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# Why Do EPS Forecast Error and Dispersion Not Vary with Scale? Implications for Analyst and Managerial Behavior

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ABSTRACT

We document a counter-intuitive finding regarding analyst forecasts of quarterly earnings per share (EPS): magnitudes of deviations from benchmarks—individual forecasts versus consensus (dispersion) and consensus versus actual (forecast error)—do not vary with scale. Seasonally differenced EPS, or time-series forecast error, also exhibits substantial lack of variation with scale, but only for firms followed by analysts. This lack of variation with scale is not observed for analyst and time-series forecasts for (a) EPS for some countries, (b) sales and cash flows for all countries, and (c) stock splits. We propose and investigate different explanations for these puzzling regularities that have important implications for practice and research. We believe the cause is managerial smoothing of EPS designed to reduce across-firm variation in EPS volatility.

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## 1. Introduction

Since both actual earnings per share (EPS) and consensus forecasts vary with scale across shares of different firms, prior research has reasonably presumed that deviations of actual EPS from consensus, or magnitudes of forecast error, also vary with scale.[1] Similarly, deviations of individual forecasts from the consensus, or forecast dispersion, are commonly assumed to vary with scale. We find, however, that both deviations vary little with scale for EPS forecasts in the United States.[2] We investigate analyst forecasts of cash flows and sales as well as forecasts in other markets for clues that explain the two surprising regularities. Our results suggest that the observed lack of scale variation arises from an unlikely source: managers of firms with large (small) shares smooth earnings more (less) such that volatility of reported EPS measured in cents per share is relatively similar for large and small shares.

As described in prior research (e.g., Barron et al. [1998]), forecast error magnitudes capture predictability of underlying EPS and forecast dispersion captures disagreement across analysts. We describe forecast error magnitudes by measures of variability, mainly the interquartile range, of the across-firm distribution of forecast errors. And we describe forecast dispersion by means and medians of the across-firm distribution of the standard deviation of individual analyst forecasts around the consensus for each firm-quarter or firm-year. Both measures are based on forecasts available on I/B/E/S just prior to earnings announcements. To illustrate the two surprising regularities, the interquartile range for EPS forecast errors is 4 or 5 cents and the median dispersion is 2 cents for all 10 price deciles, even though median share price for the highest price decile is over 10 times that for the lowest decile.[3] For convenience, we refer hereafter to forecast error magnitudes as *variability* and forecast dispersion as *disagreement*.

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[1] Even though scale at the share level appears arbitrary, since the number of shares can be altered at will, analysts focus on per share forecasts, not firm-level earnings. For example, figure 1 in Herrmann and Thomas [2005] shows that a disproportionately large fraction of EPS forecasts are rounded to multiples of 5 and 10 cents. This pattern is not expected if analysts forecast firm-level earnings and then divide by number of shares to compute EPS. Managers also seem to focus more on per share, rather than firm-level, earnings (e.g., Graham, Harvey, and Rajgopal [2005]).

[2] While the lack of scale for dispersion appears to be a new finding, lack of scale for forecast errors has been documented before: Figure 4 in DeGeorge, Patel, and Zeckhauser [1999] shows that interquartile ranges for forecast errors are relatively constant between the 10th and 90th percentiles of the price per share distribution. This result was not highlighted as being surprising, however, and seems to have been ignored in subsequent research.

[3] We use share price, rather than EPS, as our measure of scale for a number of reasons. First, being more general, price can also be used for sales and cash flow forecasts, which allows us to use the same decile cutoffs across different analyses. Second, price is less likely to be associated with measurement error (e.g., transitory deviations from underlying values). Third, price cannot be negative, and is less likely to generate unreasonably large deflated values when the scale measure is close to zero. We confirm, nevertheless, that qualitatively similar results are observed for deciles based on other measures of scale.

One important implication of these findings is that inferences from prior research based on *deflated* measures of variability and dispersion need to be reevaluated. Since variability and disagreement do not exhibit the scale variation that is commonly assumed, deflating by measures of scale, such as share price or actual/forecast EPS, creates a strong negative relation between scale and deflated variability/disagreement. Using deflated variability/disagreement as an independent (dependent) variable generates spurious results if the dependent (independent) variable happens to be correlated with scale.[4]

We consider three possible explanations for our puzzling findings. The first explanation we propose is that variability and disagreement do not vary with scale in nature, possibly because of subtle process and measurement issues associated with EPS forecasts that are missed by common intuition. For example, the average temperature measured in degrees Celsius in Florida is many times that in Alaska, and yet the process underlying temperature forecasts might cause magnitudes of forecast errors to be similar in Florida and Alaska.[5] Turning to potential reasons why EPS variability and disagreement might not vary with scale, it is possible that they are determined more by analyst/manager communication than by underlying uncertainty about EPS, since forecasts made just before earnings announcements may have been prepared after managers have observed preliminary estimates of EPS.

Our second explanation is that variability and disagreement do in fact increase naturally with scale, but other factors cause that scale variation to be reversed on average. For example, low price shares may have more stale forecasts than high price shares, and stale forecasts may be associated with higher forecast errors and forecast dispersion. In essence, regressions of variability and disagreement on scale show the predicted positive relation when controls for other variables that are relevant (e.g., forecast staleness) are included, but that relation is biased toward zero when those other variables correlated with scale are omitted.

The third explanation is motivated by our belief that the remarkable lack of variation with scale observed for EPS forecasts is unlikely to be a coincidental consequence of the net effects of different factors, as suggested by the second explanation. Instead, it is an outcome desired by analysts; that is, while variability/disagreement increases naturally with scale, analysts suppress that variation. Incentives or behavioral biases might explain why analysts focus on deviations from EPS benchmarks in cents per share,

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[4] To clarify our concern regarding deflated variability measures, bias might arise for deflated forecast error *magnitudes* (e.g., absolute forecast errors), not deflated forecast errors used to measure earnings surprise.

[5] Moving from process to measurement issues, the large difference in relative magnitudes of the two average temperatures reduces substantially when measured in degrees Kelvin, even though relative magnitudes of the two sets of forecast errors are unaffected by the switch to degrees Kelvin.

not a percentage of price or EPS levels, and why they target similar bounds for those deviations across small and large shares. For example, when comparing disagreement and variability, the financial press focuses on cents per share and does not adjust for scale. In response, analysts following high price shares might work harder to generate forecast error magnitudes and dispersion that are comparable to those for low price shares.

Our investigation produces the following results. First, variability and disagreement *increase* with scale for per share sales forecasts, unlike the patterns observed for EPS. Second, variability/disagreement for forecasts of operating cash flows per share also increases with scale. Third, whereas we find that the lack of scale variation observed in the United States for EPS is generally observed in most other large markets, there are some markets (e.g., Brazil, Italy, Japan, and Switzerland) where EPS variability and disagreement exhibit more variation with scale. Fourth, the lack of variation with scale observed for EPS forecasts made just before actual earnings are announced is also observed for forecasts made earlier. Fifth, EPS variability and disagreement decline proportionately with scale after share splits.

Finally, we find more surprising evidence when we shift our focus from analyst forecasts to time-series forecasts of EPS, sales, and cash flows, where time-series forecasts are based on a seasonal random walk expectation model. Since time-series forecasts do not involve analysts, they allow us to determine whether managers play a role in the lack of variation with scale observed for EPS forecasts for U.S. firms. Using Compustat data, we find patterns for time-series forecast errors that are similar to those for analyst forecasts; that is, deviations of EPS relative to last year's benchmark (or EPS volatility) vary only slightly with scale, whereas deviations for cash flows and sales vary substantially with scale.[6] Importantly, this relative lack of variation with scale for EPS volatility is not observed for firms without analyst following.

We believe this body of evidence is inconsistent with the first and second explanations. For example, if EPS variability and disagreement do not vary naturally with scale, per the first explanation, it seems unlikely that variability/disagreement for per share cash flows and accruals would both vary naturally with scale in such a way that variability/disagreement for the sum (=EPS) does not. And we were unable to find factors that increase (decrease) with scale and also decrease (increase) with variability/disagreement, which is the condition necessary for the second explanation, which posits that EPS variability and disagreement increase naturally with scale but that variation is reversed by omitted correlated factors. Other

[6] Again, while similar results for EPS volatility have been documented before, they were not viewed as puzzling and the implications have remained unexplored: DeGeorge, Patel, and Zeckhauser [1999, fig. 4] shows that the interquartile range for seasonally differenced EPS exhibits little variation with price once the top and bottom price deciles are excluded, where EPS is obtained from actuals according to I/B/E/S and Abel-Noser, rather than Compustat. We show in section 2.2 that results for I/B/E/S actuals and Compustat data are similar.

evidence that contradicts these two explanations is discussed in more detail later.

While the third explanation—analysts suppress natural scale variation for EPS variability and disagreement—is consistent with many of our results, it is not easily reconciled with the stock split results. Also, why does this explanation not apply to the subset of countries that exhibit more variation with scale for EPS variability/disagreement? More important, at a practical level, while increased analyst effort for high price firms can reduce disagreement to the level observed for low price firms, it's harder to see how increased analyst effort can result in a corresponding reduction in forecast errors for high price firms. Our results on the lack of scale variation observed for reported EPS volatility suggest a possible way: perhaps analysts following higher price shares are able to reduce forecast errors because managers cooperate and smooth the reported EPS being forecasted. To be sure, it is possible that analysts are not involved at all and managers of higher price firms independently seek to reduce volatility of reported EPS to the level observed for low price shares. But, for some reason, managers are less likely to engage in such differential smoothing behavior when their firms are not followed by analysts.

Overall, our results suggest that managers and analysts view deviations of EPS forecasts and reported numbers from relevant benchmarks in cents per share and do not adjust these deviations for scale. Could this tendency to ignore scale differences be due to behavioral biases? Not observing the same patterns for cash flows and sales suggests that analysts do not suffer from such biases. Managers also appear to recognize scale differences since reported EPS volatility for firms not followed by analysts exhibits more variation with scale. Apparently, managers and analysts are apprehensive about others, possibly investors, suffering from behavioral biases. Investigating these and other issues raised here has potentially important implications for our understanding of analyst and managerial behavior.

The remainder of this paper is organized as follows. The sample and our puzzling findings regarding lack of scale variation for EPS forecast variability and disagreement are described in section 2. Section 3 contains results of our efforts to investigate the three explanations we propose for the observed lack of scale variation, and section 4 concludes.

## 2. *Samples and Evidence of Lack of Scale Variation for EPS Forecast Variability/Disagreement*

### 2.1 SAMPLE SELECTION AND DESCRIPTION OF VARIABLES

For our main I/B/E/S sample, containing 129,364 firm-quarters, we include all U.S. firms on I/B/E/S with fiscal quarters ending in the 14 calendar years from 1993 to 2006. 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 includes adjustment by I/B/E/S for items analysts did not forecast.[7] We require nonmissing consensus forecasts (*FORECAST*), measured as the mean of individual forecasts, the actual EPS value according to I/B/E/S (*IBESACTL*), the standard deviation of individual forecasts around that consensus (*DISPERSION*), and stock price (*BEGPRICE*) as of the beginning of the calendar year of the fiscal quarter-end date.[8] (Details of all variables are provided in appendix A.) To allow a meaningful measure of dispersion, we delete firm-quarters with fewer than three forecasts.[9] Since our robustness investigation includes a comparison of variability/disagreement distributions across sectors, we exclude the "Miscellaneous/ Undesignated" sector as it had only a handful of firm-quarters.[10]

We focus on "unadjusted" values—not adjusted for stock splits—because of concerns about rounding in adjusted I/B/E/S data (Diether, Malloy, and Scherbina [2002]) and measure forecast error (*FCSTERR*) as *IBESACTL* minus *FORECAST*. Other I/B/E/S variables considered include the number of analysts issuing forecasts (*COVERAGE*) and the average age of individual forecasts as of the date of the consensus forecast (*MEANSTALE*). We use stock return data from CRSP to compute, fundamental volatility (*VOL*), measured as the standard deviation of daily returns over a prior 200-day window. No variables have been Winsorized or truncated.[11]

We switch to annual data for per share cash flow (CPS) because quarterly forecasts are very infrequent in the United States; only about 1% of firm-quarters in our main sample have three or more CPS forecasts. Although sales forecasts are more common in the United States—about a quarter of our main sample have three or more sales forecasts—we report results based on annual data to maintain consistency with our CPS results. (We

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

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

[9] This requirement is also observed in practice. 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).

[10] Investigation of time-series variation in sample size suggests a general increase through time, with a temporary decline in the years 1999 to 2003. Investigation of across-sector variation suggests considerable variation: Technology has the most observations (25,469) while Transportation has the fewest (3,228).

[11] One firm, Berkshire Hathaway (I/B/E/S ticker is 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 *IBESACTL* of $1,859 versus a *FORECAST* of $1,452.36). This error is so large that it skews some of our descriptive statistics (the next highest forecast error in our sample is below $11).

confirm that similar results are observed for quarterly data.) Since analysts forecast sales at the firm level, we divide sales forecasts and actuals by the numbers of shares outstanding to get the corresponding sales per share (SPS) value. We require that the CPS and SPS samples also have three or more EPS forecasts to confirm that our overall EPS patterns based on quarterly data are observed for annual data for the CPS and SPS firm-years.[12] Our CPS and SPS samples of U.S. firms with three or more forecasts contain 1,563 and 13,487 firm-years, respectively.

To increase the representativeness of the CPS and SPS analyses, we relax the three-forecast-minimum requirement and include firm-years with one or two analyst forecasts, but do so only when investigating forecast errors, not forecast dispersion. The expanded CPS and SPS samples contain 4,197 and 24,119 firm-years, respectively.

We use similar selection criteria to build I/B/E/S samples for overseas firms, but examine annual data because quarterly financial statements are not filed in many markets. We create country groups based on currency codes and geographical locations. For example, firms in mainland China whose forecasts are in Hong Kong dollars (HKD) are aggregated with other firms in Hong Kong. However, countries in the European monetary union (with forecasts denominated in Euros) are listed separately (e.g., France and Germany). We required that (a) the earnings announcement date falls after the fiscal period end date and the forecast date, (b) the currency codes of actual and forecast are the same, and (c) at least 50 observations are included each country-year to allow a reasonable sample size for different price deciles.

Although we analyze a number of countries with sufficient firm-years to provide meaningful results, we report results for eight representative countries. The first group resembles the United States in terms of exhibiting relatively little variation with scale for EPS variability and disagreement and contains 3,023, 7,316, 4,146, and 1,811 firm-years from Australia, U.K., Canada, and Germany, respectively. The second group exhibits relatively higher variation with scale for EPS variability and disagreement, and consists of 485, 1,556, 9,170, and 967 firm-years from Brazil, Switzerland, Japan, and Italy, respectively. As with the CPS and SPS analyses, we increase sample size when investigating forecast error (but not dispersion) by including firm-years with one or two forecasts. The expanded sample sizes are 4,339, 12,711, 6,079, and 3,040 firm-years from Australia, U.K., Canada, and Germany, respectively, and 691, 2,090, 19,060, and 1,349 firm-years from Brazil, Switzerland, Japan, and Italy, respectively.

For our time-series forecast samples, we include firm-quarters from Compustat with nonmissing values for *BEGPRICE* as well as seasonally differenced quarterly per share earnings, sales, and cash flows over the same 1993 to 2006 period. We drop ADRs and firms not incorporated in the United

[12] Prior research (e.g., Defond and Hung [2003]) suggests that firms with sales and cash flow forecasts differ systematically from firms without these forecasts.

States. Since forecast error equals deviations from prior year, same-quarter amounts, it is in effect a measure of underlying volatility for reported EPS, CPS, and SPS.

To allow comparisons of forecast errors from time-series and analyst forecasts, we attempt to match all firm-quarters from Compustat with observations included in our main I/B/E/S quarterly sample.[13] To contrast time-series forecast errors for firms followed by analysts with those for firms not followed by analysts, we create a second sample of Compustat firm-quarters with nonmissing data over the same sample period based on firms that do not appear on I/B/E/S. Our Compustat samples of firms with and without analyst following include 115,609 and 23,774 firm-quarters with EPS time-series forecast errors, respectively. The sample sizes for CPS and SPS are slightly smaller due to the missing values.

Price deciles are formed each calendar year within each country based on beginning-of-year share price (*BEGPRICE*). Deciles for *BEGPRICE* are created by identifying firm-quarters (firm-years for our overseas samples) that end during that calendar year and have at least three EPS forecasts on I/B/E/S. Since the firms included to form price deciles are not represented equally in our samples, the different samples we consider are not distributed evenly across the price deciles. For example, low price firms in our main I/B/E/S sample will be underrepresented since they are less likely than high price firms to have at least three EPS forecasts in the remaining quarters that year, and low price firms are overrepresented in our Compustat sample of firms without analyst following because analyst coverage increases with share price.

Panel A0 in table 1 reports means and medians for the different variables for our primary I/B/E/S sample of U.S. firm-quarters. There is considerable variation in scale across the price deciles: mean and median values of *BEGPRICE* for the highest decile are well over 10 times those for the lowest decile. This variation in the scale of share price is mirrored in corresponding variation in the magnitudes of consensus EPS forecasts (*FORECAST*) and actual EPS according to I/B/E/S (*IBESACTL*) and Compustat (*COMPACTL*). Since the one-time items excluded from *IBESACTL* are on average negative, the means and medians for *IBESACTL* are slightly higher than those for *COMPACTL*. The three remaining rows indicate that analyst following (*COVERAGE*) increases with share price, whereas the average age of forecasts (*MEANSTALE*) and return volatility (*VOL*) decrease with share price.

### 2.2 LACK OF VARIATION WITH SCALE FOR VARIABILITY/DISAGREEMENT FOR MAIN I/B/E/S SAMPLE

Panels A, B, and C of figure 1 provide a graphical view of the across-price-decile distribution of forecast variability and disagreement, both

[13] We use the IBES-CRSP linking program provided on WRDS in combination with the CRSP-Compustat Merged Database. See http://wrds.wharton.upenn.edu/support/docs/ibes/linking.shtml.

**TABLE 1**

*Distributional Statistics for EPS Forecast Error and Dispersion in Each BEGPRICE Decile*

**Panel A0: Variation Across *BEGPRICE* Deciles in Means and Medians of Selected Variables, Reported in the Top and Bottom Halves of Each Row, Respectively**

| Variable | Stats | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *BEGPRICE* | Mean | 6.0 | 10.6 | 14.5 | 18.1 | 22.0 | 26.0 | 30.8 | 36.9 | 46.0 | 75.7 | 28.7 |
| | Median | 6.1 | 10.8 | 14.7 | 18.3 | 22.3 | 26.1 | 30.8 | 36.8 | 45.3 | 64.5 | 24.0 |
| *FORECAST* | Mean | −0.02 | 0.07 | 0.14 | 0.20 | 0.28 | 0.33 | 0.40 | 0.46 | 0.56 | 0.86 | 0.33 |
| | Median | 0.01 | 0.10 | 0.17 | 0.22 | 0.29 | 0.33 | 0.40 | 0.46 | 0.55 | 0.74 | 0.28 |
| *IBESACTL* | Mean | −0.04 | 0.05 | 0.13 | 0.20 | 0.28 | 0.33 | 0.40 | 0.47 | 0.57 | 0.88 | 0.33 |
| | Median | 0.01 | 0.10 | 0.17 | 0.22 | 0.29 | 0.34 | 0.41 | 0.47 | 0.55 | 0.75 | 0.28 |
| *COMPACTL* | Mean | −0.12 | −0.01 | 0.06 | 0.14 | 0.22 | 0.28 | 0.35 | 0.41 | 0.51 | 0.82 | 0.27 |
| | Median | −0.01 | 0.08 | 0.15 | 0.21 | 0.27 | 0.32 | 0.39 | 0.44 | 0.53 | 0.72 | 0.26 |
| *COVERAGE* | Mean | 5.1 | 5.7 | 6.4 | 6.8 | 7.3 | 7.8 | 8.4 | 9.2 | 10.3 | 12.5 | 8.0 |
| | Median | 4.0 | 4.0 | 5.0 | 5.0 | 6.0 | 6.0 | 7.0 | 8.0 | 9.0 | 12.0 | 6.0 |
| *MEANSTALE* | Mean | 81.5 | 79.7 | 78.0 | 77.0 | 77.1 | 78.3 | 76.9 | 74.1 | 72.1 | 69.1 | 76.4 |
| | Median | 73.2 | 71.0 | 70.0 | 68.8 | 70.0 | 70.4 | 69.0 | 67.3 | 65.8 | 63.8 | 68.8 |
| *VOL* | Mean | 0.04 | 0.04 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.02 | 0.02 | 0.02 | 0.03 |
| | Median | 0.04 | 0.03 | 0.03 | 0.03 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.03 |

(*Continued*)

**TABLE 1** — *Continued*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | All |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A1: Distributional Statistics for *FCSTERR* in Each *BEGPRICE* Decile** | | | | | | | | | | | |
| Mean | −0.02 | −0.01 | −0.01 | −0.00 | −0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.02 | 0.00 |
| Median | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.01 |
| StdDev | 0.28 | 0.17 | 0.15 | 0.15 | 0.22 | 0.15 | 0.17 | 0.23 | 0.16 | 0.31 | 0.21 |
| QRange | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.05 | 0.05 | 0.05 | 0.04 |
| *N* | 12,946 | 12,986 | 12,838 | 12,943 | 12,973 | 12,898 | 12,962 | 12,966 | 12,927 | 12,925 | 129,364 |
| **Panel A2: Distributional Statistics for *COMPFE* in Each *BEGPRICE* Decile** | | | | | | | | | | | |
| Mean | −0.10 | −0.08 | −0.07 | −0.06 | −0.06 | −0.05 | −0.04 | −0.05 | −0.06 | −0.05 | −0.06 |
| Median | −0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.00 |
| StdDev | 0.58 | 0.56 | 0.62 | 0.49 | 0.49 | 0.57 | 0.58 | 0.67 | 0.71 | 1.13 | 0.67 |
| QRange | 0.08 | 0.09 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.09 | 0.09 | 0.13 | 0.09 |
| *N* | 12,527 | 12,670 | 12,461 | 12,551 | 12,479 | 12,446 | 12,520 | 12,537 | 12,471 | 12,535 | 125,197 |
| **Panel A3: Distributional Statistics for *DEFLFE* in Each *BEGPRICE* Decile** | | | | | | | | | | | |
| Mean | −0.0048 | −0.0010 | −0.0004 | −0.0000 | −0.0000 | 0.0001 | 0.0002 | 0.0003 | 0.0003 | 0.0003 | −0.0005 |
| Median | 0.0000 | 0.0000 | 0.0006 | 0.0005 | 0.0004 | 0.0004 | 0.0003 | 0.0003 | 0.0002 | 0.0002 | 0.0003 |
| StdDev | 0.1165 | 0.0157 | 0.0106 | 0.0083 | 0.0105 | 0.0058 | 0.0056 | 0.0061 | 0.0034 | 0.0036 | 0.0378 |
| QRange | 0.0081 | 0.0042 | 0.0030 | 0.0022 | 0.0018 | 0.0015 | 0.0014 | 0.0012 | 0.0011 | 0.0008 | 0.0019 |
| *N* | 12,946 | 12,986 | 12,838 | 12,943 | 12,973 | 12,898 | 12,962 | 12,966 | 12,927 | 12,925 | 129,364 |
| **Panel B1: Distributional Statistics for *ABSFE* in Each *BEGPRICE* Decile** | | | | | | | | | | | |
| Mean | 0.07 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.06 | 0.06 | 0.06 | 0.10 | 0.06 |
| Median | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.03 | 0.03 | 0.02 |
| StdDev | 0.27 | 0.16 | 0.14 | 0.14 | 0.21 | 0.14 | 0.17 | 0.22 | 0.14 | 0.29 | 0.20 |
| QRange | 0.05 | 0.04 | 0.04 | 0.05 | 0.04 | 0.04 | 0.05 | 0.05 | 0.06 | 0.08 | 0.05 |
| *N* | 12,946 | 12,986 | 12,838 | 12,943 | 12,973 | 12,898 | 12,962 | 12,966 | 12,927 | 12,925 | 129,364 |

(*Continued*)

**TABLE 1** — *Continued*

| **Panel B2: Distributional Statistics for *DEFLABSFE* in Each *BEGPRICE* Decile** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | All |
| Mean | 0.0154 | 0.0054 | 0.0038 | 0.0030 | 0.0024 | 0.0020 | 0.0018 | 0.0016 | 0.0014 | 0.0013 | 0.0038 |
| Median | 0.0041 | 0.0022 | 0.0015 | 0.0012 | 0.0009 | 0.0008 | 0.0007 | 0.0006 | 0.0006 | 0.0005 | 0.0010 |
| StdDev | 0.1156 | 0.0148 | 0.0099 | 0.0077 | 0.0102 | 0.0055 | 0.0053 | 0.0059 | 0.0031 | 0.0034 | 0.0376 |
| QRange | 0.0089 | 0.0044 | 0.0031 | 0.0025 | 0.0020 | 0.0017 | 0.0016 | 0.0014 | 0.0013 | 0.0011 | 0.0026 |
| *N* | 12,946 | 12,986 | 12,838 | 12,943 | 12,973 | 12,898 | 12,962 | 12,966 | 12,927 | 12,925 | 129,364 |
| **Panel C1: Distributional Statistics for *DISPERSION* in Each *BEGPRICE* Decile** | | | | | | | | | | | |
| Mean | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.04 | 0.05 | 0.03 |
| Median | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
| StdDev | 0.09 | 0.05 | 0.04 | 0.06 | 0.04 | 0.05 | 0.05 | 0.06 | 0.06 | 0.11 | 0.06 |
| QRange | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.03 | 0.03 | 0.04 | 0.02 |
| *N* | 12,946 | 12,986 | 12,838 | 12,943 | 12,973 | 12,898 | 12,962 | 12,966 | 12,927 | 12,925 | 129,364 |
| **Panel C2: Distributional Statistics for *DEFLDISP* in Each *BEGPRICE* Decile** | | | | | | | | | | | |
| Mean | 0.0070 | 0.0028 | 0.0019 | 0.0016 | 0.0012 | 0.0011 | 0.0010 | 0.0009 | 0.0008 | 0.0007 | 0.0019 |
| Median | 0.0030 | 0.0015 | 0.0012 | 0.0010 | 0.0008 | 0.0007 | 0.0006 | 0.0005 | 0.0004 | 0.0004 | 0.0008 |
| StdDev | 0.0433 | 0.0052 | 0.0030 | 0.0036 | 0.0017 | 0.0018 | 0.0017 | 0.0015 | 0.0012 | 0.0012 | 0.0140 |
| QRange | 0.0046 | 0.0021 | 0.0015 | 0.0012 | 0.0009 | 0.0008 | 0.0008 | 0.0007 | 0.0007 | 0.0006 | 0.0014 |
| *N* | 12,946 | 12,986 | 12,838 | 12,943 | 12,973 | 12,898 | 12,962 | 12,966 | 12,927 | 12,925 | 129,364 |

(*Continued*)

**TABLE 1**— *Continued*

**Panel D1: Distributional Statistics for *FCSTERR* in Each *BEGPRICE* Decile, Based on Forecasts Made 9 Months Before the End of Fiscal Quarter**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | All |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | −0.09 | −0.10 | −0.09 | −0.09 | −0.08 | −0.07 | −0.07 | −0.07 | −0.08 | −0.12 | −0.09 |
| Median | −0.04 | −0.05 | −0.04 | −0.03 | −0.03 | −0.02 | −0.02 | −0.02 | −0.03 | −0.02 | −0.03 |
| StdDev | 0.40 | 0.28 | 0.27 | 0.33 | 0.26 | 0.29 | 0.29 | 0.35 | 0.37 | 0.65 | 0.38 |
| QRange | 0.15 | 0.16 | 0.16 | 0.16 | 0.15 | 0.15 | 0.16 | 0.17 | 0.21 | 0.31 | 0.18 |
| *N* | 6,335 | 6,770 | 6,957 | 7,229 | 7,588 | 7,730 | 8,068 | 8,369 | 8,910 | 9,511 | 77,467 |

**Panel D2: Distributional Statistics for *DISPERSION* in Each *BEGPRICE* Decile, Based on Forecasts Made 9 Months Before the End of Fiscal Quarter**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | All |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.03 | 0.03 | 0.03 | 0.04 | 0.03 | 0.03 | 0.04 | 0.04 | 0.05 | 0.07 | 0.04 |
| Median | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.03 | 0.03 | 0.02 |
| StdDev | 0.05 | 0.05 | 0.05 | 0.07 | 0.05 | 0.05 | 0.05 | 0.06 | 0.07 | 0.14 | 0.07 |
| QRange | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.04 | 0.04 | 0.05 | 0.03 |
| *N* | 6,335 | 6,770 | 6,957 | 7,229 | 7,588 | 7,730 | 8,068 | 8,369 | 8,910 | 9,511 | 77,467 |

This table reports the mean, median, standard deviation (StdDev), interquartile range (QRange), and the number of observations (*N*) for distributions of different variables across deciles of *BEGPRICE*, which is the beginning-of-year share price. Price deciles are computed each calendar year, and the lowest (highest) price decile is denoted by 1 (10). *FCSTERR* is defined as *IBESACTL* minus *FORECAST*, where *IBESACTL* is the actual quarterly EPS as reported by I/B/E/S, and *FORECAST* is the most recent consensus (mean) EPS forecast for that firm-quarter. *COMPFE* is *COMPACTL* (after adjusting for dilution factor) minus *FORECAST*, where *COMPACTL* is the actual quarterly EPS as reported by Compustat. *ABSFE* is the absolute value of *FCSTERR*. *DISPERSION* is the standard deviation of the *individual* analyst forecasts around the consensus. *DEFLFE*, *DEFLABSFE*, and *DEFLDISP* are defined as *FCSTERR*, *ABSFE*, and *DISPERSION* scaled by *BEGPRICE*, respectively. *COVERAGE* is the number of estimates that constitute *FORECAST*. *MEANSTALE* is the average forecast age across individual forecasts. *VOL* is the standard deviation of stock returns over the period from day −210 to −11, relative to the fiscal quarter-end. The sample contains 129,364 firm-quarters derived from U.S. firms on I/B/E/S with available data, fiscal period end date between January 1993 and December 2006, and *COVERAGE* $\geq 3$. Additional details for all variables are provided in appendix A. All prices and forecast/actual EPS are denominated in dollars.

Panel A: Distribution of *FCSTERR* (A1), *COMPFE* (A2), and *DEFLFE* (A3) in each *BEGPRICE* decile

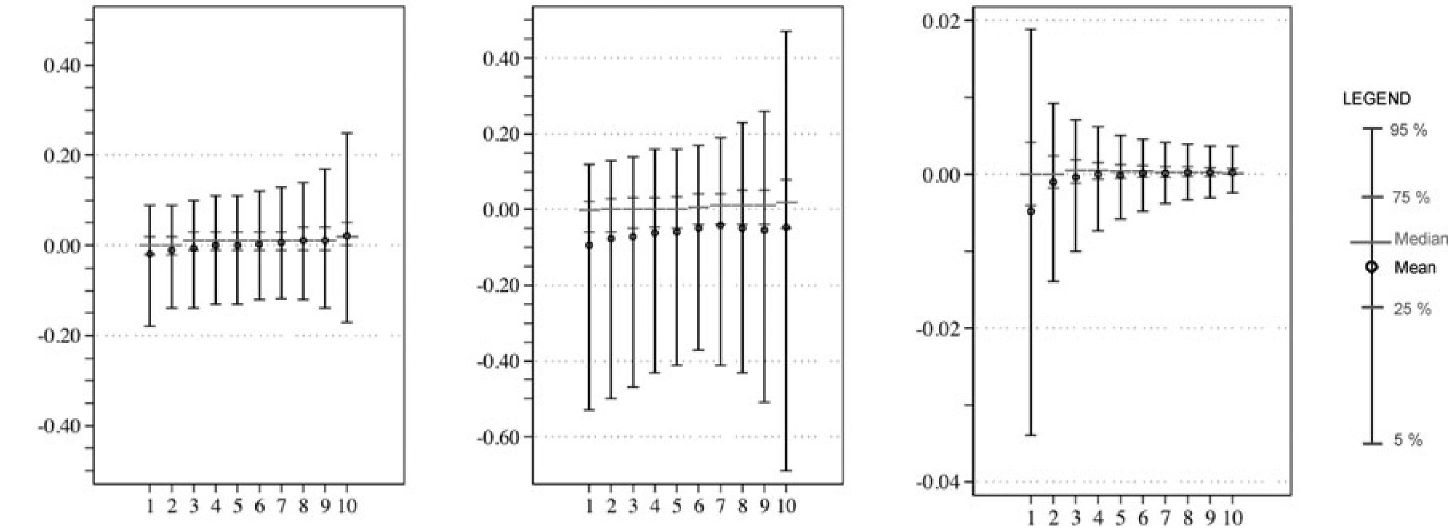


FIG. 1.—Distribution of EPS forecast error and dispersion for different *BEGPRICE* deciles. The plots describe key distributional statistics for measures of forecast error and forecast dispersion for different deciles of *BEGPRICE*, which is the beginning-of-year share price. Price deciles are computed each calendar year, and the lowest (highest) price decile is denoted by 1 (10). The mean is indicated by the solid circle, the median by the long horizontal hash mark, and the remaining hash marks locate the 5th, 25th, 75th, and 95th percentiles of the pooled distributions for the different variables. *FCSTERR* is defined as *IBESACTL* minus *FORECAST*, where *IBESACTL* is the actual quarterly EPS as reported by I/B/E/S, and *FORECAST* is the most recent consensus (mean) EPS forecast for that firm-quarter. *COMPFE* equals *COMPACTL* (after adjusting for dilution factor) minus *FORECAST*, where *COMPACTL* is the actual quarterly EPS as reported by Compustat. *ABSFE* is the absolute value of *FCSTERR*. *DISPERSION* is the standard deviation of the *individual* analyst forecasts around the consensus in that firm-quarter. *DEFLFE*, *DEFLABSFE*, and *DEFLDISP* are defined as *FCSTERR*, *ABSFE*, and *DISPERSION* scaled by *BEGPRICE*, respectively. The sample contains 129,364 firm-quarters derived from U.S. firms on I/B/E/S with available data, fiscal period end date between January 1993 and December 2006, and at least three EPS forecasts. All prices and forecast/actual EPS are denominated in dollars. All variables are described in more detail in appendix A.

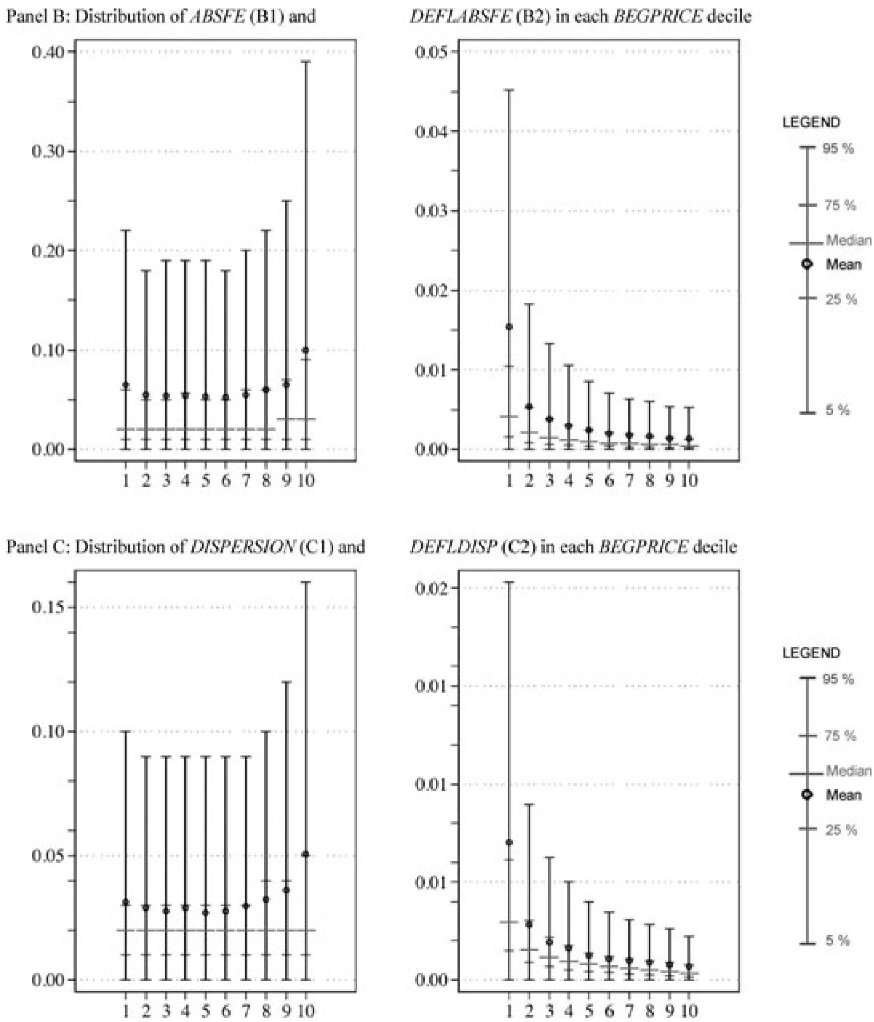


FIG. 1.—*Continued*

undeflated and deflated by share price. Each vertical bar represents the distribution for one price decile, and the different marks identify the location of the mean, median, and 5th, 25th, 75th, and 95th percentiles of the corresponding pooled distributions. Numerical values for the mean, median, standard deviation, and interquartile ranges for these distributions are provided in the corresponding panels of table 1. To ease the transition between graphical and tabular views, we use the same panel labels; for example, the left box in panel A of figure 1, which is labeled A1, and panel A1 in table 1 both describe the distributions for *FCSTERR*.

Results in panel A1 of figure 1 and table 1 suggest that forecast error magnitudes exhibit almost no variation across price deciles. For example, the spread between the hash marks for the 25th and 75th percentiles in figure 1, represented by QRange in table 1, is either 4 or 5 cents for all 10 deciles. The results in panel B1 of figure 1 and table 1 suggest the same conclusion based on the distributions of absolute values of forecast errors (*ABSFE*). The median forecast error magnitudes are 2 or 3 cents and the mean values are 5 or 6 cents for deciles 2 through 9 and slightly higher for the two extreme price deciles. Note that the absolute values in panel B1 overstate variability when the means/medians are not zero, and the degree of overstatement increases for more extreme price deciles. This is because the mean/median forecast errors in panel A1 indicate a systematic pattern of more negative (positive) deviations from zero as one moves from the middle price deciles toward lower (higher) price deciles.

There is a concern that *IBESACTL*, which proxies for the "core" earnings number that analysts attempt to forecast, may be biased in unexpected ways since I/B/E/S adjusts it after observing the price reaction to announced earnings.[14] To alleviate those concerns, we report in panel A2 the distribution of *COMPFE*, forecast errors measured relative to actual EPS as reported by Compustat. While the spreads in panel A2 are larger than the corresponding spreads in panel A1, there is once again remarkably little variation in those larger spreads across the price deciles. Overall, consensus forecasts are almost equally accurate, where accuracy is measured in cents per share, regardless of whether the EPS number being forecast is only a few cents (for firms in smaller price deciles) or almost a dollar (for firms in decile 10).

The results in panel C1 of figure 1 and table 1 suggest a similar, remarkable lack of variation with scale for disagreement across analysts, measured by forecast dispersion. As with *ABSFE* in panel B1, the focus is not on the spreads of these distributions, but on the means and medians, since the variable (*DISPERSION*) already measures spread across individual forecasts. The median value of *DISPERSION* is 2 cents for all price deciles, and the mean is 3 cents for price deciles 1 through 8, and increases slightly to 5 cents for decile 10. Again, analyst disagreement around the consensus measured in cents per share is the same even though the magnitude of the EPS being forecast in decile 10 is many times larger than it is in decile 1.

Panels A and B of figure 2 offer a more detailed view of the distributions of forecast error and dispersion, respectively, to determine whether the distributional statistics reported in figure 1 mask some unusual patterns. The histograms reported show the fraction of the sample represented by each cent of forecast error and dispersion. For brevity, we only report histograms for three price deciles: deciles 1, 5, and 10, representing low, medium, and

[14] The Wharton Research Data Services (Glushkov [2007, p. 27]) provides the following description: "IBES observes the market reaction to the earnings announcement prior to choosing exactly which earnings components to include in street earnings. This leads to a potential ex post selection bias." Bradshaw and Sloan [2002, p. 42] define street earnings as the "numbers announced by corporations in their press releases and tracked by analyst estimate clearinghouse services, such as I/B/E/S."

high price shares, respectively. Scrutiny of these histograms reveals interesting patterns, such as (a) the frequency of large negative forecast errors (less than −30 cents per share) is high for both low and high price shares, but low for medium price shares, (b) the frequency of large positive forecast errors (greater than 30 cents per share) is high only for high price

Panel A: Histograms for *FCSTERR* (for price deciles 1, 5, and 10)

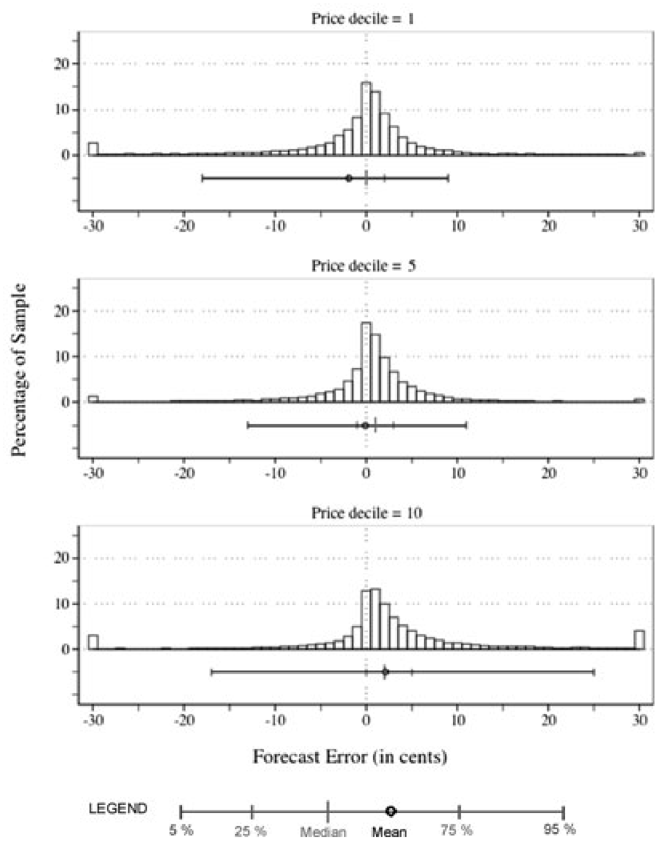


FIG. 2.—Histograms of EPS forecast error and dispersion for selected *BEGPRICE* deciles. The histograms for *FCSTERR* and *DISPERSION*, measured in cents per share, are provided for deciles 1, 5, and 10 of *BEGPRICE*, which is the beginning-of-year share price. Values below (above) −30 (30) cents are combined with observations in the −30 (30) cent group. The horizontal line below each histogram contains a solid circle to represent the mean; a long vertical hash mark for the median; and hash marks for the 5th, 25th, 75th, and 95th percentiles of each distribution. *FCSTERR* is defined as *IBESACTL* minus *FORECAST*, where *IBESACTL* is the actual quarterly EPS as reported by I/B/E/S, and *FORECAST* is the most recent consensus (mean) EPS forecast for that firm-quarter. *DISPERSION* is the standard deviation of the *individual* analyst forecasts around the consensus in that quarter. The sample contains 129,364 firm-quarters derived from U.S. firms on I/B/E/S with available data, fiscal period end date between January 1993 and December 2006, and at least three EPS forecasts. All variables relate to firm-quarters, and are described in more detail in appendix A.

Panel B: Histogram for *DISPERSION* (for price deciles 1, 5, and 10).

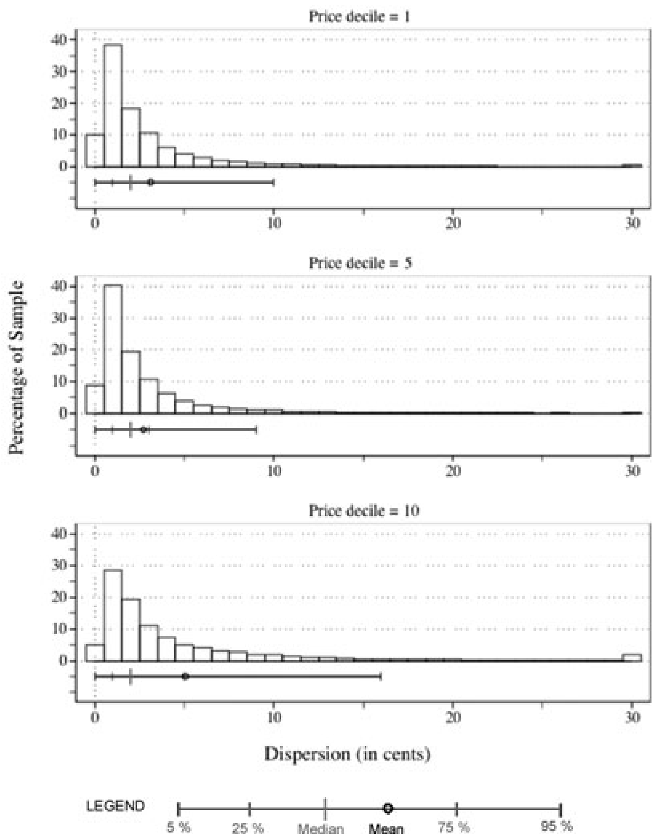


FIG. 2.—*Continued*

shares, consistent with right-skewness observed in figure 1, panel A1, (c) the fraction of observations in the "just missed" category (forecast errors of −1 and −2 cents) is lower for high price shares, and (d) the fraction of observations with dispersions of 0 and 1 cents decreases with share price.

While the figure 2 histograms indicate specific aspects that vary across share price deciles, especially regarding middle and tail asymmetries in the forecast error distributions, they confirm our main finding that variability and disagreement are fairly similar across price deciles.[15] It is not the case, for example, that observed lack of scale for variability is driven by most

[15] Abarbanell and Lehavy [2003, p. 106] define (left) tail asymmetry as "a larger number and a greater magnitude of observations that fall in the extreme negative relative to the extreme positive tail of the forecast error distributions" and middle asymmetry as "a higher incidence of small positive relative to small negative forecast errors in cross-sectional distributions."

observations having zero forecast error, where actual EPS exactly meets the consensus.

We conducted several additional analyses to gauge the robustness of our main finding. In particular, we partitioned our sample along different dimensions (e.g., year, industry, and growth) to determine whether the lack of scale variability was observed in each subsample. Our results indicate that while some subsamples exhibit levels of variability/disagreement that differ across price deciles, especially for extreme price deciles, the overall picture in each subsample is that there is relatively little systematic increase in variability/disagreement as price increases. We observe differences in the levels of variability and disagreement *across* the 11 broad industry sector groups provided by I/B/E/S.[16] For example, magnitudes of forecast errors (variability) and levels of dispersion (disagreement) are lower in the health care and technology sectors, but higher in the transport and utilities sectors. However, *within* each sector we observe the same general pattern of similar variability and disagreement across price deciles noted in the full sample.

We also confirm that our findings remain qualitatively unchanged when we (a) use the median of the individual forecasts each quarter, instead of the mean, to represent the consensus forecast, and (b) use absolute values of forecast earnings and per share level of total assets as alternative measures of scale, instead of share price.[17] Overall, these and other sensitivity analyses not discussed here suggest that the puzzling lack of scale variation we observe for variability and disagreement are indeed robust findings.

Given that variability and disagreement are relatively unrelated to scale, deflating them by a scale measure should create a strong negative relation with scale. That expectation is confirmed by the results in panels A3, B2, and C2, which provide the distributions for price-deflated values of forecast errors (*DEFLFE*), absolute forecast errors (*DEFLABSFE*), and dispersion (*DEFLDISP*), respectively. Given the strong positive correlation across measures of scale, similar results are expected for other measures of scale, such as the level of forecast or actual EPS. Appendix B provides examples of prior research that uses deflated forecast error magnitudes/dispersion as either the dependent variable or independent variable.[18] We do not

[16] We did not consider other traditional or nontraditional (e.g., Davies, Minton, and Schrand [2009]) industry partitions.

[17] For example, the interquartile range of forecast errors increases from about 4 cents for the first seven deciles based on absolute forecast EPS to 5 cents for decile 8, 6 cents for decile 9, and 10 cents for decile 10. Median dispersion ranges between 1 and 2 cents for the first nine deciles and increases to 4 cents for decile 10. Some of the higher forecast error magnitudes and dispersion observed for higher deciles are due to low price firms with large negative EPS forecasts.

[18] DeGeorge, Patel, and Zeckhauser [1999] is a notable exception. Based on the finding that magnitudes of forecast error are relatively constant for the middle eight deciles, that study examines *undeflated* forecast errors. Alternative deflators that are less likely to create a negative relation with scale include firm-specific measures of variability from (a) the time-

investigate here the extent to which the inferences made in those studies might be altered because of the strong negative relation with scale created by deflation. Nor have we conducted an analysis of ways to deal with cross-sectional differences in variability/disagreement if deflation results in biased estimates.

## *3. Investigation of Explanations for Our Puzzling Findings*

### 3.1 ARE RESULTS SENSITIVE TO FORECAST HORIZON?

Even though the prior literature tends to focus on analyst forecasts made just prior to earnings reports, we investigate next whether those forecasts are affected by information about actual outcomes. In particular, analysts may learn directly or indirectly about preliminary estimates of quarterly EPS available to managers. While magnitudes of forecast errors and dispersion would vary with scale if forecasts reflected the uncertainty underlying reported earnings, they might no longer vary with scale (as posited by our first explanation) if forecasts reflect the extent to which analysts obtain information about actual outcomes.

To explore this possibility, we consider forecast variability and disagreement associated with forecasts made nine months prior to the fiscal quarter end. At this longer horizon, analysts should indeed be faced with the uncertainty underlying reported quarterly earnings. The results reported for variability of *FCSTERR* in panel D1 (StdDev and QRange) and magnitudes of *DISPERSION* in panel D2 (means and medians) show the same lack of scale variation reported for most recent forecasts in panels A1 and C1, respectively. To be sure, the magnitudes of forecast errors at the longer horizon are slightly higher for price deciles 9 and 10 (interquartile ranges of 21 and 31 cents), relative to the remaining eight deciles (15 to 17 cents), but that increase is small compared to the variation in scale across the price deciles.

Not only is this lack of scale variation for longer horizon forecasts inconsistent with the first explanation, since it rejects the conjecture we offer in support of that explanation, it also argues against the second explanation. If the factors that reverse natural variation with scale are less intense many months before the quarter begins, relative to when the most recent forecasts are collected, we should observe clear variation with scale at the longer horizon. These results are consistent with the third explanation, since they suggest that analysts focus on undeflated deviations from relevant EPS benchmarks at all horizons.

### 3.2 ANALYSTS' ANNUAL SALES AND CASH FLOW FORECASTS FOR U.S. FIRMS

Before investigating *annual* forecasts for sales and cash flows, we check whether the lack of scale variation documented for quarterly EPS forecasts

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series distribution of prior forecast errors (e.g., Foster, Olsen, and Shevlin [1984]) and (b) the across-analyst distribution of forecast errors.

carries over to annual EPS forecasts for U.S. firms. Untabulated results confirm that annual data exhibit the same lack of variation across price deciles observed for quarterly data.[19]

The top and bottom halves of panel A of table 2 compare variability and disagreement for annual EPS and SPS, respectively, for our U.S. subsample with sales forecasts. The first row, median *BEGPRICE*, suggests that share price variation across the 10 price deciles in this subsample is similar to that for our main sample, and the median *IBESACTL* values reported in the second rows of the two halves confirm similar variation with scale for the level of EPS and SPS, respectively. The fifth row describes variation in the median *DISPERSION*, which measures disagreement, and the sixth row reports the number of observations in the sample. The third row describes variation in the interquartile range of *FCSTERR*, which measures variability, and the fourth row reports the number of observations in the expanded sample, which includes firm years with one or two analyst forecasts, used to investigate variability.

The results reported for variability (third row) and disagreement (fifth row) for EPS in the top half indicate relatively little variation across the price deciles, which suggests that the subsample with sales forecasts is not different from our primary sample along this dimension. The results reported for SPS in the third and fifth rows in the bottom half, however, indicate a strong relation with scale. The interquartile range of forecast errors increases substantially from 16 cents for the lowest price decile to 66 cents for the highest price decile, and median dispersion increases from 2 cents for the lowest price decile to 23 cents for the highest price decile.

This evidence does not support the first and second explanations. If variability and disagreement for EPS do not increase naturally with scale (as proposed by our first explanation), why then should variability and disagreement for SPS increase with scale? Given that earnings equals sales minus expenses, it seems unlikely that natural variation with scale for sales per share would be offset exactly by corresponding natural variation with scale for expense per share. Turning to our second explanation, if factors that are correlated with scale reverse natural variation with scale for EPS variability and disagreement, why do not those factors reverse natural variation with scale for SPS too?

Panel B of table 2 compares variability and disagreement for EPS versus CPS for our subsample with cash flow forecasts. The results reported for EPS in the top half of panel B confirm relatively little difference across price deciles in forecast variability (interquartile ranges for forecast errors in the third row) and disagreement (median dispersion in the fifth row)

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[19] We expect the level of forecast error variability and dispersion for our annual forecast data to be similar to that for quarterly data, since we gather the most recent forecast before earnings are announced. At that point, the annual EPS forecast is in essence a fourth quarter forecast, since actual EPS for the three interim quarters is already known. We find, however, that interquartile ranges for *FCSTERR* and median *DISPERSION* for annual EPS data are higher than those for quarterly EPS data. We are unable to explain this result.

**TABLE 2**

*Variability and Disagreement in Annual Sales and Operating Cash Flow Forecasts for U.S. Firms*

**Panel A: Subsample of U.S. Firm-Years with Data for Both EPS and SPS**

| | | | Price Deciles | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Type | Statistic | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| EPS | Median | *BEGPRICE* | 4.7 | 9.7 | 14.0 | 17.9 | 22.0 | 26.4 | 31.4 | 37.5 | 46.2 | 66.0 |
| | Median | *IBESACTL* | −0.14 | 0.22 | 0.56 | 0.84 | 1.10 | 1.30 | 1.59 | 1.79 | 2.09 | 2.65 |
| | QRange | *FCSTERR* | 0.08 | 0.06 | 0.07 | 0.05 | 0.06 | 0.05 | 0.05 | 0.05 | 0.06 | 0.06 |
| | *N* | *FCSTERR* | 3,945 | 2,705 | 2,463 | 2,271 | 2,216 | 2,136 | 2,142 | 2,113 | 2,089 | 2,039 |
| | Median | *DISPERSION* | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
| | *N* | *DISPERSION* | 1,187 | 1,232 | 1,248 | 1,254 | 1,275 | 1,313 | 1,363 | 1,443 | 1,521 | 1,651 |
| SPS | Median | *BEGPRICE* | 4.7 | 9.7 | 14.0 | 17.9 | 22.0 | 26.4 | 31.4 | 37.5 | 46.2 | 66.0 |
| | Median | *IBESACTL* | 3.32 | 7.10 | 10.37 | 12.11 | 14.72 | 14.68 | 16.37 | 17.92 | 20.44 | 23.53 |
| | QRange | *FCSTERR* | 0.16 | 0.23 | 0.29 | 0.34 | 0.42 | 0.39 | 0.48 | 0.48 | 0.53 | 0.66 |
| | *N* | *FCSTERR* | 3,945 | 2,705 | 2,463 | 2,271 | 2,216 | 2,136 | 2,142 | 2,113 | 2,089 | 2,039 |
| | Median | *DISPERSION* | 0.02 | 0.04 | 0.07 | 0.09 | 0.11 | 0.12 | 0.16 | 0.17 | 0.21 | 0.23 |
| | *N* | *DISPERSION* | 1,187 | 1,232 | 1,248 | 1,254 | 1,275 | 1,313 | 1,363 | 1,443 | 1,521 | 1,651 |

(*Continued*)

**TABLE 2** — *Continued*

**Panel B: Subsample of U.S. Firm-Years with Data for Both EPS and CPS**

| | | | Price Deciles | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Type | Statistic | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| EPS | Median | *BEGPRICE* | 5.0 | 10.0 | 13.6 | 17.6 | 21.6 | 25.7 | 30.4 | 36.6 | 44.5 | 63.9 |
| | Median | *IBESACTL* | 0.01 | 0.30 | 0.57 | 0.80 | 1.13 | 1.35 | 1.63 | 1.85 | 2.27 | 3.23 |
| | QRange | *FCSTERR* | 0.09 | 0.08 | 0.07 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.07 |
| | *N* | *FCSTERR* | 331 | 270 | 280 | 335 | 369 | 388 | 421 | 528 | 582 | 693 |
| | Median | *DISPERSION* | 0.03 | 0.04 | 0.04 | 0.05 | 0.03 | 0.04 | 0.04 | 0.05 | 0.05 | 0.05 |
| | *N* | *DISPERSION* | 128 | 95 | 92 | 108 | 132 | 123 | 149 | 194 | 240 | 302 |
| CPS | Median | *BEGPRICE* | 5.0 | 10.0 | 13.6 | 17.6 | 21.6 | 25.7 | 30.4 | 36.6 | 44.5 | 63.9 |
| | Median | *IBESACTL* | 0.57 | 1.18 | 1.53 | 1.83 | 2.30 | 2.39 | 2.98 | 3.06 | 3.55 | 5.06 |
| | QRange | *FCSTERR* | 0.30 | 0.55 | 0.60 | 0.59 | 0.67 | 0.69 | 0.73 | 0.75 | 1.04 | 1.17 |
| | *N* | *FCSTERR* | 331 | 270 | 280 | 335 | 369 | 388 | 421 | 528 | 582 | 693 |
| | Median | *DISPERSION* | 0.11 | 0.15 | 0.19 | 0.20 | 0.24 | 0.24 | 0.34 | 0.31 | 0.42 | 0.55 |
| | *N* | *DISPERSION* | 128 | 95 | 92 | 108 | 132 | 123 | 149 | 194 | 240 | 302 |

This table reports various distributional statistics in each decile of *BEGPRICE*, which is the beginning-of-year share price (in dollars). Price deciles are computed each calendar year, and the lowest (highest) price decile is denoted by 1 (10). We investigate how variability and disagreement for annual sales and operating cash flow forecasts vary across price deciles. Variability is measured as the interquartile range (QRange) of *FCSTERR*, which is defined as *IBESACTL* minus *FORECAST*, where *IBESACTL* is the actual earnings per share (EPS), cash flow per share (CPS), or sales per share (SPS), as reported by I/B/E/S and *FORECAST* is the most recent consensus (mean) forecast for that firm-year. Sales per share is obtained by deflating firm-level sales forecasts and actuals by the number of shares outstanding to get per share numbers. Disagreement is measured as the standard deviation of *individual* analyst forecasts around the consensus (*DISPERSION*). We also report median values of *BEGPRICE* and *IBESACTL* to show variation across price deciles. All U.S. firm-years with *COVERAGE* $\geq 3$ with fiscal period end date between January 1993 and December 2006 with available data on I/B/E/S database are included, resulting in sample sizes of 13,487 and 1,563 for panels A and B, respectively. *COVERAGE* is the number of forecasts underlying the consensus. For *FCSTERR*, we increase the sample size to 24,119 and 4,197 for panels A and B, respectively, by also including firm-years where *COVERAGE* equals 1 and 2. Additional details for all variables are provided in appendix A. All prices and forecast/actual amounts are denominated in dollars.

despite considerable variation in scale across the price deciles. As with SPS in panel A, the results reported for CPS in the bottom half of panel B suggest considerable variation with scale for variability and disagreement. The interquartile range of forecast errors increases from 30 cents for the lowest price decile to 117 cents for the highest price decile, and the corresponding increase for median dispersion is from 11 cents to 55 cents.[20]

The cash flow forecast evidence also appears inconsistent with the first and second explanations for reasons similar to those discussed for sales forecasts. It seems unlikely that variability and disagreement for earnings forecasts would not naturally vary with scale, per our first explanation, and yet variability and disagreement for cash flow forecasts would vary naturally with scale. Also, why would that scale variation for cash flows be offset exactly by corresponding natural variation with scale for operating accruals per share? Turning to our second explanation, it seems unlikely that there are factors that are correlated with scale that reverse the natural variation with scale for EPS forecast variability and disagreement and yet don't reverse natural variation with scale for CPS forecasts.

The results for the subsamples examined in table 2 confirm the overall sample results regarding lack of scale variation for magnitudes of EPS forecast error and dispersion, and can therefore be viewed as supporting the third explanation that it is caused by analysts suppressing scale variation relating to EPS forecasts. But if the third explanation is valid, why analysts do not seek to suppress scale variation for sales and cash flow forecasts remains an open question.[21]

### 3.3 ANALYSTS' ANNUAL EPS FORECASTS FOR OVERSEAS FIRMS

Table 3 describes scale variation for forecast error magnitudes and dispersion for annual EPS forecasts in overseas markets. Panel A contains results for four representative countries that exhibit relatively little variation with scale for EPS forecasts, similar to the U.S. results. Panel B contains results for four countries that exhibit substantial variation with scale, quite different from the U.S. results. Note that across-decile variation in price is approximately linear across price deciles for some countries (e.g., Australia, U.K., and Canada in panel A) but share price increases sharply for the tenth price decile in other countries (e.g., Brazil and Japan in panel B).

To illustrate the extent to which the two sets of countries differ from each other, compare Australia in panel A with Switzerland in panel B. Whereas

[20] The values for $N$ reported in the bottom rows of panels A and B for SPS and CPS, respectively, suggest that (a) cash flow forecasts are less frequent than sales forecasts, and (b) the relative disparity is even greater for low price shares.

[21] Note that sales forecasts are made at the firm level, not at the share level. As a result, the differences between EPS and SPS noted in panel A for variability and disagreement may be affected by this difference between earnings and sales forecasts. That potential source of difference is not relevant, however, for the panel B results that compare EPS with CPS, because cash flow forecasts are made at the share level.

**TABLE 3**

*Variability and Disagreement for Annual EPS Forecasts for Non-U.S. Firms*

**Panel A: For Selected Countries that Exhibit Little Variation with Scale for EPS (Similar to U.S.)**

| | | | Price Deciles | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country(Currency) | Statistic | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Australia(Dollar) | Median | *BEGPRICE* | 0.6 | 1.2 | 1.6 | 2.1 | 2.5 | 3.2 | 4.0 | 5.4 | 7.9 | 17.0 |
| | Median | *IBESACTL* | 0.02 | 0.08 | 0.11 | 0.15 | 0.17 | 0.21 | 0.25 | 0.33 | 0.49 | 0.91 |
| | QRange | *FCSTERR* | 0.02 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.04 | 0.03 | 0.07 |
| | *N* | *FCSTERR* | 873 | 543 | 402 | 407 | 375 | 369 | 352 | 344 | 353 | 321 |
| | Median | *DISPERSION* | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 | 0.04 |
| | *N* | *DISPERSION* | 296 | 306 | 302 | 309 | 293 | 307 | 305 | 305 | 304 | 296 |
| UK(Penny) | Median | *BEGPRICE* | 39.3 | 102.5 | 145.0 | 189.0 | 239.0 | 293.0 | 374.0 | 475.0 | 619.0 | 965.0 |
| | Median | *IBESACTL* | 1.69 | 7.00 | 10.40 | 13.20 | 15.91 | 19.80 | 23.53 | 30.80 | 37.90 | 52.99 |
| | QRange | *FCSTERR* | 1.51 | 1.65 | 1.67 | 1.68 | 1.68 | 1.88 | 2.21 | 2.35 | 2.70 | 4.50 |
| | *N* | *FCSTERR* | 2,880 | 1,557 | 1,315 | 1,195 | 1,072 | 1,059 | 967 | 916 | 873 | 877 |
| | Median | *DISPERSION* | 0.48 | 0.59 | 0.69 | 0.69 | 0.82 | 0.83 | 1.05 | 1.32 | 1.63 | 2.18 |
| | *N* | *DISPERSION* | 725 | 731 | 735 | 730 | 731 | 739 | 732 | 734 | 730 | 729 |
| Canada(Dollar) | Median | *BEGPRICE* | 1.6 | 3.6 | 5.8 | 8.5 | 11.3 | 14.8 | 18.8 | 24.5 | 31.9 | 48.0 |
| | Median | *IBESACTL* | −0.02 | 0.10 | 0.20 | 0.43 | 0.64 | 0.80 | 1.10 | 1.46 | 1.82 | 2.72 |
| | QRange | *FCSTERR* | 0.08 | 0.10 | 0.13 | 0.14 | 0.15 | 0.14 | 0.15 | 0.13 | 0.15 | 0.17 |
| | *N* | *FCSTERR* | 1,021 | 733 | 635 | 582 | 627 | 597 | 509 | 475 | 445 | 455 |
| | Median | *DISPERSION* | 0.03 | 0.04 | 0.05 | 0.05 | 0.05 | 0.06 | 0.06 | 0.07 | 0.08 | 0.11 |
| | *N* | *DISPERSION* | 406 | 417 | 418 | 409 | 420 | 416 | 420 | 416 | 415 | 409 |
| Germany(Euros) | Median | *BEGPRICE* | 3.1 | 7.6 | 11.9 | 15.4 | 19.7 | 25.8 | 34.2 | 46.0 | 73.0 | 160.9 |
| | Median | *IBESACTL* | −0.17 | 0.24 | 0.40 | 0.64 | 1.00 | 1.09 | 1.50 | 1.99 | 2.80 | 4.55 |
| | QRange | *FCSTERR* | 0.41 | 0.28 | 0.37 | 0.33 | 0.46 | 0.50 | 0.43 | 0.43 | 0.46 | 0.88 |
| | *N* | *FCSTERR* | 631 | 380 | 278 | 270 | 248 | 253 | 247 | 247 | 237 | 249 |
| | Median | *DISPERSION* | 0.12 | 0.12 | 0.15 | 0.16 | 0.19 | 0.20 | 0.20 | 0.26 | 0.33 | 0.38 |
| | *N* | *DISPERSION* | 177 | 183 | 181 | 184 | 178 | 184 | 183 | 179 | 185 | 177 |

(*Continued*)

**TABLE 3** — *Continued*

**Panel B: For Selected Countries that Exhibit Substantial Variation with Scale for EPS (Unlike U.S.)**

| | | | Price Deciles | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country (Currency) | Statistic | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Brazil (Real), per 1,000 shares | Median | *BEGPRICE* | 1.4 | 5.6 | 16.0 | 26.8 | 49.1 | 117.3 | 285.0 | 1,050.0 | 4,620.0 | 26,500.0 |
| | Median | *IBESACTL* | 0.11 | 0.54 | 1.83 | 2.68 | 5.65 | 16.53 | 43.56 | 200.00 | 602.00 | 1,686.00 |
| | QRange | *FCSTERR* | 0.24 | 0.42 | 1.14 | 3.69 | 6.83 | 7.72 | 37.47 | 101.04 | 356.62 | 626.85 |
| | *N* | *FCSTERR* | 83 | 66 | 69 | 59 | 68 | 68 | 61 | 75 | 89 | 53 |
| | Median | *DISPERSION* | 0.08 | 0.17 | 0.82 | 1.21 | 1.92 | 5.86 | 16.13 | 44.57 | 140.22 | 369.76 |
| | *N* | *DISPERSION* | 46 | 48 | 52 | 46 | 49 | 51 | 47 | 51 | 49 | 46 |
| Switzerland (Francs) | Median | *BEGPRICE* | 77.0 | 231.0 | 360.0 | 474.5 | 600.0 | 755.5 | 1,035.0 | 1,377.5 | 1,960.0 | 3,500.0 |
| | Median | *IBESACTL* | 1.27 | 8.35 | 15.70 | 16.45 | 22.38 | 24.96 | 31.75 | 58.95 | 72.40 | 122.68 |
| | QRange | *FCSTERR* | 1.56 | 1.79 | 2.47 | 3.56 | 4.87 | 6.62 | 8.01 | 7.25 | 9.07 | 17.98 |
| | *N* | *FCSTERR* | 260 | 211 | 189 | 197 | 194 | 224 | 207 | 204 | 195 | 209 |
| | Median | *DISPERSION* | 0.81 | 1.20 | 1.51 | 2.68 | 3.55 | 3.95 | 4.49 | 4.36 | 5.57 | 11.96 |
| | *N* | *DISPERSION* | 149 | 158 | 158 | 154 | 155 | 159 | 157 | 158 | 159 | 149 |
| Japan (Yen) | Median | *BEGPRICE* | 187.0 | 370.0 | 511.5 | 679.0 | 882.5 | 1,130.0 | 1,520.0 | 2,007.5 | 3,295.0 | 32,000.0 |
| | Median | *IBESACTL* | 1.30 | 9.60 | 14.05 | 24.16 | 32.23 | 45.40 | 56.40 | 72.43 | 106.08 | 347.70 |
| | QRange | *FCSTERR* | 7.43 | 7.50 | 8.51 | 9.41 | 10.46 | 13.00 | 14.69 | 14.51 | 18.25 | 136.26 |
| | *N* | *FCSTERR* | 3,323 | 2,638 | 2,302 | 2,114 | 1,784 | 1,607 | 1,465 | 1,276 | 1,180 | 1,371 |
| | Median | *DISPERSION* | 2.30 | 2.20 | 2.50 | 3.20 | 3.70 | 4.60 | 5.20 | 5.90 | 7.70 | 25.65 |
| | *N* | *DISPERSION* | 911 | 918 | 918 | 919 | 916 | 921 | 917 | 920 | 918 | 912 |

(*Continued*)

**TABLE 3** — *Continued*

**Panel B: For Selected Countries that Exhibit Substantial Variation with Scale for EPS (Unlike U.S.)**

| | | | Price Deciles | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country(Currency) | Statistic | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Italy(Euros) | Median | *BEGPRICE* | 0.8 | 1.7 | 2.5 | 3.6 | 5.1 | 7.8 | 9.5 | 12.5 | 17.9 | 37.6 |
| | Median | *IBESACTL* | 0.03 | 0.07 | 0.11 | 0.20 | 0.25 | 0.33 | 0.45 | 0.51 | 0.71 | 0.84 |
| | QRange | *FCSTERR* | 0.05 | 0.05 | 0.10 | 0.09 | 0.10 | 0.08 | 0.13 | 0.18 | 0.26 | 0.42 |
| | *N* | *FCSTERR* | 168 | 141 | 148 | 143 | 127 | 122 | 123 | 121 | 130 | 126 |
| | Median | *DISPERSION* | 0.02 | 0.02 | 0.03 | 0.03 | 0.05 | 0.04 | 0.06 | 0.08 | 0.09 | 0.18 |
| | *N* | *DISPERSION* | 93 | 97 | 98 | 97 | 98 | 96 | 100 | 95 | 100 | 93 |

This table reports various distributional statistics in each decile of *BEGPRICE*, which is the beginning-of-year share price. Price deciles are computed each calendar year, and the lowest (highest) price decile is denoted by 1 (10). We investigate variation across price deciles for variability and disagreement for annual EPS forecasts. Variability is measured as the interquartile range (QRange) of *FCSTERR*, which is defined as *IBESACTL* minus *FORECAST*, where *IBESACTL* is the actual earnings per share (EPS) as reported by I/B/E/S for that firm-year and *FORECAST* is the most recent consensus (mean) EPS forecast. Disagreement is measured as the standard deviation of *individual* analyst forecasts around the consensus (*DISPERSION*). We also report median values of *BEGPRICE* and *IBESACTL* to show variation across price deciles. For each country, all firm-years with *COVERAGE* $\geq 3$ with fiscal period end date between January 1993 and December 2006 with available data on I/B/E/S database are included. *COVERAGE* is the number of forecasts underlying the consensus. For *FCSTERR*, we increase the sample size by also including firm-years where *COVERAGE* equals 1 and 2. Additional details for all variables are provided in appendix A.

cross-sectional variation in share price is high in Australia (median *BEGPRICE* in price decile 10 is nearly 30 times larger than that for decile 1), the interquartile range of *FCSTERR* lies between 1 and 4 cents for the first nine deciles (before rising to 7 cents for the 10th decile) and median *DISPERSION* increases from 1 cent for decile 1 to 4 cents for decile 10. In contrast, interquartile ranges for *FCSTERR* and medians for *DISPERSION* in Switzerland increase more than tenfold from decile 1 to decile 10. To be sure, variation in scale based on *BEGPRICE* is about 45 times across the 10 deciles.

Even though we separate countries into two categories—relatively low and high variation with scale—the different countries actually fall along a continuum that extends from no variation to full variation. Australia in panel A is closest to the United States, whereas the United Kingdom exhibits the most variation with scale among the panel A countries that exhibit relatively little scale variation. Among countries in panel B, Japan appears to exhibit the lowest relative variation with scale. While there are large increases in both interquartile ranges for *FCSTERR* and medians for *DISPERSION* between deciles 9 and 10, those increases need to be adjusted for the corresponding sharp increases in scale.

The evidence in table 3 is not easily reconciled with any of the explanations. If it is indeed the case that EPS variability and disagreement do not vary naturally with scale, per the first explanation, why do we observe variation with scale for certain countries? The second explanation would hold only if the factors that reverse natural variation in the United States play a lesser role in the panel B countries. Similarly, the third explanation would hold only if analysts in panel B countries do not actively seek to suppress scale variation in deviations from EPS benchmarks. Investigating differences between panel B and panel A countries (including the U.S.) might reveal reasons that support the conditions necessary for the second or third explanations to be relevant.

We repeat the EPS forecast analysis described above for sales and cash flow forecasts for overseas firms to determine whether the differences between the groups noted for EPS are reflected in CPS and SPS. That is, do countries with high- (low-) scale variation for EPS variability and disagreement also have high- (low-) scale variation for CPS and SPS variability and disagreement? The alternative is that the differences observed for EPS are not reflected in CPS and SPS, and both groups exhibit high variation with scale for sales and cash flow forecasts, similar to the patterns documented for the United States.[22]

Our results (not tabulated) support the alternative description above: regardless of cross-country differences observed for EPS variability and disagreement, all countries exhibit substantial variation with scale for sales and cash flow forecasts. For example, Australia, which exhibits relatively little

[22] Whereas there is cross-country variation in the availability of cash flow and sales forecasts, relative to EPS forecasts, availability of overseas cash flow forecasts is generally much higher than that observed for the United States.

variation with scale for EPS in table 3, is associated with substantial variation with scale for SPS: interquartile ranges for *FCSTERR* increase from 6 cents for decile 1 to 80 cents for decile 10 and median *DISPERSION* increases from 4 cents for decile 1 to 50 cents for decile 10. These overseas results for CPS and SPS provide additional support for our conclusion in section 3.2 that the large differences across price deciles observed for variability and disagreement relating to sales and cash flow forecasts are inconsistent with the first and second explanations. If variability and disagreement do not naturally vary with scale for EPS in panel A countries, or if natural variation with scale is reversed by other factors correlated with scale, why do they vary naturally with scale for CPS and SPS in all countries?

### 3.4 FACTORS THAT MIGHT REVERSE NATURAL VARIATION IN SCALE FOR EPS VARIABILITY/DISAGREEMENT

Our next analysis seeks evidence directly relevant to the second explanation, which posits that variability and disagreement vary naturally with scale but they are also affected by other variables that are correlated with scale. Specifically, we search for variables that are positively (negatively) correlated with scale but are also negatively (positively) related to forecast variability and disagreement.

We consider a number of variables, but are unable to find variables that had effects on variability and disagreement that were large enough to negate natural variation with scale. We report results for three such variables that are correlated with scale: *VOL* or return volatility, *COVERAGE* or the number of analysts following the stock, and *MEANSTALE* or the mean age of the different individual forecasts underlying the most recent consensus (see panel A0 in table 1 for evidence of scale variation). Panels A, B, and C of table 4 describe variation across deciles of the three variables, respectively, for (a) measures of scale (*BEGPRICE*), and (b) measures of EPS variability (QRange of *FCSTERR*) and disagreement (median *DISPERSION*).

The results in panel A of table 4 indicate that while *VOL* is strongly, negatively related to share price, it is not positively related to forecast variability or disagreement. The interquartile ranges for forecast error exhibit a shallow U-shaped relation: 5 cents for the extreme decile and 4 cents for the deciles in between. Median dispersion also exhibits a shallow U-shaped relation with *VOL*: 2 cents for the extreme decile and 1 cent for the deciles in between.

The results in panel B indicate that although *COVERAGE* is strongly, positively related to share price, it is not strongly negatively related to forecast variability or disagreement. While the interquartile ranges for forecast error are negatively related to *COVERAGE*, consistent with our second explanation, that relation is clearly insufficient to reverse natural variation with scale: QRange decreases from 5 cents for the first three *COVERAGE* deciles to 4 cents for the next five deciles, and finally to 3 cents for the tenth decile. Moreover, median dispersion is clearly not negatively related to *COVERAGE*, since it remains at 2 cents for all *COVERAGE* deciles.

**TABLE 4**

*Variability and Disagreement for EPS Forecasts, Partitioned by Selected Variables*

**Panel A: Partitions Based on Deciles of *VOL***

| Variable | Stats | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *VOL* | Median | 0.01 | 0.01 | 0.02 | 0.02 | 0.02 | 0.03 | 0.03 | 0.03 | 0.04 | 0.05 |
| *BEGPRICE* | Median | 36.00 | 34.69 | 30.50 | 26.88 | 23.75 | 21.25 | 19.25 | 17.75 | 15.50 | 12.25 |
| *FCSTERR* | QRange | 0.05 | 0.05 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.05 |
| *DISPERSION* | Median | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.01 | 0.01 | 0.01 | 0.02 |
| | *N* | 12,906 | 12,938 | 12,940 | 12,937 | 12,932 | 12,951 | 12,938 | 12,938 | 12,941 | 12,913 |

**Panel B: Partitions Based on Deciles of *COVERAGE***

| Variable | Stats | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *COVERAGE* | Median | 3.00 | 3.00 | 4.00 | 5.00 | 6.00 | 7.00 | 8.00 | 10.00 | 13.00 | 19.00 |
| *BEGPRICE* | Median | 15.50 | 17.38 | 18.37 | 20.06 | 22.38 | 23.88 | 26.17 | 29.50 | 34.02 | 39.28 |
| *FCSTERR* | QRange | 0.05 | 0.05 | 0.05 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.03 |
| *DISPERSION* | Median | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
| | *N* | 14,521 | 10,731 | 13,092 | 13,374 | 12,740 | 13,396 | 12,888 | 12,829 | 12,840 | 12,953 |

**Panel C: Partitions Based on Deciles of *MEANSTALE***

| Variable | Stats | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *MEANSTALE* | Median | 21.00 | 37.33 | 48.85 | 57.67 | 65.67 | 73.67 | 82.30 | 93.50 | 111.63 | 152.00 |
| *BEGPRICE* | Median | 23.88 | 24.63 | 24.88 | 24.75 | 24.81 | 24.55 | 24.31 | 23.63 | 23.13 | 20.95 |
| *FCSTERR* | QRange | 0.05 | 0.06 | 0.06 | 0.05 | 0.05 | 0.04 | 0.04 | 0.04 | 0.02 | 0.02 |
| *DISPERSION* | Median | 0.03 | 0.03 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.01 | 0.01 | 0.01 |
| | *N* | 12,898 | 12,931 | 12,944 | 12,905 | 12,948 | 12,933 | 12,934 | 12,936 | 12,928 | 12,903 |

This table reports how variability of forecast error and disagreement vary across partitions based on three variables commonly used in analyst research: *VOL* (stock return volatility), *COVERAGE* (# of analysts providing forecasts), and *MEANSTALE* (mean age of those forecasts). Variability is measured by the interquartile ranges (QRange) for forecast error (*FCSTERR*) distributions and disagreement is measured by medians for forecast dispersion (*DISPERSION*). Price deciles are computed each calendar year, whereas deciles for *VOL*, *COVERAGE*, and *MEANSTALE* are computed each fiscal quarter, and the lowest (highest) price decile is denoted by 1 (10). *FCSTERR* is defined as *IBESACTL* minus *FORECAST*, where *IBESACTL* is the actual quarterly EPS as reported by I/B/E/S, and *FORECAST* is the most recent consensus (mean) forecast for that firm-quarter. *DISPERSION* is the standard deviation of the *individual* analyst EPS forecasts around the consensus. The sample of firm-quarters is derived from U.S. firms on I/B/E/S with available data, fiscal period end date between January 1993 and December 2006, and *COVERAGE* $\geq 3$. All per share prices and actual/forecast EPS are denominated in dollars and details of all variables are provided in appendix A.

The results in panel C for *MEANSTALE* suggest a weak, negative correlation with price but no evidence of a positive relation between *MEANSTALE* and variability or disagreement. In fact, both variability and disagreement decline with forecast age, which would increase rather than reverse any underlying natural variation with scale. This negative relation observed between forecast age and variability is surprising, since we expect stale forecasts to be less accurate. Apparently, forecasts made early and not subsequently revised turn out to be more accurate.

Overall, our investigation did not uncover any variables that are sufficiently correlated with scale and also with variability and disagreement to substantially reverse any natural variation with scale that may exist. To be sure, not finding such variables does not mean that they do not exist. It is possible that there are some unknown variables that have a sufficiently strong effect to reverse natural scale variation for EPS variability and disagreement. However, we do not hold much hope for the second explanation. Not only is some of the evidence provided earlier in this Section inconsistent with the presence of such unknown variables, it would be an unusual coincidence that these effects would almost *exactly* reverse natural variation with scale.

### 3.5 CHANGES IN VARIABILITY AND DISAGREEMENT AROUND STOCK SPLITS

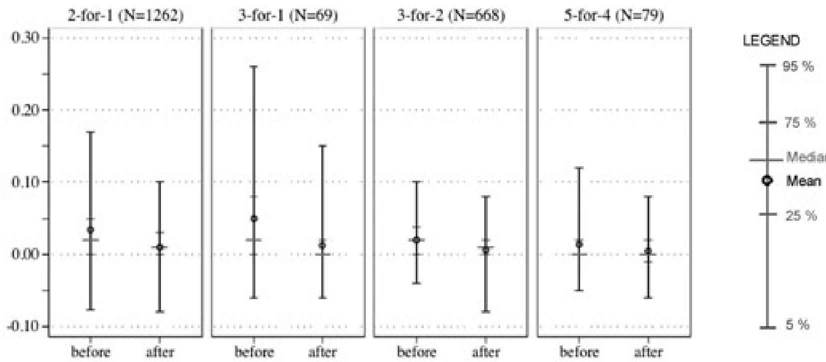
Stock splits offer an opportunity to investigate changes in scale per share, when holding other factors relatively constant. To be sure, other factors are not completely controlled for, since stock splits are endogenous and are associated with increases in price and volatility around the split (Ohlson and Penman [1985]). By holding the firm constant, we seek to limit variation across the factors that might potentially reverse the effects of any natural variation with scale. The results described below suggest that variability and disagreement decline after stock splits, and that decline is proportional to the corresponding price declines.

Panels A and B of figure 3 compare distributions for forecast errors and forecast dispersion, respectively, from four quarters before to four quarters after the four most common types of stock splits: "2-for-1" (1,262 splits), "3-for-1" (69 splits), "3-for-2" (668 splits), and "5-for-4" (79 splits).[23] Panels A and B of table 5 provide key measures of central tendency and variability for the corresponding distributions. Our results suggest that interquartile ranges for forecast errors and mean/median levels of dispersion do indeed appear to decline substantially after the split.[24] To be sure, the declines are not always proportional to the split; in fact, variability actually increases for

[23] We did not include reverse splits and other stock splits because of smaller samples (less than 50 splits).

[24] Note that the ± 4 quarter analysis is biased against observing proportional declines in variability and disagreement because prices tend to rise substantially during the four quarters before the split and continue to rise, albeit to a smaller extent, during the four quarters after the split. Therefore, the ratio of stock prices from four quarters before to four quarters after the split is less than that implied by the split.

Panel A: Percentile plots of *FCSTERR* before and after stock split (+/- 4 quarters from stock split)




Panel B: Percentile plots of *DISPERSION* before and after stock split (+/- 4 quarters from stock split)

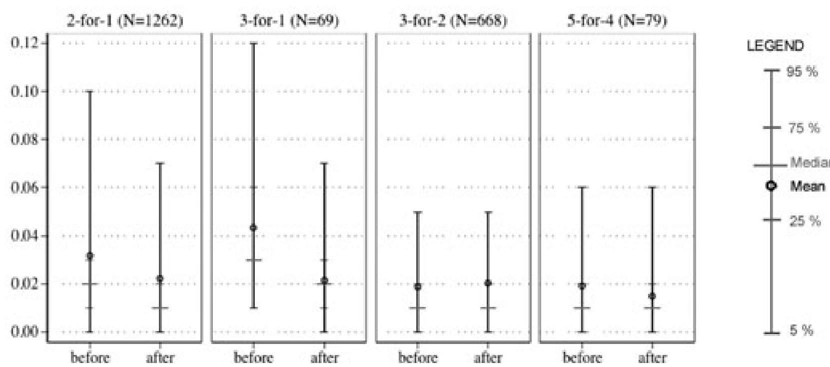



FIG. 3.—Distribution of EPS forecast error and dispersion before and after stock splits. This figure describes how the distributions of *FCSTERR* and *DISPERSION*, measured in dollars per share, vary from four quarters before to four quarters after stock splits. The mean is indicated by the solid circle, the median by the long horizontal hash mark, and the remaining hash marks locate the 5th, 25th, 75th, and 95th percentiles of the pooled distributions for the different variables. *FCSTERR* is defined as *IBESACTL* minus *FORECAST*, where *IBESACTL* is the actual quarterly EPS as reported by I/B/E/S, and *FORECAST* is the most recent consensus (mean) EPS forecast for that firm-quarter. *DISPERSION* is the standard deviation of the *individual* analyst forecasts around the consensus in that quarter. All prices and forecast/actual EPS are denominated in dollars. The sample of firm-quarters is derived from U.S. firms on I/B/E/S with available data, fiscal period end date between January 1993 and December 2006 and at least three EPS forecasts. Additional details for all variables are provided in appendix A.

"5-for-4" splits.[25] However, many of the changes around stock splits are so strongly proportional to the corresponding price changes that we view this

[25] One reason why the decline in the two measures is not exactly proportional to the split is that the measures are rounded to the nearest cent. Also, it is possible that underlying uncertainty increases after a split, which is then reflected in slightly less predictable earnings and slightly higher disagreement among analysts.

**TABLE 5**

*Distributional Statistics for Forecast Error and Dispersion Before and After Stock Splits*

**Panel A: Distributional Statistics for *FCSTERR* Before and After Stock Split (+/− 4 Quarters from Stock Split)**

| | 2-for-1 Split | | 3-for-1 Split | | 3-for-2 Split | | 5-for-4 Split | |
|---|---|---|---|---|---|---|---|---|
| | Presplit | Postsplit | Presplit | Postsplit | Presplit | Postsplit | Presplit | Postsplit |
| Mean | 0.03 | 0.01 | 0.05 | 0.01 | 0.02 | 0.01 | 0.01 | 0.01 |
| Median | 0.02 | 0.01 | 0.02 | 0.00 | 0.02 | 0.01 | 0.00 | 0.00 |
| StdDev | 0.15 | 0.08 | 0.09 | 0.08 | 0.07 | 0.06 | 0.07 | 0.04 |
| QRange | 0.05 | 0.03 | 0.08 | 0.02 | 0.04 | 0.02 | 0.02 | 0.03 |
| *N* | 1,262 | 1,262 | 69 | 69 | 668 | 668 | 79 | 79 |

**Panel B: Distributional Statistics for *DISPERSION* Before and After Stock Split (+/− 4 Quarters from Stock Split)**

| | 2-for-1 Presplit | 2-for-1 Postsplit | 3-for-1 Presplit | 3-for-1 Postsplit | 3-for-2 Presplit | 3-for-2 Postsplit | 5-for-4 Presplit | 5-for-4 Postsplit |
|---|---|---|---|---|---|---|---|---|
| Mean | 0.03 | 0.02 | 0.04 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
| Median | 0.02 | 0.01 | 0.03 | 0.02 | 0.01 | 0.01 | 0.01 | 0.01 |
| StdDev | 0.05 | 0.03 | 0.04 | 0.02 | 0.03 | 0.07 | 0.04 | 0.02 |
| QRange | 0.02 | 0.01 | 0.05 | 0.02 | 0.01 | 0.01 | 0.01 | 0.01 |
| *N* | 1,262 | 1,262 | 69 | 69 | 668 | 668 | 79 | 79 |

This table describes how the distributions of *FCSTERR* and *DISPERSION* vary from four quarters before to four quarters after stock splits. We report the mean, median, standard deviation (StdDev), interquartile range (QRange), and the number of observations (*N*) for the distributions of *FCSTERR* and *DISPERSION*. *FCSTERR* is defined as *IBESACTL* minus *FORECAST*, where *IBESACTL* is the actual quarterly EPS (in dollars) as reported by I/B/E/S, and *FORECAST* is the most recent consensus (mean) forecast for that firm-quarter. *DISPERSION* is the standard deviation of the *individual* analyst forecasts around the consensus. The sample of firm-quarters is derived from U.S. firms on I/B/E/S with available data, fiscal period end date between January 1993 and December 2006, and at least three forecasts. Additional details for all variables are provided in appendix A and *FCSTERR* and *DISPERSION* are measured in dollars.

evidence as suggesting that forecast dispersion and variability of forecast error do indeed decline proportionately after stock splits.[26]

The evidence on stock splits is seemingly inconsistent with all three explanations. Observing proportional reductions in forecast error variability and dispersion after stock splits contradicts the premise underlying the first explanation that variability and disagreement do not naturally vary with scale. Similarly, this evidence is inconsistent with the second explanation if the factors that reverse natural variation with scale are related to scale at the share level. And the evidence does not support the premise underlying the third explanation that analysts focus on undeflated deviations from benchmarks that are measured in cents per share. It is possible, however, that the change in scale around stock splits is too obvious to be ignored, and bounds for desired deviations from benchmarks are adjusted proportionately after stock splits.

### 3.6 TIME-SERIES FORECASTS

Our final analysis relates to time-series forecasts. Since disagreement across forecasters does not apply to time-series forecasts, our focus in this

[26] We also consider similar analyses based on the quarter just before and after the split (results available upon request). Our results again confirm that splits are associated with substantial declines in measures of forecast error variability and disagreement, proportional to the splits that occurred.

subsection is limited to forecast error variability. Observing similar results for variability for time-series and analyst forecasts—lack of variation with scale for EPS forecast errors but substantial variation with scale for CPS and SPS—suggests that the results observed for analyst forecasts are likely induced by managers smoothing EPS such that high and low price firms exhibit the same volatility. To determine if managers engage in such behavior regardless of whether or not they are followed by analysts, we investigate separately firms with and without analyst following.

Table 6 describes across-price decile patterns for variability, measured as the interquartile range for seasonally differenced EPS, CPS, and SPS, based on actual values (*COMPACTL*) provided by Compustat. Panel A is based on firm-quarters considered in our main I/B/E/S sample (with at least three EPS forecasts), and panel B contains firm-quarters for firms not covered by I/B/E/S. The first row in each panel describes how scale (median *BEGPRICE*) varies across the price deciles, followed by two rows each describing the interquartile range (QRange) and sample size (*N*) for seasonally differenced values ($\Delta$*COMPACTL*) for EPS, CPS, and SPS, respectively. As described in section 2, the method we use to select price deciles distributes observations unequally across the ten price deciles for the two samples, especially in panel B.

The results reported in the second row of panel A exhibit relatively little variation with scale for EPS volatility, and yet CPS and SPS volatility increase substantially with scale. The interquartile range for seasonally differenced EPS is about 20 cents for the first six price deciles, rises slightly to 31 cents for decile 9, before rising to 46 cents for decile 10. Similar results have been documented in DeGeorge, Patel, and Zeckhauser [1999] though variation with price is more evident in that paper. The results reported in the fourth and sixth rows of panel A for CPS and SPS suggest sustained increases in the magnitude of forecast errors across the ten price deciles.

To supplement our quarterly Compustat time-series forecast error analyses for U.S. firms, we report in panels C and D of table 6 similar analyses for the two sets of countries investigated in table 3: those that exhibit little and more variation with scale, respectively, for variability/disagreement relating to analysts' annual EPS forecasts. Since the actual EPS numbers reported in these countries are not easily obtained, we use the actual EPS as provided by I/B/E/S. Our results are similar to the results obtained for U.S. firms: the patterns observed for time-series EPS forecast errors in panels C and D of table 6 resemble those observed for analyst forecast errors in panels A and B of table 3, respectively.[27]

The correspondence between the patterns observed for time-series and analyst forecasts is striking. When magnitudes of analyst forecast errors for EPS exhibit little (more) variation with scale, magnitudes of time-series forecast errors also exhibit little (more) variation with scale. And magnitudes of SPS and CPS forecast errors increase substantially with scale in

[27] Results for U.S. firms based on I/B/E/S actuals are similar to the Compustat results in table 6, panel A.

**TABLE 6**

*Variability for Time-Series Forecasts*

| Panel A: Firm-Quarters on I/B/E/S and Followed by at Least Three Analysts with EPS Forecasts | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Price Deciles | | | | | | | | | |
| Type | Statistic | Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| | Median | *BEGPRICE* | 6.00 | 10.64 | 14.63 | 18.25 | 22.22 | 26.23 | 30.50 | 36.75 | 45.25 | 63.80 |
| EPS | QRange | $\Delta$ *COMPACTL* | 0.20 | 0.20 | 0.20 | 0.20 | 0.21 | 0.21 | 0.23 | 0.26 | 0.31 | 0.46 |
| | *N* | $\Delta$ *COMPACTL* | 12,009 | 11,052 | 10,976 | 11,187 | 11,295 | 11,420 | 11,577 | 11,879 | 12,242 | 11,972 |
| CPS | QRange | $\Delta$ *COMPACTL* | 0.53 | 0.70 | 0.81 | 0.83 | 0.87 | 0.95 | 1.01 | 1.04 | 1.23 | 1.66 |
| | *N* | $\Delta$ *COMPACTL* | 11,768 | 10,510 | 10,271 | 10,127 | 9,974 | 9,868 | 9,841 | 10,342 | 10,867 | 10,880 |
| SPS | QRange | $\Delta$ *COMPACTL* | 0.43 | 0.61 | 0.75 | 0.83 | 0.91 | 0.99 | 1.14 | 1.22 | 1.48 | 2.41 |
| | *N* | $\Delta$ *COMPACTL* | 12,000 | 11,024 | 10,958 | 11,177 | 11,282 | 11,401 | 11,534 | 11,860 | 12,238 | 11,966 |
| **Panel B: Firm-Quarters not Covered by I/B/E/S** | | | | | | | | | | | | |
| | Median | *BEGPRICE* | 2.19 | 10.63 | 14.50 | 18.02 | 21.95 | 25.55 | 30.75 | 36.75 | 43.58 | 72.50 |
| EPS | QRange | $\Delta$ *COMPACTL* | 0.11 | 0.17 | 0.16 | 0.17 | 0.24 | 0.24 | 0.32 | 0.44 | 0.55 | 2.29 |
| | *N* | $\Delta$ *COMPACTL* | 18,289 | 1,731 | 1,139 | 734 | 555 | 411 | 280 | 275 | 185 | 175 |
| CPS | QRange | $\Delta$ *COMPACTL* | 0.27 | 0.62 | 0.74 | 0.79 | 1.44 | 1.78 | 1.62 | 1.58 | 2.47 | 9.85 |
| | *N* | $\Delta$ *COMPACTL* | 17,508 | 1,402 | 750 | 441 | 337 | 241 | 168 | 200 | 163 | 170 |
| SPS | QRange | $\Delta$ *COMPACTL* | 0.25 | 0.45 | 0.49 | 0.49 | 0.63 | 0.83 | 0.81 | 1.16 | 1.07 | 10.30 |
| | *N* | $\Delta$ *COMPACTL* | 18,160 | 1,718 | 1,108 | 720 | 553 | 409 | 275 | 273 | 184 | 175 |

(*Continued*)

**TABLE 6** — *Continued*

**Panel C: Variability in EPS Forecast Error (Time-Series Model) for Countries on I/B/E/S with Little Variation with Scale for Variability/Disagreement for EPS Analyst Forecasts**

| | | | Price Deciles | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | Statistic | Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Australia | Median | *BEGPRICE* | 0.6 | 1.2 | 1.6 | 2.1 | 2.5 | 3.2 | 4.1 | 5.4 | 8.0 | 17.1 |
| | QRange | $\Delta$*IBESACTL* | 0.07 | 0.05 | 0.05 | 0.06 | 0.07 | 0.07 | 0.09 | 0.11 | 0.15 | 0.27 |
| | *N* | $\Delta$*IBESACTL* | 577 | 387 | 314 | 301 | 301 | 301 | 300 | 311 | 313 | 304 |
| UK | Median | *BEGPRICE* | 40.0 | 102.1 | 145.0 | 189.0 | 239.0 | 294.5 | 373.9 | 475.0 | 618.0 | 964.0 |
| | QRange | $\Delta$*IBESACTL* | 3.65 | 4.75 | 5.80 | 5.19 | 5.40 | 5.73 | 6.68 | 6.90 | 8.52 | 16.45 |
| | *N* | $\Delta$*IBESACTL* | 1,997 | 1,200 | 1,029 | 955 | 909 | 914 | 856 | 829 | 800 | 807 |
| Canada | Median | *BEGPRICE* | 1.7 | 3.7 | 5.8 | 8.5 | 11.5 | 14.8 | 18.8 | 24.5 | 31.9 | 48.0 |
| | QRange | $\Delta$*IBESACTL* | 0.32 | 0.41 | 0.45 | 0.49 | 0.47 | 0.50 | 0.57 | 0.58 | 0.72 | 1.22 |
| | *N* | $\Delta$*IBESACTL* | 671 | 503 | 479 | 444 | 469 | 488 | 428 | 433 | 410 | 428 |
| Germany | Median | *BEGPRICE* | 2.7 | 6.9 | 11.2 | 14.0 | 17.0 | 23.5 | 31.0 | 39.0 | 58.8 | 115.3 |
| | QRange | $\Delta$*IBESACTL* | 0.83 | 0.77 | 0.93 | 0.75 | 1.24 | 1.22 | 1.34 | 1.92 | 1.94 | 4.53 |
| | *N* | $\Delta$*IBESACTL* | 482 | 281 | 194 | 188 | 167 | 172 | 159 | 171 | 153 | 170 |

(*Continued*)

TABLE 6 — *Continued*

**Panel D: Variability in EPS Forecast Error (Time-Series Model) for Countries on I/B/E/S with Substantial Variation with Scale for Variability/Disagreement for EPS Analyst Forecasts**

| | | | Price Deciles | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | Statistic | Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Brazil | Median | *BEGPRICE* | 1.4 | 5.7 | 16.2 | 25.3 | 47.1 | 118.8 | 298.0 | 1,170.0 | 4,935.0 | 32,099.7 |
| | QRange | $\Delta$*IBESACTL* | 0.46 | 0.37 | 2.13 | 7.89 | 10.10 | 21.31 | 75.73 | 179.78 | 775.55 | 2,801.46 |
| | *N* | $\Delta$*IBESACTL* | 53 | 41 | 39 | 36 | 41 | 42 | 37 | 49 | 58 | 37 |
| Switzerland | Median | *BEGPRICE* | 81.0 | 229.0 | 358.2 | 473.0 | 600.0 | 755.0 | 1,040.0 | 1,382.5 | 2,001.5 | 3,500.0 |
| | QRange | $\Delta$*IBESACTL* | 8.65 | 5.94 | 9.97 | 11.82 | 15.40 | 21.63 | 31.18 | 31.24 | 52.32 | 113.20 |
| | *N* | $\Delta$*IBESACTL* | 223 | 182 | 176 | 175 | 186 | 210 | 194 | 196 | 186 | 197 |
| Japan | Median | *BEGPRICE* | 178.0 | 350.0 | 507.0 | 675.0 | 890.0 | 1,150.0 | 1,600.0 | 2,150.0 | 3,550.0 | 17,380.0 |
| | QRange | $\Delta$*IBESACTL* | 28.50 | 23.50 | 25.30 | 27.04 | 32.82 | 37.31 | 39.33 | 52.34 | 56.90 | 332.62 |
| | *N* | $\Delta$*IBESACTL* | 2,819 | 2,189 | 1,881 | 1,707 | 1,452 | 1,319 | 1,171 | 1,050 | 929 | 934 |
| Italy | Median | *BEGPRICE* | 0.8 | 1.7 | 2.5 | 3.6 | 4.8 | 7.3 | 9.2 | 11.7 | 16.3 | 31.7 |
| | QRange | $\Delta$*IBESACTL* | 0.08 | 0.11 | 0.23 | 0.17 | 0.23 | 0.22 | 0.31 | 0.35 | 0.47 | 1.03 |
| | *N* | $\Delta$*IBESACTL* | 132 | 107 | 115 | 102 | 97 | 97 | 102 | 94 | 97 | 85 |

This table reports various distributional statistics in each decile of *BEGPRICE*, which is the beginning-of-year share price. Price deciles are computed each calendar year, and the lowest (highest) price decile is denoted by 1 (10). Variability of forecast errors from time-series forecasts is measured in panels A and B from Compustat per share data as the interquartile range (QRange) of seasonally differenced (denoted as $\Delta$*COMPACTL*) quarterly earnings (EPS), cash flow (CPS), and sales (SPS). From our Compustat sample, we drop firms not incorporated in the U.S., including ADRs. Variability for time-series forecasts for overseas firms in panels C and D is measured as interquartile range (QRange) of $\Delta$*IBESACTL*, which is the first difference in annual EPS according to I/B/E/S (*IBESACTL*). For panels C and D, we begin with the sample of firm-years used to compute *FCSTERR* for each country in table 3. Additional details for all variables are provided in appendix A.

all countries, for both analyst and time-series forecasts (results for overseas time-series forecasts are available from the authors). It appears as if the puzzling patterns observed for both forecast errors and dispersion for analysts' EPS forecasts are unrelated to analysts and are driven by managers smoothing volatility of reported EPS such that EPS volatility is held within certain bounds, measured in cents per share, regardless of the scale of EPS being forecast.

The results reported in panel B of table 6, where we repeat the analysis in panel A on a sample of Compustat firms that are *not* covered by I/B/E/S, suggests that the lack of scale observed so far for EPS is not driven entirely by managers. The results there show more variation with scale for EPS volatility than that reported for the I/B/E/S sample in panel A, especially for the extreme price deciles. Even when those two deciles are set aside, EPS exhibits scale variation that is similar to that observed for CPS and SPS: the EPS interquartile range for decile 9 is more than three times that for decile 2, which is comparable to the fourfold increases for the corresponding interquartile ranges for CPS and SPS.

Why does the desire for managers to smooth earnings and suppress scale variation in EPS volatility depend on whether or not their firms are followed by analysts?[28] One possibility is that analysts desire uniform variability and disagreement across high and low price shares, and managers assist them by reporting EPS numbers that exhibit uniform volatility regardless of scale. Another possibility is that managers are more sensitive to deviations of actual EPS from benchmarks when their firms are followed by analysts, and seek to suppress scale variation for variability and disagreement for analysts' EPS forecasts. If so, the three explanations we offered earlier are rendered irrelevant, since analysts are simply bystanders. Regardless, for both possibilities, it is investors, not analysts or managers, that suffer from (or are perceived to suffer from) behavioral biases that limit their ability to adjust deviations from benchmarks for scale differences. To be sure, it is possible that there are other differences between firms followed and not followed by analysts that explain differences between the patterns reported in panels A and B of table 6.

Returning to our stock split analysis in section 3.5, it is possible that managers achieve EPS volatility that is similar across high and low price firms by splitting shares rather than directly suppressing EPS volatility of high price firms. If so, presplit firms should have relatively higher variability and disagreement, which declines to normal levels after the split. That possibility is, however, not supported by the data: interquartile ranges for *FCSTERR* from panel A1 of table 1 are similar to those in panel A of table 5 and mean/median *DISPERSION* from panel C1 of table 1 are similar to those in panel B of table 5. Firms splitting shares generally have similar or lower

[28] Yu [2008] finds that earnings management, measured by discretionary accrual magnitudes, is *lower* for firms followed by analysts.

EPS variability/disagreement than other firms prior to the split (except for the 3-for-1 split), and EPS variability/disagreement is considerably lower after the split.

## 4. *Concluding Remarks*

In this paper, we investigate a curious result: EPS forecast errors and forecast dispersion of a particular amount (say, within $\pm$ 5 cents) are equally likely for large and small shares. This result is surprising since it is reasonable to assume that the magnitudes of forecast errors and dispersion of individual analyst forecasts around the consensus would be larger for large shares. Why would large shares that have proportionately larger magnitudes of actual and forecast EPS exhibit the same magnitudes of forecast error and dispersion as small shares? We consider three explanations for this counter-intuitive result and examine a variety of different aspects of U.S. and overseas data to determine which of those explanations are supported by the data.

Our results are not fully consistent with any of our explanations. The evidence does not support the view that forecast error variability and forecast dispersion, representing how hard it is for analyst forecasts to predict actual EPS and disagreement across analysts, respectively, do not vary naturally with scale. Our evidence also appears inconsistent with the view that while variability and disagreement vary naturally with scale other factors that are correlated with scale reverse that natural variation. Finally, we find mixed results regarding the view that natural variation with scale for variability and disagreement is suppressed by analysts.

Our results suggest that the lack of scale variation observed for EPS forecast variability and disagreement is because managers intentionally suppress volatility in reported EPS. Apparently, managers view deviations from EPS benchmarks in cents per share, not as a percentage of price or the level of actual/forecast EPS. Why managers suppress EPS volatility, and why they do so more when their firm is followed by analysts are two of many questions raised in this paper. We hope that further investigation will improve our understanding of managerial and analyst behavior.

Results similar to those we report for forecast error magnitudes for both analyst and time-series EPS forecasts have been reported before in DeGeorge, Patel, and Zeckhauser [1999]. Possibly because that paper has a different focus, the authors do not highlight those results as puzzling. The prior literature using measures of forecast error magnitudes and forecast dispersion has ignored those results and intuitively presumed that both variability and disagreement increase with scale. While the original results in Degeorge, Patel, and Zeckhauser [1999] are on their own quite remarkable, we find it equally remarkable that those results have remained obscure and the important implications about managerial and analyst behavior have remained unexplored for so long.

APPENDIX A

*Variable Definitions and Sources*

| Label | Description | Source |
|---|---|---|
| *ABSFE* (in dollars) | Absolute value of *FCSTERR* | |
| *BEGPRICE* (in dollars) | Share price of firm at the beginning of calendar year. | I/B/E/S Summary Actuals + Pricing unadjusted file (WRDS file name is ibes.actpsumu). For our Compustat samples (time-series analyses), we obtain the share price from CRSP (WRDS file name is crsp.dsf). |
| *COMPACTL* (in dollars) | Actual quarterly earnings per share (EPS), sales per share (SPS), or cash flow per share (CPS), as reported by Compustat. | *COMPACTL* for EPS, SPS, and CPS are obtained from the Compustat data items [#epspxq], [#saleq/#cshprq], and [#oancfy/#cshprq] respectively (WRDS file name is comp.fundq). |
| *COMPFE* (in dollars) | Forecast error ( = *COMPACTL*/DilutionFactor – *FORECAST*). Scaling by DilutionFactor is necessary as *FORECAST* can be on a basic or diluted basis. | DilutionFactor is obtained from I/B/E/S (WRDS file name is ibes.idsum). |
| *COVERAGE* (unit-free) | Number of estimates that constitute *FORECAST.* | I/B/E/S Unadjusted Summary Data (WRDS file name is ibes.statsumu). |
| *DEFLABSFE* (unit-free) | *ABSFE/BEGPRICE* | |
| *DEFLDISP* (unit-free) | *DISPERSION/ BEGPRICE* | |
| *DEFLFE* (unit-free) | *FCSTERR/ BEGPRICE* | |
| *DISPERSION* (in dollars) | Standard deviation of the individual analyst's forecasts that constitute *FORECAST*. | See description provided for *FORECAST*. |
| *FORECAST* (in dollars) | Most recent consensus (mean) estimate of *IBESACTL* for the firm-quarter. | EPS forecast is obtained from the I/B/E/S summary file (WRDS file name is ibes.statsumu), which is unadjusted for stock splits. We divide sales forecasts (ibes.statsum), reported at the firm level, by the unadjusted number of shares outstanding (ibes.actpsumu) to get the sales per share forecast. The cash flow per share forecast (ibes.statsum), which is adjusted for stock splits, is "unadjusted" by multiplying by the unadjusted share price (ibes.actpsumu) and dividing by the adjusted share price (ibes.actpsum) at the end of the fiscal period. |

(*Continued*)

APPENDIX A—*Continued*

| Label | Description | Source |
|---|---|---|
| *FCSTERR* (in dollars) | Forecast error ( = *IBESACTL* – *FORECAST*) | |
| *IBESACTL* (in dollars) | Actual quarterly earnings per share (EPS), sales per share (SPS), or cash flow per share (CPS), as reported by I/B/E/S, after I/B/E/S has adjusted it "for comparability with estimates." | *IBESACTL* for EPS is obtained from ibes.actu, which is unadjusted for stock splits. We divide actual sales (ibes.act), reported at the firm level, by the unadjusted number of shares outstanding (ibes.actpsumu) to get per share sales. The actual cash flow per share (ibes.act), which is adjusted for stock splits, is "unadjusted" by multiplying by the unadjusted share price (ibes.actpsumu) and dividing by the adjusted share price (ibes.actpsum) at the end of the fiscal period. |
| *MEANSTALE* (in days) | The *mean* forecast age of (*effective*) individual forecasts, equals consensus forecast date minus issue date of individual forecasts. | I/B/E/S Unadjusted Detail Data (WRDS file name is ibes.detu). The definition of "*effective*" is provided at http://wrds.wharton.upenn.edu/ds/ibes/lib/IBES_Summary_from_Detail.pdf |
| *VOL* (unit-free) | Standard deviation of stock returns over the period from day −210 to −11, relative to the fiscal quarter-end. | CRSP daily file (WRDS file name is crsp.dsf). |

## APPENDIX B

Each analyst *j* makes an eps forecast $F_{ijt}$ for firm *i* in quarter *t,* which gives rise to the forecast distribution below.

The mean, $\mu_{it}$, is the ***consensus*** forecast.

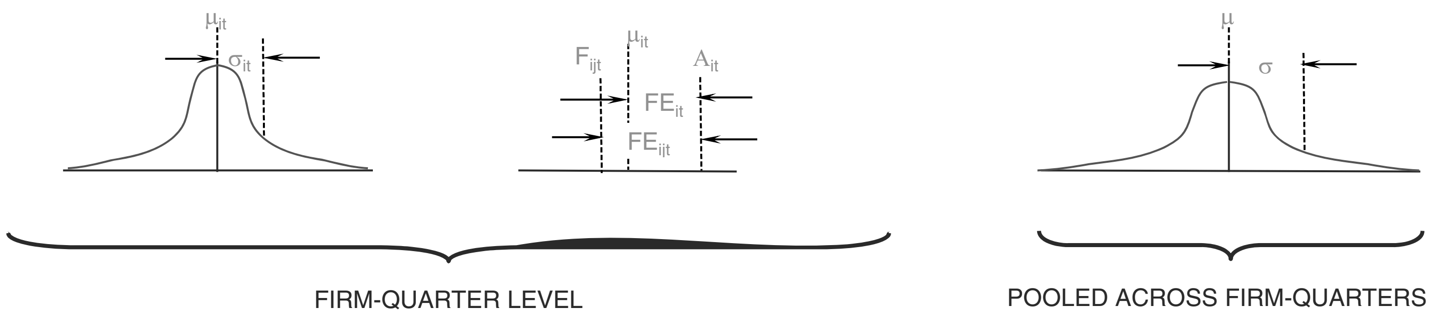
The standard deviation, $\sigma_{it}$, is referred to as ***dispersion,*** and measures ***disagreement.***

That ***consensus*** forecast, $\mu_{it}$, and individual forecasts, $F_{ijt}$, are then compared with the ***actual*** eps reported by firm *i* in quarter *t*, $A_{it}$, to generate an overall ***forecast error***, $FE_{it}$, and analyst-specific ***forecast error***, $FE_{ijt}$.

Those forecast errors $FE_{it}$ are pooled across firms and quarters to generate the forecast error distribution below.

Measures of central tendency (e.g., mean, $\mu$) represent ***bias*** in consensus forecasts.

Measures of variability (e.g., standard deviation, $\sigma$) represent ***variability*** of forecast errors.




VARIABLE

| | Disagreement ($\sigma_{it}$) | Variability ($\sigma$ or abs$\lvert FE_{it}\rvert$) |
|---|---|---|
| Dependent Variable | Case A | Case C |
| Independent Variable | Case B | Case D |

# APPENDIX B–*Continued*

To link our variables with the prior literature, we partition the prior literature into four cases based on whether the variable of interest is disagreement or variability and whether that variable appears as a dependent or independent variable. The specific papers provided below are intended to be illustrative, and are not derived from an exhaustive search.

For Case A, we consider analyses where dispersion or disagreement among analysts ($\sigma_{it}$) is the dependent variable. As an example, Lang and Lundholm [1996, table 6] investigate whether a firm's corporate disclosure policy affects its price-deflated dispersion. Other studies in this category include Barron, Kile, and O'Keefe [1999, table 5], Hope [2003, table 4 and 5], Mozes [2003, table 4], and Thomas [2002, table 4].

For Case B, we consider analyses where dispersion is the independent variable. As an example, Zhang [2006a, table III; 2006b, p. 570] investigates the effect of information uncertainty (proxied using price-deflated dispersion) on stock returns. Other studies in this category include Ajinkya, Atiase, and Gift [1991, table 3 and p. 393], Baber and Kang [2002, table 4], Bamber, Barron, and Stober [1997, table 3], Barron [1995, table 3], Diether, Malloy, and Scherbina [2002, table II], Gu and Wu [2003, table 3 and p.13], Imhoff and Lobo [1992, table 4 and p. 431], Loh and Mian [2006, table 7], and Nagel [2005, table 3].

For Case C, we consider analyses where the variability of EPS (e.g., $\sigma$ or $|FE_{it}|$) is the dependent variable. As an example, Hope [2003, table 4 and 5] investigates whether higher accounting disclosure results in greater variability (measured using absolute value of price-deflated forecast error). Other studies in this category include Duru and Reeb [2002, eq. 1 to 4], Haw, Jung, and Ruland [1994, eq. 1 and table 2], Stickel [1993, exhibit 2 and 4], and Thomas [2002, table 3].

For Case D, we consider pooled analyses where the variabilty of EPS is the independent variable. One example is Kinney, Burgstahler, and Martin[2002], which partitions the sample based on price-deflated absolute values of forecast errors.

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