The mean and median volatility of cash flow surprises for firms in each price decile increase with scale (rows 3 and 4 in Table 3, Panel B), similar to the cross-sectional patterns (row 2 in Panel A). The mean and median volatility of earnings surprises increases at a substantially lower rate with scale (rows 1 and 2 in Panel B) than that for cash flows. Although we observe a

[19] Note that the sample in Table 3 is smaller than that in Table 1, as we impose the additional requirement that seasonal differences in per share earnings, cash flows, and accruals are non-missing.

small and steady increase with scale that is not observed in the cross-sectional results (row 1 in Panel A), we do not investigate further the cause for this difference because its magnitude is relatively small.

The results reported in Table 3, Panel B represent firm-specific analogs of the cross-sectional results reported in Panel A. The focus is again on whether the correlation between cash flow and accrual surprises becomes more negative as scale increases. The magnitudes of mean and median standard deviations for surprises in per share earnings, cash flows and accruals reported in the first six rows of Panel B are all smaller than the corresponding values based on cross-sectional analyses reported in Panel A. The differences are larger for cash flow and accruals surprises, but the differences decline with price. These results suggest that firm-specific mean values of seasonally-differenced EPS, CPS and APS deviate substantially from the corresponding grand means.[20] Despite these differences in the magnitudes of the surprises, the patterns of variation across scale for the time-series results in Panel B resemble those in Panel A. The magnitudes of surprises for cash flows and accruals vary substantially with scale, whereas EPS surprises are more flat as scale increases.

Our main finding is that firm-specific Pearson and Spearman correlations between cash flow and accruals surprises, reported in rows 7 through 10 of Panel B, become more negative with scale. Managers suppress the volatility of reported earnings by making accruals to offset cash flow shocks, and the extent of such earnings management increases with scale. Also, the variation in these correlations, from –0.55 for price decile 1 to –0.83 for price decile 10, is considerably larger than the variation in correlations reported for our cross-sectional analyses (row 4 of Panel A). We believe these time-series, firm-specific results are a more reliable indicator of the extent of earnings management designed to smooth volatility of reported EPS.

[20] In contrast, the magnitudes of the firm-specific standard deviations for forecast errors in Panel D of Table 1 are similar to the cross-sectional standard deviations in Panel B.

Additional confirmation of differential forecast error compression is provided by the results in rows 11 and 12 in Table 3, Panel B, which report mean and median values of *RATIO* (i.e., ratio of volatility of unexpected per share earnings to that of cash flows) for firms in each price decile. The values reported in these rows are below 1 (except for the mean *RATIO* for price deciles 1 and 9), consistent with the expectation that earnings volatilities are in general lower than cash flow volatilities because of accruals. More relevant to our analysis, the mean (median) values reported in these two rows decline substantially with scale, from 1.32 (0.95) for price decile 1 to 0.59 (0.54) for decile 10.

Cheong and Thomas (2011) document scale variation in volatility of per share sales surprise, similar to that observed for *CPS* surprise. Because EPS equals per share sales less expenses, the variance of EPS surprise can be stated as the sum of sales and expense variances minus a covariance term, similar to the variance decomposition based on cash flows and accruals. We repeated the analysis in Table 3 for sales and expenses to determine if the decline in scale variation observed from per share sales surprise volatility to EPS surprise volatility can be explained by managers altering expenses (revenues) so that expense (revenue) surprises offset exogenous revenue (expense) shocks almost completely. Our results (not tabulated here) confirm that description: the positive correlation between per share sales and expense surprises and the ratio of those two surprises increases from price decile 1 to decile 8, and then flattens out after that.

There are two reasons why we underestimate the level of earnings management. First, we assume that cash flows are exogenously determined; i.e., managers do not suppress natural variation with scale in the volatility of *CPS*. In fact, managers seeking to suppress the volatility of reported EPS might suppress the volatility of cash flow surprises too, and might do so more for high price firms.[21] Second, we document earnings management in different deciles *relative* to that

[21] For example, managers might smooth EPS and *CPS* by increasing (reducing) R&D and maintenance when profitability is high (low).

in decile 1. Absolute levels of earnings management are higher by the amount of smoothing of EPS volatility that occurs for decile 1.

We also conducted robustness analyses to investigate the extent to which our Table 3 results are due to error in our measures of cash flow and accruals surprises. In particular, the seasonal random walk process we assume may not describe well the time-series processes underlying *APS* and *CPS*. Our concern is not that our measures contain error, but that any measurement error varies across price deciles in such a way that it induces *RATIO* to decline and the correlation between *APS* and *CPS* to become more negative as scale increases. We examine autocorrelations and partial autocorrelations at the first four lags for seasonally-differenced *APS* and *CPS* for each firm with sufficient time-series data (more than 10 quarters) and reasonably stable price levels over time. While our results suggest indicate non-zero values, especially at the fourth lag, we note that the levels of these correlations are similar across price deciles.[22]. Overall, we conclude that measurement error biases the *levels* of *RATIO* and correlations reported in Table 3, but because the extent of bias does not vary across price the *patterns* of variation across price deciles we observe are representative.

To provide additional confirmation that the results in Table 3 reflect differential smoothing of reported earnings, we consider two smoothing measures proposed recently in Lang, Lins, and Maffett (2012). They resemble the two measures used in this study, *RATIO* and the correlation between cash flow and accruals surprises, though the specifics of the calculations differ.[23] The first measure (*SMTH1*) "captures the volatility of earnings relative to the volatility of cash flows", and is "measured as the standard deviation of net income before extraordinary items divided by the

[22] 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*.

[23] Correlations between cash flows and accruals are based on levels, rather than differences. However, the authors indicate that similar results are observed when levels are replaced by differences.

standard deviation of cash flow from operations, where net income before extraordinary items and cash flow from operations are scaled by average total assets and the standard deviations are calculated using rolling time intervals requiring a minimum of three and a maximum of five years of data". The second earnings smoothness measure (*SMTH2*) is the "correlation between the cash flow from operations scaled by total assets and total accruals scaled by total assets." Untabulated results confirm the main finding in Table 3: the extent of smoothing of reported earnings increases with share price, and that trend is more evident across low and medium price deciles.

While our analyses in this subsection investigate the role of differential smoothing of reported EPS volatility in the suppression of scale variation in EPS forecast errors, the key finding is that earning management designed to reduce volatility of reported EPS is both widespread and substantial. EPS volatility is compressed considerably, especially for firms with higher share prices, by managers selecting accruals to offset cash flow shocks. Prior research, which has mainly considered whether earnings management is used to achieve certain levels of earnings, has not focused as much on earnings smoothing.

3.2.2 Strategically allocating earnings components to one-time or non-core earnings.

The second method we consider is to reduce the volatility of core EPS, relative to the volatility of reported EPS, by selectively transferring earnings components to one-time items (*ONETIME)* that are excluded from core EPS. Because removing one-time items from reported EPS is expected to substantially reduce the volatility of core EPS, we anticipated this second method would play a significant role in differential smoothing across price deciles. However, given that much of the variation in EPS volatility across price deciles has already been removed by the first approach, there is less opportunity for the second approach to play a role.

As described in relation (B4) in Appendix B, the variance of reported EPS (Δ_4*EPS_GAAP*) equals the sum of the variance of core EPS surprises (Δ_4*EPS_IBES*), the variance of surprises for one-time items (Δ_4*ONETIME*), and twice the covariance between these two surprises. Any observed reduction in volatility from reported to core EPS must arise from two sources: a) higher variance of one-time items and b) higher correlation between surprises for core EPS and one-time items. That is, holding constant the volatility of reported EPS, greater managerial efforts to reduce core EPS volatility via the strategic allocation of reported EPS components to one-time items should be associated with higher variances for one-time items and more positive (or less negative) correlation terms.

We begin with the volatility of reported EPS, described by the standard deviation of seasonally-differenced *EPS_GAAP*, reported in row 1 of Table 4, Panel A.[24] Row 2, which describes scale variation in core EPS volatility, confirms that removing one-time items from reported EPS reduces the resulting volatility of core EPS. The volatilities reported in row 2 are about half as large as those in row 1 for reported EPS. However, managers do not use one-time items to reduce scale variation in EPS volatility across price deciles. Most of the scale variation observed for reported EPS volatility in row 1 at the high price end (from 0.35 for decile 8 to 0.42 for decile 10) remains for core EPS volatility in row 2 (from 0.21 for decile 8 to 0.26 for decile 10). To be sure, the slight amount of inverse scale variation observed for *low* price firms in row 1 is largely eliminated in row 2.

Inspection of rows 3 and 4 in Panel A, which describe the volatility of one-time items and the correlation between core EPS surprises and one-time items, respectively, provide more details of the changes between rows 1 and 2. At the high price end, the two effects go in the opposite direction, and they tend to mostly cancel each other out. Whereas the volatility of one-time items increases from deciles 8 to 9 in row 3 (from 0.25 to 0.27), which should mute the scale variation reported in row 2, that effect is canceled by the decline in row 4 correlations (from 0.14 to 0.13).

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[24] Requiring non-missing data for seasonally-differenced reported EPS, core EPS, and one-time items explains the small deviations from the results reported for the full sample in row 4 of Table 1, Panel C.S

From decile 9 to 10, the increase in row 3 is only partially canceled by a decrease in row 4. This explains why the corresponding increase in volatility of core EPS in row 2 is slightly smaller than that for reported EPS in row 1.

The two effects go in the same directions for low price firms. The volatility of one-time items in row 3 is higher for decile 1 (standard deviation of 0.31) than that for decile 5 (0.26). The second effect, relating to the correlations reported in row 4, also exhibits a decline from deciles 1 to 5. As a result, the inverse scale variation observed at the low price end for reported EPS is mostly eliminated in core EPS.

We consider next whether the use of one-time items to reduce scale variation in core EPS volatility is related to the sign of core EPS surprise. Managers might not seek to reduce core EPS volatility, for example, if core EPS surprise is negative. The results from repeating the Table 4, Panel A analysis for subsamples where core EPS this quarter "meets or beats" and "misses" core EPS from four quarters ago are reported in Panels B and C, respectively. The volatilities of core EPS surprise reported in the second rows of Panels B and C are reduced sharply, relative to Panel A because the distribution of core EPS surprise is truncated at zero. Whereas there are some interesting differences between the two Panels—for example, the volatility of core EPS surprise is larger for negative surprises—managerial efforts designed to use one-time items to suppress scale variance in the volatility of core EPS appear to be unrelated to the sign of EPS surprise.

3.2.3 Increasing forecast accuracy by increased managerial guidance.

We turn finally to the third way to suppress natural scale variation in EPS forecast errors, by managerial guidance designed to differentially increase forecast accuracy, where the extent of guidance increases with scale. To consider all points where managerial guidance might play a role, we begin with the consensus forecast available 9 months before the quarter-end, representing the forecasts available when earnings are announced for quarter *t-4*. Relationship (B6) in Appendix B explains how the magnitude of forecast errors based on that early forecast are a function of the volatility of core EPS surprise, the volatility of adjustments analysts make to the earnings for quarter *t-4* when making their forecast for quarter *t*, and the correlation between those two terms.

The results reported in Panel A of Table 5 describe the extent of suppression of scale variation in forecast error magnitudes that occurs at this early stage. The standard deviations of forecast errors made 9 months before the quarter end (reported in row 1) are about a penny smaller than the standard deviations of core EPS surprises (reported in row 2), except for the highest three price deciles where the reduction in volatility caused by analyst adjustments is about 2 cents. Note that core EPS surprises can be viewed as forecast errors from a naïve time-series prediction model based on EPS following a seasonal random walk process. In effect, analyst forecasts made 9 months before the quarter end predict quarterly core EPS only slightly more accurately than the core EPS from four quarters ago.[25]

Examination of rows 3 and 4 in Panel A, which describe the two effects that explain the reduction in volatility from row 2 to row 1, suggests that the small reduction in scale variance observed at the high price end is due to a combination of slightly higher standard deviations of analyst adjustments and a slightly more positive correlation between analysts adjustments and core EPS surprise (or the forecast error from a seasonal random walk forecast). In effect, not only are analyst adjustments from the seasonal random walk forecast slightly larger in magnitude for the top three price deciles, those adjustments are on average in the right direction, toward the core EPS number that will be reported in quarter t.

We turn next to the improvement in analyst forecast accuracy as horizon declines from 9 months before the quarter end to the month just prior to earnings announcement. As described by relation (B8) in Appendix B, magnitudes of error based on the most recent forecasts are a function

[25] As described in Section 3.1, analyst forecasts made 9 months before the quarter end are systematically optimistic. By using standard deviations of forecast errors to measure accuracy we ignore any systematic bias.

of the magnitudes of error based on the early forecasts, the revisions made between those forecasts, and the correlation between early forecast errors and revisions.

The results reported in Panel B of Table 5 consider this decomposition of forecast error magnitudes. The slight increase with scale for magnitudes of error associated with the early forecast (reported in row 1) is mostly eliminated by revisions subsequent to that forecast, because magnitudes of errors associated with the most recent forecast exhibit almost no scale variation (in row 2). Rows 3 and 4 of Panel B suggest that this differential increase in accuracy is due mainly to the larger revisions made for high price firms (in row 3). The correlations reported in row 4 remain relatively constant across the price deciles. Analyst forecast accuracy increases with scale for high price firms as horizon decreases, and this differential increase in accuracy eliminates any evidence of scale variation observed in core EPS surprises.

We analyze month-by-month variation in this differential improvement in accuracy to determine if the improvement is concentrated in any month. Relation (B10) in Appendix B shows how the magnitude of forecast error at any point, *n* months before the quarter end, can be stated as a function of the magnitude of forecast error a month earlier (*n+1* months before the quarter end), the magnitude of the revision between month *n+1* and month *n*, and the correlation between the earlier forecast error and that revision.

Given that IBES provides monthly consensus forecasts as of the middle of each month, and given that earnings are announced a few weeks after the quarter end, the most recent consensus forecast (*FORECAST*) before earnings announcements is typically later than the date of *FORECAST_0*, the consensus forecast for the last month of the quarter. Relation (B12) repeats the earlier decomposition in relation (B10) to consider the revision between *FORECAST_0* and *FORECAST*.

Panel C of Table 5 provides some of the results from this month-by-month analysis. Accuracy improves each month as horizon decreases, and that improvement is slightly greater for high price deciles. The magnitudes of revisions (third row in each block) exhibit some increase with scale at the high price end for all months. But that effect is not concentrated in any month.

Overall, we believe that managers use the third approach, based on differential managerial guidance, to eliminate residual scale variation in volatility of core EPS. As with the patterns reported in Figure 1, it seems unlikely that the differential increase in forecast accuracy observed for price deciles 8 through 10 is due to differential analyst effort or information availability. While increased news arrival and effort will increase precision, why would those two effects exhibit the non-linear relation we observe, where the improvement in forecast accuracy as horizon decreases is the same for deciles 1 through 7 and then increases with scale for deciles 8 through 10? Also, why would the differential impact of these two effects be just enough to ensure that forecast error magnitudes are the same for all price deciles by the month before earnings are announced?

To review, the results in Section 3 suggest considerable management of actual and forecast EPS. Much of that management relates to the use of accruals to smooth EPS volatility, with a view toward eliminating natural increase in volatility with scale. The remainder of that management relates to guiding analyst forecasts to satisfy two objectives: a) eliminating any residual increase in volatility with scale for high price shares, and b) creating forecast pessimism, which increases with scale.

4. Investor responses to efforts by managers/analysts to influence forecast errors

The evidence in Section 3 is consistent with the conjecture that managers alter the first and second moments of forecast error distributions because they perceive investors to be naive. If investors do not recognize that EPS forecast errors vary naturally with scale they will overestimate the risk associated with high price firms. This is because investors would observe larger forecast errors, relative to their biased expectations, and potentially respond with more extreme price swings. Removing scale variation by differential compression of forecast errors reduces the likelihood of this undesirable outcome. Forecast pessimism, on the other hand, increases the likelihood of a positive outcome, if investors do not adjust appropriately. Observing more positive forecast errors than negative ones should result in more positive surprises and potentially higher prices on average. If high price firms guide analyst forecasts to achieve more pessimistic forecasts than low price firms, they should benefit more from such investor naiveté.

We consider next whether investors recognize and respond appropriately to the altered first and second moments of forecast error distributions. Specifically, do price responses adjust for the differential forecast pessimism and the differential compression of forecast errors? We conduct a granular analysis by examining frequencies and price responses for each cent of forecast error. Given the results in Kinney et al. (2002) and Burgstahler and Chuk (2010), which suggest that price responses to earnings surprises vary considerably with forecast dispersion, we split the sample into low and high dispersion subgroups. The former group contains firm-quarters with *DISPERSION* less than two cents, and represents approximately half of our sample. The remaining observations with *DISPERSION* of two or more cents are included in the high dispersion subgroup.

4.1 Adjustment for differential pessimism.

To supplement the results reported in Section 3.1, which show variation in mean/median forecast bias across price deciles, we provide in Figure 3, Panel A the frequency of firm-quarters in our sample for each cent of forecast error, between –10 and +10 cents. All forecast errors less than –10 cents and greater than +10 cents are combined in the extreme left and right columns in each plot, respectively. The top and bottom rows describe the low and high dispersion subgroups. Within each *DISPERSION* subgroup, we report the histograms for three representative price deciles: deciles 1, 5, and 10, which are intended to reflect low, medium, and high price firms, respectively.

Some descriptive findings from Figure 3, Panel A are as follows. First, a substantial fraction of the low dispersion subgroup in the top row has relatively small forecast errors, say, within ± 5¢. While the high dispersion subgroup has many observations with large forecast error magnitude (absolute values ≥ 10¢) a considerable fraction has relatively small forecast errors. Second, the similarity across price deciles observed for the overall distribution of forecast errors (e.g., Degeorge et al., 1999) is replicated within the low and high dispersion partitions; i.e., the shapes of the distributions are similar within each row.

Third, whereas the likelihood of meeting consensus forecast (forecast error = 0) substantially exceeds the likelihood of just missing (forecast error = –1¢) for the low dispersion partition, that pattern is much weaker for the high dispersion group in the bottom row, and barely discernible for low and mid-price firms. Apparently, the incentives for managers to avoid just missing consensus forecast are stronger for firms with low forecast dispersion.

Fourth, whereas the likelihood of meeting consensus forecast is greater than the likelihood of just beating (forecast error=+1¢) for low price firms and mid-price firms with low dispersion, that pattern is reversed for high price firms and mid-price firms with high dispersion. Consistent with the results in Cheong and Thomas (2011), the distribution of forecast error shifts to the right as share price increases, because forecasts become more pessimistic.

Rational investors observing differences in the distribution of forecast errors across the different price and dispersion partitions should adjust their expectations accordingly and recognize that the same forecast error should have different value implications across the partitions. For example, the news implied by just beating (just missing) actual EPS in a rational stock market should be not as good (much worse) as share price increases.

Our results in Panel B of Figure 3, which describe the mean *PRICERESP*, or 22-trading-day price response (in $) for each cent of forecast error, confirm that investors adjust rationally for differences across price deciles in the likelihood of just missing/meeting/just beating consensus forecasts. The crossover point from negative to positive price responses is lowest for the lowest price decile (between forecast errors of 0 and +1 cent for the low dispersion subgroup and between –1 and 0 for high dispersion), and increases for the highest price decile (between +1 and +2 cents for the low dispersion subgroup and between +3 and +4¢ for high dispersion). In general, the pattern of price responses in Panel B is determined by the pattern of forecast error distributions reported in Panel A. For example, a forecast error of zero is considered no news (bad news) for low (high) price deciles because the forecast error distributions peak at (to the right of) zero and price responses to zero forecast errors are accordingly zero (negative).

The results in Panels A and B of Figure 3 suggest considerable complexity that is masked by patterns documented in prior research based on aggregate data. 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 in the high dispersion row in Panel A. Similarly, disputes over the presence of a torpedo effect (e.g., Skinner and Sloan, 2002, Payne and Thomas, 2011), where high growth firms that miss forecast are penalized by excessively large negative stock price responses, need to consider cross-sectional variation in the distribution of forecast errors. Because the distribution of forecast errors for high price firms is shifted to the right, relative to that for low price firms, missing forecast by a penny is more of a negative surprise for high price firms (which are also likely to be high growth firms). If investors rationally respond more negatively, the torpedo effect is not surprising.

4.2 Adjustment for differential compression of forecast errors.

Rational investors should also adjust for differential compression of forecast errors; i.e., price responses per cent of forecast error (ERC) should increase with share price, as the degree of compression increases. As described in relation B13 of Appendix B, ERC is a function of the variances of *FCSTERR* and *PRICERESP* and the correlation between those two. Given that the variance of *FCSTERR* and the correlation term do not increase with scale (rows 1 and 7 in Panel

C of Table 1), ERC is expected to increase with the standard deviation of *PRICERESP*, which increases with scale (row 8 in Panel C of Table 1).

The gradient of a hypothetical line that connects the midpoints of the tops of the vertical bars in Panel B of Figure 3 represents the incremental share price response or ERC in each subpanel. Our first result based on variation in ERC across the six subpanels is that the gradient increases sharply with share price, for the majority of the observations that are clustered within the narrow [–5¢,+5¢] range. Note that the scale for decile 5 (10) in the middle (right) column is five (ten) times that for decile 1. That is, observing similar slopes from left to right within each row in Panel B of Figure 3 suggests that the slope for decile 5 (10) is five (10) times that for decile 1. Second, the slopes are steeper for the low dispersion subgroup in the top row, holding price constant in each column. Finally, while the gradient is steeper for small forecast errors, close to the middle of each plot, it decreases and is almost flat for larger forecast error magnitudes closer to the left and right edges of each plot.[26]

We move from our descriptive results in Panel B of Figure 3 to plotting estimates of ERC—slopes from regressions of prices responses on forecast error—for different partitions. To allow comparison with our results in Panel B of Figure 3, we estimate ERC within a different set of six subgroups created by crossing the two dispersion partitions with three partitions based on forecast error: large negative (<–5¢), small (between –5 and +5¢), and large positive (>+5¢).

The main result from Figure 3, Panel C, which is anticipated by the patterns for price responses reported in Panel B, is that the ERC varies widely across these different partitions. ERC is generally close to zero for most price deciles in the large negative and large positive forecast error groups, on the left and right sides, respectively. In contrast, ERC values are much higher for

[26] The histogram patterns are generally smooth, except for the more jagged profile observed for large negative forecast errors for the low dispersion subgroup of price decile 10. Note, however, that these bars represent very few observations (see corresponding section in Panel A).

the two small forecast error partitions in the middle, and those ERC values increase sharply with price. The ERC values for higher price deciles are higher than levels predicted by theory or observed in prior research. For example, the ERC is over 90 for decile 10 in the low dispersion group! Also, observing an ERC for decile 10 that is about ten times that for decile 1 is consistent with our conclusion in Section 3 that forecast errors for decile 10 are compressed to one-tenth their original values. Investors rationally infer and respond similarly to unsmoothed forecast errors, which distorts substantially their response to smoothed forecast errors. Finally, the level of ERCs for the low dispersion subgroup (top row, middle plot) is substantially higher than that for the high dispersion subgroup (bottom row, middle plot).

Whereas the ERCs discussed so far 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.[27] We expect ERC estimates within each cell to be relatively unaffected by deflation (see relation B14 in Appendix B). These predictions are confirmed by comparing the results for the deflated specification in Panel D of Figure 3 with the corresponding results for the undeflated specification in Panel C of Figure 3. The ERCs for the deflated specification in Panel D of Figure 3 are generally similar to the corresponding ERCs for the undeflated specification in Panel C, because variation in deflated forecast errors is restricted within price deciles.

To review, investors recognize efforts made by managers to alter the distribution of forecast errors and respond appropriately. Similar forecast errors are interpreted differently across different price deciles. Rather than naively view positive and negative forecast errors as good and bad news, investors adjust for differential underlying pessimism. And rather than view similar magnitudes of forecast error as representing similar value effects, investors adjust for differential compression of forecast error magnitudes.

[27] In some studies (e.g., Beaver, Lambert, and Morse (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.

5. Conclusion

Our results suggest that management of actual and forecast EPS plays an important role in the anomalous distribution of forecast errors observed for analyst-followed firms in the US: EPS forecast error magnitudes do not increase with scale whereas mean forecast errors increase with scale (e.g., Degeorge et al., 1999 and Cheong and Thomas, 2011). Lack of variation in forecast error magnitudes is largely achieved by differential smoothing of reported EPS volatility, where EPS is smoothed by selecting accruals to offset cash flow shocks. The extent of smoothing is pervasive and substantial, especially for high price firms. And differential forecast guidance explains why mean forecast errors increase with scale: managers of high price firms guide analysts to make more pessimistic forecasts than those for low price firms.

We find that investors recognize these differential efforts to smooth volatility of reported earnings, and guide analysts toward pessimistic forecasts. When responding to observed forecast errors, investors infer the errors that would have been observed if the differential earnings smoothing and forecast guidance had not occurred. For example, because a forecast error of 5¢ for the highest price decile is the compressed equivalent of a 50¢ forecast error for the lowest price decile, the price response per cent of forecast error is 10 times higher for the top price decile (ERC of 90 for decile 10 versus ERC of 9 for decile 1). And beating consensus forecast by 1¢ is viewed as good news for decile 1, but viewed as bad news for decile 10, because forecasts are on average unbiased for decile 1 but pessimistic by 2¢ for decile 10. Finding that investors recognize and adjust for earnings smoothing and forecast guidance is intriguing as these managerial efforts are likely motivated by perceived investor naiveté.

Our results offer new avenues for future research and also have implications for prior research. Our understanding of managerial behavior and their interaction with analysts should be enhanced by future research that investigates alternative explanations for the earnings smoothing and forecast guidance we document. Even though altering the natural distribution of forecast errors is only one of many factors that affect the manager/investor relation, which is itself only one of many relations that create incentives to manage reported earnings and analyst forecasts, the scale and scope of the managerial efforts we document here suggest that careful study will yield valuable insights. And the unexpected finding that these efforts vary with scale at the share level has important implications for prior research that investigates specific aspects of earnings management and forecast guidance. The strong relation with price noted here may affect inferences of those studies.

Our results also shed light on the discussion in Ball (2011), which we view as an effort to describe the extent to which forecast error variances would vary with scale if managers did not differentially compress forecast error magnitudes.[28] That is, what forecast error distributions are expected under the null hypothesis of no managerial intervention? We see two ways to provide some evidence on that question, if we assume as a first approximation that the forecast errors for the first price decile have not been compressed. First, we could assume that price responses to unmanaged forecast errors do not vary with scale, and project the ERCs observed for the lowest decile onto the other deciles to infer the magnitudes of uncompressed forecast errors for different deciles. Second, we could assume that the negative correlation between per share accruals and cash flows does not vary with scale and project the correlation observed for the first decile onto other price deciles. Equation (B2) in Appendix B allows us to estimate the projected variance of EPS differences that would be observed for the other price deciles. Intuitively, scale variation projected for the variance of EPS differences should be reflected in the variance of EPS forecast errors.

[28] Ball (2011) also provides an alternative explanation for the observed lack of scale variation in forecast error magnitudes, which relies on available data being too coarse: Predicted forecast errors are generally less than a penny, based on multiplying price changes by 0.01 (a typical ratio of quarterly EPS to share price), which limits our ability to see variation with scale because actual and forecast EPS are rounded to the nearest penny. Because the substantial pricing errors are omitted in equations (1) and (2) in Ball (2011), these predicted magnitudes for forecast errors are severely understated. Also, the evidence in this paper suggests that rounding is unlikely to explain why forecast error magnitudes do not increase with scale. For example, the magnitude of the negative correlation between per share cash flows and accruals, rounded to the penny, and the price response to each cent of observed forecast error increase substantially with price.

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 9 months before quarter-end for quarter t.	= *FORECAST_9* – EPS_IBES_{t-4} = Δ_4*EPS_IBES* – *FCSTERR_9*
BEGPRICE (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	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 * (in $)	Cash flow per share.	Quarterly net cash flow from operating activities (data item #oancfy from WRDS filename comp.fundq), divided by # 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.
EPS_GAAP (in $)	Actual quarterly earnings per share before extraordinary items, as derived from the Cash Flow Statement. *	Quarterly Income from Cash Flow Statement (data item #ibcy from WRDS filename comp.fundq), divided by # 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 earnings per share (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 (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.

Label	Description	Source
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.
ONETIME (in $)	One-time items.	= *EPS_GAAP – EPS_IBES*
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).
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_n (in $)	EPS forecast revision from *n+1* months before quarter-end to *n* months before quarter-end.	*REV_n* = *FORECAST_*(*n+1*) – *FORECAST_n*
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*
Δ_4	Operator to denote seasonal difference.	$\Delta_4 X_t = X_t - X_{t-4}$

* 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

This Appendix derives some of the relations we use in our empirical analyses.

(I) Differential suppression of EPS forecast errors

Lack of variation with scale observed for EPS forecast error magnitudes (e.g., Degeorge et al., 1999, Figure 4, and Cheong and Thomas, 2011, Table 1, Panel A1) could be achieved in different ways. We begin by assuming that cash flow shocks (which vary with scale) are exogenous, and explore three mechanisms that might be used to differentially suppress these shocks, namely, the use of accruals, one-time items, and management guidance of analyst forecasts. We assume that quarterly per-share earnings, cash flows from operations, and accruals follow a seasonal random walk process. (Analyses available from the authors suggest that the measurement error created by this assumption does not alter the main conclusions.) Below, we describe relations that link the variances of unexpected EPS (seasonally-differenced EPS or $\Delta_4 EPS$) and forecast errors, where these variances are measures of forecast error magnitudes, to variances and correlations of related components.

(a) Using accruals to offset cash flow shocks

To determine the extent to which accruals are used to smooth cash flow, we add accrual (*APS*) to cash flow (*CPS*) to form GAAP earnings (*EPS_GAAP*).

$$\Delta_4 EPS\_GAAP = \Delta_4 CPS + \Delta_4 APS \tag{B1}$$

$$\mathrm{Var}\,(\Delta_4 EPS\_GAAP) = \mathrm{Var}\,(\Delta_4 CPS + \Delta_4 APS) =$$
$$\mathrm{Var}\,(\Delta_4 CPS) + \mathrm{Var}\,(\Delta_4 APS) + 2\,\mathrm{Corr}\,(\Delta_4 CPS, \Delta_4 APS) \cdot \sqrt{\mathrm{Var}(\Delta_4 CPS)\,\mathrm{Var}(\Delta_4 APS)} \tag{B2}$$

(b) Using one-time items to smooth core earnings (EPS_IBES).

Next, to incorporate the extent to which one-time items are used to smooth core earnings, we subtract one-time items (*ONETIME*) from the EPS reported on Compustat (*EPS_GAAP*) to obtain the EPS reported by I/B/E/S (*EPS_IBES*), which is the core earnings that analysts seek to forecast.

$$\Delta_4 EPS\_IBES = \Delta_4 EPS\_GAAP - \Delta_4 ONETIME \tag{B3}$$

$$\mathrm{Var}\,(\Delta_4 EPS\_GAAP) = \mathrm{Var}\,(\Delta_4 EPS\_IBES + \Delta_4 ONETIME)$$
$$= \mathrm{Var}\,(\Delta_4 EPS\_IBES) + \mathrm{Var}\,(\Delta_4 ONETIME) +$$
$$2\,\mathrm{Corr}\,(\Delta_4 EPS\_IBES, \Delta_4 ONETIME) \cdot \sqrt{\mathrm{Var}(\Delta_4 EPS\_IBES)\,\mathrm{Var}(\Delta_4 ONETIME)} \tag{B4}$$

(c) Analysts are more accurate than forecasts based on EPS following a seasonal random walk

Analyst forecasts include insights about the firm and industry that are excluded from core earnings for quarter *t–4* (EPS_IBES_{t-4}). We consider the EPS forecast made 9 months before the quarter-end (*FORECAST_9*), which is typically the earliest consensus forecast available after announcement of EPS_IBES_{t-4}. We denote the difference between *FORECAST_9* and EPS_IBES_{t-4} as the analyst adjustment (*ANALYADJ*), which describes the analysts' incremental information content.

$$FORECAST\_9 = EPS\_IBES_{t-4} + ANALYADJ$$

The forecast error, *FCSTERR*_9, for this early forecast (*FORECAST*_9) compares it to the core EPS reported for quarter *t*.

$$FCSTERR\_9 = EPS\_IBES - FORECAST\_9 = EPS\_IBES - (EPS\_IBES_{t-4} + ANALYADJ)$$

$$FCSTERR\_9 = \Delta_4 EPS\_IBES - ANALYADJ \qquad \text{(B5)}$$

$$\text{Var}\ (FCSTERR\_9) = \text{Var}\ (\Delta_4 EPS\_IBES - ANALYADJ)$$

$$= \text{Var}\ (\Delta_4 EPS\_IBES) + \text{Var}\ (ANALYADJ) -$$

$$2\ \text{Corr}\ (\Delta_4 EPS\_IBES, ANALYADJ) \cdot \sqrt{Var(\Delta_4 EPS\_IBES)\ Var(ANALYADJ)} \qquad \text{(B6)}$$

If analysts differentially compress forecast errors, their adjustments (*ANALYADJ*) would differentially offset scale variation in the underlying volatility of *EPS_IBES*.

(d) Using guidance to suppress forecast errors (FCSTERR)

Forecast errors are expected to reduce over time as analysts receive more information about upcoming EPS. Managers could also reduce forecast errors by guiding analysts toward the EPS they anticipate reporting, as their estimate becomes more precise. To determine if managers differentially guide analysts, we analyze how forecast errors decline from forecasts made 9 months before the quarter end to the most recent monthly consensus forecast before earnings is announced (*FORECAST*), for which the error (*FCSTERR*) is = *EPS_IBES – FORECAST*.

FORECAST can be viewed as *FORECAST_9* plus the revision in forecasts since then (*REVISION* = *FORECAST – FORECAST_9*).

$$FCSTERR = EPS\_IBES - (FORECAST\_9 + REVISION)$$

$$FCSTERR = FCSTERR\_9 - REVISION \qquad \text{(B7)}$$

$$\text{Var}\ (FCSTERR) = \text{Var}\ (FCSTERR\_9 - REVISION)$$

$$= \text{Var}\ (FCSTERR\_9) + \text{Var}\ (REVISION) -$$

$$2\ \text{Corr}\ (FCSTERR\_9, REVISION) \cdot \sqrt{Var(FCSTERR\_9)\ Var(REVISION)} \qquad \text{(B8)}$$

To analyze the month-by-month evolution of forecast revisions, we denote the forecast made *n* months before quarter-end as *FORECAST_n*, and *REV_n* is the EPS forecast revision from *n+1* months before quarter-end to *n* months before quarter-end. Note that IBES computes monthly consensus forecasts as of the middle of each month. *FORECAST_0* is the consensus forecast as of the middle of the last month of the quarter, which is typically one month before the most recent forecast before earnings announced.

REV_n = *FORECAST_n – FORECAST_*(*n+1*), for $0 \le n < 9$.

Following Eq (B7), we can express the *FCSTERR_n* as:

$$FCSTERR\_n = FCSTERR\_(n+1) - REV\_n \qquad \text{(B9)}$$

Similarly, following Eq (B8),

$$\text{Var}\ (FCSTERR\_n) = \text{Var}\ (FCSTERR\_(n+1)) + \text{Var}\ (REV\_n) -$$

$$2\ \text{Corr}\ (FCSTERR\_(n+1), REV\_n) \cdot \sqrt{Var(FCSTERR\_(n+1))\ Var(REV\_n)} \qquad \text{(B10)}$$

We repeat below the decomposition conducted in (B9) and (B10) for that final forecast revision (*REV*) between the dates of *FORECAST_0* and *FORECAST*.

$$FCSTERR = FCSTERR\_0 - REV \qquad \text{(B11)}$$

$$\text{Var}(FCSTERR) = \text{Var}(FCSTERR\_0) + \text{Var}(REV) - 2\,\text{Corr}(FCSTERR\_0, REV) \cdot \sqrt{Var(FCSTERR\_0)\; Var(REV)} \qquad \text{(B12)}$$

(II) 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 varies 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

$$ERC = \frac{\text{Cov}\,(FCSTERR, PRICERESP)}{\text{Var}\,(FCSTERR)}$$

$$= \frac{Corr\,(FCSTERR, PRICERESP)\,\sqrt{Var\,(PRICERESP) Var\,(FCSTERR)}}{Var\,(FCSTERR)} \qquad \text{(B13)}$$

If the correlation between forecast errors and price responses 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*)

$$ERC = \frac{Corr\,(FCSTERR/LPRICE, PRICERESP/LPRICE)\,\sqrt{Var\,(PRICERESP/LPRICE) Var\,(FCSTERR/LPRICE)}}{Var\,(FCSTERR/LPRICE)} \qquad \text{(B14)}$$

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 (B14) reverts to the expression in (B13) for *undeflated* regressions. That is, as long as the correlation terms is relatively constant across price deciles, *ERC* should increase with price

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Table 1
Descriptive statistics

The sample contains 184,227 firm-quarters derived from U.S. firms on I/B/E/S with available data, fiscal period end date between January 1993 and December 2011, and with at least three EPS forecasts from analysts. Panel A reports the number of observations (N), the mean, standard deviation (StdDev), interquartile range (IQR), minimum, 25^{th} percentile, median, 75^{th} percentile, and maximum 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 9 months before the quarter-end (*FORECAST_9*). *FCSTERR_n* is the forecast error corresponding to *FORECAST_n*, where *n* refers to the months before the quarter-end. *REVISION* is the EPS forecast revision from nine months before quarter-end to most recent forecast before earnings announcement. *PRICERESP* is the price response in dollars over 22 trading days, adjusted for market movements. Δ_4*EPS_IBES*, Δ_4*EPS_GAAP*, and Δ_4*CPS*, are the seasonally differenced value of *EPS_IBES*, *EPS_GAAP*, and *CPS* respectively. The variables *FCSTERR*, *FCSTERR_n*, Δ_4*EPS_IBES*, Δ_4*EPS_GAAP*, and Δ_4*CPS* are Winsorized at 5% and 95% each year, and the variables Δ_4*APS*, Δ_4*ONETIME*, *ANALYADJ*, and *REVISION* are derived from the Winsorized variables using relations (B1), (B3), (B5), and (B7) in Appendix B respectively. Additional details for all variables are provided in Appendix A. All variables are denominated in dollars.

Panel A: Univariate statistics

Variable	**N**	**mean**	**StdDev**	**IQR**	**min**	**p25**	**median**	**p75**	**max**
BEGPRICE	184,227	27.46	26.58	23.21	0.05	12.60	22.42	35.81	983.02
FORECAST	184,227	0.32	0.54	0.43	-14.96	0.07	0.26	0.50	28.19
EPS_IBES	184,227	0.31	0.68	0.45	-64.05	0.07	0.27	0.52	30.29
FCSTERR	184,227	0.01	0.08	0.05	-0.41	-0.01	0.01	0.04	0.26
EPS_GAAP	183,976	0.24	1.01	0.48	-75.12	0.03	0.24	0.51	30.29
CPS	173,201	0.56	2.10	0.90	-173.36	0.02	0.37	0.92	115.68
APS	173,191	-0.35	2.18	0.66	-114.16	-0.61	-0.18	0.05	175.12
ONETIME	183,976	-0.08	0.75	0.03	-72.24	-0.02	0.00	0.00	40.60
ANALYADJ	133,376	0.08	0.13	0.09	-1.14	0.03	0.06	0.12	1.42
REVISION	149,766	-0.08	0.17	0.15	-1.20	-0.14	-0.03	0.01	0.65
PRICERESP	182,594	0.08	4.87	2.82	-200.64	-1.37	-0.02	1.45	161.84

Panel B: Statistics describing first moments (medians) of distributions, by price decile.

#	Medians for Variable	Price decile 1	2	3	4	5	6	7	8	9	10
1	*BEGPRICE*	4.53	8.94	13.09	16.92	20.75	25.12	29.94	36.24	45.25	64.88
2	*FORECAST*	-0.02	0.06	0.14	0.20	0.26	0.32	0.39	0.46	0.57	0.82
3	*EPS_IBES*	-0.04	0.06	0.14	0.20	0.26	0.33	0.40	0.48	0.59	0.84
4	*EPS_GAAP*	-0.06	0.04	0.11	0.18	0.24	0.31	0.38	0.45	0.56	0.81
5	Δ_4 *EPS_GAAP*	0.00	0.00	0.00	0.01	0.01	0.02	0.03	0.04	0.05	0.09
6	Δ_4 *EPS_IBES*	-0.01	-0.01	0.00	0.01	0.02	0.03	0.03	0.05	0.06	0.10
7	*FCSTERR_9*	-0.06	-0.06	-0.05	-0.04	-0.03	-0.02	-0.02	-0.01	-0.01	0.00
8	*FCSTERR_6*	-0.04	-0.04	-0.03	-0.02	-0.02	-0.01	-0.01	-0.01	0.00	0.01
9	*FCSTERR_3*	-0.02	-0.02	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.01
10	*FCSTERR*	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02

Panel C: Statistics describing second moments of distributions, by price decile.

#	Statistic & Variable	Price decile 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	0.07	0.08	0.09
2	IQR *FCSTERR*	0.05	0.06	0.05	0.05	0.04	0.04	0.05	0.05	0.05	0.07
3	StdDev Δ_4*EPS_IBES*	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.21	0.22	0.26
4	StdDev Δ_4*EPS_GAAP*	0.37	0.37	0.37	0.35	0.34	0.34	0.34	0.35	0.37	0.42
5	StdDev Δ_4*CPS*	0.44	0.51	0.55	0.58	0.60	0.61	0.64	0.68	0.73	0.81
6	StdDev Δ_4*APS*	0.54	0.59	0.62	0.65	0.65	0.66	0.68	0.71	0.75	0.83
7	Corr (*FCSTERR*, *PRICERESP*)	0.18	0.21	0.24	0.23	0.24	0.22	0.22	0.20	0.18	0.16
8	StdDev *PRICERESP*	1.29	1.71	2.20	2.65	2.94	3.57	4.03	4.98	6.18	10.96

Panel D: Volatilities of analyst forecast error (*FCSTERR*), estimated in time-series for each firm. 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 the quarters equals, or is adjacent to, the modal price decile. Reported below are the means and medians across firms, and the number of firms in each price decile.

#	Statistic & Variable	Price decile 1	2	3	4	5	6	7	8	9	10
1	Mean [StdDev (*FCSTERR*)]	0.06	0.06	0.06	0.07	0.06	0.06	0.07	0.07	0.07	0.08
2	Median [StdDev (*FCSTERR*)]	0.05	0.06	0.05	0.06	0.06	0.05	0.06	0.06	0.07	0.07
3	Number of firms	614	517	435	370	349	325	315	316	317	354

Table 2
First and second moments of distributions, using an alternative measure of *BEGPRICE*

The main results in this paper are described for deciles of price (*BEGPRICE*) that are based on price as of the first day of the calendar quarter that the firm-quarter ends in. For example, prices as of October 1, 2010, are used to form deciles for all firm-quarters ending between October 1 and December 31 of 2010. The distributions for seasonal differences, which are effectively errors for forecasts based on seasonal random walk processes, and for errors based on forecasts made earlier than that date are biased because those prices are not available at the forecast date. For example, firms that receive bad news over the year will report lower forecast errors relative to these early forecasts and also be more likely to be in lower deciles of *BEGPRICE*. In effect, a positive relation is induced between forecast errors and *BEGPRICE* deciles. To mitigate that bias, we report below the first and second moments of different distributions for deciles based on *PRICE_9*, which is the price as of 9 months before the date we used to measure *BEGPRICE*. These prices are observed before financial variables are reported for quarter *t-4*, and before the dates for the early analyst forecasts we use. *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. *FCSTERR_n* is the forecast error corresponding to *FORECAST_n*, where *n* refers to the months before the quarter-end. Δ_4*EPS_IBES* and Δ_4*EPS_GAAP*, are the seasonally differenced value of *EPS_IBES* and *EPS_GAAP*. The variables *FCSTERR*, *FCSTERR_n*, Δ_4*EPS_IBES* and Δ_4*EPS_GAAP* are Winsorized at 5% and 95% each year. Additional details for all variables are provided in Appendix A. All prices and forecast/actual EPS are denominated in dollars.

#		**Price decile**									
	Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	median *PRICE_9*	5.16	9.74	13.77	17.43	21.25	25.29	30.00	36.18	45.00	64.38
2	median Δ_4 *EPS_GAAP*	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01
3	median Δ_4 *EPS_IBES*	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.04	0.03
4	median *FCSTERR_9*	-0.02	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.04
5	median *FCSTERR_6*	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
6	median *FCSTERR_3*	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00
7	median *FCSTERR*	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
8	StdDev Δ_4 *EPS_GAAP*	0.33	0.34	0.35	0.35	0.34	0.34	0.35	0.36	0.39	0.47
9	StdDev Δ_4 *EPS_IBES*	0.18	0.19	0.19	0.20	0.19	0.20	0.21	0.21	0.24	0.30
10	StdDev *FCSTERR_9*	0.16	0.17	0.18	0.18	0.18	0.18	0.19	0.20	0.22	0.27
11	StdDev *FCSTERR_6*	0.14	0.15	0.16	0.16	0.16	0.16	0.17	0.17	0.19	0.23
12	StdDev *FCSTERR_3*	0.12	0.13	0.13	0.13	0.13	0.13	0.14	0.14	0.16	0.18
13	StdDev *FCSTERR*	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.08	0.08	0.09

Table 3
Use of accruals to reverse cash flow shocks

Earnings per share (EPS) smoothing should increase the magnitude of the normally negative correlation between unexpected per share cash flows (CPS) and unexpected accruals (APS), and decrease the ratio (*RATIO*) of firm-specific volatilities of unexpected per share earnings to cash flows. We use seasonal differences of EPS, CPS, and APS, represented by Δ_4*EPS_GAAP*, Δ_4*CPS*, and Δ_4*APS*, respectively, to proxy for the corresponding unexpected components. We investigate whether EPS smoothing increases 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 Δ_4*EPS*, Δ_4*CPS*, and Δ_4*APS*, measured by their standard deviations, and the correlation between Δ_4*CPS* and Δ_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 the quarters equals, or is adjacent to, the modal price decile. We report the mean and median volatilities of Δ_4*EPS*, Δ_4*CPS*, and Δ_4*APS*, correlations between Δ_4*CPS* and Δ_4*APS*, and *RATIO*. The variables Δ_4*EPS_GAAP* and Δ_4*CPS* are Winsorized at 5% and 95% each year, and Δ_4*APS* is derived from the Winsorized variables using relation (B1) in Appendix B. Details of all variables are provided in Appendix A.

Panel A: Volatilities of unexpected quarterly earnings per share (EPS), cash flow per share (CPS), and accruals per share (APS), and the correlation between unexpected quarterly APS and CPS, estimated using pooled samples for each price decile. 159,588 firm-quarter observations.

#		**Price decile**									
	Statistic & Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	StdDev (Δ_4*EPS_GAAP*)	0.37	0.37	0.37	0.36	0.35	0.35	0.35	0.35	0.38	0.43
2	StdDev (Δ_4*CPS*)	0.44	0.51	0.55	0.58	0.60	0.61	0.64	0.68	0.73	0.81
3	StdDev (Δ_4*APS*)	0.54	0.59	0.62	0.65	0.65	0.66	0.68	0.71	0.75	0.83
4	Pearson Corr (Δ_4*CPS*, Δ_4*APS*)	-0.73	-0.78	-0.81	-0.83	-0.85	-0.85	-0.86	-0.87	-0.87	-0.86
5	Spearman Corr (Δ_4*CPS*, Δ_4*APS*)	-0.63	-0.73	-0.78	-0.82	-0.84	-0.84	-0.86	-0.87	-0.87	-0.88

Panel B: Volatilities of unexpected quarterly earnings per share (EPS), cash flow per share (CPS), accruals per share (APS), the ratio of volatility of unexpected per share earnings to that of cash flows (*RATIO*), and the Pearson and Spearman correlation between unexpected quarterly CPS and APS, estimated in time-series for each firm (reported below are the means and medians across firms in each price decile).

#		**Price decile**									
	Statistic & Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	Mean [StdDev (Δ_4*EPS_GAAP*)]	0.27	0.28	0.28	0.31	0.28	0.29	0.32	0.32	0.35	0.41
2	Median [StdDev (Δ_4*EPS_GAAP*)]	0.24	0.26	0.25	0.27	0.24	0.25	0.29	0.29	0.32	0.39
3	Mean [StdDev (Δ_4*CPS*)]	0.30	0.42	0.46	0.55	0.53	0.55	0.63	0.67	0.67	0.75
4	Median [StdDev (Δ_4*CPS*)]	0.23	0.34	0.38	0.48	0.49	0.49	0.60	0.67	0.66	0.74
5	Mean [StdDev (Δ_4*APS*)]	0.38	0.48	0.51	0.60	0.58	0.60	0.68	0.71	0.70	0.77
6	Median [StdDev (Δ_4*APS*)]	0.31	0.40	0.44	0.55	0.53	0.53	0.64	0.66	0.67	0.73

7	Mean [Pearson Corr ($\Delta_4 CPS$, $\Delta_4 APS$)]	-0.55	-0.70	-0.76	-0.78	-0.82	-0.82	-0.84	-0.86	-0.84	-0.83
8	Median [Pearson Corr ($\Delta_4 CPS$, $\Delta_4 APS$)]	-0.65	-0.80	-0.84	-0.87	-0.88	-0.89	-0.89	-0.91	-0.88	-0.87
9	Mean [Spearman Corr ($\Delta_4 CPS$, $\Delta_4 APS$)]	-0.54	-0.69	-0.75	-0.78	-0.81	-0.81	-0.83	-0.85	-0.83	-0.82
10	Median [Spearman Corr ($\Delta_4 CPS$, $\Delta_4 APS$)]	-0.59	-0.77	-0.80	-0.86	-0.86	-0.87	-0.88	-0.89	-0.87	-0.85
11	Mean [RATIO]	1.32	0.96	0.77	0.70	0.65	0.63	0.59	0.53	2.16	0.59
12	Median [RATIO]	0.95	0.71	0.63	0.55	0.52	0.50	0.51	0.46	0.53	0.54
13	Number of firms	613	508	427	357	325	311	292	302	305	339

Table 4
Use of one-time items to smooth EPS forecast error

This Table investigates the extent to which one-time items are used to smooth EPS forecast error across price deciles by selectively reclassifying large spikes in reported EPS (*EPS_GAAP*) as one-time items to reduce the volatility of core EPS (*EPS_IBES*). 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 the seasonally differenced value of *EPS_IBES* and *EPS_GAAP* respectively. The variables Δ_4*EPS_IBES* and Δ_4*EPS_GAAP* are Winsorized at 5% and 95% each year, and Δ_4*ONETIME* is derived from the Winsorized variables using relation (B3) in Appendix B. Additional details for all variables are provided in Appendix A. All variables are denominated in dollars.

Panel A: Analysis of one-time items, estimated in cross-section, across price deciles. Sample has 150,147 firm-quarter observations.

#		Price decile									
	Statistic & Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	StdDev (Δ_4*EPS_GAAP*)	0.40	0.38	0.38	0.36	0.35	0.35	0.35	0.35	0.37	0.42
2	StdDev (Δ_4*EPS_IBES*)	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.21	0.22	0.26
3	StdDev (Δ_4*ONETIME*)	0.31	0.29	0.29	0.28	0.26	0.26	0.25	0.25	0.27	0.30
4	Corr (Δ_4*EPS_IBES*, Δ_4*ONETIME*)	0.18	0.18	0.19	0.15	0.16	0.15	0.15	0.14	0.13	0.13

Panel B: Repeats Panel A for Δ_4*EPS_IBES* ≥ 0. Sample has 89,453 firm-quarter observations.

#		Price decile									
	Statistic & Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	StdDev (Δ_4*EPS_GAAP*)	0.32	0.30	0.28	0.28	0.28	0.27	0.27	0.26	0.29	0.33
2	StdDev (Δ_4*EPS_IBES*)	0.13	0.12	0.12	0.12	0.11	0.11	0.12	0.12	0.12	0.14
3	StdDev (Δ_4*ONETIME*)	0.28	0.25	0.24	0.24	0.24	0.23	0.23	0.22	0.25	0.28
4	Corr (Δ_4*EPS_IBES*, Δ_4*ONETIME*)	0.15	0.13	0.11	0.09	0.12	0.09	0.09	0.11	0.10	0.14

Panel C: Repeats Panel A for Δ_4*EPS_IBES* < 0. Sample has 60,694 firm-quarter observations.

#		Price decile									
	Statistic & Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	StdDev (Δ_4*EPS_GAAP*)	0.39	0.39	0.40	0.38	0.35	0.37	0.36	0.37	0.39	0.42
2	StdDev (Δ_4*EPS_IBES*)	0.17	0.17	0.18	0.17	0.17	0.17	0.17	0.18	0.18	0.20
3	StdDev (Δ_4*ONETIME*)	0.33	0.32	0.33	0.31	0.28	0.29	0.28	0.29	0.31	0.34
4	Corr (Δ_4*EPS_IBES*, Δ_4*ONETIME*)	0.15	0.17	0.19	0.16	0.17	0.20	0.19	0.18	0.19	0.17

Table 5
Use of analyst adjustment and management guidance to smooth EPS forecast error

This Table investigates whether analyst adjustment and management guidance is used to smooth EPS forecast error across price deciles. We report the statistics for 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*. *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 9 months before the quarter-end (*FORECAST_9*). *FCSTERR_n is* the forecast error corresponding to the forecast made *n* months before quarter-end (*FORECAST_n*). *REVISION* is the EPS forecast revision from nine months before quarter-end to most recent forecast before earnings announcement. *REV_n* is the forecast revision from *n+1* months before quarter-end to *n* months before quarter-end. *REV* is the EPS forecast revision from the last month of the quarter to the month with the most recent consensus before earnings announcement. The variables *FCSTERR*, *FCSTERR_n*, and Δ_4EPS_IBES are Winsorized at 5% and 95% each year, and *ANALYADJ*, *REVISION*, and *REV_n* are derived from the Winsorized variables using relations (B5), (B7) and (B9) in Appendix B respectively. Additional details for all variables are provided in Appendix A. All variables are denominated in dollars.

Panel A: Analysis of analyst adjustment, estimated in cross-section, across price deciles. Sample has 133,376 firm-quarter observations.

#		Price decile									
	Statistic & Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	StdDev (*FCSTERR_9*)	0.20	0.20	0.19	0.19	0.19	0.19	0.19	0.20	0.21	0.24
2	StdDev (Δ_4EPS_IBES)	0.21	0.21	0.20	0.20	0.20	0.20	0.20	0.22	0.23	0.26
3	StdDev (*ANALYADJ*)	0.14	0.13	0.13	0.12	0.12	0.12	0.12	0.13	0.13	0.15
4	Corr (Δ_4EPS_IBES, *ANALYADJ*)	0.41	0.40	0.40	0.40	0.40	0.39	0.40	0.44	0.41	0.44

Panel B: Analysis of management guidance, estimated in cross-section, across price deciles. Sample has 149,766 firm-quarter observations.

#		Price decile									
	Statistic & 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 (*FCSTERR*)	0.08	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.08	0.09
3	StdDev (*REVISION*)	0.15	0.16	0.16	0.15	0.16	0.16	0.16	0.17	0.18	0.21
4	Corr (*FCSTERR_9*, *REVISION*)	0.92	0.93	0.93	0.92	0.93	0.93	0.93	0.93	0.93	0.93

Panel C: Month-by-month analysis of management guidance, estimated in cross-section, across price deciles. Sample has 145,442 firm-quarter observations.

#		**Price decile**									
	Statistic & 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 (*FCSTERR_8*)	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.19	0.20	0.23
3	StdDev (*REV_8*)	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.05	0.05	0.06
4	Corr (*FCSTERR_9*, *REV_8*)	0.29	0.29	0.29	0.29	0.28	0.28	0.29	0.29	0.28	0.28
5	StdDev (*FCSTERR_6*)	0.17	0.17	0.17	0.16	0.16	0.16	0.16	0.17	0.18	0.21
6	StdDev (*FCSTERR_5*)	0.16	0.16	0.16	0.15	0.15	0.15	0.15	0.16	0.17	0.20
7	StdDev (*REV_5*)	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.05	0.05	0.05
8	Corr (*FCSTERR_6*, *REV_5*)	0.32	0.35	0.34	0.32	0.32	0.33	0.33	0.34	0.32	0.30
9	StdDev (*FCSTERR_3*)	0.14	0.14	0.14	0.13	0.13	0.13	0.13	0.13	0.15	0.17
10	StdDev (*FCSTERR_2*)	0.13	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.13	0.16
11	StdDev (*REV_2*)	0.03	0.04	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.06
12	Corr (*FCSTERR_3*, *REV_2*)	0.45	0.44	0.47	0.45	0.44	0.45	0.44	0.43	0.43	0.44
13	StdDev (*FCSTERR_0*)	0.09	0.09	0.09	0.08	0.08	0.08	0.08	0.09	0.09	0.10
14	StdDev (*FCSTERR*)	0.08	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.08	0.09
15	StdDev (*REV*)	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.05
16	Corr (*FCSTERR_0*, *REV*)	0.56	0.57	0.57	0.56	0.55	0.56	0.54	0.53	0.55	0.57

Figure 1
Differential walk-down of analyst forecasts across deciles of share price

This figure shows the median of different variables across deciles of *PRICE_9*, which is the price as of 9 months before the beginning of the calendar quarter. For example, prices as of January 1, 2010, are used to form deciles for all firm-quarters ending between October 1 and December 31 of 2010. 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_3*, *FCSTERR_6*, and *FCSTERR_9* are forecast errors corresponding to forecasts made 3, 6, and 9 months before quarter-end. Earnings per share (*EPS_GAAP*) is the per share quarterly income before extraordinary items, obtained from the Cash Flow Statement. Δ_4*EPS_GAAP* is the seasonally differenced value of *EPS_GAAP*. The variables *FCSTERR*, *FCSTERR_3*, *FCSTERR_6*, *FCSTERR_9*, and Δ_4*EPS_GAAP* are Winsorized at 5% and 95% each year. Additional details for all variables are provided in Appendix A. All variables are denominated in dollars.

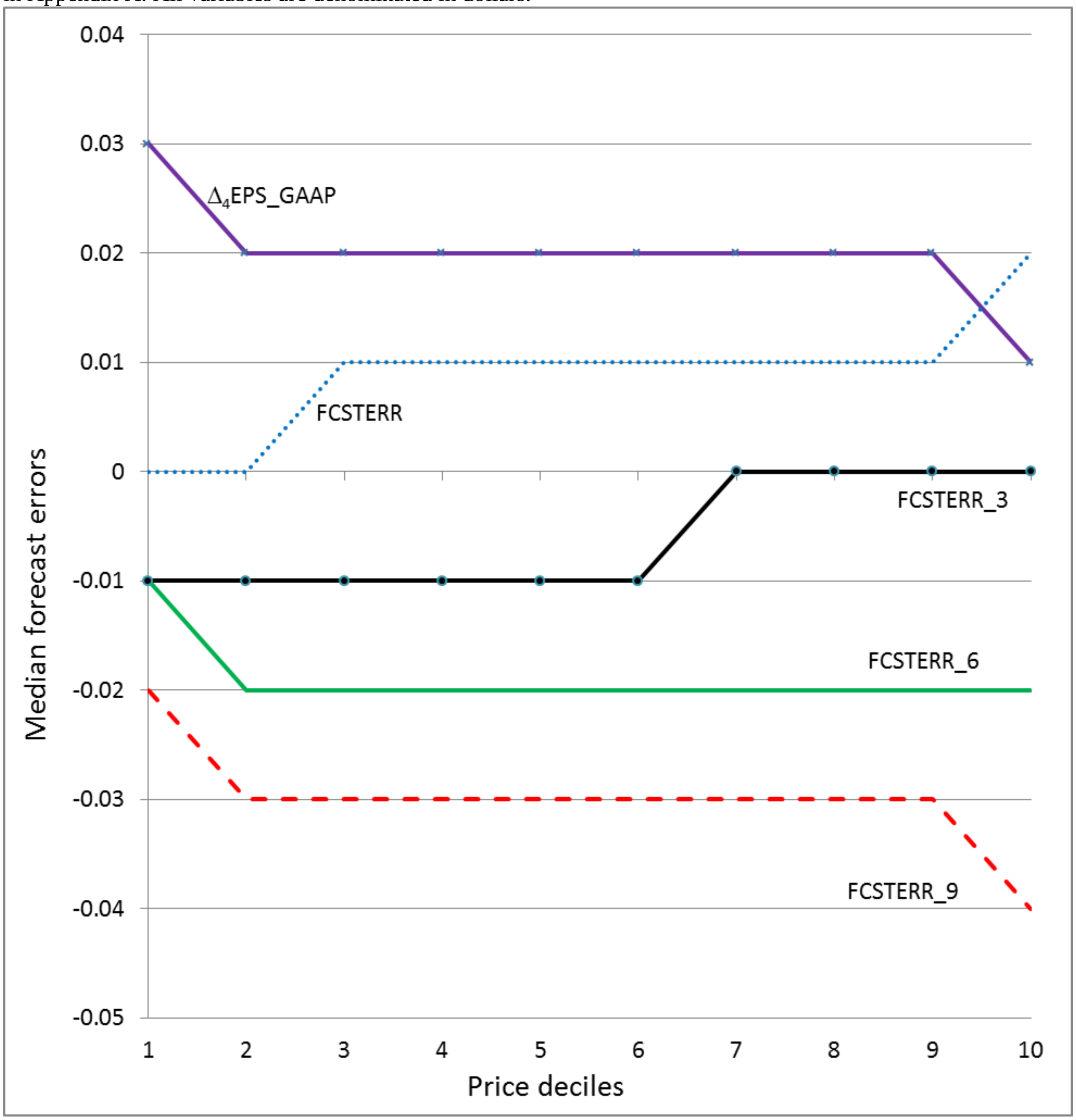


Figure 2
Volatility of different variables across deciles of share price

This Figure describes how unexpected cash flow gradually evolves to analyst forecast error, 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 the forecasts made *9* 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. Δ_4*EPS_IBES*, Δ_4*EPS_GAAP*, and Δ_4*CPS*, are the seasonally differenced value of *EPS_IBES*, *EPS_GAAP*, and *CPS* respectively. The variables *FCSTERR*, *FCSTERR_9*, Δ_4*EPS_IBES*, Δ_4*EPS_GAAP*, and Δ_4*CPS* are Winsorized at 5% and 95% each year. Additional details for all variables are provided in Appendix A. All variables are denominated in dollars.

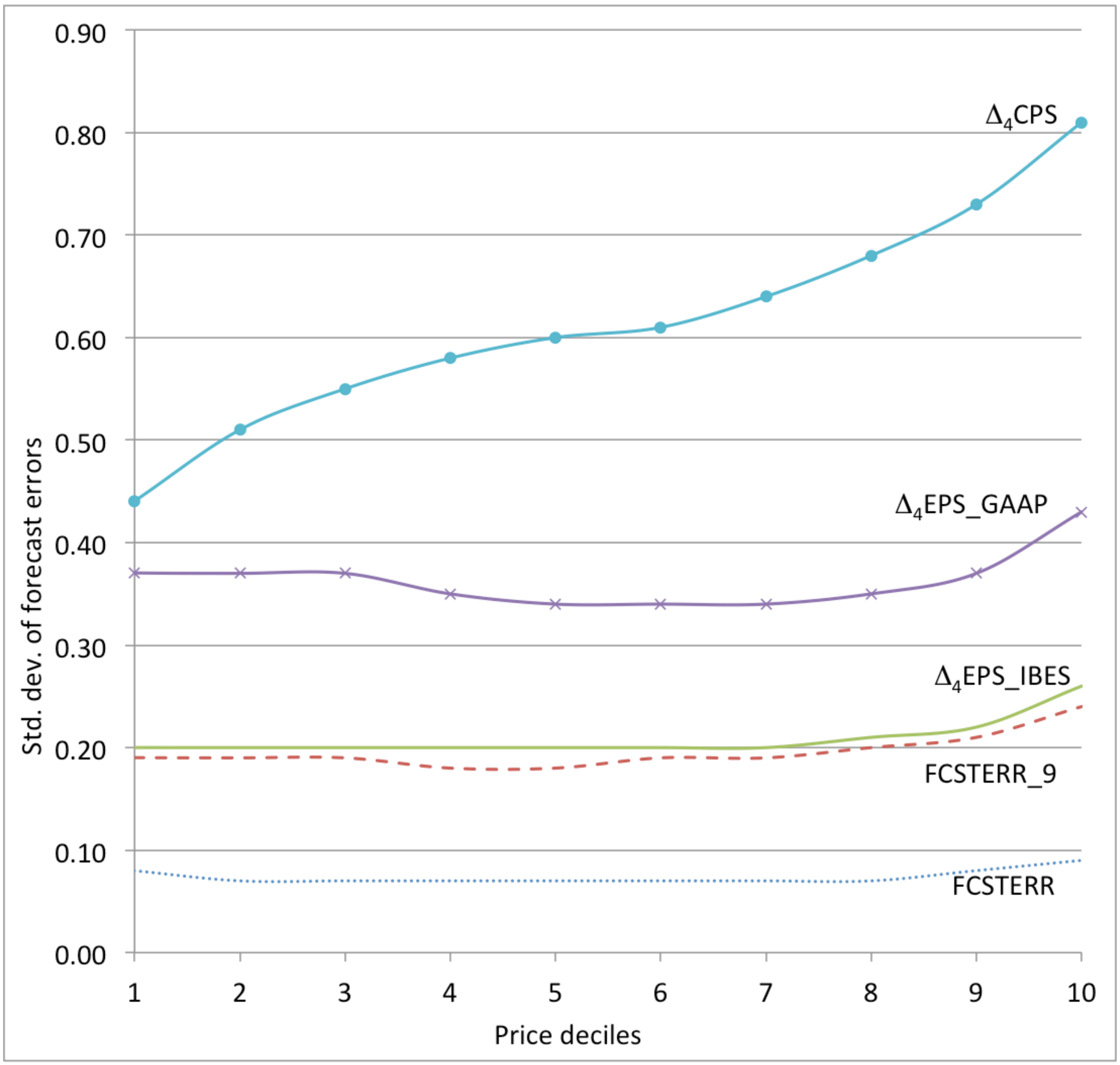
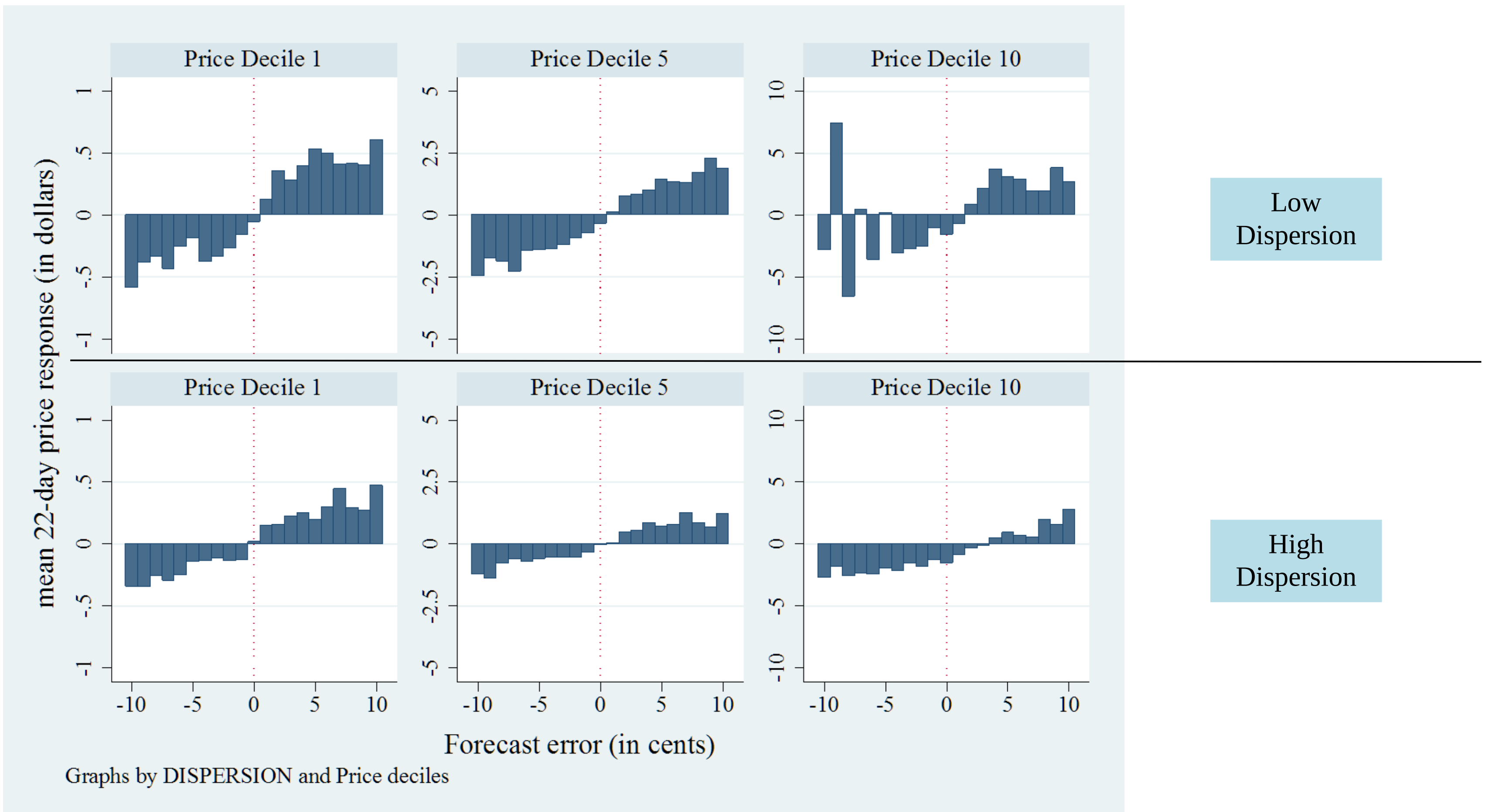


Figure 3. Variation across price deciles in price response to forecast errors

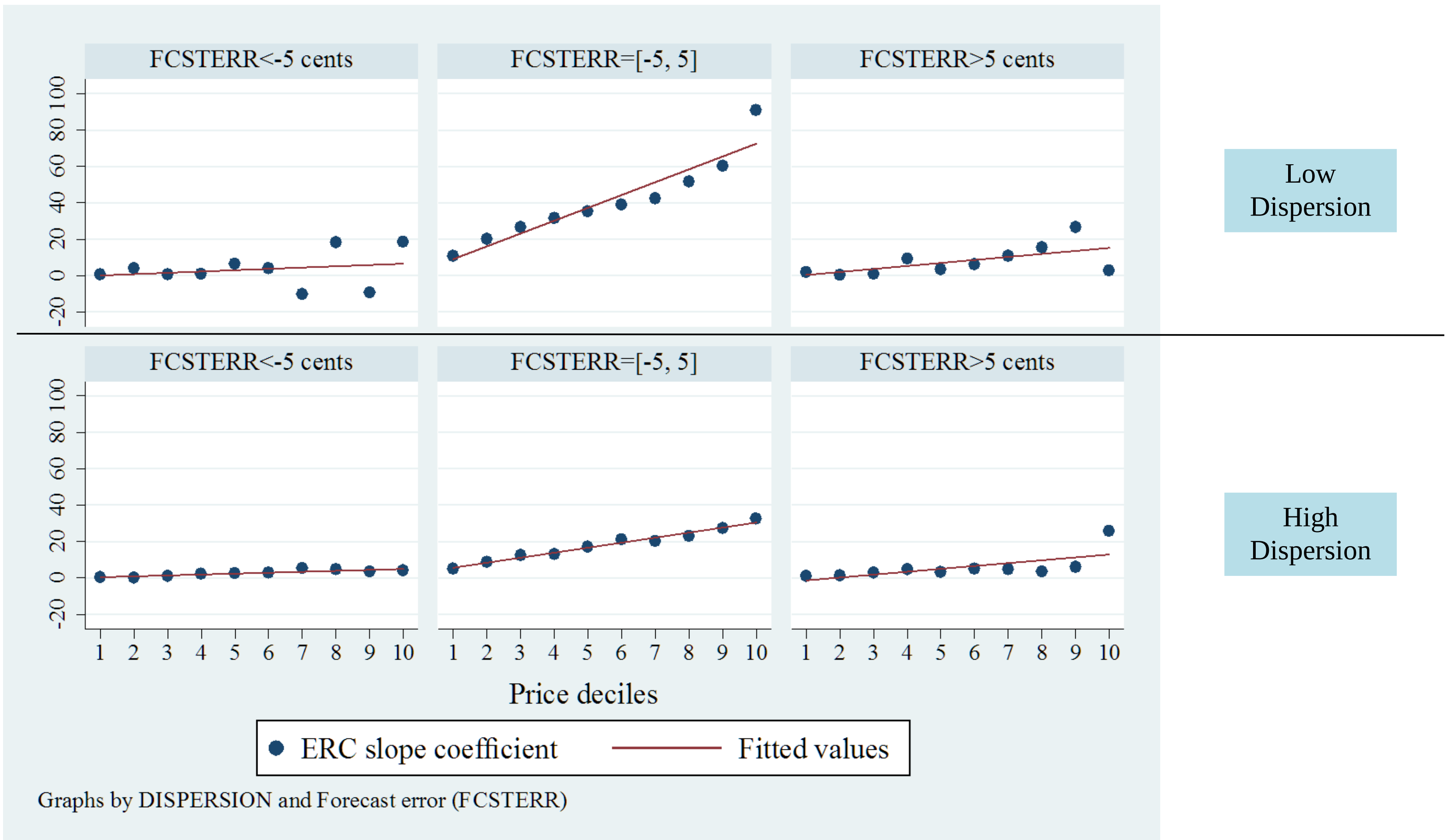
Our I/B/E/S sample of 184,227 firm-quarters with available data is split into price deciles based on beginning of quarter share price. The sample is also split approximately evenly into high (*DISPERSION* ≥ 2 cents) and low dispersion (*DISPERSION* < 2 cents) subgroups, where *DISPERSION* is the standard deviation of forecasts made by different analysts. The histograms in Panel A provide the number of firm quarters with forecast errors that lie within each cent between –10 and +10 cents. All observations with forecast errors ≤ –10 cents (≥ 10 cents) are included in the left-most (right-most) 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 3 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 cents, between –5 and +5 cents, and > +5 cents. Panel D repeats the Panel C analysis for price-deflated price responses and forecast errors.

Panel A: Frequency of firm-quarters for each cent of forecast error
(the –10 and +10 groups also include all observations <–10 and >+10, respectively).

Panel B: Mean price change (in \$) over 22 trading days before earnings announcement, for each cent of forecast error (the –10 and +10 groups also include all observations <–10 and >+10, respectively).
Note that the scale for the Y-axes differs across price deciles. Observing columns of similar height across the price deciles indicates that the price responses for decile 5 (10) are five (ten) times larger than those for decile 1.



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: < –5 cents, between –5 and +5 cents, and > +5 cents.



Panel D. ERC or slope of regression of 22-day price change on forecast error, both deflated by lagged share price, estimated separately for each price decile, over three forecast error ranges: < –5 cents, between –5 and +5 cents, and > +5 cents.