Managerial smoothing of analysts' EPS forecast errors: explanations and implications

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Current Version: August, 2011

Abstract

We investigate explanations for and implications of the puzzling lack of scale variation exhibited by errors associated with analysts' forecasts of earnings per share (EPS). Our results suggest that managers of analyst-followed firms smooth reported EPS via accruals and also guide analyst forecasts toward that smoothed EPS, and the extent of smoothing/guidance increases with scale. The EPS smoothing (forecast guidance) effort is more relevant for low and mid price (high price) firms. Because of these managerial efforts to suppress natural variation with scale for forecast errors, the volatility of EPS and dispersion of forecasts across analysts also do not vary much with scale. Two important implications arise as a result. First, the intuitive practice of deflating forecast error magnitudes, EPS volatility, or forecast dispersion by scale results in a variable that is highly negatively related to scale. Using such deflated variables as dependent (independent) variables in analyses that include independent (dependent) variables that happen to be correlated with scale might result in biased estimates. Second, price responses to EPS surprise (or ERCs) for the highly compressed surprises of high price shares can exceed 90, much greater than levels expected in prior research. This strong positive relation between ERC and scale might bias studies investigating cross-sectional variation in ERC if the variation studied is related to scale.

We thank Ian Gow for suggesting the ERC implication, Jeff Ng, Tjomme Rusticus, Shawn Thomas, and Rodrigo Verdi for their generous efforts to help us replicate their studies, Ed Kaplan for deriving the relation for pooled ERCs, and the Yale School of Management for financial support.

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1. Introduction

DeGeorge et al. [1999] document a puzzling finding: even though the levels of actual and forecast quarterly earnings per share (EPS) increase proportionately with share price, the difference, which represents analysts' forecast errors, exhibits little variation with share price,. This result, referred to hereafter as EPS forecast error smoothing, remained unexplored for over a decade until Cheong and Thomas [2011]. The evidence in that study suggests that EPS forecast errors would increase naturally with scale but managers of analyst-followed firms suppress that variation by suppressing natural scale variation in volatility of reported EPS. That is, managers smooth reported EPS and the extent of smoothing increases with scale [1] Evidence consistent with differential smoothing of reported EPS by analyst-followed firms includes substantial variation with scale observed for cash flow and sales forecast errors as well as for EPS volatility of firms not followed by analysts. We investigate differential smoothing of reported EPS and other potential ways to smooth EPS forecast errors and then develop two important implications for research in this general area.

There are two ways for managers to smooth EPS forecast errors, measured as "core" EPS—or the recurring portion of reported EPS that analysts seek to forecast—minus the consensus of analysts' EPS forecasts available just before earnings announcements. First, managers might smooth the volatility of core EPS, by making discretionary accruals to offset cash flow surprises or strategically allocate reported EPS into its recurring and non-recurring components. The evidence in Cheong and Thomas [2011] regarding smoothing of reported EPS, core plus non-recurring, is consistent with managers smoothing core EPS. The second approach is to guide analysts' forecasts toward the core EPS that managers anticipate for the upcoming quarter.

[1] We use share price to measure scale, consistent with prior literature, and use the two terms interchangeably.

Our results suggest that managers employ both approaches to smooth EPS forecast errors, and the extent of smoothing increases with scale, but different approaches are used in different regions. Differential smoothing of core EPS volatility, which is the main way that managers smooth EPS forecast errors, is relevant for low and mid-price shares. The interquartile range (IQR) of seasonally-differenced core EPS, our measure of core EPS volatility, is constant at about 17 cents for price deciles 1 through 7, and then rises at an increasing rate to 29 cents for decile 10.[2] And our measure of smoothing via discretionary accruals, the correlation between seasonally-differenced cash flow per share (CPS) and accruals per share (APS), falls from –0.52 to –0.80 for price deciles 1 through 7, and holds constant after that.[3] Both sets of results suggest that the extent of smoothing of core EPS for low and mid-price deciles increases sufficiently with scale to reverse natural scale-variation in forecast errors. For higher price deciles, some natural scale-variation remains because the level of core EPS smoothing does not increase.

The natural variation in scale for core EPS volatility that remains for higher price deciles is offset by increased analyst guidance. We find that magnitudes of error associated with forecasts made nine months before the quarter-end, when managers are still uncertain about actual performance, exhibit the same pattern observed for core EPS volatility. The IQR of forecast errors is about 17 cents for price deciles 1 through 8 and then increases to 25 cents for decile 10. As forecast horizon declines and managers are better able to discern upcoming performance, the IQR of forecast errors falls, but it falls more rapidly for high price deciles; i.e., the uptick observed for higher price deciles at the nine-month horizon flattens out over time.

We believe that managerial efforts to smooth EPS forecast errors are associated with lack of scale variation not only for forecast error magnitudes and volatility of core EPS but also for

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[2] These results resemble those reported in Figure 4 of DeGeorge et al. [1999] for an earlier period.

[3] Given that EPS surprise equals CPS surprise plus APS surprises, the variance of EPS surprise equals the sum of the variances of CPS and APS surprises plus two times the covariance. As the variances of CPS and APS surprise increase with share price, EPS variability will remain unchanged only if the covariance term (and the underlying correlation) is negative and increases sufficiently to offset fully the increasing variance terms.

the lack of scale variation documented in Cheong and Thomas [2011] for volatility of reported EPS and the dispersion of individual analysts' forecasts around the consensus. Note that dispersion, which represents disagreement across analysts about the level of core EPS, is not the same as forecast error magnitudes, which represent the difficulty of predicting core EPS.

The first implication of managerial smoothing of EPS forecast errors is that scale deflation of all four variables that are relatively constant across scale—forecast error magnitude, volatility of reported/core EPS, and forecast dispersion—results in deflated variables that are strongly, negatively related to scale. Prior research has intuitively deflated those variables by scale before using them as dependent or independent variables (see Appendix B in Cheong and Thomas, 2011). Given that deflated variables are strongly related to scale, estimates of regression coefficients are likely to be biased when those deflated variables appear as dependent (independent) variables and other included independent (dependent) variables happen to be related to scale.

To illustrate the potential for such biases, we extend the analyses in Thomas [2002] that relate variation in price-deflated magnitudes of forecast errors and dispersion to the degree of firm diversification. Our results confirm that deflation can cause substantial biases and suggest the following approach. Avoid scale-deflation of core/reported EPS volatility, forecast error magnitudes, or analyst dispersion by scale, unless called for by theory. At a minimum, report results for both undeflated and deflated results, and include share price (inverse of share price) as an additional regressor for the undeflated (deflated) specification.

The second implication is that the price response per unit of EPS surprise, known as the earnings response coefficient (ERC), is also likely to increase with share price. This is because the magnitude of the dependent variable (price response) increases with scale whereas the magnitude of the independent variable (earnings surprise) does not. As a result, the ERC, or the slope coefficient that links earnings surprises to price responses, must increase with scale. Stated

differently, a cent of EPS surprise for the highly smoothed EPS forecast error stream associated with high price firms must have a considerably larger valuation impact than a cent of EPS surprise for low price firms. The ERC for high price firms must also be considerably higher than the expected ranges predicted in prior research (e.g., Kormendi and Lipe [1987], and Collins and Kothari [1989]), as those studies do not incorporate smoothing of EPS forecast errors.

We conduct a comprehensive exploration of how the relation between EPS forecast error smoothing and share price affects ERC. We control for two factors that have been shown to be related to ERC and might also be related to EPS forecast error smoothing: a) dispersion of forecasts across analysts following the same stock, and b) magnitudes of forecast error. Forecast dispersion and forecast error magnitudes, which are negatively related to ERC (e.g., Kinney et al. [2002] and Freeman and Tse [1992], respectively), might be lower for firms that engage in more smoothing of EPS forecast errors.

To control for these two factors and glean the separate impact on ERC of the positive relation between share price and EPS forecast error smoothing, we partition our sample into six groups obtained by crossing two partitions based on forecast dispersion (low and high dispersion) with three partitions based on forecast error magnitudes (large negative, small, and large positive forecast errors), and report variation in ERC across price deciles within the six groups. Our results indicate a strong positive relation between ERC and share price for the 70 percent of our sample that is contained in the small forecast error groups (within ± 5 cents). The remaining firms with large forecast errors exhibit ERC close to zero for all price deciles.

Although our main focus here is on the general relation between EPS forecast error smoothing and ERC, our investigation reveals a number of fascinating patterns of cross-sectional variation across the six groups. First, the ERC is very high, much higher than levels predicted by prior research (e.g., Kormendi and Lipe [1987], and Collins and Kothari [1989]): it exceeds 90

for the highest price decile, when we focus on the subgroup with small forecast errors and low dispersion. Second, even though the large forecast error subgroups include relatively few observations they have a disproportionate effect on the pooled ERC.[4] Third, deflating both price responses and forecast errors by share price, as is the traditional practice when estimating ERC, results in ERC estimates that are more representative of ERCs for low price firms.[5]

We recognize that these patterns of cross-sectional variation in the price response to earnings surprises are not due entirely to managerial efforts to smooth EPS forecast errors; some of it is likely due to factors that have been hypothesized to affect ERCs, such as audit quality (e.g. Teoh and Wong [1993]), audit independence (e.g., Francis and Ke [2006]), ownership structure (e.g., Francis, Schipper, and Vincent [2005]), default risk (e.g., Billings [1999]), and earnings quality (e.g., Wang [2006]). Our results do, however, suggest that research investigating cross-sectional variation in ERCs should confirm that the results are not simply reflecting the relation between ERC and scale caused by managerial smoothing of EPS forecast errors. To illustrate this potential we show how the strong negative relation between ERC and transactions costs reported in Ng et al. [2008] becomes insignificant when we incorporate share price, which is negatively related to their measures of transactions costs.

The remainder of this study is organized as follows. Section 2 describes our sample selection procedure, and Section 3 investigates the two ways in which managers suppress scale variation in EPS forecast error magnitudes. Section 4 considers the impact of EPS forecast error

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[4] Pooling two partitions with different regression slopes should generate a pooled regression slope that is a weighted average of the two slopes, where the weight for each partition is the product of the variance of the regressor and the fraction of the pooled sample coming from that partition. As the regressors (forecast errors) for observations from the large forecast error partitions have considerably larger variances, those observations have a disproportionate impact on the pooled slope.

[5] This impact of deflating forecast errors differs from the impact of deflating forecast error *magnitudes* considered in the first implication of managerial smooth of EPS forecast errors. There the variable being deflated is the magnitude of forecast errors (e.g., absolute values or variances of forecast error) whereas forecast errors are being deflated here. There regression coefficients are biased because deflated forecast error magnitudes, which are negatively related to scale, reflect a relation with other regression variables that happen to be related to scale. Here the estimated ERC slope is skewed toward the ERC of low price firms because the variance of deflated forecast errors, the regressor in the ERC regression, is much larger for low price firms (see previous footnote). This effect is not observed for the undeflated ERC regression.

smoothing on the use of deflated earnings volatility, forecast error magnitudes, and forecast dispersion in research. Section 5 considers the impact of such smoothing on estimated ERCs. Section 6 concludes.

2. Sample selection and descriptive statistics.

For our main sample, containing 165,698 firm-quarters, we include all U.S. firms on I/B/E/S with fiscal quarters ending in the 18 calendar years from 1993 to 2010. 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*), standard deviation of individual forecasts around that consensus (*DISPERSION*), stock price (*BEGPRICE*) from CRSP as of the beginning of the calendar quarter of the fiscal quarter-end date, and the earnings announcement date from COMPUSTAT.[7] To allow for a meaningful measure of dispersion, 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]).

We measure forecast error (*FCSTERR*), or the earnings surprise associated with earnings announcements, as *EPS_IBES* minus *FORECAST*, based on I/B/E/S data. As an alternative measure of earnings surprise, we consider seasonal differences for *EPS_IBES*, based on the

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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. For example, Thomson First Call includes a filter to "… eliminate any reported surprises that did not have at least three corporate analysts … to eliminate the possibility of one analyst poorly estimating earnings and therefore skewing the consensus figure to the point of exceptional earnings surprises" (http://help.yahoo.com/l/us/yahoo/finance/tools/research-03.html)

assumption that core quarterly earnings follow a seasonal random walk process. The magnitudes of earnings surprises represent our measure of volatility of core EPS.

We collect COMPUSTAT quarterly data for our main sample, by matching each I/B/E/S observation with a firm-quarter on COMPUSTAT.[9] We estimate reported per share earnings (*EPS_CFS*) by dividing the net income imputed from quarterly cash flow statements by the number of shares underlying the computation of basic EPS before extraordinary items reported on income statements (*EPS_IS*).[10] While *EPS_CFS* is generally very close to *EPS_IS* we prefer to use *EPS_CFS* to increase comparability with per share operating cash flows (*CPS*) obtained from cash flow statements, and also to estimate per share accruals (*APS*), which equal *EPS_CFS* minus *CPS*. As with surprises for core EPS, we use seasonal differences for *EPS_CFS*, *CPS*, and *APS* to represent surprises for these variables.[11] Again, the magnitudes of these surprises represent our measure of volatility of the corresponding variables.

We collect stock prices and daily stock return data from CRSP. Price deciles are formed each calendar quarter based on beginning-of-calendar-quarter share price (*BEGPRICE*) for firm-quarters ending during that calendar quarter. To compute a price response associated with each quarterly earnings announcement we cumulate returns over a 22-*trading* day window (approximately one month) leading up to the earnings announcement date (from COMPUSTAT), 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*). No variables have been Winsorized or truncated and details of all variables are provided in Appendix A.

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[9] 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.

[10] Since the 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.

[11] We recognize that seasonal differences are a noisier measure of surprise for reported EPS relative to core EPS because reported EPS 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. As measurement error in CPS surprise is negatively correlated with measurement error in APS surprise, this biases downward correlations between the two surprises. We are not aware if the extent of this downward bias varies across price deciles.

Table 1, Panel A, provides descriptive statistics for different variables for our sample, some of which are discussed below. The distribution of *BEGPRICE* suggests considerable concentration around the middle of the distribution, which is expected because 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 cent, which suggests that forecasts are generally slightly pessimistic. The mean is, however, negative (−1 cent), possibly because of the longer left tail (minimum value of −59.08). The median *DISPERSION* is 2 cents, and the 25th and 75th percentiles are 1 and 4 cents, respectively.

Panel B of Table 1 provides key distributional statistics within each decile of *BEGPRICE* for relevant variables derived from those described in Panel A. We use the interquartile range (IQR) of the pooled distributions as our measure of the magnitudes of forecast errors and surprises for (or volatilities of) earnings, cash flows, accruals, and price responses to forecast errors. The median values of *BEGPRICE* range from about $5 for the lowest price decile to about $65 for the highest price decile.

We provide next a summary of the overall patterns observed in Panel B and defer until Section 3 a more detailed description of the different rows. First, consistent with the results reported in DeGeorge et al. [1999] and Cheong and Thomas [2011], the magnitudes of EPS forecast error (IQR of *FCSTERR*), volatility of reported and core EPS (IQR of *ΔEPS_CFS* and *ΔEPS_IBES*), and analyst dispersion (median *DISPERSION*) do not vary much with share price.[12] Given this lack of variation, deflating these variables by share price creates deflated

[12] There is some evidence of a slight increase in magnitudes of *FCSTERR* and *DISPERSION* for the higher price deciles, whereas the results reported in Cheong and Thomas [2011], which is based on a sample period that ends

variables that are analogous to the inverse of price, and creates a strong negative relation between those deflated variables and scale. Second, consistent with the results reported in Cheong and Thomas [2011], the volatility of per share cash flows and accruals (IQR of *ΔCPS* and *ΔAPS*) as well as the volatility of price responses to earnings announcements (IQR of *ΔPRICERESP*) increase proportionately with scale.

3. Managerial efforts to smooth EPS forecast errors

As described in the Introduction, there are two ways that managers can suppress natural variation in the magnitude of EPS forecast errors: suppress natural variation in the volatility of core EPS and guide analyst forecasts toward core EPS. To investigate the first way we examine variation across price deciles in a) the volatility of core EPS, b) the ratio of the volatilities of core EPS and *CPS*, and c) the correlation between surprises in *CPS* and *APS*. We assume that managers do not suppress natural variation with scale in the volatility of *CPS*, but suppress natural variation in the volatility of core EPS by making discretionary accruals that reverse the effects of *CPS* surprises.[13] To the extent this first way is employed by managers, the volatility of core EPS will not increase proportionately with scale, the ratio of the volatilities of core EPS and *CPS* will decline with scale, and the correlation between surprises in *CPS* and *APS* will become more negative as scale increases (see footnote 3).

The evidence in row 8 of Table 1, Panel B, confirms that the volatility of core EPS, measured as the IQR of *ΔEPS_IBES*, remains relatively unchanged (16 or 17 cents) between price deciles 1 through 7, but increases at an increasing rate thereafter, and rises to 29 cents for

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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 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.

[13] Some types of EPS smoothing might also involve *CPS* smoothing. For example, managers might smooth EPS and *CPS* by increasing (reducing) R&D and maintenance when profitability is high (low). If *CPS* smoothing increases with scale, our estimates of the relation between scale and EPS smoothing will be understated.

decile 10. In contrast, rows 10, 11, and 12 indicate substantial increases with scale for volatilities of *CPS*, *APS*, and *PRICERESP*, respectively.

This evidence suggests that managerial smoothing of core EPS increases with scale between deciles 1 and 7 such that any natural increase in the volatility of core EPS is successfully suppressed, but the extent of smoothing beyond decile 7 does not increase sufficiently to offset natural increases in core EPS volatility. Differential smoothing of core EPS, which increases forecast accuracy as scale increases, is the main reason why forecast error magnitudes do not vary with scale.

We consider next the ratio of the volatilities of core EPS and *CPS*, but use firm-specific time-series, rather than cross-sectional, analyses. To do so, we need to assign firms to a specific share price decile. Untabulated results confirm that firms commonly move across price deciles over time. Whereas much of that movement occurs because of 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 assign firms to the modal share price decile, and require that a) the firm have more than 10 firm-quarters in our sample and b) the price decile for more than half the firm-quarters be no more than one decile removed from the modal decile. The first requirement reduces our sample from 7,744 to 4,086 firms and the second requirement reduces it further to 3,311 firms.

The volatilities of core EPS and *CPS* are not directly comparable because core EPS excludes certain nonrecurring items that are included in reported EPS and also included in *CPS*. In response, we consider comparing the volatility of *CPS* with reported EPS rather than core EPS. Fortunately, we find a pattern of variation for volatility of reported EPS that is similar to that for core EPS. Consistent with the results in Cheong and Thomas [2011], the evidence in row 9 of

Table 1, Panel B indicates that the IQR of *ΔEPS_CFS* is relatively constant, around 23 cents, between deciles 1 and 7, and increases thereafter at an increasing rate to 41 cents for decile 10.

Not only does the similarity in volatility patterns observed for reported and core EPS allow us to substitute the volatility of reported EPS for core EPS volatility, it suggests that managers seek to smooth the volatilities of both core and reported EPS. Given that the difference between the two EPS measures represents nonrecurring items, managers apparently smooth the magnitudes of nonrecurring items such that natural scale variation in nonrecurring items is also largely suppressed.

Our firm-specific measure of reported EPS smoothing (*RATIO*) is the ratio of the IQR of reported EPS surprise, *ΔEPS_CFS*, to the IQR of cash flow surprise, *ΔCPS*. *RATIO* should decline with share price if the amount of reported EPS smoothing increases with share price. Panel C of Table 1 provides the mean/median values of *RATIO* for firms in each price decile with the requisite data. The results in Panel C show the predicted negative relation between *RATIO* and share price for low and mid-price firms. Whereas the IQR for *ΔEPS_CFS* is only slightly below the IQR for *ΔCPS* for the lowest price decile, indicated by a mean (median) *RATIO* of 0.93 (0.75), the IQR for *ΔEPS_CFS* for the highest price decile is considerably lower than that for *ΔCPS* by decile 8, indicated by a mean (median) *RATIO* of 0.44 (0.34).

Our final investigation of EPS smoothing considers the correlation between *CPS* and *APS* surprises to determine whether EPS smoothing is achieved by discretionary accruals that offset the impact of cash flow shocks. Given that *EPS_CFS* equals *CPS* plus *APS*, managers wishing to smooth EPS would make negative (positive) discretionary accruals when *CPS* is unusually high (low). Increased efforts to smooth EPS should increase this negative relation between *CPS* and *APS*.

We recognize that there are a number of reasons why CPS and APS surprises might be negatively related, separate from the negative relation induced by smoothing EPS. 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_CFS* remains unaffected. Therefore, we expect a negative relation between *CPS* and *APS* surprises even in the absence of EPS smoothing, and the extent of that negative relation is caused by operational decisions.[14]

Table 2, Panel A, describes how the Spearman correlation (*RHO*) between *ΔCPS* and *ΔAPS* varies across price deciles. We compute the correlations each calendar year, and report the mean values across the 18 years covered by our sample. To control for possible variation in book measures of scale within the narrow price partitions, we scale *ΔCPS* and *ΔEPS_CFS* by total assets per share from four quarters ago.[15] As mentioned in the Introduction, to focus on the relation between EPS smoothing and share price, we control for possible links between EPS smoothing and forecast dispersion and magnitude of forecast errors by forming six groups obtained by crossing two dispersion partitions with three forecast error partitions. Low (high) dispersion is defined as *DISPERSION* equal to 0 and 1 cents (more than 1 cent). The small forecast error group includes forecast errors within the −5 and +5 cent range, and the large negative (positive) forecast error group includes forecast errors less than −5 (more than +5) cents.

The main finding from Panel A of Table 2 is that *RHO* becomes more negative as share price increases, consistent with a positive relation between EPS smoothing and share price, between price deciles 1 and 6, and remains constant for higher price deciles. See, for example, the bottom row in Panel A which combines all six partitions. Similar patterns are observed in each of the six groups considered. Consistent with a link between EPS smoothing and forecast

[14] The similarity between patterns observed for firm-specific and cross-sectional results reported later in Table 2 suggest that the negative relation between *CPS* and *APS* surprises induced by operational decisions does not vary with scale; i.e., observed scale variation in the negative relation reflects variation induced by EPS smoothing.

[15] Our results remain similar if we do not deflate by total assets per share.

dispersion (forecast error magnitudes), which are the two variables we control for by forming partitions, we find that the level of *RHO* is slightly more negative for the low dispersion (small forecast error) groups.

Given that normal levels of *ΔCPS* and *ΔAPS* vary across firms, and given that deviations from normal levels due to operating decisions should properly be compared against firm-specific norms, we also compute the correlation between *ΔCPS* and *ΔAPS* separately for each firm, using time-series data. To determine if firm-level correlations between *ΔCPS* and *ΔAPS* are related to share price, we return to our sample of firms described in Panel C of Table 1, which have sufficient time-series data to allow meaningful estimates of firm-level correlation and relatively stable membership in one price decile.

Panel B of Table 2 provides the mean across firms of firm-specific Spearman correlations between *ΔCPS* and *ΔAPS*. Because forecast error magnitudes differ across quarters within each firm, we do not classify firms into the three groups based on forecast error magnitudes. We do, however, partition firms into low and high dispersion groups based on the modal level of *DISPERSION* observed across quarters for each firm. (We exclude the firm if it does not have a unique mode.) As noted in the cross-sectional analysis in Panel A, we find that *RHO* becomes more negative as share price increases, and that trend is evident across low and medium price deciles.

Taken together, our results so far suggest that smoothing of core EPS volatility represents an important way in which managers smooth EPS forecast errors. Almost all of the natural scale variation in EPS forecast errors for low and mid price firms and some but not all of the natural scale variation for high price firms is suppressed successfully using this approach.

We turn next to the second way for managers to suppress natural scale variation in EPS forecast errors, by differential guidance of analyst forecasts toward core EPS, to determine if this

way explains the residual smoothing of EPS forecast errors for high price firms that remains unexplained by smoothing of core EPS volatility. To do so, we consider errors associated with analysts' forecasts that are made earlier in time, before core EPS is known to managers. We believe long-horizon forecast errors offer a benchmark that represents outcomes that would be observed if guidance did not play a role in the differential smoothing of EPS forecast errors. We allow for long-horizon forecasts to also be differentially guided, where the level of guidance increases with share price.[16] But that differential guidance will be toward managers' expectations of the core EPS that will be disclosed many quarters hence, not the actual EPS that is eventually disclosed. To the extent that managers' long-horizon forecasts are not as accurate as their short-horizon forecasts, managers' long-horizon forecasts will reflect the underlying volatility of core EPS that remains after managerial efforts to smooth EPS. If so, analysts' long-horizon forecasts will also reflect this remaining uncertainty, and managers will guide analysts toward the core EPS that is eventually disclosed as managers become informed over time.

We consider errors associated with analysts' forecasts made one, two, three, six, and nine months before the quarter end. Row 14 in Table 1, Panel B, provides the IQR for errors associated with forecasts made nine months before quarter-end (*FCSTERR_9*), the longest horizon we consider. The levels reported in that row as well as the rising pattern for high price firms is similar to that reported in row 8 for core EPS volatility. The IQR for *FCSTERR_9* declines slightly from 19 cents for price decile 1 to 16 cents for decile 7, before rising to 25 cents for decile 10. Results for shorter horizons indicate that the uptick noted for high price deciles in row 14 flattens gradually as the forecast horizon decreases. As managers are better able to predict the core EPS that will actually be disclosed, the guidance for high prices firms improves

[16] Consistent with such differential guidance, the dispersion across analysts' long-horizon exhibits very little scale variation.

such that almost all natural scale variation in EPS forecast errors is suppressed by the month before EPS is announced.

In sum, the results in Section 3 confirm our conjecture that lack of scale variation observed for EPS forecast errors is due to managerial efforts to suppress that variation. Much of that objective is achieved by differential smoothing of the underlying core EPS that analysts seek to forecast. The remainder is achieved by differential guidance of analyst forecasts toward core EPS. These managerial efforts to smooth EPS forecast errors result in lack of scale variation not only for EPS forecast errors, but also for the volatility of core EPS, volatility of reported EPS, volatility of one-time items, as well as for dispersion across analysts' forecasts.

4. Scale deflation can cause unintended biases

We consider now the first implication of the positive relation between EPS forecast error smoothing and share price: estimated coefficients are likely to be biased for studies using deflated measures of volatility of reported/core EPS, magnitudes of error associated with analysts' EPS forecasts, or dispersion across EPS forecasts made by different analysts following the same stock. Unaware that these variables do not vary much with scale, prior research has intuitively deflated them by scale, typically by share price, resulting in deflated variables that are negatively related to scale. As a result, these deflated variables will likely exhibit spurious relations with other included variables that happen to be related to scale.

As described in Appendix B of Cheong and Thomas [2011], there are many studies that use forecast error magnitudes and dispersion as dependent or independent variables, and both variables are deflated in the primary analyses in all the studies investigated.[17] We examine the impact of deflation on estimated coefficients for one of those studies: Thomas [2002], which considers the extent to which the degree of firm diversification across different lines of business

[17] In some cases, footnotes indicated that similar results were obtained with undeflated proxies for these two variables; examples include Barron et al. [1999, footnote 13] and Barron [1995, footnote 13].

affects information asymmetry between managers and investors/analysts. Under the transparency hypothesis, firms with fewer lines of business should be more transparent and be associated with lower information asymmetry. Under the diversification hypothesis, forecast errors for separate lines of business are less likely to cancel out for firms with fewer lines of business and such firms will therefore be associated with more information asymmetry.

Two of many measures of information asymmetry considered in Thomas [2002] are price-deflated values of absolute forecast errors (|*FCSTERR*|) and dispersion (*DISPERSION*), and diversification is measured by the Herfindahl Index (*HERF*) computed for each firm-year based on segment assets. Our objective is to determine the extent to which the results of that study are affected when a) |*FCSTERR*| and *DISPERSION* are not deflated by price, b) inverse of price is included as an additional regressor to the original deflated specifications, and c) price is added as an additional regressor to the undeflated specifications.[18]

Panel A of Table 3 contains Pearson and Spearman correlations among pairs of key variables from Thomas [2002] as well as other variables we created from the underlying data.[19] The dependent variables in the regressions estimated in Thomas [2002] are labeled |*DEFLFE*| and *DEFLDISP*, which are price-deflated values of absolute forecast errors and forecast dispersion, where deflation is based on share price five days before the annual earnings announcement (*BEGPRICE*). We focus here only on two of the regressors, *HERF* and *RESIDVOL* considered in the different equations. *HERF*, which measures diversification, varies between 0 and 1, with lower values representing greater diversification across different segments. *RESIDVOL*, which measures the standard deviation of market model residuals, is included in the final specification in Thomas [2002] to control for potential relations between idiosyncratic

[18] Our objective is not to question the final conclusions in Thomas [2002], but to illustrate how estimated coefficients are affected by these three extensions. The conclusions reached in Thomas [2002] are ultimately supported in analysis conducted on alternative measures of asymmetric information that are not subject to the scaling issues investigated in the present paper, i.e., abnormal returns to seasoned equity offerings (Hadlock et al. [2001]) and market microstructure metrics (Clarke et al. [2004]).

[19] See Appendix A for minor differences between our variables and the corresponding variables in Thomas [2002].

volatility and forecast error magnitudes/dispersion. The variables we introduce are undeflated absolute forecast errors (|*FCSTERR*|), dispersion (*DISPERSION*), and the inverse of share price (*INVPRICE*). Key correlations are introduced where relevant in the discussion below.

Panels B and C of Table 3 contain the results of extending the analyses in Tables 3 and 4 of Thomas [2002], which explain variation in price-scaled absolute forecast error and dispersion, respectively. The row labeled Specification I in both panels refers to the original results and columns (1) through (5) refer to the corresponding equations estimated in Thomas [2002]. The main finding from the results for specification I in both panels that is relevant for our purposes is that the coefficient on *HERF* is positive and significant in equations (1) through (4), but that relation switches to a negative and significant coefficient in equation (5), when volatility is introduced. That is, lower diversification (larger *HERF*) is associated with higher variability of forecast errors and forecast dispersion, but that relation reverses when a control for idiosyncratic volatility is introduced in equation (5). Recall that the dependent variables in both panels are deflated by share price.

Specification II considers the impact of introducing the inverse of share price as an additional regressor. This extension would be appropriate if theory calls for forecast error magnitudes and dispersion to be scaled by share price, but there remains a concern about that deflation inducing a spurious correlation with variables that are related to price. Panel A of Table 3 indicates that price-deflated absolute forecast errors and dispersion are strongly positively related to the inverse of price. Introducing the inverse of share price offers a simple way to mitigate such a concern. The main result in specification II for both panels B and C is that including *INVPRICE* to the right hand side eliminates all of the significant positive coefficients on *HERF* observed in the original results for equations (1) through (4). These results can be anticipated by the negative correlation between *HERF* and price in Panel A of Table 3. The

substantially lower coefficients on *RESIDVOL*, relative to those for specification I, are likely related to the positive correlation between volatility and inverse of price.

Specification III is similar to the original specification, but the dependent variables are no longer deflated by price. As with specification II, no significant *positive* coefficients are observed on *HERF* in either Panel B or C. These results suggest that the significant positive coefficients observed on *HERF* for equations (1) through (4) in Specification I are likely due to the negative correlation between *HERF* and share price, which then induces a positive correlation between *HERF* and the price-deflated dependent variables. Introducing a variable that is related to share price, such as *RESIDVOL* in equation (5), as an additional regressor in Specification I controls for this correlation between *HERF* and the price-deflated variables.

Specification IV adds share price as an additional regressor to specification III to control for the small positive relations observed in Panel A of Table 3 between share price and undeflated measures of |*FCSTERR*| and *DISPERSION*. We observe a positive coefficient on *BEGPRICE* that is especially significant in Panel C, which illustrates the importance of controlling for the positive relation with share price that is observed for undeflated measures of forecast error magnitudes and dispersion.

In sum, the results generated by extending the analyses in Thomas [2002] suggest the following implications for research that employs measures of forecast error magnitudes, volatility of core/reported EPS, and forecast dispersion. First, these measures should not be deflated, unless called for by theory, in which case both sets of results based on deflated and undeflated measures should be reported. Second, if deflated measures are used, it is important to include the inverse of price as an additional regressor, to confirm that the coefficients are not biased because of the strong negative relation between deflated measures and share price. Third, even if undeflated measures are used, it is appropriate to include price as an additional regressor, to mitigate any bias due to potential relations between undeflated measures and share price.

5. Increased smoothing results in higher ERC

We turn now to the second implication of a positive relation between EPS forecast error smoothing and share price: ERC, or price response per unit of earnings surprise, should be higher for high price firms with more smoothed EPS forecast errors. Our objective is simply to illustrate that the positive relation between EPS forecast error smoothing and price can have a substantial impact on ERC. We do not seek to control for the effects of different factors that have been shown in prior research to be related to ERC. As explained in Section 3, we do however control for two determinants of ERC that are also likely related to EPS forecast error smoothing: a) the magnitude of forecast errors, and b) dispersion of analysts' forecasts. Similar to the analysis in Panel A of Table 3, we control for these two variables by investigating the relation between ERC and share price within each of six groups created by interacting three partitions based on forecast error magnitudes with two partitions based on dispersion.

Given the descriptive bent of our analysis, we begin by providing granular graphical results for the distribution of forecast errors and price responses to those forecast errors. Figure 1, Panel A contains histograms, indicating the frequency 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 row describes the low dispersion subgroup, which contains firm-quarters with *DISPERSION* less than two cents, and represents approximately half of our sample. The remaining observations with high dispersion are described in the bottom row. Within each *DISPERSION* subgroup, we report the histograms for three representative price deciles: deciles 1, 5, and 10.

Some descriptive results from Figure 1, Panel A are as follows. First, a substantial fraction of the sample has relatively small forecast errors, say, within ± 5 cents, especially for the low dispersion subgroup in the top row. The high dispersion group has many more observations

with large forecast error magnitude (absolute values ≥ 10 cents) than the low dispersion group. Second, the distribution of forecast errors is similar across price deciles, holding constant the level of dispersion in each row. Third, whereas the frequency of forecasts exactly meeting actual EPS (forecast error=0) generally exceeds the frequency of cases where forecasts just miss (forecast error=−1 cent) by a substantial amount, that pattern is weaker for the high dispersion group in the bottom row, and barely discernable for price decile 1. Fourth, whereas the frequency of forecasts exactly meeting actual EPS is slightly more than the frequency of cases where forecasts just beat (forecast error=+1 cent), that pattern is reversed for price decile 10.

Consistent with the results in Cheong and Thomas [2011], which show that the distribution of forecast error shifts to the right as share price increases, the third and fourth results above suggest that the same forecast error should have different value implications across price deciles. Specifically, 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.

Panel B of Figure 1 describes the mean 22-trading-day price response (in $) for each cent of forecast error. The main result from Panel B is that the incremental share price response for each incremental cent of forecast error increases considerably with share price. This incremental share price response, represented by the gradient of the curve that connects the tips of the bars, is equivalent to an ERC. Two related results are: a) the ERC is higher for low dispersion firm-quarters in the top row, holding price constant, and b) while the ERC is quite large for smaller forecast errors closer to the middle of each plot, that gradient decreases for larger forecast error magnitudes closer to the left and right edges of each plot.[20] Overall, greater EPS forecast error smoothing, proxied by higher share price and also by smaller forecast error magnitudes and lower dispersion, is associated with higher ERC.

[20] 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).

Another important result observed in Figure 1, Panel B, which is unrelated to EPS forecast error smoothing, is that the crossover point from negative to positive price responses is lowest for the lowest price decile (between forecast errors of –1 and 0 cents), increases slightly for price decile 5 (between 0 and +1 cents), and increases further for the highest price decile (between +1 and +2 cents for the low dispersion subgroup and between +3 and +4 for high dispersion). Consistent with a rational stock market, the pattern of price responses in Panel B is determined partially 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).

Panel C in Figure 1 presents estimated ERCs, or the slope estimates from a regression of abnormal price responses (*PRICERESP*) over the 22-trading-day period on forecast errors. These regressions are estimated separately for each price decile, within the six subgroups obtained by crossing the two dispersion partitions with the three forecast error magnitude partitions. The main result from 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. The ERC is close to zero for most price deciles in the large negative and positive forecast error groups, on the left and right sides, respectively. (The lone exception is the highest price decile which is associated with ERC above 10 in all four cases.) In contrast, the ERC values are much higher for the firm-quarters contained in the small forecast error groups, and those ERC values increase sharply with price. The ERC values for higher price deciles are higher than levels predicted or observed in prior research; for example, the ERC is over 90 for the highest price decile in the low dispersion group! 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).

Panel A of Table 4 provides more detail of this cross-sectional variation in ERC by also showing the impact on ERC of pooling together different partitions based on share price, forecast error magnitudes, and dispersion. ERC values are repeated in three panel segments for the low dispersion group, high dispersion group, and both groups combined. Within each segment, the first three rows refer to the large negative, small, and large positive forecast error groups, respectively, and the fourth row combines all three forecast error magnitude groups. The first 10 columns refer to the 10 price deciles and the right-most column combines all price deciles for that row.

The pooled ERC is a weighted average of the separate ERCs for the different partitions being pooled, where the weight for each partition is the product of the variance of the regressor and the fraction of the pooled sample from that partition (proof available from authors). The variances of the regressor—forecast error for the undeflated regression—are similar across price deciles, but very different across partitions based on forecast error magnitudes and dispersion. If the regressor is price-deflated, however, the variances are negatively related to price deciles. When the variances of the different partitions are similar, the resulting pooled ERC is an average of the ERCs for the separate partitions, holding constant the number of observations in these partitions, but when the variances are different the pooled ERC is skewed substantially toward the ERC of the high variance partitions. Overall, the extent to which the pooled ERC is skewed toward the ERC of certain partitions depends on the partitions being pooled as well as whether the undeflated or deflated specification is used.

Some of the findings from Panel A of Table 4 are as follows. First, the ERC for all price deciles combined, reported in the right-most column, is approximately an average of the ERCs reported for the different price deciles. The one exception is for large forecast errors rows for the high dispersion segment and the combined segment, where the overall ERC resembles the

relatively high ERC observed for price decile 10.[21] Second, the ERC values reported in the fourth row of each panel segment, which combines all three forecast error subgroups, is influenced disproportionately by the relatively few observations in the large negative and large positive forecast error partitions, which are associated with higher variances. Third, combining the two dispersion groups results in pooled ERCs in the bottom row that are closer to the lower ERCs observed for the fourth row in the high dispersion group, relative to the higher ERCs observed in the fourth row of the low dispersion group. This effect is caused by the high dispersion group containing a larger fraction of observations with large forecast error magnitudes, which are associated with very low ERCs (see Panel A in Figure 1).

The joint impact of the second and third findings above is that the ERC values reported in the bottom row, which combine both dispersion groups and all three forecast error magnitude groups, are quite low: ERCs increase from 0.1 for decile 1 to 0.7 for decile 9. The ERC for decile 10 is much higher (=13.8), however, and the overall ERC of 12.9 reflects mainly the high ERC of decile 10. (As mentioned in the footnote above, the high overall ERC is due to a few observations from decile 10 with very high price responses and forecast errors.)

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.[22] We expect ERC estimates within each cell to be relatively unaffected by deflation, but the results for pooling across price deciles should be affected by deflation, as the variance of the regressor is now much higher for low price deciles. That is, the pooled ERC is disproportionately influenced by low price observations with lower ERCs, because they have higher forecast error magnitudes when deflated.

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[21] The high overall ERC observed in the right-most column appear to be due to a few observations in price decile 10 with extreme values for both price response and forecast error. Dropping the lowest and highest 1 percent of forecast errors causes the overall ERC to be an average of the different price deciles.

[22] 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.

These predictions are confirmed by comparing the results for the deflated specification in Panel D of Figure 1 and Panel B of Table 4 with the corresponding results for the undeflated specification in Panel C of Figure 1 and Panel A of Table 4, respectively. The ERCs for the deflated specification in Panel D of Figure 1 are generally similar to the corresponding ERCs for the undeflated specification in Panel C, as long as we compare results within price deciles where variation in deflated forecast errors is restricted.[23] However, pooling together results for all price deciles (see the "All" column) causes the ERC for the deflated regression in Panel B of Table 4 to be closer to the ERC for the low price deciles. In contrast, the corresponding ERCs in Panel A under the "All" column appear to reflect equally the ERC of all price deciles. Our main finding here is that ERCs should be estimated using undeflated, rather than price-deflated, price responses and forecast errors, because managers engage in differential smoothing of forecast errors.

As in Panel A of Table 4, pooling together observations of different forecast error magnitudes for the deflated specification considered in Panel B results in ERC estimates that are close to the low ERCs estimated for the large negative and large positive forecast error subgroups. The combined reduction in ERC due to all three effects—observed for deflated regressions estimated on samples pooled across price deciles, dispersion groups, and forecast error groups—is described by the zero ERC reported in the right-most cell in the bottom row of Panel B in Table 4.

The typical response in the literature to this low observed value of ERC is to truncate or Winsorize forecast errors in an effort to mitigate the impact of extreme forecast errors. The assumption is that large forecast errors are due to data errors or include large price-irrelevant

[23] One exception is price decile 1, which exhibits lower ERCs for the deflated regressions described in Panel B, relative to those for the undeflated regressions in Panel A. We believe this is caused by the relatively wider variation in share price within price decile 1, which results in the lowest priced observations receiving greater weight.

earnings components. Price responses are considered to be reliable, and no adjustments are made typically for extreme values. We conducted a sensitivity analysis of the impact of different ways to mitigate the effect of extreme forecast error values on estimated ERC. We considered Winsorization and truncation, as well as different ranges to define extreme values (both measured in cents as a percent of price). Our results (available upon request) suggest that eliminating even a few observations with large forecast errors increases the estimated ERC substantially, and the ERC continues to increase toward the values reported for those reported for ± 5 cent small forecast error group, as larger ranges of extreme observations are excluded.

We illustrate next the potential for studies documenting cross-sectional variation in ERC to be impacted by the positive relation between ERC and share price created by EPS forecast error smoothing.[24] Table 2 in Ng et al. [2008] documents a strong negative relation between ERC and transactions costs, consistent with their hypothesis that "firms with higher transaction costs have lower earnings response coefficients because transaction costs prevent informed trades required for the price adjustment to earnings news" (p. 676). They consider three measures of transaction costs—*ESPREAD*, *QSPREAD*, and *LDV*—where *ESPREAD* (*QSPREAD*) is the average daily effective (quoted) spread plus commissions in the month of earnings announcement and *LDV* is a measure of transaction costs developed by Lesmond, Ogden, and Trzcinka [1999]. Given that estimates of transactions costs are negatively related to share price, we investigate whether their results are sensitive to the inclusion of share price as an additional variable that explains variation in ERC.

While ERCs are estimated in that study using returns over different windows and different measures of forecast error, we focus on the specifications closest to those considered in

[24] As with our replication of Thomas [2002], there are minor differences between our variables and the corresponding variables in Ng et al. [2008] (see Appendix A), and our intent here is not to dispute the ultimate conclusions of that study, but to illustrate how coefficients documenting cross-sectional variation in ERC might be biased by the positive relation between ERC and share price created by EPS forecast error smoothing.

this study; i.e., regressions of abnormal returns around earnings announcements (*CAR*) on analysts' forecast errors (*DEFLFE*), defined as the actual EPS according to I/B/E/S minus the most recent consensus forecast, deflated by share price at the end of the fiscal quarter (*BEGPRICE*). Regressions (7), (8), and (9) in that study investigate the coefficient on the interaction between *DEFLFE* and *ESPREAD*, *QSPREAD*, and *LDV*, respectively. All three measures of transactions costs have been transformed into quintiles and scaled to range between 0 and 1. The share price variable we include (*PRICEDEC*) is based on deciles of *BEGPRICE*, also scaled to range between 0 and 1.

Table 5, Panel A reports pair-wise correlations for selected variables from Ng et al. [2008]. As we expect, all three measures of transactions costs are strongly negatively related to share price. Panel B reports the original regressions in Table 2 of Ng et al. [2008], referred to as Specification I, as well as Specification II, which includes price decile (*PRICEDEC*) as an additional variable that is interacted with *DEFLFE*.

The results reported in Panel B of Table 5 suggest that the negative relation between ERC and transactions costs documented in Ng et al. [2008] is explained by two joint effects: a) the positive relation between ERC and share price described earlier, and b) the negative relation between transactions costs and share price described in Panel A of Table 5. Whereas the coefficients on the interaction between forecast errors and all three measures of transactions costs are negative and statistically significant in Specification I, those relations become insignificant in Specification II. The interaction between forecast errors and share price is always strongly positive in Specification II.

The main takeaway from our ERC analyses is that researchers should be aware of the strong positive relation between ERC and scale induced by EPS forecast error smoothing. Studies examining cross-sectional variation in ERC should control for scale. Our results also suggest that researchers should consider controls for the magnitude of forecast errors because of

the substantial variation in ERC across forecast error magnitudes. Finally, our results suggest that ERC is best estimated using undeflated price responses and forecast errors, because ERCs for the deflated specification are skewed toward the lower ERC of low price firms.

6. Conclusion

We consider here why analysts' EPS forecast error magnitudes do not vary with scale and develop two implications of that empirical regularity for research. Our results suggest that EPS forecast errors would vary naturally with scale, as intuition suggests, but managers intervene and smooth or suppress that natural variation using two approaches. First, the volatility of EPS, both reported and core earnings, is smoothed such that observed volatility for low and mid-price firms is almost the same. While earnings volatility for high price firms is also substantially smoothed, the degree of smoothing is not sufficient to completely suppress natural variation with scale. As a result of managerial smoothing of EPS volatility, analysts' forecast errors are also smoothed such that forecast error magnitudes vary little across low and mid-price firms, and rise with scale for higher price deciles. The residual variation with scale observed in earnings volatility for higher price firms is offset by differential managerial guidance of analysts' forecasts leading up to the earnings announcement, such that forecast errors for higher price firms also shrink to the levels observed for low and mid-price firms.

We do not investigate why managers are motivated to smooth EPS forecast errors. Two possible motivations suggested in Cheong and Thomas [2011] are as follows. First, managers smooth forecast errors at the request of analysts, possibly because analysts believe that their performance is not adjusted for scale differences. Second, managers engage in forecast error smoothing because they believe that investors do not adjust for scale differences.

We consider two implications of EPS forecast error smoothing for research. First, the intuitive practice of scale-deflation of EPS forecast errors, EPS volatility, or forecast dispersion creates a negative relation between the deflated variable and scale. Researchers unaware of that

negative relation might observe spurious results in regressions that include other variables that happen to be related to scale. Second, firms for which EPS forecast error is highly smoothed must be associated with high ERCs because each cent of forecast error has a large price impact. Researchers should be aware of the strong positive relation between ERC and scale, as well as the strong negative relation between ERC and magnitudes of forecast error.

Appendix A
Variable definitions and sources

Label	Description	Source
APS (in $)	Accruals per share.	= *EPS_CFS – CPS*
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 EPS (data item #cshprq).
DEFLDISP	Price-deflated dispersion.	= *DISPERSION / BEGPRICE*
DEFLFE	Price-deflated forecast error.	= *FCSTERR / BEGPRICE*
DISPERSION (in $)	Standard deviation of the individual analyst's forecasts that constitute *FORECAST*.	Standard deviation of forecasts is obtained from I/B/E/S (WRDS filename is ibes.statsumu_epsus).
EPS_CFS * (in $)	Actual quarterly basic 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 EPS (data item #cshprq). We use *EPS_IS* whenever the data item #ibcy is missing.
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.
EPS_IS (in $)	Actual quarterly basic earnings per share (EPS), excluding extraordinary items, as reported on the Income Statement.	Data item #epspxq from COMPUSTAT (WRDS filename is comp.fundq).
ESPREAD	Average daily effective spread plus commissions in the announcement month.	See Ng et al. [2008] for details.

FCSTERR (in $)	EPS forecast error.	= *EPS_IBES – FORECAST*
FCSTERR_9 (in $)	EPS forecast error, associated with forecasts made nine months before quarter-end.	
FORECAST (in $)	Most recent consensus (mean) estimate of *EPS_IBES* for the firm-quarter.[§]	EPS forecast is obtained from the I/B/E/S summary file (WRDS filename is ibes.statsumu_epsus), which is unadjusted for stock splits.
HERF	A measure of firm diversification, which is the Herfindahl Index based on assets reported for different segments.	See Thomas [2002] for details.
INVPRICE	Inverse of *BEGPRICE*.	= 1/*BEGPRICE*
LDV	A measure of transaction costs developed by Lesmond, Ogden, and Trzcinka [1999].	See Lesmond, Ogden, and Trzcinka [1999] and Ng et al. [2008] for details.
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).
QSPREAD	Average daily quoted spread plus commissions in the announcement month.	See Ng et al. [2008] for details.
RESIDVOL	Standard deviation of the market model residuals over the period from 210 to 11 days before the earnings announcement date.	See Thomas [2002] for details.

[§] *BEGPRICE* refers to the share price five days before the earnings announcement for Thomas [2002] and price at the end of the fiscal quarter for Ng et al. [2008]. In our analysis of Ng et al. [2008], *CAR* is based on the 3-day announcement window. In our analyses of Thomas [2002] and Ng et al. [2008], *FORECAST* refers to the *median* consensus forecast.

* 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.

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Table 1. Descriptive statistics

The sample contains 165,698 firm-quarters derived from U.S. firms on I/B/E/S with available data, fiscal period end date between January 1993 and June 2010, quarterly earnings announced by December 2010, 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, 25th percentile, median, 75th percentile, and maximum for different variables. Panel B reports the distributions of different variables across deciles of *BEGPRICE*, which is the beginning-of-quarter share price. Price deciles are computed 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*. *DISPERSION* is the standard deviation of the individual analyst forecasts around the consensus. *DEFLFE* and *DEFLDISP* are defined as *FCSTERR* and *DISPERSION* scaled by *BEGPRICE*, respectively. Earnings per share (*EPS_CFS*) 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_CFS* minus *CPS*. Δ*EPS_IBES,* Δ*EPS_CFS*, Δ*CPS*, and Δ*APS* are the seasonally differenced value of *EPS_IBES, EPS_CFS*, *CPS*, and *APS* respectively. *PRICERESP* (*CAR*) is the price response in dollars (cumulative abnormal stock returns) over 22 trading days, adjusted for market movement. Additional details for all variables are provided in Appendix A. All prices and forecast/actual EPS are denominated in dollars, and the variables *DEFLFE* and *DEFLDISP* in Panels A and B below are expressed as a percentage of share price.

Panel A: Univariate statistics

Variable	N	mean	StdDev	IQR	min	p25	median	p75	max
BEGPRICE	165,698	33.50	827.65	22.99	0.12	12.88	22.63	35.86	141600.00
FORECAST	165,698	0.39	10.36	0.43	-14.96	0.07	0.26	0.50	1606.00
EPS_IBES	165,698	0.38	10.66	0.44	-64.05	0.07	0.27	0.51	1859.00
FCSTERR	165,698	-0.00	1.33	0.05	-229.98	-0.01	0.01	0.04	406.64
DEFLFE (%)	165,698	-0.23	11.04	0.23	-3091.20	-0.07	0.03	0.16	926.09
DISPERSION	165,698	0.04	0.94	0.03	0.00	0.01	0.02	0.04	223.06
DEFLDISP(%)	165,698	0.29	2.47	0.17	0.00	0.04	0.09	0.21	672.58
EPS_CFS	165,698	0.33	14.56	0.48	-75.12	0.03	0.25	0.51	2942.00
CPS	154,571	0.68	15.82	0.91	-182.26	0.01	0.37	0.92	2918.17
APS	154,571	-0.35	7.77	0.67	-1559.02	-0.61	-0.18	0.05	1129.45
PRICERESP	165,606	0.14	48.56	2.89	-5434.81	-1.41	-0.02	1.48	16011.32
CAR	165,606	0.00	0.17	0.15	-0.95	-0.07	-0.00	0.07	4.93

Panel B: Univariate statistics by price decile.

#		Price decile										
	Statistic & Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**All**
1	median *BEGPRICE*	4.75	9.25	13.40	17.18	21.07	25.38	30.06	36.27	45.13	64.44	22.63
2	IQR *FCSTERR*	0.05	0.05	0.05	0.05	0.04	0.04	0.05	0.05	0.05	0.07	0.05
3	median |*FCSTERR*|	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.04	0.03
4	IQR *DEFLFE (%)*	1.28	0.57	0.38	0.28	0.21	0.17	0.16	0.15	0.11	0.10	0.23
5	median |*DEFLFE*| *(%)*	0.62	0.28	0.20	0.15	0.12	0.10	0.09	0.08	0.07	0.06	0.13
6	median *DISPERSION*	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02
7	median *DEFLDISP (%)*	0.42	0.19	0.13	0.11	0.09	0.07	0.06	0.05	0.05	0.04	0.09
8	IQR *ΔEPS_IBES*	0.16	0.16	0.16	0.17	0.16	0.17	0.17	0.19	0.21	0.29	0.18
9	IQR *ΔEPS_CFS*	0.23	0.22	0.23	0.22	0.22	0.22	0.24	0.26	0.30	0.41	0.26
10	IQR *ΔCPS*	0.28	0.40	0.46	0.52	0.56	0.60	0.65	0.72	0.79	1.02	0.57
11	IQR *ΔAPS*	0.36	0.46	0.52	0.57	0.61	0.63	0.68	0.73	0.81	1.02	0.62
12	IQR *PRICERESP*	0.93	1.67	2.13	2.54	2.91	3.28	3.71	4.27	5.12	6.94	2.89
13	IQR *CAR*	0.23	0.20	0.17	0.16	0.15	0.14	0.13	0.12	0.12	0.11	0.15
14	IQR *FCSTERR_9*	0.19	0.18	0.18	0.18	0.16	0.16	0.16	0.17	0.20	0.25	0.18

Panel C: Ratio of firm-specific volatilities of per share earnings and cash flows, based on seasonal differences. The modal price decile for each firm is the price decile assigned to that firm. We keep firms 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. For each firm, we compute the ratio (*RATIO*) of its interquartile range of seasonally-differenced *EPS_CFS* to its interquartile range of seasonally-differenced *CPS*. We expect this ratio to decline (become more negative) with EPS smoothing. Reported below are the mean and median *RATIO* and N (number of firms) in each price decile.

		Price decile									
Statistics	**Variable**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Mean	*RATIO*	0.93	0.70	0.63	0.55	0.48	0.45	0.53	0.44	0.46	0.52
Median	*RATIO*	0.75	0.52	0.51	0.41	0.37	0.37	0.38	0.34	0.37	0.43
N	*RATIO*	490	439	371	299	311	271	239	275	286	328

Table 2
Variation in correlation between seasonally-differenced operating cash flows and accruals (*RHO*)

Earnings per share (EPS) smoothing should increase the magnitude of the normally negative correlation between unexpected per share cash flows (CPS) and accruals (APS). We investigate whether EPS smoothing increases with share price, in the presence of controls for two other factors that are potentially related to EPS smoothing: magnitude of forecast errors (*FCSTERR*) and dispersion of forecasts across individual analysts (*DISPERSION*). Our I/B/E/S sample of 165,698 firm-quarters with available data is split into price deciles based on beginning of quarter share price. The sample is also split into two subgroups based on *DISPERSION* and three subgroups based on *FCSTERR* magnitudes. We report below the Spearman correlation (*RHO*) between unexpected quarterly APS and CPS, where unexpected values are seasonal differences in APS and CPS, deflated by lagged assets per share. Details of all variables provided in Appendix A. In Panel A we compute *RHO* in the cross-section each year and report means over the 18 years in our sample. In Panel B, we compute *RHO* separately for each firm and report means across firms. For Panel B, we keep firms 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. The modal price decile for each firm is the price decile assigned to that firm. Likewise, we assign firms into low and high dispersion groups based on the modal level of *DISPERSION* observed across quarters for each firm.

Panel A: *RHO* estimated in cross-section each year (reported below is the mean over 18 years)

DISPERSION	FCSTERR	Price decile										All
		1	2	3	4	5	6	7	8	9	10	
Low < 2 cents	< –5 cents	-0.47	-0.57	-0.59	-0.67	-0.72	-0.78	-0.80	-0.75	-0.84	-0.81	-0.63
	[–5, +5]	-0.61	-0.73	-0.76	-0.81	-0.82	-0.82	-0.85	-0.85	-0.84	-0.83	-0.77
	> +5 cents	-0.42	-0.69	-0.68	-0.69	-0.74	-0.72	-0.78	-0.80	-0.79	-0.82	-0.72
	All	-0.57	-0.71	-0.74	-0.79	-0.81	-0.81	-0.84	-0.85	-0.84	-0.83	-0.76
High ≥ 2 cents	< –5 cents	-0.49	-0.57	-0.59	-0.67	-0.71	-0.70	-0.66	-0.72	-0.75	-0.71	-0.62
	[–5, +5]	-0.53	-0.66	-0.71	-0.76	-0.77	-0.79	-0.81	-0.82	-0.81	-0.81	-0.73
	> +5 cents	-0.47	-0.56	-0.63	-0.70	-0.71	-0.73	-0.75	-0.78	-0.77	-0.75	-0.69
	All	-0.49	-0.60	-0.65	-0.72	-0.73	-0.75	-0.76	-0.79	-0.78	-0.77	-0.69
All	< –5 cents	-0.48	-0.57	-0.60	-0.67	-0.71	-0.70	-0.68	-0.73	-0.76	-0.73	-0.62
	[–5, +5]	-0.57	-0.70	-0.74	-0.79	-0.80	-0.81	-0.83	-0.84	-0.82	-0.82	-0.75
	> +5 cents	-0.47	-0.58	-0.64	-0.70	-0.72	-0.73	-0.76	-0.79	-0.78	-0.76	-0.70
	All	-0.52	-0.65	-0.69	-0.75	-0.76	-0.77	-0.80	-0.81	-0.80	-0.78	-0.72

Panel B: *RHO* estimated in time-series for each firm (reported below are the means across firms in each price decile and the number of firms).

DISPERSION	Statistics	Price decile									
		1	2	3	4	5	6	7	8	9	10
Low < 2 cents	Mean	-0.53	-0.68	-0.76	-0.77	-0.80	-0.81	-0.80	-0.83	-0.79	-0.85
	N	237	233	198	134	149	128	85	89	72	74
High ≥ 2 cents	Mean	-0.53	-0.65	-0.67	-0.75	-0.77	-0.79	-0.78	-0.81	-0.80	-0.76
	N	288	227	183	184	176	154	158	196	220	259
All	Mean	-0.53	-0.67	-0.72	-0.76	-0.78	-0.80	-0.78	-0.82	-0.80	-0.78
	N	524	459	380	317	324	281	242	284	291	332

Table 3
Extension of analyses in Tables 3 and 4 of Thomas [2002] to show price deflation effect

Panel A reports the Pearson (Spearman) correlation of selected variables from Thomas [2002] below (above) the main diagonal. Panel B (C) reports a partial view of the regression results based on Table 3 (Table 4) of Thomas [2002], which investigates the relation between absolute forecast error (forecast dispersion) and diversification. Absolute forecast error (|*FCSTERR*|) and dispersion (*DISPERSION)* are measured as |*EPS_IBES –FORECAST*| and standard deviation of analyst forecasts, respectively. When scaled by *BEGPRICE*, which is share price five days before the annual earnings announcement, we denote them as |*DEFLFE*| and *DEFLDISP*. Diversification is measured by *HERF*, which is the Herfindahl Index, based on assets reported for different segments. A smaller value of *HERF* represents more diversification or more balanced asset investments spread across more segments. *RESIDVOL*, measured as the standard deviation of the market model residuals over the period from 210 to 11 days before the earnings announcement date, is a control variable that is included in equation (5) in both Panels. See Thomas [2002] for more details. Specification I refers to the regressions estimated in the original study. Specification II includes the inverse of *BEGPRICE* (*INVPRICE*) as an additional regressor. Specification III returns to specification I but considers undeflated values of the dependent variables. Specification IV adds price as an additional regressor to specification III. Associated White [1980] t-statistics are reported in parentheses below each coefficient estimate, and significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

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

	|FCSTERR|	*|DEFLFE|*	*DISPERSION*	*DEFLDISP*	*BEGPRICE*	*INVPRICE*	*HERF*	*RESIDVOL*
|FCSTERR|		0.89	0.45	0.48	-0.13	0.13	-0.10	0.12
|DEFLFE|	0.56		0.32	0.63	-0.54	0.54	0.03	0.39
DISPERSION	0.50	0.14		0.75	0.14	-0.14	-0.25	-0.17
DEFLDISP	0.27	0.53	0.49		-0.51	0.51	-0.03	0.30
BEGPRICE	0.10	-0.26	0.29	-0.25		-1.00	-0.29	-0.69
INVPRICE	0.04	0.58	-0.09	0.52	-0.48		0.29	0.69
HERF	-0.09	0.06	-0.17	0.03	-0.26	0.18		0.40
RESIDVOL	0.05	0.42	-0.11	0.35	-0.47	0.64	0.34	

Panel B: Selected coefficients from regressions based on Table 3 of Thomas [2002].

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

Panel C: Selected coefficients from regressions based on Table 4 of Thomas [2002].

Specification Dep. Var.	Variable	Equation				
		(1)	(2)	(3)	(4)	(5)
I *DEFLDISP*	*HERF*	0.29 (5.49)***	0.17 (2.66)***	0.18 (2.84)***	0.13 (2.01)**	-0.16 (2.83)***
	RESIDVOL					0.68 (25.54) ***
II *DEFLDISP*	*HERF*	-0.39 (7.85)***	0.09 (1.63)	0.09 (1.75)*	0.04 (0.76)	-0.04 (0.74)
	INVPRICE	11.53 (21.12)***	12.57 (20.39)***	12.18 (19.80)***	12.12 (19.72)***	10.52 (15.51)***
	RESIDVOL					0.22 (7.75) ***
III *DISPERSION*	*HERF*	-0.1401 (16.02)***	-0.0062 (0.57)	-0.0060 (0.55)	-0.0124 (1.15)	-0.0228 (2.15)**
	RESIDVOL					0.0241 (12.31)***
IV *DISPERSION*	*HERF*	-0.0766 (7.37)***	0.0017 (0.15)	0.0032 (0.28)	-0.0022 (0.20)	-0.0153 (1.43)
	BEGPRICE	0.0026 (11.61)***	0.0016 (6.07)***	0.0018 (6.83)***	0.0019 (7.15)***	0.0023 (8.82)***
	RESIDVOL					0.0360 (13.86)***

Table 4. Variation in ERC across share price

The first implication of a positive relation between EPS forecast error smoothing and share price is that ERC (earnings response coefficient) should increase with share price. We control for two other factors that are potentially related to ERC and forecast error smoothing: magnitude of forecast errors (*FCSTERR*) and dispersion of forecasts across individual analysts (*DISPERSION*). Our I/B/E/S sample of 165,698 firm-quarters with available data is split into price deciles based on beginning of quarter share price. The sample is also split into two subgroups based on *DISPERSION* and three subgroups based on *FCSTERR* magnitudes. Reported below is the ERC (slope from regression of 22-day price response on forecast error, estimated separately for each price decile over three forecast error ranges: a) large negative (< -5 cents); b) small (between -5 and +5 cents); and c) large positive (> +5 cents). The analysis is repeated for the low dispersion subgroup (*DISPERSION* < 2 cents), the high dispersion subgroup (*DISPERSION* ≥ 2 cents), and both subgroups combined. The bottom row in each Panel segment combines observations across all three forecast error ranges, and the right-most column combines observations across all price deciles. Panels A and B provide results for undeflated and price-deflated values, respectively, of price responses and forecast errors.

Panel A. ERC slope coefficient based on undeflated price response and forecast error

DISPERSION	**FCSTERR**	Price Deciles										
		1	2	3	4	5	6	7	8	9	10	All
Low < 2 cents	< –5 cents	0.0	-0.1	-0.2	0.7	-0.1	-0.7	-1.4	5.9	-0.2	12.7	0.2
	[–5, +5]	11.3	20.7	27.2	32.6	36.8	40.0	42.5	52.2	61.6	92.2	37.4
	> +5 cents	1.3	-0.7	0.2	1.4	0.9	15.8	-1.7	2.1	8.8	11.0	2.5
	All	0.9	1.9	2.5	6.9	4.3	9.9	13.6	15.9	19.6	17.8	5.4
High ≥ 2 cents	< –5 cents	0.1	0.0	0.0	0.1	0.1	0.2	0.3	0.6	0.1	12.9	10.4
	[–5, +5]	5.3	9.2	13.7	13.0	17.4	22.5	20.8	24.1	27.2	34.1	17.7
	> +5 cents	-0.1	0.1	0.0	1.5	0.5	0.4	0.3	0.9	1.0	14.2	14.1
	All	0.1	0.3	0.4	1.0	1.0	0.6	1.4	2.4	0.6	13.8	12.9
All	< –5 cents	0.1	-0.0	0.0	0.1	0.0	0.2	0.3	0.6	0.0	12.9	10.4
	[–5, +5]	7.6	13.9	19.1	20.8	24.7	29.1	28.9	33.3	38.1	50.2	25.0
	> +5 cents	-0.0	0.0	-0.0	1.4	0.3	0.5	0.1	0.7	0.6	14.2	14.1
	All	0.1	0.3	0.5	1.2	1.2	0.7	1.6	2.7	0.7	13.8	12.9

Panel B. ERC slope coefficient based on price-deflated price response and forecast error

DISPERSION	**FCSTERR**	Price Deciles										
		1	2	3	4	5	6	7	8	9	10	All
Low < 2 cents	< –5 cents	0.1	-0.3	-0.1	0.6	-0.1	-0.6	1.3	6.3	3.2	11.7	0.0
	[–5, +5]	2.6	17.1	23.9	29.9	34.6	36.7	42.0	52.4	61.4	87.6	4.9
	> +5 cents	-0.2	-0.5	0.5	4.2	0.8	3.4	-1.2	2.0	5.9	12.4	0.3
	All	0.5	1.4	1.8	6.2	2.9	8.2	14.5	16.7	19.9	21.5	0.8
High ≥ 2 cents	< –5 cents	-0.0	-0.1	0.1	0.2	0.2	0.4	0.7	0.7	0.1	0.6	-0.0
	[–5, +5]	2.4	7.1	11.3	12.2	14.6	22.0	21.6	22.9	28.6	31.8	3.8
	> +5 cents	0.0	0.2	0.5	1.5	0.6	0.8	0.1	0.9	1.3	1.4	0.1
	All	-0.0	0.1	0.4	0.8	0.9	0.7	1.8	2.5	0.7	2.9	0.0
All	< –5 cents	-0.0	-0.1	0.1	0.2	0.1	0.3	0.6	0.7	0.1	0.6	-0.0
	[–5, +5]	2.5	11.2	16.5	19.1	22.0	27.5	29.2	32.3	39.0	47.1	4.4
	> +5 cents	0.0	0.1	0.4	1.5	0.5	0.7	-0.1	0.7	0.9	1.3	0.1
	All	-0.0	0.2	0.5	0.9	1.1	0.8	2.1	2.9	0.8	3.3	0.0

Table 5
Extension of analyses in Table 2 of Ng et al. [2008] to show price effect on ERC

Ng, Rusticus, and Verdi [2008] hypothesize that "firms with higher transaction costs have lower earnings response coefficients because transaction costs prevent informed trades required for the price adjustment to earnings news" (p. 676). This table examines how their result is affected by the positive relation between ERC and share price, induced by EPS forecast error smoothing. Panel A reports pair-wise correlations for selected variables from Ng et al. [2008]. Panel B reports the regressions in Table 2 of Ng et al. [2008] based on 3-day announcement window abnormal returns (*CAR*) on price-deflated analyst forecast errors (*DEFLFE*). These regressions investigate the relation between ERC and three measures of transaction costs: *ESPREAD*, *QSPREAD*, and *LDV*. *ESPREAD* (*QSPREAD*) is the average daily effective (quoted) spread plus commissions in the announcement month. *LDV* is a measure of transaction costs developed by Lesmond, Ogden, and Trzcinka [1999]. All three variables have been transformed into quintiles and scaled to range between 0 and 1. Forecast error equals actual EPS according to I/B/E/S less the most recent monthly consensus forecast deflated by share price at the end of the fiscal quarter (*BEGPRICE*). See Ng et al. [2008] for details. Specification I refers to the original specification in Ng et al. [2008], whereas Specification II includes price decile (*PRICEDEC*) as an additional variable that is interacted with *DEFLFE*. *PRICEDEC* is scaled so that it ranges from 0 to 1. Fama-Macbeth [1973] t-statistics are reported in parentheses below each coefficient estimate, and significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

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

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

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

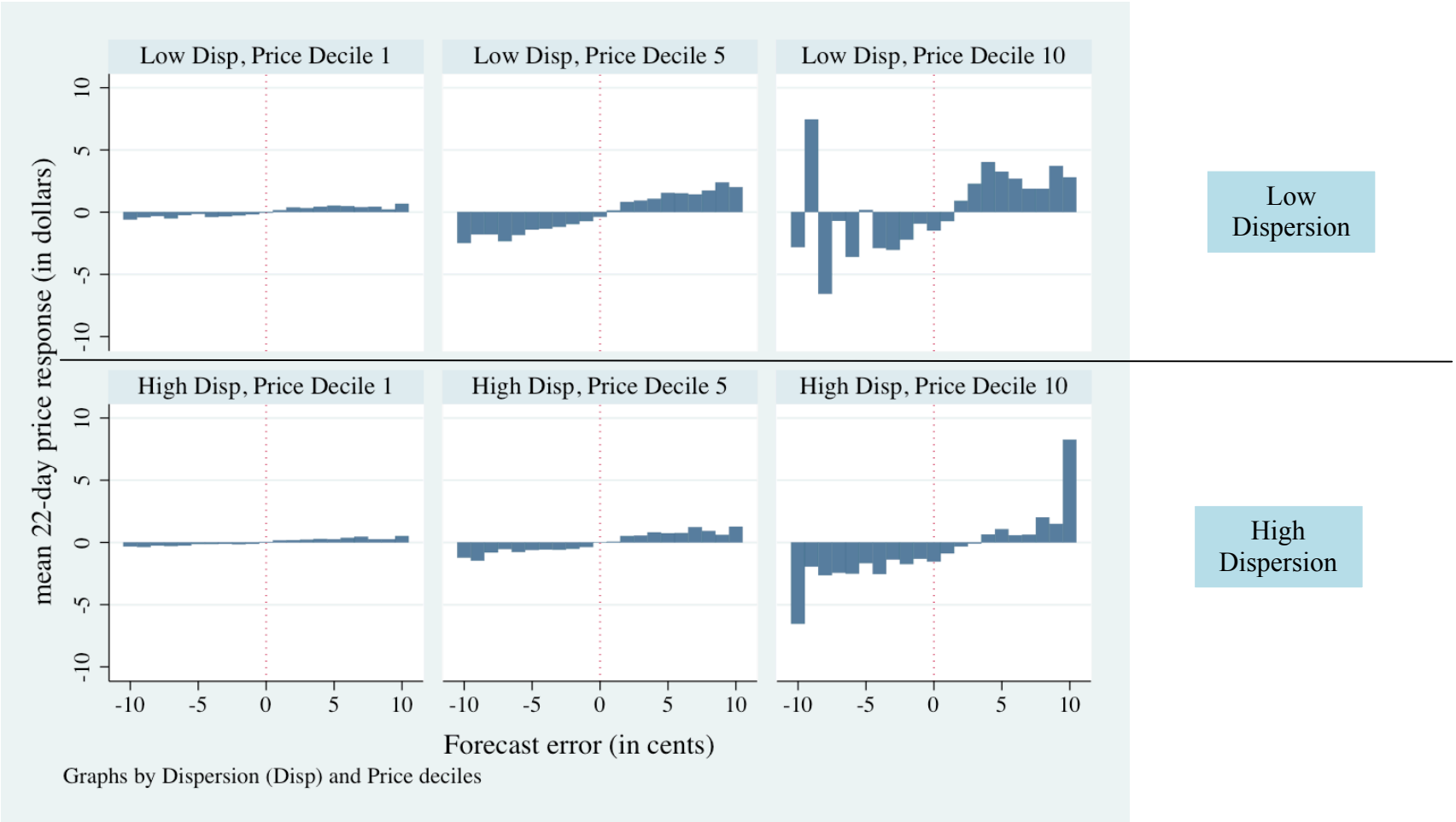
	Regression specification I			Regression specification II		
	(7)	(8)	(9)	(7)	(8)	(9)
DEFLFE	2.60 (6.35)***	2.23 (7.11)***	2.04 (8.76)***	1.08 (2.20)**	0.62 (1.77)*	0.80 (3.14)***
DEFLFE×*ESPREAD*	-1.68 (-4.56)***			-0.27 (-0.62)		
DEFLFE×*QSPREAD*		-1.27 (-4.77)***			0.18 (0.59)	
DEFLFE×*LDV*			-1.11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

Figure 1. Variation across price deciles in price response to forecast errors

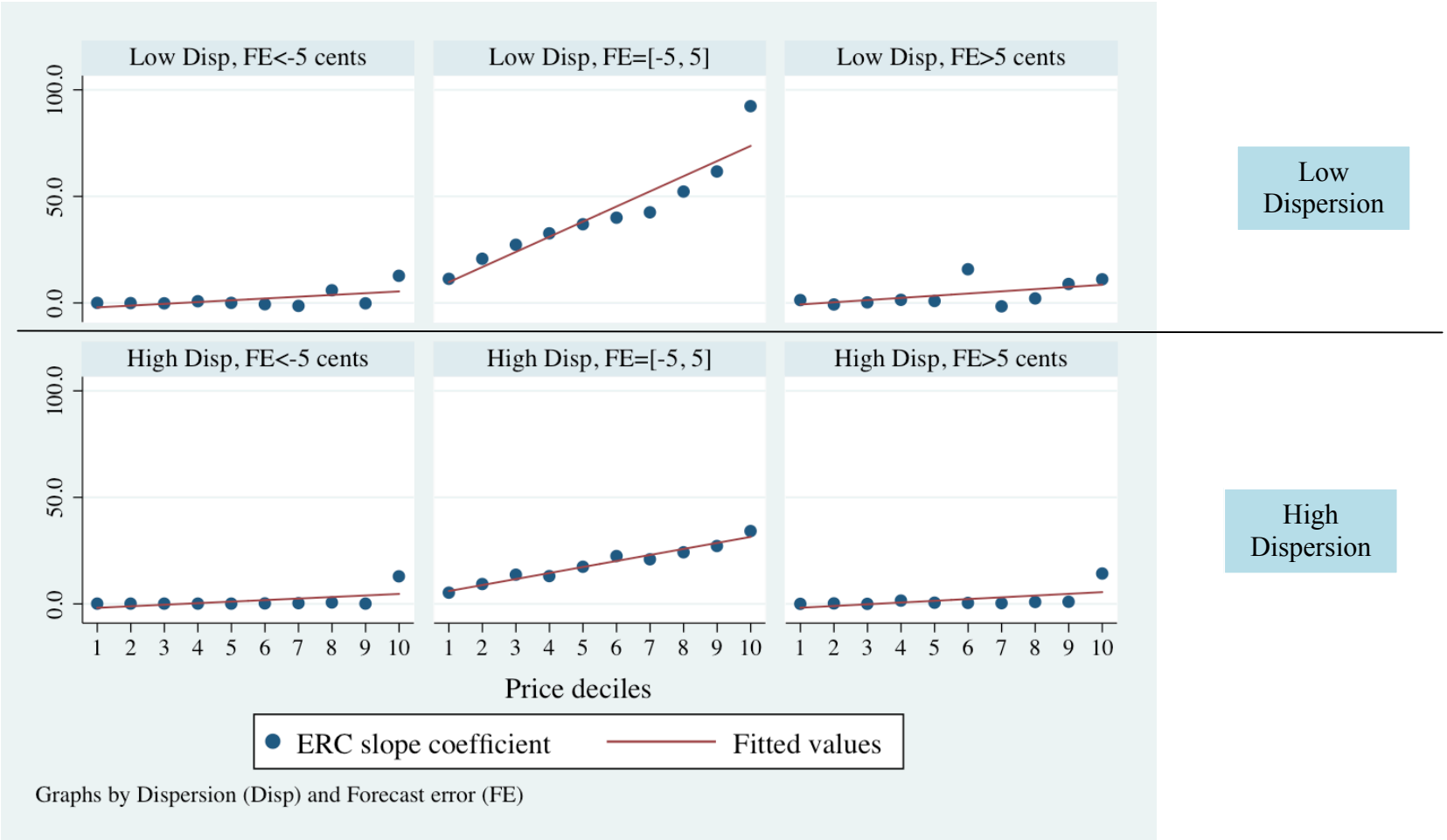
Our I/B/E/S sample of 165,698 firm-quarters with available data is split into price deciles based on beginning of quarter share price. The sample is also split approximately evenly into high (*DISPERSION* ≥ 2 cents) and low dispersion (*DISPERSION* < 2 cents) subgroups, where *DISPERSION* is the standard 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 <-10 and >+10, respectively).

Panel B: Mean price change (in $) over 22 trading days before earnings announcement, for each cent of forecast error between –10 and +10 cents.



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.