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RETURN-EARNINGS REGRESSIONS: A MISMEASURED EARNINGS EXPECTATIONS PERSPECTIVE

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I. INTRODUCTION

The relation between earnings and stock returns has occupied much of the accounting literature during the past two decades. A rich variety of metrics were used in estimating the earnings response coefficient (ERC), such as returns and levels of earnings, typically scaled by prices, and returns and the unexpected portion of earnings, quantified using expectations models for earnings (time series models, analyst forecasts, etc.) and for returns (size-adjusted, market-model-predicted-returns, etc.).

When unexpected earnings are associated with abnormal returns in generating ERCs, errors in measurement invariably confound the association and bias the estimated coefficient towards zero. Specifically, the measurement error is the difference between whatever proxy is used to represent the earnings expected by the market and the unobserved expectation. The larger this measurement error and its variability, the larger the attenuation of the ERC.

In this paper, we assess the degree to which ERCs reported in the literature may be attenuated due to measurement errors in the proxies for the earnings expected by the market. We use the cross-sectional dispersion of analyst forecasts as a variable to calibrate the measurement error inherent in these proxies. We explore whether forecast dispersion is inversely related to the magnitude of ERCs, and whether ERCs approach their theoretical values as the dispersion decreases sufficiently.

The intuition underlying our approach can be derived from market equilibrium, as in

Abarbanell et al. (1995).[1] It could also be developed less formally. Disagreements among market participants as reflected in divergent earnings forecasts inject error into the measure of market expectations used by researchers. The larger the disagreement, the larger the uncertainty that the consensus forecast or an individual forecast matches the market's expectation, and hence the larger the measurement error in unexpected earnings. The market may assign different weights to different analyst forecasts when forming earnings expectations, depending on such factors as the analyst's reputation (Stickel 1992) and the currency of the forecast (Brown and Kim 1991). These weights, however, are unobservable to researchers, who typically use the consensus (simple average) forecast. The resulting measurement error will attenuate the estimated ERCs, and lead to a negative relation between dispersion and the ERCs. The cross-sectional dispersion in analysts' earnings forecasts reflects such disagreement as would render any of the commonly used proxies, including the IBES consensus earnings forecast, or any individual analyst forecast, a less reliable estimate of the market's expectation (hence magnifying the measurement error in unexpected earnings).

If a significant measurement error is responsible for attenuating the ERCs that are documented in the literature, then identification of firm-periods for which consensus forecasts

[1]Using a noisy rational expectations equilibrium model with the standard assumptions, they show that the variance of measurement error created by using the mean (consensus) forecast to proxy for investors' average expectation of earnings increases in the dispersion of analysts forecasts. Moreover, Abarbanell et al. (1995) demonstrate that, even in the absence of measurement error and under the assumption that private information precision is endogenous, the earnings response coefficient increases in forecast precision, which decreases in forecast dispersion. This presents yet another reason for the hypothesis that ERCs decrease in dispersion. Note, however, that this latter explanation is not testable independently because the precision of private information or the degree to which it is endogenously acquired is not observable. More pointedly, regardless of the precision of private information or its endogeneity, the measurement error in using proxies is always present (average market expectations are not observable), and it always increases with dispersion.

measure average market expected-earnings with less error should yield higher ERCs. Indeed if, consistent with theory, an ERC measures the change in the present value of expected future cash flows per dollar of unexpected earnings, then, in the absence of measurement error and under plausible assumptions concerning time series properties of earnings such as persistence, the ERC should equal the present value (computed using an appropriately risk-adjusted rate of return) of future cash flows per dollar of current earnings. Thus, at the limit, with zero measurement error ERCs should range in the low teens assuming a reasonable required rate of return and earnings growth (see the further discussion in the next section).

To begin, we find that using various measures of analysts earnings forecasts as proxies for earnings expectations improves on the estimation of the ERCs vis-a-vis mechanical models. For example, the median ERC using consensus forecasts is 3.82, which is substantially higher than the median of 1.40 we obtain when using mechanical models to generate earnings expectations. While these findings are in line with results in prior research, they point to ERCs that are still well below the theoretical values that we would expect in the absence of measurement error.

To investigate the effect of noise in the proxy for expected earnings due to dispersion of analysts' forecasts on the magnitudes of observed ERCs, we partition our sample into quintiles on the basis of the dispersion measure. The results support the view that dispersion is important for explaining small ERCs. Specifically, our results indicate that the association between dispersion and ERCs is negative. Most importantly, when unexpected earnings are estimated on the basis of analysts' forecasts and dispersion is small, the ERC is quite close to what might resemble a plausible theoretical value (median greater than 10), but when dispersion is high the ERC is much too low (median smaller than 2).

The dispersion of analyst forecasts might also be a reflection of the inherent uncertainty in anticipated cash-flows or the earnings generating process (e.g., Imhoff and Lobo 1992), rather than or in addition to gauging the extent of error in the estimation of unexpected earnings. To discriminate between these two potential sources for the dispersion, we investigate the impact of dispersion of analysts' earnings forecasts on ERCs after controlling for the cross-sectional variation in cash from operations. The results show that the negative correlation between ERCs and our measure of the error in unexpected earnings persists even after controlling for the variability of cash flow, thereby supporting our hypothesis that error in the measurement of expected earnings explains the small ERCs observed in prior research.

Finally, we explore whether dispersion could be correlated with the magnitude of earnings surprises so that the nonlinearity effect documented by Freeman and Tse (1992) rather than disagreement among traders, would explain the results. We find that the negative association between dispersion and ERCs persists even after controlling for the magnitude of earnings surprises.

Collectively, our results provide a new explanation for the small ERCs observed by prior researchers (e.g., Easton and Zmijewski 1989, Kothari and Sloan 1992, Lipe 1990, and Teets and Wasley 1996.) The results suggest that measurement error in the earnings surprise variable, not merely poor earnings quality (e.g., Lev 1989, p. 155), nonlinearity (e.g. Freeman and Tse 1992), or cash flow uncertainty (e.g., Imhoff and Lobo, 1992) explains the small ERCs.

Our findings have implications for both investment analysis and management and research focusing on ERCs. With respect to the former, if smaller analysts' forecast dispersion is a precursor of higher ERCs, information gathering and analysis designed to predict earnings is then best focused on companies associated with less dispersion. The return on investment analysis activities would then be maximized. As to the latter, extant research draws a variety of inferences from comparing the magnitudes of ERCs of different sets of firms. For example, Collins and Salatka (1993) investigate the valuation relevance of alternative foreign currency methods by comparing the magnitudes of ERCs of two sets of firms on the basis of their choice of the functional currency. Teets (1992) studies the effects of regulations on the market valuation of earnings surprises by comparing the magnitudes of ERCs of nonregulated firms and regulated electric utilities. If the two sets of firms differ with respect to the divergence of beliefs about their expected earnings, then inferences on the basis of differential ERCs are difficult to make without controlling for this divergence.

The next section discusses prior research, the motivation, and the research question. Section 3 presents the research design, and defines the variables. Section 4 outlines the sample selection procedure and describes the data. Section 5 reports the empirical findings, and the final section summarizes our study.

II. BACKGROUND, MOTIVATION, AND RESEARCH QUESTION

One of the most persistent features of returns/earnings-relation research is the finding of "small" earnings response coefficients. If, consistent with theory, an ERC measures the change in the present value of expected future cash flows per dollar of unexpected earnings, then, under plausible assumptions concerning the time-series properties of earnings, such as persistence, the ERC should be approximately equal, in perpetuity, to 1/(r-g). With an r, the equity cost of capital, of 12 percent (see, e.g., Ross et al. 1996, P. 234, Table 9.2) and a g (growth) of three percent (i.e. the expected annual growth of the GDP), a typical ERC should be around 11. Existing research findings briefly reviewed below, however, point to considerably smaller ERCs, typically not exceeding 3.[2]

Both cross-sectional and time-series studies consistently report small ERCs. While response coefficients estimated from cross-sectional regressions seemed to increase steadily with the length of the return interval in the study by Easton, Harris and Ohlson (1992, p. 138), they still lay within a low range of 0.53 for a one-year interval and 1.66 for a ten-year interval.

Time-series, firm-specific, response coefficients are only slightly higher, and still well below their theoretical value. For example, Kothari (1992), using firm-specific time-series price-earnings regressions over one-year windows, estimates response-coefficients with a mean of 2.61 and median of 2.00 (using earnings levels scaled by prices), a mean of 3.31 and a median of 1.82 (using earnings changes scaled by price), and a mean of 0.26 and a median of 0.13 (using earning changes scaled by lagged earnings.) While Kothari (1992) does not attempt price-earnings regressions that employ unexpected earnings as the explanatory variable, he claims that unexpected earnings is the logical variable to use in price-earnings regressions. That is, an accurate proxy for market-unexpected earnings should outperform both earnings-level and earnings-change-deflated-by-price variables. But an accurate proxy for the market expectation may be difficult to identify. Time-series-based proxies for earnings expectations fail to capture new information incrementally useful in predicting more accurately current earnings that have

[2]The only exception to the findings of "small" ERCs is in Freeman and Tse (1992). They hypothesize that the absolute value of unexpected earnings is negatively correlated with persistence, and their nonlinear regression yields results consistent with this premise, exhibiting an average ERC of 14.0 in cross-section. Thus, as part of our sensitivity tests, we examine the effects of magnitudes of earnings surprises on our results.

become available to the market since the previous earnings announcement.

Using analyst forecasts (scaled by stock prices) instead in an attempt to obtain a more accurate proxy for the market's earnings expectations at the time of the earnings announcement, Easton and Zmijewski (1989, Table 2), for example, estimate ERCs using firm-specific time-series regressions and two-day-return windows around quarterly earnings with a mean of 1.649 and median of 1.279.[3] Collins et al. (1992) show that the use of unexpected earnings, deflated by prices, outperforms the earnings-deflated-by-price variable on the dimensions of bias and explanatory power: annual returns are better explained by more accurately capturing the current period's earnings surprise than by earnings-level-deflated-by-price.

Clearly, the ERC is a function of multiple factors: growth, risk, the persistence of earnings, accounting principles, measurement errors, quality (in the sense of reliably predicting cash flows), the probability of misrepresentations, timeliness (prices leading earnings), etc. Past work has identified a subset of determinants of ERCs. Easton and Zmijewski (1989) and Collins and Kothari (1989) both show persistence and systematic risk to be cross-sectional explanatory variables. Collins and Kothari (1989) additionally identify growth (proxied by market value to book ratio) as a cross-sectional determinant of ERCs, and the risk-free rate of interest as a variable that contributes to the explanation of their temporal variation. But they point to noise in reported earnings (as an indicator of future expected dividends) as being a factor that could affect the estimated covariance between the unexpected earnings measure (annual changes in earnings) and unexpected return.

[3]For an insightful review of the role of analysts' earnings forecasts in capital market research generally see e.g. Brown (1993).

Overall, prior studies have left two important questions largely unanswered: what is the likely impact of measurement error on ERC estimates, and what variables can be reasonably used as proxies for this measurement error? We attempt to answer these questions by focusing on a yet unexplored but potentially important source for the error in measuring unexpected earnings: the uncertainty surrounding the market's earnings expectations when beliefs and forecasts diverge. To investigate the effect of noise in the proxy for expected earnings due to dispersion of analysts' forecasts on the magnitudes of observed ERCs, we partition our sample into quintiles on the basis of the dispersion measure and explore whether ERCs approach their theoretical values as the dispersion decreases sufficiently.

Imhoff and Lobo's (1992) study resembles ours in that they hypothesize and test whether the standard deviation of analysts' annual forecasts (obtained from the IBES summary tapes) is negatively related to ERCs. However, while they use analyst forecasts' standard deviation as a proxy for the inherent uncertainty in cash flows, we use analyst forecasts' dispersion (i.e., the temporal average of the absolute coefficients of variation of consensus forecasts) to gauge the extent of error in the estimation of unexpected earnings. We discriminate between Imhoff and Lobo's hypothesis (cash flow or earnings uncertainty) and ours (measurement error in unexpected earnings) by examining the impact of the dispersion of analysts' earnings forecasts on ERCs after controlling for the variation in cash flow. We thus can ascertain whether the measurement error caused by disagreement has a significant residual impact on ERCs beyond cash flow uncertainty.[4]

[4]We also control for price-earnings ratios. Price-earnings ratios are known to increase in persistence and decrease in the perceived risk associated with future cash flows (see e.g. Beaver and Morse 1978, and 1989). The results, not reproduced here but available from the authors, are very similar to those obtained using the variability of cash flows as a controlling variable.

There are other important aspects of research design that distinguish our study from Imhoff and Lobo. They cumulate abnormal returns over two-day windows but measure what should be the corresponding unexpected earnings over one-month intervals, whereas we match the two windows closely. Furthermore, they use pooled data rather than time-series data. As a consequence, Imhoff and Lobo document no more than an ERC of 0.046 in pooled cross-sections of the whole sample and 0.77 under low uncertainty.

III. RESEARCH DESIGN AND VARIABLE DEFINITIONS

Research Design

Along the lines of prior research, we use analysts' earnings forecasts to improve on the measurement of market expectations of earnings relative to the use of mechanical models that generate expected earnings, since the former are presumed to incorporate non-earnings information about future cash flows. Our methodology, however, differs in an important way: we control for the adverse effect on ERCs of divergent beliefs among market participants. The proxy we use for these divergent beliefs is the temporal average of a firm's monthly standard deviation of IBES analysts' forecasts scaled by the absolute value of their mean, i.e., the temporal average coefficient of variation of IBES forecasts for the firm.

We use firm-specific regressions rather than cross-sectional or pooled time-series cross-section estimation. Using pooled estimation could lead to incorrect inferences about the magnitude of estimated earnings response coefficients because of the typically negative relation between firm-specific earnings response coefficients and unexpected earnings variances (see, e.g., Teets and Wasley 1996).

Our choice of an abnormal return holding period (estimated forecast-date to earnings-announcement-date) reflects a trade-off. While using a short window (such as a two-day holding period) for accumulating abnormal returns minimizes the impact of confounding events, it increases the measurement error in unexpected earnings due to a mismatch between the return window and the horizon of the expected-earning measure (see, e.g., Brown et al. 1987, and Easton and Zmijewski 1989). We conjecture that press releases and other news affecting prices between the date of the forecast and the date of the earnings-announcement convey mostly information about the earnings to be announced. This suggests the confounding-event problem in stock returns is not as severe as the measurement error in unexpected earnings. Hence, we accumulate returns from the estimated date of the forecast to the date of the earnings-announcement.[5] This accumulation period closely matches the period over which unexpected earnings are measured.

To compare the importance of mismeasured (by researchers) earnings expectations and noise in reported earnings for explaining the observed small ERCs, we perform two types of analyses. First, we compare the ERCs' estimates derived from models using "naive" market-expectations of earnings (seasonal-random-walk) and those using analyst forecasts. We expect the forecast-based-models to yield higher ERCs because the naive expectations fail to fully consider information in stock returns that also affect the earnings expectations of the market. Analyst forecasts, however, most likely incorporate more of the information embedded in stock

[5]The median return accumulation periods are as follows (full sample): Early Consensus: 71 days (99th percentile = 113 days); Late Consensus: 43 days (99th percentile = 66 days); Early Detailed: 84 days (99th percentile = 118 days).

returns, and thus provide a better matching between stock returns and unexpected earnings.

Second, and most importantly, we examine the relation between the magnitudes of ERCs and levels of disagreement about expected earnings among market participants. Should these levels be an important contributor to the mismeasurement of earnings expectations, *ceteris paribus*, the value of the ERC will be negatively related to the level of disagreement and will approach its theoretical value as disagreement among market participants regarding expected earnings becomes sufficiently small. As noted above, we control for the possibility that disagreement could also reflect noise in reported earnings (as a predictor of future cash flows) by examining the relation between ERCs and levels of disagreement after controlling for the cross-sectional variability of cash from operations.

Variable Definitions

Our analysis requires calculations of unexpected earnings (UE), disagreements among market participants (DIS), and cumulative abnormal returns (CARs). Unexpected earnings of the i*th* firm in year t ($UE_{i,t}$) is the difference between actual and expected earnings for this firm-quarter observation. Forecasted earnings (FE) are estimated in two alternative ways. The first assumes that quarterly earnings follow a seasonal random walk process:

$$FE_{i,t} = E_{i,t-4} \tag{1}$$

where $E_{i,t}$ refers to the actual earnings per share reported by firm *i* in quarter *t*.

The second way to estimate FE relies on analysts' earnings forecasts retrieved from the IBES database. Three alternative measures based on analysts' forecasts are used: (a) *Early Consensus* is the earliest consensus forecast for quarterly earnings after the previous quarter's earnings announcement as reported in the IBES summary file. The forecast date is estimated as the middle of the month preceding the IBES "statistical date" due to publication lags -- the time between the date of an analyst forecast and the date the forecast first appears on IBES, averaging approximately one month (see, e.g., O'Brien 1988, p. 59),[6] (b) *Late Consensus* is the *latest* consensus forecast in the period between the previous quarterly earnings announcement and the current announcement, with the forecast date estimated as before, and (c) *Early Detailed* [7] is the earliest individual forecast made after the previous quarterly earnings announcement, with a forecast date estimated as the IBES estimate date, which is defined as the date in which the estimate was received by IBES.[8]

Disagreements among market participants regarding expected earnings are proxied for each firm by the time-series-average over the whole sample period of the absolute coefficients of variation of the IBES summary tape's analyst forecasts of quarterly EPS.[9]

We obtained cumulative abnormal returns (CARs) from the CRSP NYSE/AMEX daily beta excess return file (1997 version, data ending December 31, 1996). This file contains daily

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[6]The statistical date refers to the month and year in which IBES recorded the consensus. For example, earnings forecast data with a May 1998 statistical date were recorded on IBES on May 14, 1998. In general, each month IBES updates its tape on the Thursday preceding the third Friday of the month.

[7] Results for a "late detailed" specification have not been reported, since the noise inherent in using the IBES estimate date as our proxy for the forecast date can have a material effect on the estimation of our return windows, which are relatively short in this case. We did however run our analysis for this specification too, with results which were similar to those reported here for the mechanical model.

[8]The individual forecasts are taken from the IBES detailed file. If several forecasts were reported as being made on the relevant date, the average is used.

[9] The standard deviations used in this computation are taken directly from the IBES summary tape. The computation excludes observations for which the reported mean or standard deviation is not available or is reported as zero. Thus firm-quarters with less than two analyst forecasts are excluded. Moreover, only firms with 20 quarters of data that satisfy our criteria are included.

returns for each stock in the database in excess of the daily returns on a portfolio of stocks with similar risk (i.e., same beta decile). CRSP determines risk using beta values, which are estimated using the method developed by Scholes and Williams (1977). We cumulate CAR over a window that commences one day before the estimated forecast date as defined above and ends one day after the actual earnings announcement date as reported by IBES. For the seasonal random walk model, the window is the same as the one used in the early consensus case.

We scale the unexpected earnings variables by the price on the estimated forecast date (in the case of the seasonal random walk, they are scaled by the price corresponding to the date for the early consensus forecast). Prices are retrieved from the CRSP daily stock file and adjusted for stock splits using the adjustment factor provided by IBES.

IV. DATA

Our sample spans the 13-year period, 1984-1996. Table 1 reconciles our final sample size of 590 distinct firms with the initial size of 6,737. We exclude 5838 firms that lacked sufficient time-series data on the IBES tape to make possible the estimation of ERCs, or have changed their cusip number during our sample period. Additionally, one firm was not listed on the CRSP database, and 308 firms lacked sufficient market data to conduct the regression analyses. A portion of the analysis was performed on a subsample formed by removing from our final sample firms with less than 25 quarters of data on the IBES tape with positive reported earnings and positive earnings forecasts and by winsorizing standardized unexpected earnings numbers at three standard deviations. The size of this subsample is 498 firms.

We have taken steps to ensure the quality of data collected from IBES. Firstly, the computation of our measure of disagreement among analysts excludes observations for which the reported mean or standard deviation is not available or is reported as zero. Thus firm-quarters with less than two analyst forecasts are excluded. Moreover, only firms with 20 quarters of data that satisfy our criteria are included in this computation. Secondly, our choice of long windows reduces noise owing to errors in estimating the forecast date. Thirdly, we use both the consensus and detailed tapes, and obtain similar results. This gives us confidence in the reliability of these results.

Table 2 contains descriptive data for the final sample (590 firms), as well as for the subsample (498 firms). These data come from the Compustat industrial tape and pertain to the year 1992, approximately the midpoint of the sample period. Table 2A (full sample) and Table 2B (subsample) report descriptive statistics by quintiles based on the time-series-average of the absolute coefficients of variation of the forecasted quarterly EPS of each firm.[10] Reading across these tables we note the negative mean and median forecast-based SUEs. This finding of optimistic bias in analysts' earnings forecasts increases confidence in the representativeness of our sample as it has also been documented by previous literature using various data sources and sample periods (see, e.g., Brown 1997 for the optimistic bias in forecasting quarterly earnings; and Fried and Givoly 1982 for the optimistic bias in forecasting annual earnings).

We also note the absence of an obvious monotonic relation between our proxies for disagreement among market participants (i.e., the variables used to construct the quintiles) and variables that explain cross-sectional variation in ERCs such as firm size, market-to-book ratios

[10] The negative mean price to earnings ratio in Table 2A 4th quintile results from an outlying observation, as does the negative mean market-to-book ratio for the 5th quintile in Table 2A.

(proxying for growth opportunities), and price earnings ratios (proxying for risk). This makes it less likely that omitted variables drive our results. Nevertheless, it appears that the magnitudes of the earnings surprise variables (SUE) are positively associated with our partitioning variables. For example, in Table 2A the mean of the early consensus SUE variable increases (in absolute value) from 0.0003 in quintile 1 to 0.0053 in quintile 5. This may confound our tests if the returns-earnings relation is non-linear in the magnitudes of the earnings surprise. Our sensitivity analyses (reported in the next section) thus examine this possibility as well as other potential research confounders. Finally, it is noteworthy that, as expected, late consensus forecasts are the most accurate among our four measures of earnings surprise.

V. TESTS AND RESULTS

Divergent Beliefs and ERCs

We estimate ERCs by firm, using the following time-series returns/earnings regression:

$$CAR_{i,t} = a_i + b_i\,(UE_{i,t} / P_{i,t}) + u_{i,t} \qquad (2)$$

where CAR_{it} refers to the cumulated abnormal return of the i*th* firm in quarter t. As explained above, when early detailed forecasts are used to proxy for earnings expectations, we cumulate CAR from one day before the date assigned to the forecast by the analyst to one day after the actual earnings announcement date as reported by IBES. When we use IBES consensus data, the CAR window begins at the middle of the month prior to the corresponding IBES statistical date and ends one day after the actual earnings announcement date as reported by IBES. For the seasonal random walk model, the window is identical to the one used for the early consensus case.

UE_{it} refers to unexpected earnings of the i*th* firm in quarter t as defined above, and P_{it} represents the price per common share of the i*th* firm on the estimated date of the forecast of quarter t.

Throughout, we report mean and median ERCs and adjusted R-squares for our sample firms by quintiles (displayed in ascending order) constructed on the basis of our proxy for divergence of earnings expectations, as well as for the unpartitioned sample. As mentioned, our proxy is based on the temporal average of the absolute coefficients of variation of consensus forecasts of each firm, which represents a measure of the level of disagreement among analysts. We use four alternative proxies for earnings expectations: Seasonal random walk, early consensus, late consensus, and early detailed. The results for our four proxies are shown in separate panels of each table.

Table 3 reports the results for the full sample (590 firms). For all proxies the mean and median ERCs are monotonically declining across the five quintiles. For example, when unexpected earnings are derived from a seasonal random walk model (Panel A), the median ERCs are 4.18, 2.33, 1.56, 1.00, and 0.66 in quintiles 1 through 5, respectively, and the median ERC for the full sample is 1.40. The variation in ERCs is even more pronounced in panels B, C, and D, where the earnings surprise variables used in the regressions to estimate ERCs are based on analyst forecasts. For example, in Panel D, the means of ERCs monotonically decrease from 12.85 (quintile 1) to 2.11 (quintile 5), and the medians from 8.86 (quintile 1) to 1.46 (quintile 5). Overall, these results may be considered *prima facie* evidence of the important impact of divergent beliefs on estimating ERCs. We hasten to add, however, that our tests may be confounded by omitted variables and/or misspecified functional forms.[11] To evaluate the effects of these potential problems on our findings, we subject our analysis to a battery of sensitivity tests, reported below.

Sensitivity Tests

We perform five types of sensitivity analysis. First, we replicate the analysis after removing negative forecasts and/or realizations of EPS and winsorizing the standardized unexpected earnings numbers at three times their standard deviation. We delete negative EPS numbers because losses are less informative than profits about the firm's future prospects (see, e.g., Hayn 1995). We winsorize extreme values of the earning surprise variables to alleviate problems arising from the inordinate effects that outliers may have on OLS parameter estimates. Removing negative EPS reduces the number of observations available for estimating ERCs for many firms. Firms for which the number of observations falls below 25, a total of 92 firms, are removed from the sample. This subsample thus consists of 498 firms. Table 4 reports the results. As expected, the removal of negative EPS leads to higher estimated ERCs, thereby bringing them closer to their expected theoretical values. For example, ERC medians reported in panel B of table 4 range from 13.31 to 5.65, while in panel B of table 3 they range from 10.85 to 1.64.

Second, we replicate our tests after randomizing the cross-sectional variation in the absolute temporal coefficient of variation of annual cash from operations (hereafter, CVCFO)

[11]Tests for auto-correlation show that it is not a problem in our sample. Using the Durbin-Watson statistic and a conservative test based on critical values of its upper bound, the null hypothesis of no autocorrelation (either positive or negative) cannot be rejected for over 85% of our firms under any specification.

across the five quintiles.[12] This analysis is important as at this point it is not totally clear whether the negative relation between ERCs and our proxies for divergent beliefs is due to increased noise in the earnings-expectation measure used by researchers or increased risk associated with greater cash flow uncertainty. We randomize CVCFO by first sorting into quintiles based on the values of CVCFO. Each of these quintiles is then sorted again into sub-quintiles using our measures of divergent beliefs. We create final portfolios by merging matching sub-quintiles. That is, the lowest five sub-quintiles with respect to divergent beliefs of the five quintiles are merged to form the lowest-ranking portfolio, and so on. We thus form portfolios ranked on the levels of divergent beliefs after controlling for differences in CVCFO. In Table 5 we report the results for the full sample (524 firms) and in Table 6 for the subsample containing only positive earnings and forecasts (442 firms). The results in Table 5 show that the monotonic decline in ERCs across the five quintiles noted before continues to hold. Still, we are only partially successful in controlling for the variation in cash flows as the median CVCFO monotonically increases from 0.38 (first quintile) to 0.45 (fifth quintile). The results in table 6, however, clearly show that the negative relation between our measure of divergent beliefs and ERCs holds even after the variation in cash flows is effectively controlled. Together, these findings enhance confidence that errors in estimating expected returns due to divergent beliefs among market participants, not the riskiness of cash flows, explain the small ERCs observed in prior research.[13]

[12]The coefficient of variation for each firm is estimated over the nine-year period, 1988 - 1996. Annual cash from operation is as reported by Compustat (annual item # 308). This item was available for about 90 percent of our sample firms.

[13]Table 2 demonstrates the absence of an obvious relation between PE ratios and divergent beliefs. Still we replicated the analyses in tables 5 and 6 by using PE ratios rather than CVCFO to control for cash flow uncertainty. The results, not reported for parsimony, were similar to those reported in tables 5 and 6.

Our third type of sensitivity analysis involves replicating our tests after controlling for the variation in the magnitude of the earnings surprise variables across our five quintiles. We employ this procedure because the magnitudes of the earnings surprise variables (SUE) are positively associated with our partitioning variables (see, e.g., Tables 2A above), and because the returns-earnings relation may be nonlinear in the magnitude of the earnings surprise (see, e.g., Freeman and Tse 1992). We create quintiles on the basis of divergent beliefs after successfully randomizing (see second column of tables 7 and 8) on the temporal average of the firm's earnings surprise magnitudes (in absolute values).[14] Table 7 reports the results for the full sample and Table 8 for the subsample of firms for which we used only positive EPS forecasts and realizations to estimate ERCs. Our previous results hold for the subsample, but the relation between our proxies for the levels of divergent beliefs and magnitudes of ERCs weakens for the full sample. Together, these findings suggest that: 1. the nonlinearity in the returns-earnings relation documented by Freeman and Tse (1992) is driven primarily by losses, and 2. divergent beliefs are important for explaining the magnitudes of ERCs above and beyond nonlinearity. While the first point has already been shown by prior research (e.g., Hayn 1995), we are the first to provide evidence on the importance of divergent beliefs for explaining the magnitudes of ERCs.

Fourthly, since prior work in this area has relied on a variety of data sources, sample selection procedures, and research designs, our fourth type of sensitivity analysis is designed to evaluate the representativeness of our sample and the generalizibility of our findings. We replicate the work of Easton and Zmijewski (1989) (hereafter EZ), whose sample was retrieved from Value

[14]The randomization procedure is similar to the one we used for randomizing cash flow variability measures.

Line and covered the six-year period, 1975-1980, using our sample. Table 9 reports the results of replicating their Table 2, Panel A. There are three points to notice. First, our parameter estimates are quite similar to theirs. For example, for the full sample our mean and median intercept are 0.0026 and 0.0023, respectively, and EZ's are 0.001 and 0.002. Similarly, our mean and median ERCs are 2.36 and 1.03, and theirs are 1.649 and 1.279.[15] These findings increase our confidence that our findings are not sample-specific; rather, they can be generalized to samples generated from other databases and/or other time periods.

Second, one of our research design choices involves accumulating stock returns over long windows, from the estimated forecast-date to the earnings-announcement-date, as opposed to two-day windows around earnings announcements. As discussed in detail in section 2 above, this choice follows from our conjecture that matching closely the period over which unexpected earnings are measured with the return accumulation period is more important than reducing confounding effects by using short windows. The lower ERCs reported in Table 9 vis-a-vis those reported in Table 3 confirm our conjecture, and suggest that future studies making inferences from ERCs (e.g., Teets 1992; Collins and Salatka 1993) should match the return-accumulation period and the forecast-date to the earnings-announcement-date period, rather than using a short window around earnings announcements.

Third, the relation between our measures of divergent beliefs and ERCs holds even when returns are measured over two-day periods around earnings announcements. For example, Table

[15]Note their use of actual return as an additional explanatory variable in the regression. This variable surrogates for information released between the earnings forecast date and the date on which they commence the accumulation of abnormal returns. Our approach matches closely the abnormal return accumulation period and the period over which unexpected earnings is measured. Hence we have no need to include an actual return explanatory

9 shows that mean and median ERCs decline monotonically from 5.17 and 3.41 (quintile 1) to 0.60 and 0.27 (quintile 5). These results demonstrate that our findings are not sensitive to the return accumulation period, and thus increase confidence in their validity.

Finally, to further validate our results, we run a multiple regression of earnings response coefficients on our measure of disagreement (DIS) and a number of other factors. These include the time-series mean standardized unexpected earnings measure, the average number of analysts following a firm, the logged market capitalization at the end of 1992 as a proxy for firm size, the market-to-book ratio at the end of 1992, and the price earnings ratio at the end of 1992. We would expect to see a negative coefficient on our measure of disagreement if it has an incremental effect on ERCs. As Table 10 shows, the coefficient on DIS is significantly negative under all specifications. γ_2 is significantly negative (except in the "Early Detailed" case, demonstrating the non-linearity effect discussed above). Number of Analysts, and Market to Book ratios are significantly and positively related to ERC whereas size is significantly and negatively related to ERC, all as expected.

VI. CONCLUSION

This study demonstrated that at least one important contributor to the explanation of "surprisingly small" ERCs documented in past research is noise in measuring earnings expectations due to disagreement among market participants in predicting the magnitude of future earnings. For the lowest dispersion quintile (ranked on the basis of the temporal average of the absolute analysts' forecasts coefficients of variation) we document ERCs that range in means

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variable in our models.

from 12.85 to 13.94, and in medians from 7.83 to 10.85. For the quintile with the highest dispersion, ERCs range only from 1.99 to 2.16 (means), and 1.10 to 1.64 (medians). Furthermore, we obtain these ranges when unexpected earnings are measured on the basis of analysts' forecasts, and they are considerably higher than those obtained on the basis of a seasonal random walk model.

The ERCs we obtain for subsamples with low divergence of beliefs regarding future earnings are substantially higher than those documented in past studies, ranging up to no more than three when, as in our study, linear regressions are used. The only notable exception is the non-linear fitting by Freeman and Tse (1992), who were able to obtain an ERC of about 14 for very small magnitudes of earnings surprise. We were able to show that nonlinearity, as demonstrated in Freeman and Tse (1992), cannot account for the significant increases in our ERCs as disagreement decreases. We obtain large ERCs even when magnitudes of earning surprises are not small, especially for the subset of firms with positive earning surprises. This is to be expected in light of the evidence that negative earning surprises are associated with small ERCs (see, Hayn 1995).

The ranges of ERCs characterizing the lowest dispersion quintile come close to the range of a plausible theoretical value, based on a reasonable required rate of return and earnings growth. This evidence is comforting because it accords with valuation theories. Moreover, our study demonstrates the obstacles faced by researchers attempting to identify reasonably good proxies for market expectations. Pitfalls abound: disagreements among informed traders and analysts inject measurement error into estimates of market expectations, and consequently bias estimated ERCs down from their expected values.

Implications of our findings extend to both the practice of investment management and to research. The higher ERC's associated with small analysts' forecast dispersion should direct information acquisition efforts to stocks of companies known to or predicted to have low dispersions. As to research, the findings point to the need to control for dispersion in any attempt to perform ERC comparison across different types of firms.

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Table 1
Sample Selection

(A) All firms listed on the IBES consensus tape	6737
(B) Firms in (A) that have 25 or more quarters of complete relevant information on IBES, after excluding firms that have more than one CUSIP code corresponding with the IBES ticker, and after excluding observations in which the month of the previous earnings announcement was more than four months prior to the current one	899
(C) Firms in (B) that are listed on the CRSP 1997 daily stock tape	898
(D) **FINAL SAMPLE**: Firms in (C) with 25 quarters or more of complete relevant information on CRSP (beta excess returns and prices at relevant dates)	590
(E) Subsample of firms in (D) with 25 quarters or more of complete information after observations with negative EPS forecasts and realizations are deleted.	498

Table 2A
Sample Descriptive Statistics
Full sample (590 firms)

Quintile[1]	Number of Observations	Variable	Mean	Median	Standard Deviation
1	118	Capitalization[2]	8322.65	3921.49	11824.27
		Market to Book Ratio[3]	3.42	3.06	2.05
		Cash Flow from Operations[4]	2.93	2.29	1.92
		Earnings Per Share[5]	1.81	1.56	0.92
		Price Earnings Ratio[6]	18.89	17.91	11.61
		Dispersion[1]	0.05	0.05	0.01
		Number of Analysts[1]	4.64	4.32	1.95
		Early Consensus SUE[7]	-0.0003	-0.0001	0.0011
		Late Consensus SUE[7]	-0.0002	0.0000	0.0011
		Early Detailed SUE[7]	-0.0002	-0.0001	0.0013
		Seasonal Random Walk SUE[7]	0.0019	0.0015	0.0022
2	118	Capitalization[2]	5133.82	2511.33	10650.43
		Market to Book Ratio[3]	2.89	2.32	2.14
		Cash Flow from Operations[4]	2.97	2.46	2.22
		Earnings Per Share[5]	1.64	1.38	1.39
		Price Earnings Ratio[6]	15.18	17.20	115.09
		Dispersion[1]	0.08	0.08	0.01
		Number of Analysts[1]	3.90	3.71	1.65
		Early Consensus SUE[7]	-0.0010	-0.0005	0.0021
		Late Consensus SUE[7]	-0.0006	-0.0003	0.0016
		Early Detailed SUE[7]	-0.0038	-0.0006	0.0262
		Seasonal Random Walk SUE[7]	0.0009	0.0010	0.0017
3	118	Capitalization[2]	4147.31	1890.92	5583.14
		Market to Book Ratio[3]	2.23	1.90	1.71
		Cash Flow from Operations[4]	2.97	2.52	2.23
		Earnings Per Share[5]	1.35	1.28	1.58
		Price Earnings Ratio[6]	21.46	17.20	78.81
Table 2A		Dispersion[1]	0.12	0.12	0.01

(contd.)

		Number of Analysts[1]	3.93	3.56	1.86
		Early Consensus SUE[7]	-0.0013	-0.0006	0.0031
		Late Consensus SUE[7]	-0.0010	-0.0004	0.0029
		Early Detailed SUE[7]	-0.0014	-0.0006	0.0031
		Seasonal Random Walk SUE[7]	0.0010	0.0009	0.0026
4	118	Capitalization[2]	2234.32	993.72	3644.48
		Market to Book Ratio[3]	1.96	1.74	0.91
		Cash Flow from Operations[4]	2.58	2.23	1.77
		Earnings Per Share[5]	0.72	0.92	1.70
		Price Earnings Ratio[6]	-1.46	16.15	184.44
		Dispersion	0.21	0.20	0.04
		Number of Analysts	3.50	3.14	1.57
		Early Consensus SUE[7]	-0.0020	-0.0011	0.0035
		Late Consensus SUE[7]	-0.0015	-0.0007	0.0032
		Early Detailed SUE[7]	-0.0027	-0.0013	0.0069
		Seasonal Random Walk SUE[7]	0.0008	0.0003	0.0037
5	118	Capitalization[2]	2031.06	966.94	3524.73
		Market to Book Ratio[3]	-1.05	1.53	32.81
		Cash Flow from Operations[4]	2.14	2.06	3.01
		Earnings Per Share[5]	-0.43	0.09	3.18
		Price Earnings Ratio[6]	11.61	10.97	138.38
		Dispersion[1]	0.62	0.53	0.30
		Number of Analysts[1]	3.65	3.46	1.62
		Early Consensus SUE[7]	-0.0053	-0.0040	0.0067
		Late Consensus SUE[7]	-0.0039	-0.0029	0.0062
		Early Detailed SUE[7]	-0.0056	-0.0040	0.0066
		Seasonal Random Walk SUE[7]	-0.0004	-0.0004	0.0052

Table 2B
Sample Descriptive Statistics
Subsample of 498 firms with only positive EPS forecasts and realizations

Quintile[1]	Number of Observations	Variable	Mean	Median	Standard Deviation
1	99	Capitalization[2]	9326.35	4188.83	12645.66
		Market to Book Ratio[3]	3.47	3.10	2.10
		Cash Flow from Operations[4]	3.11	2.42	2.01
		Earnings Per Share[5]	1.89	1.63	0.90
		Price Earnings Ratio[6]	17.86	18.01	4.30
		Dispersion[1]	0.05	0.05	0.01
		Number of Analysts[1]	4.68	4.40	2.00
		Early Consensus SUE[7]	-0.0001	0.0000	0.0009
		Late Consensus SUE[7]	0.0000	0.0000	0.0009
		Early Detailed SUE[7]	-0.0001	0.0000	0.0009
		Seasonal Random Walk SUE[7]	0.0016	0.0016	0.0009
2	100	Capitalization[2]	5757.76	2768.20	11434.55
		Market to Book Ratio[3]	3.17	2.55	2.32
		Cash Flow from Operations[4]	2.72	2.20	2.17
		Earnings Per Share[5]	1.65	1.24	1.43
		Price Earnings Ratio[6]	20.67	18.49	13.52
		Dispersion[1]	0.07	0.07	0.01
		Number of Analysts[1]	4.09	3.82	1.79
		Early Consensus SUE[7]	-0.0003	-0.0003	0.0008
		Late Consensus SUE[7]	-0.0001	-0.0001	0.0007
		Early Detailed SUE[7]	-0.0005	-0.0005	0.0015
		Seasonal Random Walk SUE[7]	0.0010	0.0010	0.0018
3	100	Capitalization[2]	3638.26	1799.49	4830.04
		Market to Book Ratio[3]	2.15	1.89	1.62
		Cash Flow from Operations[4]	3.20	2.85	2.23
		Earnings Per Share[5]	1.56	1.47	1.43
		Price Earnings Ratio[6]	32.59	16.88	68.74
		Dispersion[1]	0.10	0.10	0.01
		Number of Analysts[1]	3.94	3.57	1.81

(contd.)

		Early Consensus SUE[7]	-0.0002	-0.0002	0.0012
		Late Consensus SUE[7]	0.0000	0.0000	0.0012
		Early Detailed SUE[7]	-0.0034	-0.0034	0.0285
		Seasonal Random Walk SUE[7]	0.0008	0.0008	0.0016
4	100	Capitalization[2]	3520.26	1617.46	5241.01
		Market to Book Ratio[3]	2.12	1.76	1.27
		Cash Flow from Operations[4]	2.79	2.06	2.05
		Earnings Per Share[5]	0.84	0.95	1.96
		Price Earnings Ratio[6]	24.31	17.31	23.20
		Dispersion[1]	0.15	0.20	0.02
		Number of Analysts[1]	3.64	3.29	1.56
		Early Consensus SUE[7]	-0.0001	-0.0003	0.0017
		Late Consensus SUE[7]	0.0002	0.0001	0.0016
		Early Detailed SUE[7]	-0.0001	-0.0003	0.0017
		Seasonal Random Walk SUE[7]	0.0009	0.0007	0.0019
5	99	Capitalization[2]	2948.49	1602.82	4047.33
		Market to Book Ratio[3]	2.08	1.74	1.12
		Cash Flow from Operations[4]	2.84	2.86	2.58
		Earnings Per Share[5]	0.38	0.95	2.62
		Price Earnings Ratio[6]	35.83	20.93	53.76
		Dispersion[1]	0.39	0.32	0.22
		Number of Analysts[1]	4.05	3.75	1.66
		Early Consensus SUE[7]	-0.0002	-0.0003	0.0018
		Late Consensus SUE[7]	0.0003	0.0000	0.0017
		Early Detailed SUE[7]	-0.0003	-0.0003	0.0019
		Seasonal Random Walk SUE[7]	-0.0001	0.0002	0.0024

Notes to Table 2:
[1]The quintiles are constructed on the basis of the time-series-average of the absolute coefficients of variation of the forecasted quarterly EPS's for each company (Source: IBES Summary File). Summary statistics for this measure are reported for each quintile under the head "Dispersion". The reported "Number of Analysts" refers to the time series average of the number of estimates recorded in the IBES summary file over a firm's IBES history. See Table 1 for details of the criterion for inclusion in the sub-sample.
[2] Shares outstanding (Compustat item No. 25) multiplied by the closing price (Compustat item No. 24) as of the beginning of 1993.
[3]Closing price on Fiscal Year End (Compustat item No. 199) divided by book value per share (Common Equity [item

60] divided by the number of shares outstanding [item 25]). Data pertains to 1992.
[4]Depreciation and amortization (item 14) plus income before extraordinary items (item 18) divided by adjusted common shares (item 54 x item 27). Data pertains to 1992.
[5]Earnings per share (primary) excluding extraordinary items (item 58) adjusted for stock splits and dividends (item 27). Data pertains to 1992.
[6]Closing price at Fiscal Year End (item 199) divided by Primary EPS excluding extraordinary items (item 58). Data pertains to 1992. In Table 2B, summary statistics for this variable are reported after excluding observations with negative EPS numbers in 1992, since these include a few large outliers that distort some summary statistics.
[7] SUE is the temporal average of unexpected earnings for each firm over the entire series of observations available for that firm.The Standardised Unexpected Earnings (SUE_{it}) numbers were calculated by determining the relevant Expected Earnings Proxy (EE_{it}), the reported Earnings number (E_{it}), and the adjusted price (P) at the forecast-date in the case of the early detailed proxy, or at the 15th day of the month preceding the IBES statistical date in the case of the early consensus or late consensus proxies (in the case of the mechanical model, the same date is used as for the corresponding early consensus forecast), and calculating:

$$SUE_{it} = \frac{(E_{it} - EE_{it})}{P_{it}}$$

Table 3

Estimated ERCs: Summary Statistics for Time Series Regression

$CAR_{it} = a_i + b_i(UE_{it} / P_{it}) + e_{it}$

Full Sample (590 firms), no winsorizing

	A. SEASONAL RANDOM WALK				<--- B. EARLY CONSENSUS ---->			
Quintile[a]	<-- ERC-->		ADJUSTED R-SQ.		<-- ERC-->		ADJUSTED R-SQ.	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1	6.83	4.18	0.034	0.011	13.94	10.85	0.055	0.032
2	3.51	2.33	0.022	-0.001	7.26	4.65	0.056	0.022
3	2.89	1.56	0.038	0.003	7.32	4.43	0.073	0.028
4	1.74	1.00	0.028	0.004	5.44	3.46	0.080	0.046
5	0.80	0.66	0.034	0.006	2.47	1.64	0.065	0.030
Full Sample	3.15	1.40	0.031	0.004	7.29	3.82	0.066	0.031
	<---- C. LATE CONSENSUS------>				<---- D. EARLY DETAILED------>			
Quintile[a]	<-- ERC-->		ADJUSTED R-SQ.		<-- ERC-->		ADJUSTED R-SQ.	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1	13.19	7.83	0.056	0.028	12.85	8.86	0.058	0.034
2	7.37	5.02	0.065	0.020	6.26	4.11	0.050	0.020
3	6.73	4.08	0.064	0.034	7.42	4.16	0.077	0.027
4	4.97	2.60	0.072	0.024	4.66	3.68	0.071	0.036
5	1.99	1.21	0.045	0.009	2.11	1.46	0.057	0.021
Full Sample	6.85	3.34	0.060	0.023	6.66	3.57	0.063	0.027

[a] See note 1 to Table 2.

A. *Seasonal Random Walk*: Unexpected Earnings computations are based on a "naïve" model of expected earnings, viz., actual earnings four quarters previous. Abnormal returns are cumulated over a window starting one day before the date of the earliest consensus forecast after the previous quarter's earnings announcement and ending one day after the actual earnings announcement date. The date associated with an IBES consensus forecast is estimated as the midpoint (15th) of the month preceding the "statistical date" reported by IBES. The price by which unexpected earnings is deflated is the price at the early consensus forecast-date determined as described above.

Notes to Table 3 (contd.)

B. *Early Consensus*: Unexpected earnings are calculated using the earliest consensus forecast after the previous quarterly earnings announcement as the proxy for expected earnings. Cumulative abnormal returns are computed using a window that starts from one day before the date of the earliest consensus forecast after the previous quarter's earnings announcement, where the consensus forecast-date is determined as described above, and ends one day after the actual announcement date. The price by which unexpected earnings is deflated is the closing stock price at forecast-date.

C. *Late Consensus:* Unexpected earnings are calculated using the latest consensus forecast before the current quarterly earnings announcement as the proxy for expected earnings. Cumulative abnormal returns are computed using a window that starts from one day before the date of the latest consensus forecast after the previous quarter's earnings announcement and before the current announcement, (where the consensus forecast-date is determined as described above), and ends one day after the actual current earnings announcement date. The price by which unexpected earnings is deflated is the closing stock price at forecast-date.

D. *Early Detailed*: Unexpected earnings are calculated using the earliest individual forecast after the previous quarterly earnings announcement as the proxy for expected earnings. If more than one forecast was made on the same date, the average is taken. Abnormal returns are cumulated over a window that starts one day prior to the forecast-date, and ends one day after the actual earnings announcement date. The price by which unexpected earnings is deflated is the closing stock price at the forecast-date.

Table 4

Estimated ERCs: Summary Statistics for parameters of time series regression
$CAR_{it} = a_i + b_i(UE_{it} / P_{it}) + e_{it}$

Subsample (498 points) with only positive EPS forecasts or realizations allowed standardized unexpected earnings numbers winsorized at three standard deviations.

	A. SEASONAL RANDOM WALK				<---- B. EARLY CONSENSUS ---->			
Quintile[a]	<-- ERC-->		ADJUSTED R-SQ.		<-- ERC-->		ADJUSTED R-SQ.	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1	8.12	6.13	0.035	0.011	16.62	13.31	0.053	0.031
2	5.41	3.80	0.037	0.008	11.17	9.01	0.071	0.052
3	3.52	2.45	0.030	0.011	10.59	7.07	0.100	0.071
4	3.71	2.84	0.053	0.027	9.36	8.35	0.109	0.089
5	2.72	1.91	0.034	-0.005	7.03	5.65	0.087	0.053
Full Sample	4.69	2.97	0.038	0.009	10.95	8.38	0.084	0.055
	<----- C. LATE CONSENSUS ----->				<----- D. EARLY DETAILED ----->			
Quintile[a]	<-- ERC-->		ADJUSTED R-SQ.		<-- ERC-->		ADJUSTED R-SQ.	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1	16.43	11.81	0.056	0.026	16.06	12.15	0.063	0.039
2	9.79	7.62	0.070	0.033	8.95	7.33	0.064	0.029
3	9.70	6.20	0.096	0.055	10.16	6.56	0.094	0.062
4	8.49	7.15	0.101	0.074	8.74	7.67	0.096	0.073
5	7.04	5.14	0.083	0.042	7.32	5.26	0.089	0.055
Full Sample	10.28	7.39	0.081	0.048	10.24	7.58	0.081	0.050

[a] See note 1 to Table 2.

See Notes to Table 3.

Table 5

Estimated ERCs: Summary Statistics for Time Series Regression

$$CAR_{it} = a + b\,(UE_{it} / P_{it}) + e_{it}$$

Full Sample (524 firms*), no winsorizing

Quintiles formed after controlling for cross-sectional variation in the absolute temporal coefficient of variation of annual cash flow from operations as reported by Compustat for the years 1988 through 1996[a]

Quintile[a]	A. SEASONAL RANDOM WALK <-- ERC--> Mean	Median	ADJUSTED R-SQ. Mean	Median	<---- B. EARLY CONSENSUS ----> <-- ERC--> Mean	Median	ADJUSTED R-SQ. Mean	Median
1	6.82	4.82	0.037	0.005	14.70	11.04	0.060	0.026
2	4.18	2.63	0.026	0.006	7.86	5.44	0.052	0.027
3	2.89	1.73	0.037	0.010	7.58	4.64	0.084	0.037
4	1.61	0.86	0.023	0.003	5.13	3.39	0.073	0.040
5	0.87	0.66	0.035	-0.003	2.28	1.86	0.064	0.035
Full Sample	3.27	1.54	0.031	0.004	7.50	4.16	0.067	0.035

Quintile[a]	<----- C. LATE CONSENSUS -----> <-- ERC--> Mean	Median	ADJUSTED R-SQ. Mean	Median	<----- D. EARLY DETAILED -----> <-- ERC--> Mean	Median	ADJUSTED R-SQ. Mean	Median
1	13.29	7.69	0.062	0.029	12.64	8.00	0.056	0.014
2	8.22	5.76	0.051	0.020	7.76	6.16	0.059	0.028
3	7.58	4.73	0.086	0.046	6.95	4.92	0.072	0.039
4	4.34	2.59	0.057	0.020	4.80	2.49	0.070	0.025
5	2.09	1.31	0.047	0.013	1.81	1.67	0.057	0.024
Full Sample	7.09	3.54	0.061	0.025	6.78	3.67	0.063	0.028

*66 firms (out of 590) were excluded from this analysis owing to insufficient cashflow data on Compustat.

[a] Quintiles formed using the time-series-average of the absolute coefficients of variation of the forecasted quarterly EPS's for each company (source: IBES Summary File), after controlling for cross-sectional variation in CVCFO, i.e., the absolute temporal coefficient of variation of annual cash flow from operations as reported by Compustat from 1988 through 1996. The median CVCFO for quintiles 1 through 5 is respectively 0.38, 0.39, 0.42, 0.43, and 0.45. The median CVCFO for the full sample is 0.41.

See notes to Table 3.

Table 6

Estimated ERCs: Summary Statistics for parameters of time series regression
$CAR_{it} = a + b\ (UE_{it} / P_{it}) + e_{it}$

Subsample (442 points*) with only positive earnings or forecast numbers allowed standardised unexpected earnings numbers winsorized at three standard deviations.
Quintiles formed after controlling for cross-sectional variation in the absolute temporal coefficient of variation of annual cash flow from operations as reported by Compustat for the years 1988 through 1996[a]

	A. SEASONAL RANDOM WALK				<---- B. EARLY CONSENSUS ---->			
Quintile[a]	<-- ERC-->		ADJUSTED R-SQ.		<-- ERC-->		ADJUSTED R-SQ.	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1	8.56	7.43	0.045	0.015	17.85	13.91	0.065	0.046
2	6.74	4.92	0.038	0.015	13.07	10.99	0.080	0.046
3	3.08	2.46	0.031	0.001	8.91	6.40	0.087	0.052
4	3.36	2.57	0.041	0.018	9.21	6.99	0.093	0.069
5	2.46	1.53	0.033	-0.005	6.60	5.78	0.090	0.062
Full Sample	4.81	3.16	0.037	0.008	11.08	8.97	0.083	0.053

	<----- C. LATE CONSENSUS ----->				<----- D. EARLY DETAILED ----->			
Quintile[a]	<-- ERC-->		ADJUSTED R-SQ.		<-- ERC-->		ADJUSTED R-SQ.	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1	16.24	11.42	0.062	0.029	15.81	11.82	0.061	0.033
2	12.98	10.36	0.080	0.037	11.91	9.59	0.087	0.072
3	8.10	6.90	0.082	0.060	8.55	6.65	0.078	0.052
4	8.39	5.75	0.080	0.055	8.74	7.15	0.087	0.051
5	6.90	5.83	0.097	0.059	6.62	5.56	0.084	0.052
Full Sample	10.48	7.61	0.080	0.049	10.29	7.81	0.080	0.047

*56 firms (out of 498) excluded due to insufficient cashflow data on Compustat.

[a] Quintiles formed using the time-series-average of the absolute coefficients of variation of the forecasted quarterly EPS's for each company (source: IBES Summary File), after controlling for cross-sectional variation in CVCFO, i.e., the absolute temporal coefficient of variation of annual cash flow from operations as reported by Compustat from 1988 through 1996. The median CVCFO for quintiles 1 through 5 is, respectively, 0.37, 0.38, 0.38, 0.36, and 0.35. The median CVCFO for the full sample is 0.37.

See notes to Table 3.

Table 7

Estimated ERCs: Summary Statistics for Time Series Regression

$CAR_{it} = a_i + b_i(UE_{it} / P_{it}) + e_{it}$
Full Sample (590 firms), no winsorizing
Quintiles formed after controlling for cross-sectional variation in the time-series mean of the standardized unexpected earnings measure[a]

Panel **A: Seasonal Random Walk**[A]

Quintile[a]	Median	<-- ERC-->		ADJUSTED R-SQ	
	SUE*	Mean	Median	Mean	Median
1	0.0011	5.15	2.81	0.027	-0.004
2	0.0009	4.13	2.22	0.030	0.006
3	0.0009	3.24	1.59	0.033	0.007
4	0.0009	2.08	1.10	0.039	0.009
5	0.0009	1.19	0.69	0.026	-0.004
Full Sample	0.0009	3.15	1.40	0.031	0.004

Panel B: Early Consensus[B]

Quintile[a]	Median	<-- ERC-->		ADJUSTED R-SQ	
	SUE*	Mean	Median	Mean	Median
1	-0.0005	10.23	4.32	0.040	0.014
2	-0.0008	8.74	4.28	0.053	0.020
3	-0.0008	6.87	4.09	0.073	0.042
4	-0.0007	6.22	3.99	0.092	0.043
5	-0.0007	4.37	3.05	0.071	0.046
Full Sample	-0.0007	7.29	3.82	0.066	0.031

Panel C: Late Consensus[C]

Quintile[a]	Median	<-- ERC-->		ADJUSTED R-SQ	
	SUE*	Mean	Median	Mean	Median
1	-0.0003	8.88	2.96	0.038	0.008
2	-0.0005	8.91	4.60	0.056	0.027
3	-0.0004	6.58	3.87	0.074	0.035
4	-0.0004	6.05	2.73	0.071	0.040
5	-0.0005	3.80	2.01	0.061	0.020
Full Sample	-0.0004	6.85	3.34	0.060	0.023

Table 7 (contd.)

Panel D: Early Detailed[D]

Quintile[a]	Median SUE*	< -- ERC--> Mean	Median	ADJUSTED R-SQ Mean	Median
1	-0.0007	9.94	4.53	0.048	0.012
2	-0.0008	7.19	3.61	0.046	0.018
3	-0.0008	6.68	4.08	0.074	0.033
4	-0.0009	5.60	3.94	0.076	0.047
5	-0.0009	3.92	2.18	0.069	0.029
Full Sample	-0.0008	6.66	3.57	0.063	0.027

* temporal mean of standardized unexpected earnings measure for each firm under a particular specification.

[a] Quintiles formed on the basis of the time-series-average of the absolute coefficients of variation of the forecasted quarterly EPS's for each company (source: IBES Summary File), after controlling for cross-sectional variation in the temporal mean of the standardized unexpected measure for each firm under the specification described by the panel heading.

See Notes to Table 3.

Table 8

Estimated ERCs: Summary Statistics for parameters of time series regression
$CAR_{it} = a_i + b_i(UE_{it} / P_{it}) + e_{it}$

Subsample (498 points) with only positive EPS forecasts or realizations allowed
Standardized unexpected earnings numbers winsorized at three standard deviations.
Quintiles formed after controlling for cross-sectional variation in the time-series mean (before winsorizing) of the standardized unexpected earnings measure[a]

Panel **A: Seasonal Random Walk**[A]

Quintile[a]	Median	< -- ERC-->		ADJUSTED R-SQ	
	SUE*	Mean	Median	Mean	Median
1	0.0011	6.08	3.68	0.024	-0.001
2	0.0010	6.25	4.31	0.044	0.018
3	0.0010	4.46	2.77	0.038	0.007
4	0.0009	3.59	3.01	0.046	0.018
5	0.0010	3.11	1.89	0.037	0.004
Full Sample	0.0010	4.69	2.97	0.038	0.009

Panel B: Early Consensus[B]

Quintile[a]	Median	< -- ERC-->		ADJUSTED R-SQ	
	SUE*	Mean	Median	Mean	Median
1	-0.0002	14.81	12.19	0.058	0.032
2	-0.0002	12.54	9.87	0.074	0.050
3	-0.0002	10.62	8.57	0.095	0.070
4	-0.0002	9.67	8.33	0.113	0.097
5	-0.0002	7.20	5.88	0.080	0.049
Full Sample	-0.0002	10.95	8.38	0.084	0.055

Panel C: Late Consensus[C]

Quintile[a]	Median	< -- ERC-->		ADJUSTED R-SQ	
	SUE*	Mean	Median	Mean	Median
1	0.0000	13.12	9.27	0.053	0.025
2	0.0000	12.31	8.66	0.077	0.033
3	0.0001	9.58	7.48	0.091	0.053
4	0.0000	8.31	6.06	0.091	0.069
5	0.0000	8.16	6.19	0.095	0.064
Full Sample	0.0000	10.28	7.39	0.081	0.048

Table 8 (contd.)

Panel D: Early Detailed[D]

Quintile[a]	Median SUE*	< -- ERC--> Mean	Median	ADJUSTED R-SQ Mean	Median
1	-0.0003	14.67	11.75	0.068	0.042
2	-0.0002	10.39	7.61	0.074	0.040
3	-0.0003	9.13	6.76	0.080	0.036
4	-0.0002	9.76	7.49	0.102	0.080
5	-0.0002	7.35	5.94	0.082	0.051
Full Sample	-0.0002	10.24	7.58	0.081	0.050

* temporal mean of standardized unexpected earnings measure for each firm under a particular specification.

[a] Quintiles formed on the basis of the time-series-average of the absolute coefficients of variation of the forecasted quarterly EPS's for each company (source: IBES Summary File), after controlling for cross-sectional variation in the temporal mean of the standardized unexpected measure for each firm under the specification described by the panel heading.

See Notes to Table 3.

Table 9

Estimated Coefficients for a
two-day holding period Easton-Zmijewski [1989] model,
reported by forecast dispersion quintiles[a]

$$CPE(-1,0)_{jt} = a_{j0} + a_{j1}[FE_{jt} / P_{jt}] + a_{j2}R_{jt} + e_{jt}$$

Quintile	ADJUSTED R-SQ		<-- a_{j0}--->		<-- a_{j1}-->		<-- a_{j2}-->	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1	0.105	0.058	0.0025	0.0024	5.17	3.41	-0.053	-0.043
2	0.072	0.040	0.0011	0.0017	2.58	1.23	-0.031	-0.033
3	0.071	0.041	0.0025	0.0021	1.70	1.14	-0.029	-0.023
4	0.079	0.059	0.0038	0.0031	1.75	0.93	-0.029	-0.017
5	0.051	0.020	0.0029	0.0024	0.60	0.27	-0.021	-0.021
Full Sample	0.076	0.042	0.0026	0.0023	2.36	1.03	-0.032	-0.029

[a] See note 1 to Table 2.

Variable definitions: $CPE(s,0)_{jt}$ = beta excess returns, computed using Scholes-Williams betas and directly retrieved from the CRSP excess returns tape, cumulated from trading day *s* through the earnings announcement date for the quarter (day 0); FE_{jt} = forecast error for quarter t earnings, computed using IBES data based on the late consensus forecast as defined above; P_{jt}=Price at the start of the window over which abnormal returns are cumulated, i.e., one trading day before the earnings announcement date; R_{jt}=stock returns for firm *j* from the day after the late consensus forecast-date determined as described above (15th day of the month preceding the IBES statistical date corresponding to the forecast) through two days before the earnings announcement for quarter t.

Table 10

Multiple regression of Earnings response coefficients on various firm-specific measures

$$ERC_j = g_0 + g_1 DIS_j + g_2 MEDSUE_j + g_3 NUM_j + g_4 LCAP_j + g_5 MBRATIO_j + \tilde{e}_j$$

Full Sample results (n=538)				
	Naïve	Early Consensus	Late Consensus	Early Detailed
γ_0	5.71 (0.001)	14.80 (0.000)	14.12 (0.000)	15.33 (0.000)
γ_1	-3.79 (0.013)	-7.92 (0.003)	-6.14 (0.030)	-12.03 (0.000)
γ_2	-1.58 (0.032)	-7.35 (0.007)	-11.65 (0.001)	-0.40 (0.262)
γ_3	0.36 (0.051)	1.77 (0.000)	1.71 (0.000)	1.72 (0.000)
γ_4	-0.43 (0.110)	-1.63 (0.001)	-1.53 (0.003)	-1.84 (0.000)
γ_5	0.35 (0.000)	0.49 (0.001)	0.50 (0.002)	0.40 (0.001)
Adj R^2	0.10	0.15	0.14	0.11

Notes to Table 10

1. Numbers in brackets represent p-values (two-tailed).
2. ERC_j refers to the earnings response coefficient for firm *j* ; DIS_j is our measure of disagreement; $MEDSUE_j$ is the time-series median of the absolute standardized unexpected earnings measure for firm *j* multiplied by 100; NUM_j is the average number of the analysts in a quarter providing forecasts for firm *j*; *LCAPj* is logged market capitalization for firm *j* at the end of 1992, our proxy for firm size; *MBRATIOj* is the market-to-book ratio for firm *j* at the end of 1992; Firms with negative *MBRATIO* were excluded from the analysis.