Earnings Precision and the
Relations Between Earnings and Returns*

David Burgstahler
Julius A. Roller Professor of Accounting
University of Washington

Elizabeth Chuk
University of Southern California

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Abstract

The accounting concept of earnings quality focuses on the amount of information that current earnings provide about future earnings (Dechow and Schrand 2004). Numerous studies have examined the coefficient relating security prices to announcements of new earnings information, commonly referred to as the earnings response coefficient or ERC, as a measure of earnings quality (Dechow, Ge, and Schrand 2010). However, there is a striking lack of agreement between estimated ERCs, which are typically somewhere between 1 and 3 (Kothari 2001) versus theoretical predictions for the coefficient relating revisions in firm value to revisions in expected earnings, which are typically somewhere between 10 and 30, an order of magnitude larger. Using a simple Bayesian model similar to the model in Subramanyam (1996), this paper reconciles the large gap between empirical estimates and theoretical values and demonstrates the empirical importance of proxies for Bayesian precision as measures of accounting quality.

In the Bayesian model, lower precision unexpected earnings receive a lower weight in revisions of expected future earnings, resulting in a lower coefficient on unexpected earnings. Therefore, for lower precision earnings signals, the coefficient on observable unexpected earnings is much lower than the coefficient on unobservable earnings revision. Further, because the magnitude of unexpected earnings is inversely related to precision and because the mechanics of least-squares regression place larger weight on larger magnitude unexpected earnings observations, the presence of even a few low precision unexpected earnings observations leads to low ERC estimates. Building on results in Kinney, Burgstahler, and Martin (2002), we show that ex post and ex ante proxies for precision together explain a broad range of estimated ERCs, with estimates ranging from near 0 up to 30, a much larger range than is explained by other factors proposed as proxies for earnings quality.

JEL classification: G14, M40

Key Words: Earnings quality, earnings response coefficients, analyst forecasts, uncertainty, adaptation value
1. Introduction

The accounting concept of earnings quality focuses on the amount of information that current earnings provide about future earnings (Dechow and Schrand 2004). Numerous studies have examined the coefficient relating security prices to announcements of new earnings information, commonly referred to as the earnings response coefficient or ERC, as a measure of earnings quality (Dechow, Ge, and Schrand 2010). However, there is a large gap between empirical estimates of the ERC and theoretical predictions for the coefficient relating firm value to revisions of expectations about future earnings. The ERC is the coefficient relating the revision of firm value to the difference between realized and expected earnings, referred to henceforth as the unexpected earnings response coefficient (UERC). Empirical estimates of the UERC are generally in the range of 1 to 3 (Kothari 2001). Theoretical models often describe firm value as the product of 1) an earnings multiplier, $c$, that reflects risk and other factors that determine the discount applied to expected future earnings, and 2) an expected earnings scalar that captures expectations about the series of future earnings. Based on these models, the coefficient relating the revision of firm value to the unobservable revision of expected future earnings, referred to henceforth as the earnings revision response coefficient (ERRC), is expected to be equal to the earnings multiplier, roughly corresponding to price-earnings multiples, typically in the range of 10 to 30.

We discuss the gap between the ERRC and the UERC in the context of a simple Bayesian model similar to the model in Subramanyam (1996), Holthausen and Verrechia (1988), or DeGroot (1970). In a Bayesian model, revised beliefs about expected future earnings after an earnings announcement can be described as a relative weighting of prior information versus new information in the announcement, where the relative weights depend on the precision of the new

\[^1\text{See especially Kothari (2001) section 4.1.1 for an extensive review and discussion.}\]
information relative to the precision of the prior information. Because the relative weight on new
information is often small, the earnings revision is often smaller than the unexpected earnings, and
therefore the UERC is often smaller than the ERRC. The distinction between the ERRC and the
UERC that is highlighted in the Bayesian model is important for several reasons.

First, the model highlights the distinction between the observable unexpected earnings,
deefined as the difference between announced and expected earnings, and unobservable earnings
revision, defined as the change in beliefs about expected future earnings due to the earnings
announcement. Because unexpected earnings and the earnings revision are different, the
coefficients relating the two quantities to the revision in firm value are different in terms of both
the economic and accounting properties of earnings, where both economic and accounting
properties determine the UERC and earnings quality. The UERC depends on the fundamental
relation between current and future economic earnings – a weaker relation between current and
future economic earnings leads to a lower coefficient on current earnings information. The UERC
also depends on error in the measure of economic earnings, as larger measurement error in
economic earnings leads to downward bias in UERCs.²

Second, the Bayesian model specifies how precision, a summary measure that describes
the statistical characteristics of the earnings signal, determines the relation between the ERRC and
UERC. Low precision implies a low weight on new earnings information, which in turn implies
that the earnings revision is smaller than the unexpected earnings and the UERC is
correspondingly smaller than the ERRC. For example, when the ERRC, the coefficient on

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² These two aspects of earnings quality are related to the concepts of time-series persistence and time-series variance.
Persistence is intended to capture the extent to which earnings in one period carry over to the next period, while time-
series variance is intended to capture the random component of earnings that is not modeled by the time-series
process. However, the fundamental economic relation between current and future earnings refers to the unobservable
relation between current and future economic income measured without error, whereas time-series persistence is
affected by the amount of measurement error – as measurement error grows, persistence falls. Measurement error
refers to the conceptual, and again unobservable, difference between economic income and accounting measures of
income, whereas time-series variance is affected by both measurement error and by random components of realized
economic income -as random components increase, time-series variance increases.
unobservable earnings revision, is $c$ and the earnings revision is ¼ of the unexpected earnings, the UERC, the coefficient on observable unexpected earnings, is $\frac{1}{4}c$.

Third, precision has the potential to be an empirically important proxy for earnings quality. Precision summarizes the outcome of multiple economic and measurement factors that determine the strength of the relation between current earnings and expected future earnings, i.e., earnings quality. The amount of variation in earnings quality explained by proxies for precision depends on both the amount of variation in precision across observations and on the quality of proxies for precision. High-quality precision proxies coupled with large variation in precision have the potential to explain large variation in earnings quality and to substantially improve tests for the effects of individual earnings quality factors. The empirical results below validate the potential empirical importance of precision measures, using a combination of ex post and ex ante proxies. Where both proxies indicate low precision, the estimated UERC is essentially 0. Where both proxies indicate high precision, the estimated UERC is on the order of 30.

The paper is organized as follows. Section 2 provides background. Section 3 uses a Bayesian model to characterize the effect of precision of the earnings signal on the relation between unexpected earnings and firm value. Section 4 provides results, and Section 5 concludes. Results in the appendix provide an example showing how the ability of two precision proxies to empirically explain a broad range of UERCs can lead to substantial improvement in the design of tests of other determinants of UERCs.

2. Background

In an equity valuation decision context, the accounting concept of earnings quality focuses on the amount of information that current earnings provide about future earnings, and hence about
firm value. For example, Dechow and Schrand (2004, Chapter 2) define earnings quality in terms of how well the earnings number represents the annuity of expected future cash flows: "We define earnings to be of high quality when the earnings number accurately annuitizes the intrinsic value of the firm." A variety of models express firm value as a function of the stream of future earnings. It is often further assumed that expectations about the stream of future earnings can be summarized in a scalar expected earnings number and that firm value can be expressed as an earnings capitalization factor, \( c \), multiplied by the scalar expected earnings. These earnings capitalization models predict that the change in value in response to new information is equal to the earnings multiplier, \( c \), times the revision in expected earnings in response to new information.

Earnings quality is determined by both the fundamental economics of the earnings process and by the accounting processes used to measure earnings and the effects of some properties are straightforward. Earnings measures that capture more persistent (or more permanent) components of earnings result in a more informative signal about future earnings whereas less persistent (or more transitory) earnings components result in a less informative signal. Transitory components of the economic earnings process (such as temporary fluctuations in factor input prices, temporary dislocations of output prices that do not change expectations of long-run equilibrium prices, and.

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3 Dechow, Ge, and Schrand (2010, henceforth DGS) provide a comprehensive review of the recent literature on earnings quality. DGS summarize evidence on ten proxies for, and eighteen determinants of, earnings quality in a variety of decision contexts, including equity valuation decisions.

4 See, for example, Beaver 1968, Kormendi and Lipe 1986, or Ohlson 1995.

5 See, for example, Miller and Modigliani 1966, Ramakrishnan and Thomas 1998, or Easton et al 2000.

6 The value of the earnings multiplier depends on the assumptions incorporated in the valuation model. For example, in a simple model that assumes a perpetuity of annual earnings, the multiplier on earnings is \( c = 1/r \), where \( r \) is the annual expected rate of return (which in turn depends on risk). When a perpetual annual growth rate \( g \) is added to the model, the multiplier becomes \( c = 1/(r-g) \). For annual expected returns on the order of 10% and perpetual growth approximately 0, these models suggest typical earnings multipliers on the order of 10 (\( c = 1/(10\%-0\%) \)). Higher multipliers result from smaller values of \( r \) or higher values of \( g \). While there are multiple plausible and important reasons to expect \( c \) to vary, we maintain the simplifying assumption that \( c \) is constant across observations.

7 Kormendi and Lipe (1987) develop and test the hypothesis that the coefficient relating earnings to returns is related to persistence assessed based on the parameters from a moving-average time-series model. These time series predictions rely on the assumptions that the time series process is stable over time and that the time series parameters provide a good description of the underlying properties of all the individual elements of earnings. Note that while this literature has identified statistically significant relations between time-series properties and the magnitude of ERCs, the magnitude of the largest estimated ERCs remain far below the range of plausible earnings multipliers.
the effects of other random or non-recurring events such as one-time gains and losses on disposition of assets) and transitory components of the accounting measurement process (such as random accounting errors) reduce the informativeness of current earnings for future earnings.\footnote{Section 2 of Dechow, Ge, and Schrand (2010) includes a related example drawn from Graham and Dodd to illustrate how the effects of production and pricing decisions on current earnings for a small oil producing firm may provide little information about future earnings for the firm.}

For other properties of earnings, the relation to earnings quality is ambiguous. For example, accruals could make current earnings either more or less informative about future earnings.\footnote{For example, Dechow (1994) asserts the fundamental purpose of accrual accounting is to mitigate timing and matching problems inherent in cash-based measures of firm performance, making earnings a superior summary measure of firm performance. On the other hand, Sloan (1996) shows that the accrual component of earnings is less persistent than the cash flow component, and Richardson, Sloan, Soliman, and Tuna (2005) show that accruals with greater estimation error have lower persistence and are associated with greater mispricing.}

Similarly, accounting processes that smooth earnings may lead to earnings that are either more or less informative about future earnings.\footnote{See Dechow and Schrand (2004). Note that the key is whether signal variability is related to the construct being predicted, i.e., whether variability of current earnings is related to expected future earnings. Factors that decrease the noise component of the variance of current earnings increase informativeness of earnings but factors that decrease variation in current earnings that is predictive of expected future earnings decrease the informativeness of earnings. Because smoothing can decrease either or both components of variance, its effect is ambiguous.} Thus, both accounting processes and the fundamental economics of earnings processes affect the extent to which current earnings provides information about future earnings.

Dechow, Ge, and Schrand (2010) review numerous studies that examine individual determinants of earnings quality, but these determinants generally explain only a small portion of the large gap between estimated UERCs and plausible earnings capitalization factors.\footnote{A large number of studies have estimated the effect of individual determinants of earnings quality on ERCs. While these studies typically show statistically significant effects on ERCs, the magnitude of estimated ERCs, and the estimated effects of the determinants on ERCs, remain far below plausible values for earnings multipliers. For example, Ali and Zarowin (1992) report in their Table 4 annual ERCs of 2.16 (1.35) for high (low) persistence earnings shocks. Choi and Jeter (1992) document that quarterly ERCs decline after the issuance of qualified audit reports; using a two-day return window, their Table 4 reports that ERCs are 0.434 to 0.471 before the qualified audit report and 0.410 to 0.438 afterwards. Wilson (2008) uses a 3-day return window and documents that quarterly ERCs decrease after restatements; starting with an UERC of 6.66 in the quarter before the restatement, her Table 4 reports ERCs are reduced to 5.62, 5.43, 5.43, and 5.92 in the first, second, third, and fourth quarters, respectively, after the restatement.}

Therefore, we focus on precision, a summary measure of the combined effect of multiple determinants of earnings quality.
In a Bayesian model of revision of beliefs about future earnings, precision captures the extent to which new earnings information leads to revision of beliefs about expected future earnings. Thus, the statistical concept of precision closely parallels the accounting concept of earnings quality, i.e., the extent to which current earnings is informative about expected future earnings. In the Bayesian model, precision summarizes the effect of multiple factors that determine the extent to which current earnings (the signal) is informative about expected future earnings and hence firm value (the object of prediction). In the accounting model, higher quality earnings signals lead to larger revisions in beliefs about expected future earnings.

The prior literature suggests two types of measures of precision of the earnings signal. First, there is a long stream of empirical evidence demonstrating that the aggregate relation between unexpected earnings and security market returns is S-shaped, i.e., the relation is more steeply-sloped for smaller magnitude unexpected earnings and more nearly-flat for larger magnitude unexpected earnings. Beaver, Clarke, and Wright (1979) report average returns for portfolios formed on the magnitude of unexpected annual earnings and the relation exhibits an S-shape. Freeman and Tse (1992) examine the relation for unexpected quarterly earnings and find an S-shaped relation that they fit using a functional form based on the arctangent function. Kinney, Burgstahler, and Martin (2002) use an extended portfolio approach similar to the original Beaver, Clarke, and Wright methodology, and also report strong visual and statistical evidence of the S-shape. Together with the model in Subramanyam (1996), these results suggest the realized magnitude of unexpected earnings is inversely related to precision.13

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12 Holthausen and Verrecchia (1988, p. 83) model the relation between accounting signals and price changes and characterize the variance of the error in the signal (the inverse of its precision) as the "quality" of the signal: "The potential usefulness of the information is determined, in part, by the variance of its error term (its 'quality')." 
13 In the Subramanyam model, uncertainty about precision is incorporated in a prior distribution over precision and market participants use the magnitude of realized unexpected earnings (the absolute deviation of the signal from the prior expectation of the signal) to infer the precision of the earnings signal. Therefore, the price reaction to unexpected earnings is proportionately smaller for larger magnitude unexpected earnings, yielding an S-shaped relation between unexpected earnings and returns.
The magnitude of unexpected earnings is observable only ex post (after the signal is realized) but there are other precision proxies observable ex ante (prior to the realization of current earnings). In Sections 4 and 5, we examine three ex ante proxies.\(^\text{14}\) One ex ante measure, the amount of dispersion among analyst forecasts of earnings was examined in Kinney, Burgstahler, and Martin (2002). The intuition behind this proxy is that the more disagreement there is among analysts' predictions of the earnings signal, the lower the precision of the forthcoming signal.\(^\text{15}\) We examine two additional ex ante precision measures, 1) previous forecast dispersion, and 2) magnitude of previous forecast errors.

The two ex ante measures based on forecast dispersion can be viewed as proxies for the dispersion of the predictive distribution of the earnings signal. Forecasts represent the output of models that incorporate the expertise of analysts and the broad set of information available to analysts, and therefore should proxy for the dispersion of the predictive distribution of the earnings signal. Previous-year dispersion should capture aspects of precision of the earnings signal that are stable over time. However, to the extent that there are important year-specific aspects of precision, the current year forecast dispersion is likely to be a higher-quality proxy for precision of the current year signal.

The rationale for using absolute magnitude of previous forecast errors is closely tied to the rationale for the ex post precision proxy, magnitude of current forecast error. That is, lower precision processes are more likely to generate higher magnitude forecast errors. Surprise

\(^{14}\) In the extreme, perfect ex ante information about precision could subsume the ex post information provided by magnitude of unexpected earnings, though we do not expect to find a perfect ex ante proxy for precision (for reasons discussed further below). Thus, we expect market reactions to depend on both ex ante precision information and ex post inferences about differences in precision.

\(^{15}\) Forecast dispersion might be affected by a variety of factors including heterogeneity of information or information processing skill among analysts and precision of the prior distribution over expected future earnings (Barron et al. 1998). Higher forecast dispersion might also reflect more limited availability of information before the earnings announcement, in which case higher forecast dispersion might proxy for lower precision of prior information. For example, Yeung (2009) finds that larger revisions of analyst forecasts of earnings are associated with greater earnings uncertainty, as proxied by several measures including analyst forecast dispersion. Because different assumptions about the role of forecast dispersion lead to different predictions about the relation between precision and dispersion, the relation between forecast dispersion and earnings precision is ultimately an empirical issue.
magnitude averaged over multiple years has the potential to provide a better proxy than magnitude in the current year but, as this potential advantage will be diminished by year-specific aspects of precision.

Empirically, ex post and ex ante proxies for precision might be complements, where each explains substantial variation not explained by the other, or substitutes, where both proxies explain essentially the same variation in precision. Because both types of proxies measure the same statistical construct, we expect a positive correlation between ex post and ex ante proxies. To the extent that earnings precision is the result of economic earnings and accounting measurement processes that are stable over time, we expect measures of precision to be positively autocorrelated. Unless the processes are completely stable, the autocorrelation is likely to decline over longer lags as changes in economic earnings and accounting processes accumulate. In summary, we have the following empirical predictions:

- The ex post and ex ante precision proxies are contemporaneously correlated.
- Both types of precision proxies are positively autocorrelated.
- Both types of precision proxies are positively associated with UERC estimates.
- If the two types of precision proxies are complements, each proxy is positively associated with UERC estimates holding the value of the other proxy constant, and the highest UERC estimates are concentrated in the subsample where the proxies simultaneously indicate high precision.

The ability of precision proxies to explain variation in earnings quality is ultimately an empirical issue. If there is little variation in the precision of new earnings information so that the weights on earnings information vary only over a narrow range (say, between 5% and 10%), then differences in precision will explain only a narrow range of UERCs. If there is large measurement error in the proxies, the proxies will again not explain much variation in UERCs. On the other
hand, if the precision proxies allow us to accurately identify differences in weights that vary over a broad range (say, between 0% and 100%), then the model has the potential to explain a large range of earnings quality.

Results reported below show that variation in precision proxies explains substantial variation in earnings quality as reflected in UERCs. The results show that a minority of observations with low precision (as indicated by the precision proxies) have very low UERCs, while the remaining observations have much higher UERCs, consistent with much higher earnings quality. The mechanics of least squares regression effectively place much larger weight on observations with much smaller unexpected earnings coefficients, which further explains why estimated UERCs in the prior literature have consistently been far smaller than the UERCs reported here for firms with higher precision.

3. Model

Consider a Bayesian model of the revision of firm value in response to the announcement of earnings where precision of earnings signals is known to market participants but known precision varies across observations. Let pre-announcement firm value be the mean, \( m' \), of a normal prior distribution with precision \( I' \). Let the earnings signal about firm value, \( m \), be generated by a normal distribution with known precision \( I \). The predictive distribution for \( m \) is normal with expectation equal to the prior expectation of firm value, \( m' \).

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16 For example, elimination of 45% of our sample with low values of the precision proxies results in an estimated sample UERC of more than 12 for the remaining 55% of the sample.

17 We use a generic Bayesian revision mechanism and notation from Winkler (1972, pp. 162-174) but the model is also consistent with DeGroot (1970) Section 9.5.
Post-announcement firm value is the posterior mean, $m''$, a weighted average of the prior mean, $m'$, and the signal, $m$, where the weights reflect the relative precisions of the prior and the signal:\footnote{Equations (3.1) and (3.2) also correspond to equations for the revision of price in period 1 in the model of Holthausen and Verrecchi (1988, pp. 84-85).}

$$m'' = \frac{(I \ m + I' \ m')}{(I + I')}.$$  \hfill (3.1)

Equation (3.1) implies the revision in firm value due to the earnings signal (i.e., the change from the prior belief $m'$ to the posterior belief $m''$) is

$$m'' - m' = \frac{I}{(I + I')} (m - m').$$  \hfill (3.2)

The revision in value is the product of two terms: 1) a weight, defined as $w = I / (I+I')$, and 2) the difference between the realized signal and its expectation.

The signal and its expectation, $m$ and $m'$, are in firm value units while the empirical model is operationalized in terms of an earnings signal and its expectation. To convert the earnings signal and its expectation to units of firm value, each is multiplied by the earnings multiplier, $c$. Substituting $c \times$ realized earnings for $m$ and $c \times$ expected earnings for $m'$ converts the final term in (3.2) to $c \times$ unexpected earnings, or $cUE$. Further, dividing both sides of (3.2) by pre-announcement firm value scales unexpected earnings by pre-announcement firm value and converts the left-hand-side change in firm value to a return measure:

$$\frac{m'' - m'}{m'} = w \frac{cUE}{m'}.$$  \hfill (3.3)

Thus, the coefficient on scaled unexpected earnings is the product of the weight, $w$, and the earnings capitalization factor. The empirical relation between returns and unexpected earnings for firm $i$ in earnings announcement period $t$ is:

$$R_{it} = \alpha + \omega_{it} \ c \ UE_{it} + e_{it}$$  \hfill (3.4)
where the error term, \( e_{it} \), captures the effects of non-earnings information related to firm \( i \) during period \( t \) and the intercept, \( \alpha \), allows for a non-zero expected return during the period.

The weight on the earnings signal in (3.3) varies with precision, approaching zero for the lowest precision signals and one for the highest precision signals. Therefore, the relative precision of the earnings signal determines earnings quality, as reflected in the coefficient on \( UE \) in (3.4). The coefficient on \( UE \) in (3.4), approaches zero when the precision of the earnings signal is low relative to the precision of the prior (where the weight approaches zero) and approaches \( c \) when the precision of the earnings signal is high relative to the precision of the prior (where the weight approaches one).\(^{19}\)

Equations (3.3) and (3.4) show that the slope of the relation between unexpected earnings and returns varies directly with the precision of the signal relative to the precision of the prior information. Thus, ex ante information about precision can potentially explain variation in earnings quality. However, the amount of variation explained by ex ante precision measures is an empirical question. First, variation in the slope depends on variation in relative precision and it is possible that relative precision is approximately constant across observations. Second, even if there is a substantial amount of variation in relative precision, it may be difficult to find empirical proxies for precision that are closely related to the variation.

While it is clear from this simple model that the slope of the relation between earnings and returns may be directly related to ex ante differences in relative precision, Subramanyam (1996) outlines reasons to believe that precision is not known perfectly to the market:

(A)n examination of institutional features and the information environment reveals that the market is unlikely to have perfect knowledge of the signal precision ex ante. For example, in the case of an earnings announcement, a number of the determinants of information accuracy—such as the proportion of transitory cash flows and other non-recurring items, and the effect of changes in accounting methods—are specific to each announcement, and

\(^{19}\) To focus on the effects of precision and simplify the discussion, we assume that \( c \) is constant across observations. A more general form of (3.4) would allow \( c \) to also vary across firms and time.
the market is unlikely to have perfect a priori knowledge of them. In addition, accrual earnings incorporates estimates of future events, but managers rarely report the precision of those estimates. Therefore, a descriptively richer analysis is one which incorporates ex ante uncertainty regarding signal precision. Note that uncertain precision does not imply that the market has no ex ante information regarding signal quality, it merely implies that the market does not have perfect ex ante information. (p. 208)

When the assumption that precision of the signal is known is relaxed, as in the Subramanyam (1996) model, larger magnitude unexpected earnings are more likely to result from lower precision signals. The resulting ex post relation between magnitude and precision leads to an s-shaped relation with larger slope for smaller magnitude unexpected earnings. However, because ex post magnitude of unexpected earnings is an imperfect proxy for precision, an ex ante proxy can provide additional complementary information about precision.

4. Results

We obtain unexpected earnings data from the IBES database for the years 1992-2012, resulting in a sample that is both more current and about four times larger than the First Call sample from 1992-1997 reported in Kinney, Burgstahler, and Martin (2002). We measure the following variables from IBES: unexpected earnings (defined as actual EPS minus the consensus forecast as of the last update before the announcement of earnings for the year), the number of analyst forecasts used in computing the consensus forecast, and the standard deviation of analyst forecasts.²⁰

Accounting and stock return data are obtained from Compustat and CRSP. Consistent with KBM, we measure announcement period returns as raw return minus the value-weighted market return accumulated over a 22-day window extending from day -20 to +1 relative to the day

²⁰ Payne and Thomas (2003) report that versions of IBES data adjusted for stock splits and then rounded to the nearest penny sometimes incorrectly include zero forecast error for firms with stock splits even when the actual forecast error is non-zero. Also, the standard deviation of analyst forecasts computed using the split-adjusted and rounded forecasts is mechanically reduced for firms with stock splits. However, because we use the unadjusted IBES data, our measures of unexpected earnings and dispersion of analyst forecasts should not be affected by these issues.
of the announcement of earnings.\textsuperscript{21} We scale unexpected earnings and forecast dispersion by price at the end of the fiscal year (Compustat data item PRCC\_F), which is typically shortly before the beginning of the return period.

Table 1 provides descriptive statistics for the final sample of 88,478 firm-years with the necessary IBES analyst forecast, accounting, and stock return data. To provide descriptive statistics comparable to those reported in KBM Table 1, in this table we restrict the range of price-scaled unexpected earnings to be between -0.02 and +0.02.\textsuperscript{22} Consistent with results in KBM, Table 1 Panel A shows that all four size measures have right-skewed distributions with means greater than the 75\textsuperscript{th} percentile. The firms in our sample are somewhat larger than those in KBM using any of the four size measures, at least in part due to the fact that IBES tends to cover larger firms than First Call.

Table 1 Panel B indicates a general growth in the number of analyst forecast observations available over time through 1997 (the end of the KBM sample period), followed by a few years of decline through 2002, after which growth resumes through 2007, followed by a sharp decline in 2008 and modest, erratic growth in subsequent years. Forecast age in our sample is lower than in KBM, consistent with the tendency of IBES to cover larger firms, which on average have less “stale” forecasts. Over the years, the average analyst forecast dispersion generally decreases, the average forecast age decreases, and the proportion of positive unexpected earnings increases, consistent with changes observed in KBM over their shorter sample period. Despite the

\textsuperscript{21} We also computed our primary results 1) using raw returns minus the equally-weighted market return, and 2) using a shorter 3-day return window extending only from day -1 to +1. Results using the equally-weighted market return are similar to those reported here. Results using 3-day returns are similar except that the magnitude of the return reactions and the associated ERCs are reduced by as much as 50\% for the 3-day return window, consistent with the hypothesis that a substantial portion of earnings information "leaks" to market participants during days -20 to -2 prior to the actual announcement.

\textsuperscript{22} 88\% of KBM’s sample have price-scaled unexpected earnings that fall in this restricted range of ±0.02. Similarly, 81\% of our sample have unexpected earnings that fall in this restricted range. Note that although the range in our \textit{figures} is similarly restricted to the range between -.02 and +.02, the \textit{tables} later in the paper provide results for the entire unrestricted range of unexpected earnings.
differences noted above, descriptive statistics for our sample using IBES and including a later sample period are reasonably comparable to those for the KBM sample. Finally, while the sample is not representative of the entire population of Compustat firms because it excludes firms not covered by analysts, the market value of firms in our sample represents a large proportion of the total market value of firms in the Compustat population.

Figure 1 shows the unconditional relation between returns and unexpected earnings for portfolios of 1,000 observations formed on unexpected earnings. Consistent with KBM Figure 1 (and with results in Freeman and Tse 1992 and Beaver, Clarke, and Wright 1979), the unconditional relation (which does not condition on the ex ante proxy for precision) exhibits a pronounced S-shape. The S-shape is reflected in all of the return distribution statistics (mean, median, 25th, and 75th percentile returns). Thus, the patterns described here and in subsequent figures represent broad distributional effects and are not attributable to the effects of a few extreme observations.

Following KBM, we operationalize the ex ante proxy by sorting observations with at least four analyst forecasts into three approximately equal-sized subsets based on price-scaled analyst dispersion. These subsets formed conditional on ex ante precision comprise 15,614 observations

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23 Data for unexpected earnings beyond the range plotted in Figure 1 show that the S-shape turns back toward zero for more extreme unexpected earnings, consistent with the Subramanyam model. Note also that there is no evidence in Figure 1 (nor later in Figure 3) of an asymmetrically larger effect for slightly negative unexpected earnings than for slightly positive unexpected earnings. Thus, the "torpedo effect" reported in Skinner and Sloan (2002) for a subsample of high growth firms does not generalize to our broad sample of firms. In fact, unreported statistical tests for our broad sample suggest that the coefficient on small positive unexpected earnings is usually significantly larger than the coefficient on small negative unexpected earnings.

24 The remaining 41,583 observations with three or fewer analyst forecasts are placed in a separate “undefined dispersion” group. The plot of return distributions for the undefined dispersion group (not presented) has the same overall shape as the aggregate results in Figure 1. We do not have specific predictions for this group that comprises an unknown (and unmeasurable) mix of ex ante precisions. Therefore, we provide only brief descriptions of undefined dispersion results in Panel C of Table 3 and in footnotes. Because the decision by analysts to produce forecasts for a firm is not random, firms in the undefined dispersion group are likely to differ systematically from defined dispersion firms. For example, there is evidence in the literature that analysts are less likely to cover firms with earnings that are more difficult to forecast (Stickel 1992 and Mikhail, Walther, and Willis 1999) which might suggest that firms with undefined dispersion also have systematically lower precision. We do not explore this possibility in detail, but the results in Table 3 are consistent with this conjecture.
with low analyst dispersion, 15,648 with medium analyst dispersion, and 15,633 with high analyst dispersion. Figure 2 illustrates the relation between the two precision proxies by plotting distributions of unexpected earnings by dispersion subset. The low dispersion subset includes mainly small magnitude unexpected earnings, tightly concentrated around zero. As we move to higher dispersion subsets, the proportion of larger unexpected earnings increases.\(^{25}\) Figure 2 illustrates two important facts: First, the two proxies are positively correlated, as expected if the proxies measure the same construct.\(^{26}\) Second, the correlation between the proxies is less than perfect so there is the potential for the proxies to be empirical complements that provide incremental information relative to each other.

Table 2 shows the autocorrelations for both the forecast dispersion proxy (Panel A) and the magnitude of unexpected earnings proxy (Panel B). Precision is likely to change over time due to changes in economic conditions, changes in accounting policies, and period-specific decisions and events reflected in earnings. Thus, there are reasons to conjecture that the relation between measures of precision should become weaker across longer time lags. The results in Table 2 are consistent with this conjecture. For both proxies, the autocorrelations are positive and highly significant and decrease for longer time lags. The correlations are generally higher for forecast dispersion than for unexpected earnings magnitude, which may reflect differences in how the two proxies are measured. Forecast dispersion is variation among at least four analyst forecast observations, whereas unexpected earnings magnitude is based on the deviation of a single observation from its expectation.

\(^{25}\) The vertical bars at the endpoints of the unexpected earnings axis represent the combined frequency of all observations that fall beyond the limits of the horizontal axis. For instance, in the high dispersion subset, the height of the bar at the extreme unexpected earnings of -0.02 indicates there are about 1,900 observations with unexpected earnings less than -0.02. In each histogram, the checkered bar represents the frequency of exact zero unexpected earnings. Consistent with prior research (e.g., Burgstahler and Eames 2006), each histogram exhibits a prominent discontinuity at zero unexpected earnings.

\(^{26}\) The Spearman (Pearson) correlation coefficient between the two proxies is 0.60 (0.54). (To reduce the impact of extreme observations on the Pearson correlation, we winsorized at the 1\(^{st}\) and 99\(^{th}\) percentiles.)
The three panels of Figure 3 show return distribution statistics for portfolios of 500 observations formed on scaled unexpected earnings for the low, medium, and high forecast dispersion subsets. Because forecast dispersion is inversely related to precision, larger dispersion observations are predicted to have lower UERCs due to a lower weight on the unexpected earnings signal. Consistent with this prediction, the slope of the relation is much steeper for the low dispersion subset in Panel A than for the high dispersion subset in Panel C, with the slope for the medium dispersion subset falling between the slopes for the low and high dispersion subsets.

Within each of the subsets conditioned on forecast dispersion, the overall relation is also more nearly linear than in the unconditional relation in Figure 1, as expected if partitioning based on forecast dispersion yields subsets with more homogeneity of precision. The conditional relations in the three panels also provide a visual explanation as to how the S-shaped unconditional relation arises. Because of the strong correlation between forecast dispersion and unexpected earnings magnitude shown in Figure 2, a large proportion of the large magnitude unexpected earnings observations correspond to the less-steeply-sloped relation in Panel C, forming the less-steeply-sloped tails of the S-shape, while a large proportion of the small magnitude unexpected earnings observations correspond to the more-steeply-sloped relation in Panel A, forming the more-steeply-sloped center of the S-shape.

To the extent that precision (and earnings quality) results from firm characteristics that are reasonably stable over time (as suggested by the large positive autocorrelations in Table 2), alternative ex ante proxies for precision can be constructed using measures from previous years. We consider two alternative ex ante proxies directly related to the two precision proxies discussed

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27 For reasons outlined in Section 3, the earnings-return relations within the three ex ante precision subsets is expected to be more linear but still S-shaped unless precision within each subset is completely homogeneous. The individual subsets are not likely to reflect strictly constant precision, both because the partitioning variable is subject to proxy error and because each of the three partitions includes a range, rather than a single value, of the precision proxy.
so far: (i) dispersion of forecasts of earnings for the immediately preceding year,\textsuperscript{28} and (ii) average absolute unexpected earnings for the four preceding years.\textsuperscript{29} If precision is determined by firm characteristics that are reasonably stable over time, we expect to observe results similar to those in Figure 3 using either of the alternative proxies.

Figure 3’ Panels A’, B’, and C’ show return distributions where ex ante precision is based on forecast dispersion from the preceding year.\textsuperscript{30} The results are similar to, though slightly weaker than, results using contemporaneous forecast dispersion as the ex ante precision proxy. The relations in Figure 3’ have lower slopes than the corresponding relations in Figure 3 (as confirmed by numerical estimates of the slopes reported later in Table 4), consistent with the conjecture that forecast dispersion in the preceding year is not quite as strongly related to precision of the current signal as is forecast dispersion in the current year. The relation between the slope of the earnings-return relation and the precision proxy based on lagged forecast dispersion is nonetheless still highly significant, consistent with the conjecture that precision (and earnings quality) is reasonably stable across time.

Figure 3” Panels A”, B”, and C” show return distributions conditioned on average absolute unexpected earnings from the four preceding years.\textsuperscript{31} The relations plotted in Figure 3” are qualitatively similar to the results in Figures 3 and 3’. However, the slopes in each precision group

\textsuperscript{28} Forecast dispersion for the year preceding the year t announcement of earnings is dispersion of forecasts of year t-1 earnings issued prior to the announcement of year t-1 earnings. As explained in a later footnote, we also calculated unreported results using forecast dispersion from 2 or 3 years prior to the unexpected earnings period.

\textsuperscript{29} The magnitude of current unexpected earnings is an ex post proxy in the current year because it is only available after the realization of the current year earnings signal. However, magnitude of unexpected earnings from previous years is an ex ante proxy because it is available before the realization of the current year signal.

\textsuperscript{30} Because the dispersion measure from the preceding year is not available for every observation, the sample sizes are slightly smaller – the low dispersion subset comprises 13,946 observations, the medium dispersion subset comprises 13,968 observations, and the high dispersion subset includes 13,957 observations.

\textsuperscript{31} A related measure of the difficulty of predicting earnings is the variance of the error terms from earnings time-series models, which represent deviations of realized earnings from time-series predicted values. Lipe (1990) reports evidence that smaller time-series variances translate into higher sample ERCs, as expected if time-series variance is a measure of earnings persistence (and also expected if time-series variance is inversely related to precision). However, the range of ERCs explained by time-series persistence of earnings in Lipe (1990) is much smaller than the range explained by the precision measures considered here.
are lower than the corresponding slopes in Figure 3 or in Figure 3’ (as confirmed by numerical estimates reported later in Table 4) and the relations in Figure 3” also show greater evidence of S-shapes within each precision group. Both these findings are consistent with the conjecture that there is more proxy error in average absolute magnitude of unexpected earnings over the four preceding years than in either current or lagged forecast dispersion. Nonetheless, as with the alternative proxy examined in Figure 3’, the relation between average absolute unexpected earnings from preceding years and the slope of the earnings-return relation remains highly significant.

We now turn to numerical estimates of UERCs. We first present results in Table 3 corresponding to Figure 1 that reflect only the effect of the ex post proxy, magnitude of unexpected earnings. We then turn to results in Table 4 corresponding to Figures 3, 3’, and 3” that condition on both the ex post proxy and on one of the three ex ante proxies.

Table 3 shows estimated UERCs and tests of statistical significance for different values of the ex post proxy, magnitude of unexpected earnings. Panel A reports estimates for the entire sample, while Panel B shows results for the subsample with 4 or more analysts and Panel C shows results for the subsample with less than 4 analysts. In all panels, the UERC for the unrestricted range of unexpected earnings is a very small positive value that is significantly greater than zero (though the significant positive values are so small that they round to .00 in Panels A and C). The ex post proxy for precision increases as the range of unexpected earnings is narrowed, and the corresponding UERCs grow substantially, consistent with previous empirical results in Freeman and Tse (1992) and KBM.32 The effects of unexpected earnings magnitude for the two subsamples in Panels B and C are qualitatively similar to the effects in Panel A for the overall

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32 We also examined results for one narrower range of unexpected earnings (.00125). These unreported results are generally but not uniformly consistent with results reported in Table 3 and in Table 4 below. Less consistent results for the narrower range are not unexpected because as the range of unexpected earnings is narrowed, the number of observations is reduced and the range of the independent variable is reduced, thereby reducing reliability (increasing sampling variability) of regression estimates of the UERC.
sample. The UERCs for the defined dispersion subsample in Panel B are consistently larger than those for the undefined dispersion subsample in Panel C, suggesting that for firms in Panel B covered by four or more analysts, the precision is generally higher and/or the consensus forecast contains less error as a measure of expectations.

Turning now to numerical estimates of the joint effects of ex post and ex ante precision proxies, Table 4 Panels A, B, and C show UERCs and tests of statistical significance for each of the three subsets formed on the alternative ex ante proxies for varying ranges of the ex post proxy, unexpected earnings magnitude. We first discuss results using ex ante precision based on the dispersion of analyst forecasts in the current year (corresponding to Figure 3), followed by brief discussions of results using ex ante precision based on the dispersion of analyst forecasts in the preceding year (corresponding to Figure 3'), and results using ex ante precision based on the average absolute unexpected earnings in the four preceding years (corresponding to Figure 3").

Beginning with the ex ante proxy based on the dispersion of contemporaneous analyst forecasts, within each dispersion subset, the ex post precision proxy continues to have significant explanatory power as the estimated UERCs increase significantly as the magnitude of unexpected earnings decreases. The ex ante precision proxy has significant explanatory power across dispersion subsets. The UERCs for the low dispersion subset are typically at least 3 to 4 times larger than the corresponding UERCs for the high dispersion subset and about 1.5 to 2.5 times larger than the UERCs for the medium dispersion subset. All but one of the differences between the UERCs for the medium and high dispersion subsets and the corresponding UERC for the low dispersion subset are statistically significant with p-values \( \leq 0.01 \). Further, the differences in UERCs documented here are economically much larger than the typical cross-sectional effects of individual determinants of earnings quality in prior studies.\(^33\) Finally, subsets comprising a large

\(^33\) See Kothari (2001) and the examples discussed in Section 4.
majority of sample observations have much higher UERCs than those in most previous research. Specifically, subsets consisting of 87.8%, 74.7%, and 54.8% of all observations have UERC estimates greater than 3, 6, and 12, respectively. 34

Figure 4 provides a visual summary of the numerical results in Table 4. The three lines plot the numerical estimates for the three ex ante precision proxy groups from Panels A, B, and C. As noted above, the UERCs for the high precision group are typically 3 to 4 times larger than the UERCs for the low precision group and 1.5 to 2 times larger than UERCs for the medium precision group. The ex post proxy for precision also has substantial explanatory power, as illustrated by the steep upward slope in estimated UERCs for each of the three forecast dispersion groups as the ex post proxy for precision increases moving from left to right along the horizontal axis. 35

Figure 4 also depicts the reduction in the number of observations as the range of unexpected earnings is narrowed within each ex ante precision group. Because of the relation between ex post unexpected earnings magnitude and ex ante precision depicted in Figure 2, the effect of narrowing the range of unexpected earnings depends on the precision group. For the high precision group, there is only a small reduction in observations as the range of unexpected earnings is narrowed, as 87.9% of the high precision observations have unexpected earnings

34 The exact numbers from Table 4 are, respectively, 41,189/46,895 = 87.8%, 35,047/46,895 = 74.7%, and 25,697/46,895 = 54.8%.

35 The marginal effect of each precision proxy on the UERC can alternatively be described in terms of the percentage attenuation in the UERC explained by variation in the precision proxy. Specifically, we calculate the UERC for the lowest level of the precision proxy as a percentage of the UERC for the highest level of the precision proxy, and 100% minus this calculated percentage is the percentage attenuation in UERC explained by the precision proxy. For example, if the UERC for the highest level of precision proxy A and a fixed level of precision proxy B is 20 and the UERC for the lowest level of precision proxy A and the same fixed level of precision proxy B is 2, then the precision proxy explains a 90% (100% - (2÷20)) reduction in UERC for this fixed level of precision proxy B. These percentage attenuations are then averaged across all the levels of precision proxy B to find the average percentage attenuation in precision proxy A.

This alternative evaluation also leads to the conclusion that both proxies are empirically important. The percentage attenuation in ERCs explained by the ex post proxy averaged across the three ex ante precision subsets is 99%. The percentage attenuation in ERCs explained by the ex ante proxy averaged across the five different ranges for the ex post proxy is 78%.
within ±.0025. For the medium and low precision groups, there are progressively larger reductions in the number of observations as the range is narrowed, with 66.4% of the observations within ±.0025 in the medium precision group and only 26.9% of the observations within ±.0025 in the low precision group.

Returning to Table 4, results for the ex ante proxies based on dispersion of forecasts in the preceding year or average absolute unexpected earnings in the preceding four years are qualitatively similar to those using contemporaneous dispersion. However, there are moderate decreases in both the magnitude and statistical significance of the effect of ex ante precision, likely attributable to a combination of two factors: First, because these two proxies based on data from preceding years are not always available in the current year, there is a small decline in sample size, which tends to decrease the statistical significance of results. Second, as noted earlier, changes in economic conditions, changes in accounting policies, and period-specific decisions and events likely induce changes over time that make precision measures from preceding years inferior proxies for precision of earnings in the current year.36

We suggested earlier that typical earnings multipliers should be on the order of 10 to 30. In evaluating the estimated UERCs reported here, it is important to keep in mind that the “annual” unexpected earnings is effectively a fourth-quarter unexpected earnings because actual earnings for the first three quarters of the fiscal year are almost always known before the annual forecast used here (and also used in many previous studies) is formulated.37 The multiplier that applies to quarterly earnings should clearly be higher than the annual earnings multiplier, though it is impossible to specify exactly how much higher it should be. For example, for a simple random

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36 Additional results (not reported) based on forecast dispersion two or three years prior to the year of unexpected earnings are consistent with the results and explanations offered here. That is, results based on forecast dispersion measured farther in advance of the unexpected earnings show the same general pattern as those reported in Figure 3' and Table 4, though magnitudes and statistical significance decline further as the time lag grows.

37 Note also that because fourth-quarter earnings represent the final period in the annual reporting period and are subject to more scrutiny by auditors and others, the implications of fourth-quarter unexpected earnings may be different from the implications of unexpected earnings in other quarters.
walk in quarterly earnings, a 1 cent quarterly unexpected earnings implies a 1 cent upward revision in expected earnings for *every* subsequent quarter (i.e., a 4 cent upward revision in expected earnings for every subsequent year), and a multiplier for quarterly unexpected earnings approximately 4 times the annual earnings multiplier. However, there is evidence that suggests quarterly earnings series have a strong seasonal component in quarterly earnings where the effect on annual earnings expectations is less than 4 times the effect on corresponding quarterly earnings expectations. For example, the quarterly time-series estimates and example in Bernard and Thomas (1990) suggest the quarterly unexpected earnings multiplier could be as little as 1.35 times the annual unexpected earnings multiplier - the Bernard and Thomas estimates imply that on average a $1 innovation in quarterly earnings translates into effects over the next four quarters that cumulate to a $1.35 increase in expected earnings for the next year.

While we cannot specify exactly what the typical quarterly earnings multiplier ($c_q$) should be, it is certainly plausible that it is on the order of 2 times the annual earnings multiplier ($c_a$). A multiple of 2 combined with an annual earnings multiplier of 10 (at the low end of our suggested range) implies a $c_q$ of 20. Combined with an annual earnings multiplier of 15 or 20 from the middle of the range, the multiple of 2 implies a $c_q$ of 30 or 40. From this perspective, the estimated UERC of approximately 30 for observations with high values of both precision proxies is clearly within the range of plausible quarterly earnings multipliers.

Finally, the results in Tables 3 and 4 also clarify why empirical estimates of UERCs in the literature have been consistently low. Least-squares regression estimates of a sample UERC can be described as a weighted average of the underlying unexpected earnings multipliers in the sample, where the regression weight on each unexpected earnings multiplier is approximately
proportional to the square of the unexpected earnings. Because the absolute magnitude of unexpected earnings is positively related to the regression weight and negatively related to the unexpected earnings multiplier, the largest regression weights are applied to observations with the lowest unexpected earnings multipliers, while the smallest regression weights are applied to observations with the highest unexpected earnings multipliers. Consequently, the expectation of the least-squares estimate of the UERC for a sample is far lower than the equally-weighted average of the underlying unexpected earnings multipliers.

We can use the evidence in Table 3 to assess the empirical importance of the regression weighting effect. In Table 3, roughly 1/6 of the observations fall in a group where the unexpected earnings magnitude is about 10 times larger than the magnitude of a group that contains ½ of the observations. Because the least-squares weight on each observation is proportional to the square

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38 More precisely, the regression weight is proportional to the squared deviation of the unexpected earnings from the mean unexpected earnings. Because the sample mean unexpected earnings is typically close to zero, the regression weight is approximately proportional to the squared magnitude of the unexpected earnings.

39 Teets and Wasley (1996) make a related point about relative weighting in regression estimates. They show that firm-specific UERC estimates are on average larger than cross-sectional estimates because of a strong negative cross-sectional correlation between the magnitude of unexpected earnings and firm-specific ERCs.

40 The downward bias that results when the unexpected earnings systematically overstates the revision is separate from the widely-recognized downward bias that results when the unexpected earnings is an unbiased estimate of the revision but is subject to measurement error. Downward bias exists when the unexpected earnings overstates the revision, even when unexpected earnings is measured without error. At the same time, the downward bias due to measurement error exists when unexpected earnings is measured with error, even when unexpected earnings is an unbiased estimate of the revision. The downward bias due to measurement error can, in principle, be eliminated by improving measures of expectations used in research. The downward bias due to low precision reflects a fundamental property of the earnings signal, as discussed previously in Section 4.

Beaver, Lambert, and Morse (1980) estimate that when unexpected earnings is measured relative to time-series expectations, measurement error could cause ERCs to be downward biased by as much as 70-80%. If estimated ERCs are low primarily because of the downward bias due to error in measuring expectations, we would have expected a substantial increase in reported ERCs as time-series expectations were supplanted by improved measures of expectations. However, as research designs switched to widespread use of analyst forecasts as expectations, ERCs increased only marginally. For example, a recent paper that uses analyst forecasts and examines bias due to measurement error shows that the downward bias due to measurement error is statistically significant but still reports low estimated ERCs ranging from .2 to 1.8 (see Cohen, Hann, and Ogneva 2007, Figures 2 and 3).

41 These numbers are rounded versions of the results in Table 3 to simplify the calculations and discussion. The unrounded versions of these numbers from Panel A show that there are 16,470 of a total of 88,478 observations with scaled unexpected earnings greater than .02 and 40,350 observations with scaled unexpected earnings less than .0025. The multiple of 10 discussed in the text assumes that the average weight for the observations in the interval less than .0025 is equivalent to the weight for unexpected earnings of .002. In fact, this multiple of 10 almost certainly understates the difference in weights for the two groups because the 16,470 unexpected earnings greater than .02 are
of the distance from the mean of the independent variable, the individual weights on 1/6 of the observations with the largest unexpected earnings are on the order of $10^2=100$ times (or more) greater than the individual weights on the ½ of the observations with the smallest unexpected earnings. Collectively, the largest unexpected earnings observations have about 33 times more influence on the estimated UERC than do the smallest unexpected earnings observations.\textsuperscript{42} Thus, the least-squares estimate of the UERC is determined almost entirely by the set of the smallest underlying unexpected earnings coefficients corresponding to the largest magnitude unexpected earnings observations.

In summary, the tests in Tables 3 and 4, and the visual summary in Figure 4 provide four main conclusions:

1) Both the ex post and ex ante proxies individually explain substantial variation in earnings quality as measured by UERCs. Further, the differences between the highest and lowest UERC associated with the highest and lowest levels of each proxy are statistically and economically significant.

2) The ex post and ex ante proxies have substantial incremental effects relative to each other. For each of the three levels of the ex ante precision proxy, the effect of the ex post precision proxy is uniformly positive and large, as reflected in the upward slope of the lines within each dispersion group in Figure 4. Similarly, for each of the five levels of the ex post precision proxy, the effect of the ex ante precision proxy is uniformly positive and large, where the UERCs for the low dispersion group are typically 3 to 4 times the UERCs for the high dispersion group.

3) Together, the ex post and ex ante precision proxies allow us to partition observations into subsets with expected UERCs ranging from approximately 0 (for the lowest levels of both precision proxies in the lower left corner of Figure 4) to approximately 30 (for the highest levels of both precision proxies in the upper right corner of Figure 4).

4) Significantly higher sample UERCs are obtained by eliminating a relatively small minority of observations with low levels of the precision proxies and dramatically high UERCs are obtained by eliminating a larger minority of observations. For example, Table 3 shows that elimination of just 18.6% of the lowest precision observations based only on magnitude of unexpected earnings results in an estimated UERC greater than 3. Table 4 shows that when both forecast dispersion and unexpected earnings magnitude proxies are used to narrow the sample, elimination of a total of 45% of the

\textsuperscript{42} Specifically, $(1/6 \times 100) ÷ (1/2 \times 1) = 33.33$. Also remember that these calculations assume the largest unexpected earnings are all equal to just the value of .02.
lowest precision observations results in an UERC for the remaining observations in excess of 12.

Overall, the results demonstrate that two empirical proxies for precision jointly segment the sample into subsets with sample UERCs ranging from near zero up to plausible earnings capitalization factors. Thus, in combination, the ex ante and ex post precision proxies explain a large range of earnings quality.

The analysis and results presented thus far assume a single earnings multiplier applies for all observations. However, even the simple valuation models discussed in Section 2 predict that earnings multipliers depend on other factors such as risk and growth, and there are a variety of other reasons to expect differences in earnings multipliers. Empirical evaluations of the effect of characteristics such as risk or growth have typically provided statistically significant but economically small estimated effects on UERCs.\textsuperscript{43} In the appendix, we explain further why failing to account for the effects of precision makes it difficult to detect the effects of characteristics that influence the multiplier, and we provide an example how the precision proxies can be used to mitigate this problem.

5. Conclusion

In this paper we use a Bayesian model to develop the expected empirical relation between earnings quality, as reflected in UERCs, and precision. In the Bayesian model, the effect of current earnings on expected future earnings depends on the precision of the signal provided by the current earnings announcement. When precision is low, the UERC can be far smaller than the earnings multiplier and approaches the earnings multiplier only for high precision signals.

Consistent with previous research, the range of UERCs explained by unexpected earnings magnitude, an ex post proxy for precision, is large. For example, without controlling for the effect

\textsuperscript{43} Examples of research examining other determinants of ERCs include Collins and Kothari (1989), Hayn (1995), Kormendi and Lipe (1987), Kothari and Sloan (1992), and Lundholm and Myers (2002).
of the ex ante proxy, the estimated UERCs for the entire sample increase from approximately zero when the magnitude of unexpected earnings is unrestricted, to 3, 5, 8, and 13 for unexpected earnings in the ranges ±.02, ±.01, ±.005, and ±.0025, respectively.

We also find a strong empirical relation between estimated UERCs and the ex ante proxy for precision, dispersion of analyst forecasts. Holding the ex post proxy constant, the estimated UERCs for the low dispersion subset are 3 to 4 times larger than the corresponding estimated UERCs for the high dispersion subset. Similarly, the estimated UERCs for the low dispersion subset are about 1.5 to 2.5 times larger than the corresponding UERCs for the medium dispersion subset. These comparisons apply for any given magnitude of unexpected earnings, suggesting that dispersion of analyst forecasts is an important ex ante precision proxy, incremental to the ex post precision proxy, magnitude of unexpected earnings. We also obtain similar, though slightly weaker, results for two alternative ex ante precision proxies from prior periods, consistent with the idea that precision is determined by firm characteristics that change only slowly over time.

Together, the ex ante and ex post proxies explain a still larger range of estimated UERCs. For observations with both large magnitude unexpected earnings and high dispersion of analyst forecasts, estimated UERCs are near zero. For observations with both small magnitude unexpected earnings and low dispersion of analyst forecasts, estimated UERCs approach 30, a plausible theoretical value for a quarterly earnings capitalization factor.

The results presented here have immediate implications for interpreting past results, for understanding the fundamental role of accounting earnings as a determinant of firm value, and also for improving future tests of models relating earnings to firm value. The dual role of unexpected earnings magnitude as both a major determinant of the unexpected earnings coefficient and a direct determinant of the weight placed on each unexpected earnings coefficient in least-squares estimation of UERCs explains the large gap between plausible earnings capitalization
factors and previously reported estimates of UERCs. For observations where both the ex post and ex ante proxies imply moderate or high precision, UERCs are high, suggesting that proxies for statistical precision effectively capture multiple determinants of accounting earnings quality. For the majority of firms in our sample, estimated unexpected earnings coefficients are far larger than the low UERCs reported in previous research, providing evidence that earnings play a far more important role in determining firm value for many firms than suggested by the low UERCs documented in prior studies. Finally, the predictable and large effects of the two precision proxies can be used to construct more powerful tests of other determinants of the relation between earnings and firm value.
Appendix. Using precision proxies to evaluate effects of the adaptation option on UERCs

In this appendix, we explain why failing to account for the effects of precision makes it difficult to detect the effects of characteristics that influence earnings quality, and demonstrate how the precision proxies can be used to mitigate this problem. To illustrate why it is difficult to detect and estimate effects on capitalization factors, consider the following example. Suppose some firm characteristic, Z, is related to the earnings capitalization factor, where low values, Z=z_{low}, lead to capitalization factors equal to 5 and high values, Z=z_{high}, lead to capitalization factors equal to 15. Now suppose the effect of Z is to be tested on a set of observations where the Bayesian weight on current earnings varies from low to high due to differences in precision. Specifically, consider the observable coefficients on unexpected earnings for two specific weights, w=80% and w=10%. For w=80%, the unexpected earnings coefficients will range between 5 \times 80\% = 4 and 15 \times 80\% = 12, and the range of effects of Z on unexpected earnings coefficients in this subset is 12 – 4 = 8. For w=10%, the unexpected earnings coefficients will range between 5 \times 10\% = .5 and 15 \times 10\% = 1.5, and the range of effects of Z in this subset is only 1.5 – .5 = 1.

Thus, in a sample comprising only observations with low Bayesian weights of 10%, researchers might conclude that Z does not have economically meaningful effects. Further, even if the effect of Z is tested in a sample consisting of a combination of observations with weights of 10% and observations with weights of 80%, the estimated UERC will be strongly biased toward a value somewhere in the range between .5 and 1.5, and comparisons of the difference between the sample UERCs corresponding to z_{low} versus z_{high} will be biased toward an observed difference of no more than 1. Thus, even when there is a large effect of a characteristic (such as Z) on earnings capitalization factors, the mechanics of least-squares regression and the effects of precision in the

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44 To make the example more concrete, consider a model of firm value where expected earnings is a perpetuity so that the capitalization factor for earnings is simply the inverse of expected return. Now suppose that the firm characteristic Z is a measure of risk that causes risk-adjusted expected return to vary between 20% (yielding a capitalization factor of 5) and 6.66% (yielding a capitalization factor of 15).
Bayesian model combine to make it difficult to estimate and detect the effect by estimating sample UERCs.

The ex ante and ex post precision proxies can be used to minimize this problem by focusing tests on subsets of observations with higher precision, where the product of the weight and the earnings multiplier is closer to the earnings multiplier. As illustrated by the example above, tests that focus on higher precision observations will yield estimated sample UERCs larger and closer to underlying earnings multipliers, resulting in a correspondingly larger, and therefore more easily detectable, effect on estimated UERCs. In principle, the downward bias that remains can be further reduced by narrowing the focus to subsamples where weights are closer to 100%. In practice, narrowing the focus to a subsample with high weights comes at the price of reduced sample size. Fortunately, the results in Table 4 and Figure 4 suggest it is possible to use the precision proxies to define subsamples that retain the majority of observations but also achieve large increases in weights that determine the unexpected earnings coefficients.

We illustrate the empirically important role of the precision proxies by testing a multiplier determinant that arises in the adaptation model of Burgstahler and Dichev (1997).\textsuperscript{45} The adaptation option model assumes firm value is a convex combination of the value derived from continuing the current earnings process (recursion value) and the value derived from adapting firm assets to an alternative use (adaptation value). When recursion value is low relative to adaptation value, the current earnings process is not expected to continue. Firm value is approximately equal to adaptation value and information about current earnings has little or no effect on expected future earnings and therefore little or no effect on firm value. As recursion value grows relative to adaptation value, firm value is determined more and more by recursion value, firm value becomes

\textsuperscript{45} We illustrate this point using the adaptation example because the predicted effects of the adaptation option on earnings multipliers (and on unexpected earnings coefficients) are straightforward, relatively easy to measure, and reasonably large.
approximately equal to capitalized current earnings, and information about current earnings becomes the primary determinant of firm value. The ratio of firm value to recursion value should approach one, and the slope of the empirical relation between firm value and expected future earnings should approach a plausible earnings capitalization factor for expected future earnings from an earnings-based valuation model.

Figure A1 summarizes evidence of the adaptation option relation for our sample by plotting market value divided by book value on the vertical axis and expected future earnings divided by book value on the horizontal axis. As in Burgstahler and Dichev (1997), market value is measured as end-of-the-current-year market value of equity and adaptation value is proxied by beginning-of-the-year book value. Expected future earnings, as a measure of recursion value, is proxied here by forecasted current earnings. In order to summarize the relation represented by the individual observations, Figure A1 plots median market value divided by beginning-of-the-year book value, represented by large dots, for portfolios of 500 observations formed based on forecasted earnings divided by beginning-of-the-year book value.

Figure A1 shows evidence strongly consistent with the adaptation model, at least for observations with positive forecasted earnings: At low levels of earnings relative to book value,

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46 Firm value is assumed to be the present value of expected future earnings. The prediction in the model is that the primary determinant of expected future earnings moves from adaptation value (proxied by book value) to recursion value (proxied by a multiple of current earnings). Thus, the model does not predict a change in how expected future earnings are capitalized, but rather a change in the multiplier that applies to current earnings.


48 There is little overlap between our sample period, 1992-2012, and the 1977-1994 sample period used in Burgstahler and Dichev (1997), so the results here provide an essentially independent replication of the earlier results.

49 Book value from the beginning-of-the-year is used to avoid incorporating any of the effects of current year earnings in measured book value. The end of the fiscal year, when we measure market value, is always prior to the announcement of earnings and is almost always prior to the date of the forecast of earnings.

50 Burgstahler and Dichev (1997) use earnings from the previous year as the proxy for expected future earnings but in our sample we have access to forecasted earnings for the current year, which is likely to provide a better proxy for expected future earnings. In any event, the results reported in this section do not change substantially if we use earnings from the previous year in place of forecasted earnings.

51 The discussion in the remainder of this section focuses primarily on results for the positive earnings observations, which represent the majority of the observations, fit the adaptation model more closely, and are more easily interpretable. The loss observation data are broadly consistent with the prediction that the ratio of market value to
the ratio of median market value to book value is in the vicinity of one. Moving toward higher levels of earnings relative to book value, market value begins to rise proportional to current earnings, consistent with current earnings becoming the primary determinant of market value. The slope of the relation approaches 20, consistent with plausible annual earnings capitalization factors from conventional earnings-based valuation models like those discussed in Section 2. Thus, empirical evidence here and in Burgstahler and Dichev (1997) supports the simple yet highly significant convex relation between market value and accounting measures of earnings and book value predicted by the adaptation option model.

The adaptation relation suggests that earnings multipliers should increase as earnings relative to adaptation value increases. We can construct a powerful test of the differences in earnings capitalization factors predicted by the adaptation model by focusing on higher precision observations where unexpected earnings coefficients are closer to earnings multipliers.\(^{52}\)

In order to formulate predictions of earnings multipliers based on the adaptation model, we partition observations into four groups based on the level of earnings relative to book value. The dashed lines in Figure A1 illustrate the partitioning of positive earnings observations into three equal-sized groups, each with approximately the same number of observations, and another group

---

52 The results below show that a test that fails to account for the effects of the precision proxies does not identify a statistically significant effect predicted by the adaptation model.
of negative forecasted earnings observations. Throughout the remainder of this section, we refer to the four groups (three groups with positive earnings and one group of firms with negative earnings) as the adaptation groups.

The adaptation model predicts a multiplier for current earnings approximately equal to the slope of the adaptation option relation in Figure A1. We estimate the average slope for observations in each adaptation group by regressing the median market value on the median earnings for the portfolios within each the adaptation group. The estimated slopes (rounded for simplicity to the nearest integer) for the three positive earnings groups are 6, 15, and 18, respectively. These slopes, which represent annual earnings capitalization factors, translate into a still larger implied quarterly earnings capitalization factor. To convert these annual earnings multipliers to approximate quarterly earnings multipliers as discussed in Section 4, the slopes are multiplied by 2, yielding quarterly earnings multipliers of 12, 30, and 36.

The relative attenuation expected for the various combinations of the precision proxies can be predicted using the results in Table 4. Specifically, we estimate the attenuation effects of lower precision for various combinations of the ex ante and ex post precision proxies by converting each UERC in Panels A, B, and C in Table 4 into a relative attenuation percentage, measured relative to the UERC for the group with the highest ex post and ex ante precision (27.70). This approach yields 15 estimated relative attenuation percentages (for 3 values of the ex ante precision proxy combined with 5 values of the ex post proxy.) To illustrate the calculations for 4 of the 15 combinations of precision proxies, the attenuation percentages range from the maximum of 100% (27.70/27.70) for the highest ex post and ex ante precision group, to about 22.4% (6.21/27.70) for the highest ex post but lowest ex ante precision group, to 8.8% (2.24/27.70) for the lowest ex post

53 These attenuation percentages that compare ERCs for various combinations of the precision proxies to the UERC for the highest values of both precision proxies should be interpreted as relative comparisons. That is, while the estimated UERC for the subsample comprising only the highest values of both precision proxies is expected to be the highest observed UERC, it does not necessarily correspond to the theoretical limiting case where the weight on unexpected earnings is 100%.
but highest ex ante precision group, to 0.0% (0.00/27.70) for the lowest ex post and lowest ex ante precision group.

To generate a total of 45 (3 adaptation groups x 15 combinations of the precision proxies) specific predictions of unexpected earnings coefficients, we multiply the fifteen estimated attenuation effects of precision derived from Table 4 by the three estimated quarterly earnings multipliers of 12, 30, and 36 for the three adaptation groups.\textsuperscript{54} These predictions are plotted in Panels A, B, and C of Figure A2 for the three forecast dispersion subsets, illustrating three main predicted effects of precision on unexpected earnings coefficients:

1) Within each panel, the lines are upward sloping because the ex post precision proxy increases moving from left to right along the horizontal axis.

2) Moving from left to right across panels A, B, and C, the slope of each lines decreases as the ex ante precision proxy decreases.

3) As precision measured by either the ex ante or ex post proxy decreases, the differences between unexpected earnings coefficients for the three adaptation groups decline.

Although the specific predictions cannot be expected to hold precisely, they provide useful qualitative summaries of how precision will interact with differences in earnings capitalization factors to create observable UERC estimates.\textsuperscript{55} Panels D, E, and F of Figure A2 provide a visual summary and preview of the estimates of UERCs reported in detail in Table A1 below. Despite the limitations of the specific predictions discussed above, the actual results are qualitatively

\textsuperscript{54} To illustrate, the predictions in Figure A2 assume the highest ex post and ex ante precision observations have ERCs equal to 100% of the estimated slopes of the adaptation relation so the predicted ERCs plotted at the right side of Panel A are 12, 30, and 36 for the small, medium, and high profit groups respectively. As a second example, the predictions that assume the highest ex post but lowest ex ante precision observations have ERCs equal to 25% of the estimated slopes of the adaptation relation so the predicted ERCs plotted at the right side of Panel C are 3 (25% * 12), 7.5 (25% * 30), and 9 (25% * 36) for the small, medium, and large profit groups, respectively.

\textsuperscript{55} There are multiple reasons to not expect the specific predictions to hold precisely. First, predictions based on the average slope for the three positive earnings groups are inherently imprecise in that we are transforming a variable that theoretically varies continuously within each group into a single discrete empirical approximation based on the average slope that applies to the entire group. Second, the conversion from an annual multiplier to a quarterly multiplier by multiplying by 2 is only a rough empirical approximation. Third, at a more fundamental level, the predicted effect of a change in expected future earnings is only approximately the slope of the adaptation relation at the original level of expected future earnings. More precisely, the predicted effect is measured by the change in firm value as we move along the adaptation relation, and thus also depends on the direction and magnitude of the change in expected future earnings. Fourth, and perhaps most important, results are always subject to estimation error.
consistent with the predictions in Panels A, B, and C. The magnitude of the UERCs, and the relative differences between UERCs for adaptation groups are largest for the low dispersion (high ex ante precision) subset and small unexpected earnings magnitude (high ex post precision) unexpected earnings at the right side of Panel D. The magnitude of the UERCs, and the differences between adaptation groups become predictably weaker and less consistent as we move toward lower levels of precision as measured by either proxy (toward Panel E and then Panel F for the ex ante proxy and toward the left side of each panel for the ex post proxy). Overall, the estimated UERCs for the adaptation groups shrink and converge as we move to lower levels of precision.

Table A1 provides the detailed numerical estimates and tests of statistical significance that underlie the results plotted in Figure A2. In order to examine the differential effects of precision between the adaptation groups, we perform a dependent sort on precision and adaptation profit levels. Specifically, within each adaptation group, we further partition observations into three equal-sized dispersion subsets with approximately the same number of observations. Table A1 Column A provides estimated UERCs for each of the four adaptation groups for the low dispersion subset, while Columns B and C provide UERCs for the medium and high dispersion subsets, respectively. Moving down the rows within each column, major divisions show estimated UERCs for increasing levels of precision as measured by the ex post proxy. Comparing UERCs from corresponding rows across the columns shows the effect of precision as measured by the ex ante proxy.

As illustrated in Figure A2, results in Table A1 are consistent with the predictions that follow from combining the effects of precision in the Bayesian model with the predicted effects on

---

56 We partitioned all profit observations, including observations with undefined dispersion, into three equal-sized adaptation groups. Because there are fewer observations with undefined dispersion in the large profit adaptation group than in the medium group, which in turn has more observations with undefined dispersion than the small profit groups, there are unequal numbers of observations in the different profit adaptation groups in Table A1.
UERCs from the adaptation model. Results in Column A for the high ex ante precision subset show a clear and consistent pattern of UERCs increasing across adaptation groups as predicted by the adaptation model, and all but one of the differences between the low profit adaptation group and the high profit group are statistically significant. Moving from left to right across columns, results for the medium and low ex ante precision subsets in Columns B and C show smaller UERCs with less significant differences across adaptation groups, as predicted by the Bayesian model. In Column B, the UERCs for small and medium profit levels are significantly less than the UERCs for large profit levels in only one case, for unexpected earnings in the range ±.005. In Column C, the UERCs are smaller and vary within a fairly narrow range, and differences across the three positive profit adaptation groups are not significant.

In summary, the results illustrate how either (or both) precision proxy(ies) can be used to design more effective tests of determinants of earnings capitalization factors or other determinants of UERCs. A test that accounts for neither the ex ante proxy nor the ex post proxy for precision shows no significant evidence of the differences in UERCs predicted by the adaptation model. In contrast, tests that incorporate the ex ante and/or ex post proxies for precision show economically important and statistically significant effects consistent with those predicted by the adaptation model.\(^{57}\) Estimated UERCs for adaptation earnings groups, and the differences between estimated UERCs for the groups, are much larger and more significant for observations corresponding to lower dispersion of analyst forecasts (the ex ante proxy for precision) or more restricted ranges of unexpected earnings (the ex post proxy for precision).

\(^{57}\) Note that because the differences in ERCs across adaptation groups are large, especially for low dispersion and small unexpected earnings magnitude, future researchers might consider adding the adaptation variable as an additional control in analyses of other determinants of ERCs.
References


Table 1
Descriptive Statistics for Observations with Earnings Surprise Scaled By Price (ES) Within ±0.02

Panel A: Size Measures (In $ Millions)

<table>
<thead>
<tr>
<th></th>
<th>n</th>
<th>Mean</th>
<th>Std Dev</th>
<th>1</th>
<th>25</th>
<th>50</th>
<th>75</th>
<th>99</th>
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</thead>
<tbody>
<tr>
<td>Revenues</td>
<td>51,929</td>
<td>2,916</td>
<td>12,366</td>
<td>1</td>
<td>94</td>
<td>343</td>
<td>1,363</td>
<td>47,061</td>
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<td>Assets</td>
<td>51,943</td>
<td>7,888</td>
<td>60,058</td>
<td>15</td>
<td>152</td>
<td>572</td>
<td>2,225</td>
<td>124,788</td>
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<tr>
<td>Book value</td>
<td>51,913</td>
<td>1,393</td>
<td>5,715</td>
<td>-36</td>
<td>68</td>
<td>200</td>
<td>702</td>
<td>22,226</td>
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<tr>
<td>Market value</td>
<td>51,947</td>
<td>4,007</td>
<td>16,974</td>
<td>18</td>
<td>158</td>
<td>499</td>
<td>1,778</td>
<td>71,660</td>
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Table 1 (Continued)
Panel B: Descriptive Measures

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<th></th>
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<tbody>
<tr>
<td>Number of observations</td>
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<td>2,907</td>
<td>3,363</td>
<td>3,524</td>
<td>3,537</td>
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<td>3,868</td>
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<td>3,645</td>
<td>3,524</td>
<td>2,748</td>
<td>52,038</td>
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<td>ES Mean</td>
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<td>0.000</td>
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<td>0.000</td>
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<tr>
<td>Median</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
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<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
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<td></td>
</tr>
<tr>
<td>Percent firms by sign of surprise Zero</td>
<td>0.08</td>
<td>0.07</td>
<td>0.11</td>
<td>0.09</td>
<td>0.09</td>
<td>0.09</td>
<td>0.10</td>
<td>0.11</td>
<td>0.14</td>
<td>0.14</td>
<td>0.11</td>
<td>0.11</td>
<td>0.10</td>
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<td>0.09</td>
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<td>Positive</td>
<td>0.47</td>
<td>0.51</td>
<td>0.53</td>
<td>0.55</td>
<td>0.57</td>
<td>0.56</td>
<td>0.56</td>
<td>0.57</td>
<td>0.57</td>
<td>0.56</td>
<td>0.57</td>
<td>0.56</td>
<td>0.55</td>
<td>0.54</td>
<td>0.52</td>
<td>0.50</td>
<td>0.51</td>
<td>0.53</td>
</tr>
<tr>
<td>Mean 22-day returns, by sign of surprise</td>
<td>-0.0008</td>
<td>-0.0027</td>
<td>-0.0047</td>
<td>-0.0014</td>
<td>-0.0023</td>
<td>-0.0027</td>
<td>-0.0024</td>
<td>-0.0023</td>
<td>-0.0020</td>
<td>-0.0019</td>
<td>-0.0017</td>
<td>-0.0017</td>
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<td>-0.0017</td>
<td>-0.0016</td>
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<td>Median</td>
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<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
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<td>0.0001</td>
<td>0.0001</td>
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</tr>
<tr>
<td>No. of Analysts</td>
<td>6,001</td>
<td>7,131</td>
<td>7,675</td>
<td>8,125</td>
<td>8,973</td>
<td>9,763</td>
<td>9,030</td>
<td>8,725</td>
<td>8,057</td>
<td>7,633</td>
<td>7,989</td>
<td>8,369</td>
<td>8,417</td>
<td>8,708</td>
<td>8,765</td>
<td>7,755</td>
<td>30,627</td>
<td>33,579</td>
</tr>
<tr>
<td>Aggregate MVE ($b)</td>
<td>5,545</td>
<td>6,671</td>
<td>6,851</td>
<td>9,183</td>
<td>11,403</td>
<td>14,700</td>
<td>17,584</td>
<td>23,182</td>
<td>25,096</td>
<td>22,125</td>
<td>16,790</td>
<td>20,724</td>
<td>24,491</td>
<td>26,190</td>
<td>30,627</td>
<td>33,579</td>
<td>20,950</td>
<td></td>
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<tr>
<td>Entire IBES sample, including observations</td>
<td>2,406</td>
<td>2,866</td>
<td>3,230</td>
<td>3,466</td>
<td>3,762</td>
<td>5,066</td>
<td>5,986</td>
<td>8,125</td>
<td>9,066</td>
<td>11,123</td>
<td>14,582</td>
<td>15,730</td>
<td>18,497</td>
<td>21,125</td>
<td>25,096</td>
<td>22,125</td>
<td>16,790</td>
<td></td>
</tr>
<tr>
<td>Aggregate MVE ($b)</td>
<td>2,880</td>
<td>3,558</td>
<td>3,726</td>
<td>5,066</td>
<td>6,589</td>
<td>9,086</td>
<td>11,123</td>
<td>14,582</td>
<td>15,730</td>
<td>18,497</td>
<td>21,125</td>
<td>25,096</td>
<td>22,125</td>
<td>16,790</td>
<td>20,724</td>
<td>24,491</td>
<td>26,190</td>
<td>30,627</td>
</tr>
<tr>
<td>Sub-sample as % of CompuStat MVE</td>
<td>52%</td>
<td>53%</td>
<td>54%</td>
<td>55%</td>
<td>58%</td>
<td>62%</td>
<td>63%</td>
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<td>63%</td>
<td>71%</td>
<td>74%</td>
<td>75%</td>
<td>76%</td>
<td>76%</td>
<td>76%</td>
<td>76%</td>
<td>76%</td>
<td>76%</td>
</tr>
<tr>
<td>Final IBES sample with non-missing price</td>
<td>1,190</td>
<td>1,469</td>
<td>1,569</td>
<td>1,694</td>
<td>1,900</td>
<td>2,051</td>
<td>2,147</td>
<td>2,088</td>
<td>1,899</td>
<td>1,821</td>
<td>1,834</td>
<td>1,898</td>
<td>2,059</td>
<td>2,178</td>
<td>2,395</td>
<td>2,422</td>
<td>2,225</td>
<td></td>
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<tr>
<td>Sample relative to entire CompuStat universe</td>
<td>46%</td>
<td>48%</td>
<td>48%</td>
<td>47%</td>
<td>50%</td>
<td>54%</td>
<td>56%</td>
<td>59%</td>
<td>55%</td>
<td>61%</td>
<td>61%</td>
<td>58%</td>
<td>60%</td>
<td>60%</td>
<td>59%</td>
<td>57%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Observations consist of the analyst forecasts from IBES with accounting data in Compustat and stock returns data in CRSP. Observations from IBES consist of U.S. firms that have at least one forecast and associated actual earnings per share reported for annual earnings amounts for fiscal years ending from January 1, 1992, through December 31, 2008. Accounting and stock return data are from Compustat and CRSP for the relevant period. Observations are included in this table if ES is within ±0.02, where ES is defined as the annual per share earnings surprise divided by fiscal year-end price per share. Limiting observations for this table to ES within ±0.02 reduces the number of observations from 65,099 to 52,038. Earnings surprise is the actual EPS less the average per share forecast as of the last update before the announcement of earnings for the year. Price per share is Compustat data item PRCC_F (fiscal year-end price).

Size measures are defined as: Revenues = Compustat data item SALE; Assets = Compustat data item AT; Book Value = Compustat data item CEO; and Market Value = Compustat data item PRCC_F (fiscal year-end price) times Compustat data item CSHO (common shares used to calculate primary EPS). Variables are defined as follows. ES is the annual per share earnings surprise divided by fiscal year-end price per share. Earnings surprise is the actual EPS reported by IBES less the average forecast as of the last IBES update before the announcement of earnings for the year. Price per share is Compustat data item PRCC_F (fiscal year-end price). Percent firms, by surprise is the percentage of firms with negative, none, or positive surprise, where surprise is negative for firms if the forecast mean exceeds actual earnings, positive for firms if actual earnings exceed the forecast mean, and none if actual earnings and the forecast mean are equal. Mean 22-day window returns, by surprise is the average cumulative 22-day return, adjusted for a value-weighted market index, for the period beginning 20 days before and ending 1 day after the earnings announcement date, by surprise category. Forecast age is the number of days between the date of the last IBES forecast update before the announcement of earnings and the earnings announcement date, both from the IBES database. No. of analysts is the number of forecasts in the IBES database as of the date of the last forecast update before the announcement of earnings. Forecast dispersion is the standard deviation of the forecasts in IBES as of the date of the last forecast update, scaled by fiscal year-end price per share (Compustat data item PRCC_F). This variable is defined only if the number of forecasts is greater than one.
Table 2
Correlation of Precision Variables Across Time

Panel A: Dispersion of Analyst Forecasts

<table>
<thead>
<tr>
<th></th>
<th>Contemporaneous Dispersion (n = 33,017)</th>
<th>Dispersion One Year Ago (n = 29,697)</th>
<th>Dispersion Two Years Ago (n = 26,413)</th>
<th>Dispersion Three Years Ago (n = 23,460)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contemporaneous Dispersion</td>
<td></td>
<td>0.423 ***</td>
<td>0.2849 ***</td>
<td>0.2461 ***</td>
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<tr>
<td>Dispersion One Year Ago</td>
<td>0.6138 ***</td>
<td></td>
<td>0.4499 ***</td>
<td>0.3411 ***</td>
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<tr>
<td>Dispersion Two Years Ago</td>
<td>0.5273 ***</td>
<td>0.6284 ***</td>
<td></td>
<td>0.4659 ***</td>
</tr>
<tr>
<td>Dispersion Three Years Ago</td>
<td>0.4812 ***</td>
<td>0.5548 ***</td>
<td>0.637 ***</td>
<td></td>
</tr>
</tbody>
</table>

Panel B: Magnitude of Earnings Surprise (Absolute Value)

<table>
<thead>
<tr>
<th></th>
<th>Contemporaneous Earnings Surprise (n = 63,099)</th>
<th>Earnings Surprise One Year Ago (n = 54,840)</th>
<th>Earnings Surprise Two Years Ago (n = 47,426)</th>
<th>Earnings Surprise Three Years Ago (n = 41,113)</th>
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</thead>
<tbody>
<tr>
<td>Contemporaneous Earnings Surprise</td>
<td></td>
<td>0.3551 ***</td>
<td>0.1779 ***</td>
<td>0.1243 **</td>
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<tr>
<td>Earnings Surprise One Year Ago</td>
<td>0.4497 ***</td>
<td></td>
<td>0.3526 ***</td>
<td>0.2141 **</td>
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<tr>
<td>Earnings Surprise Two Years Ago</td>
<td>0.3564 ***</td>
<td>0.4352 ***</td>
<td></td>
<td>0.3582 **</td>
</tr>
<tr>
<td>Earnings Surprise Three Years Ago</td>
<td>0.3094 ***</td>
<td>0.3606 ***</td>
<td>0.4362 ***</td>
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</tr>
</tbody>
</table>

Spearman (Pearson) coefficients appear below (above) the diagonal.
Variables are winsorized at the 1st and 99th percentiles.

*** Significantly different from zero at 0.001 level
** Significantly different from zero at 0.01 level
* Significantly different from zero at 0.05 level
Table 3
Estimates of ERCs By Earnings Surprise Magnitude

\[ \text{CAR} = \beta_0 + \beta_1 \text{ES} + \epsilon \]

Panel A:
Entire Sample

<table>
<thead>
<tr>
<th>ES Magnitude</th>
<th>N</th>
<th>( \beta_0 )</th>
<th>( \beta_1 )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unrestricted</td>
<td>63,099</td>
<td>0.01</td>
<td>0.00</td>
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</tr>
<tr>
<td>± 0.02</td>
<td>52,122</td>
<td>0.01</td>
<td>3.32</td>
<td>0.017</td>
</tr>
<tr>
<td>± 0.01</td>
<td>46,578</td>
<td>0.01</td>
<td>5.38</td>
<td>0.017</td>
</tr>
<tr>
<td>± 0.005</td>
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<td>± 0.0025</td>
<td>30,238</td>
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<td>13.74</td>
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Panel B:
Subsample With Defined Dispersion (i.e., At Least 4 Analysts)

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<th>ES Magnitude</th>
<th>N</th>
<th>( \beta_0 )</th>
<th>( \beta_1 )</th>
<th>( R^2 )</th>
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<td>33,018</td>
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<tr>
<td>± 0.005</td>
<td>25,636</td>
<td>0.00</td>
<td>10.70</td>
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<tr>
<td>± 0.0025</td>
<td>20,831</td>
<td>0.00</td>
<td>16.36</td>
<td>0.017</td>
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</table>

Panel C:
Subsample With Undefined Dispersion (i.e., Fewer Than 4 Analysts)

<table>
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<th>( \beta_1 )</th>
<th>( R^2 )</th>
</tr>
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<td>± 0.01</td>
<td>17,632</td>
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<td>0.013</td>
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<td>± 0.005</td>
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<tr>
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<td>9,407</td>
<td>0.00</td>
<td>9.78</td>
<td>0.007</td>
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*** Significantly greater than zero at p=0.01
** Significantly greater than zero at p=0.05
* Significantly greater than zero at p=0.10
<table>
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<td>Ex Ante Precision Proxied By</td>
</tr>
<tr>
<td></td>
<td>Contemporaneous Dispersion</td>
<td>Prior-Year Dispersion</td>
</tr>
<tr>
<td>Ex Ante Precision Proxied By</td>
<td></td>
<td>Absolute Earnings Surprise Magnitude</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Averaged Over the Past Four Years</td>
</tr>
<tr>
<td></td>
<td>N  β₀  β₁  R²</td>
<td>N  β₀  β₁  R²</td>
</tr>
<tr>
<td>Unrestricted</td>
<td>11,026 0.01 2.44 *** 0.006</td>
<td>9,893 0.01 0.01 0.000</td>
</tr>
<tr>
<td>± 0.02</td>
<td>10,954 0.00 8.52 *** 0.020</td>
<td>9,663 0.00 7.39 *** 0.025</td>
</tr>
<tr>
<td>± 0.01</td>
<td>10,826 0.00 14.34 *** 0.030</td>
<td>9,473 0.00 11.20 *** 0.031</td>
</tr>
<tr>
<td>± 0.005</td>
<td>10,563 0.00 21.10 *** 0.036</td>
<td>9,034 0.00 16.21 *** 0.032</td>
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<td>± 0.0025</td>
<td>9,852 -0.01 29.22 *** 0.033</td>
<td>8,156 0.00 22.05 *** 0.025</td>
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</table>

<table>
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<th>Panel B: Medium Ex Ante Precision</th>
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<td>Contemporaneous Dispersion</td>
<td>Prior-Year Dispersion</td>
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<td>Absolute Earnings Surprise Magnitude</td>
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<tr>
<td></td>
<td></td>
<td>Averaged Over the Past Four Years</td>
</tr>
<tr>
<td></td>
<td>N  β₀  β₁  R²</td>
<td>N  β₀  β₁  R²</td>
</tr>
<tr>
<td>Unrestricted</td>
<td>10,971 0.01 0.66 *** 0.005</td>
<td>9,904 0.00 0.07 *** 0.004</td>
</tr>
<tr>
<td>± 0.02</td>
<td>10,774 0.00 7.48 *** 0.038</td>
<td>9,381 0.00 5.58 *** 0.032</td>
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<tr>
<td>± 0.01</td>
<td>10,490 0.00 10.03 *** 0.040</td>
<td>8,910 0.00 7.82 *** 0.030</td>
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<tr>
<td>± 0.005</td>
<td>9,588 0.00 12.53 *** 0.031</td>
<td>7,971 0.00 10.48 *** 0.024</td>
</tr>
<tr>
<td>± 0.0025</td>
<td>7,668 0.00 14.63 *** 0.017</td>
<td>6,391 0.00 15.48 *** 0.019</td>
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</table>

<table>
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<th>Panel C: Low Ex Ante Precision</th>
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<td>Prior-Year Dispersion</td>
</tr>
<tr>
<td>Ex Ante Precision Proxied By</td>
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<td>Absolute Earnings Surprise Magnitude</td>
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<tr>
<td></td>
<td></td>
<td>Averaged Over the Past Four Years</td>
</tr>
<tr>
<td></td>
<td>N  β₀  β₁  R²</td>
<td>N  β₀  β₁  R²</td>
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<td>± 0.02</td>
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<td>8,142 0.01 2.60 *** 0.012</td>
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<tr>
<td>± 0.01</td>
<td>7,629 0.00 3.98 *** 0.012</td>
<td>7,023 0.00 4.05 *** 0.012</td>
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<tr>
<td>± 0.005</td>
<td>5,483 0.00 5.20 *** 0.007</td>
<td>5,440 0.00 6.13 *** 0.009</td>
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<td>± 0.0025</td>
<td>3,310 0.00 7.38 *** 0.004</td>
<td>3,708 0.00 10.85 *** 0.009</td>
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*** Significantly greater than zero at p=0.01
** Significantly greater than zero at p=0.05
* Significantly greater than zero at p=0.10

*** Significantly less than β₁ for high precision subset at p=0.01
** Significantly less than β₁ for high precision subset at p=0.05
* Significantly less than β₁ for high precision subset at p=0.10
Figure 1
Distributions of Returns Versus Price-Scaled Earnings Surprise
All Observations n = 63,099
Portfolios of 1,000 Observations Except Zero Surprise Portfolio with 5,474 Observations
Figure 2 - Frequency of Earnings Surprises By Dispersion Subset

Low Dispersion Subset

Medium Dispersion Subset

High Dispersion Subset

Earnings Surprise Scaled By Price
Figure 3
Distributions of Returns Versus Price-Scaled Earnings Surprise
Portfolios of 500 Observations Except Zero Surprise Portfolio
Partitioned on Dispersion from Current Year

Panel A
Low Dispersion Subset n = 11,026
Zero Surprise Portfolio with 1,889 Observations

Panel B
Medium Dispersion Subset n = 10,971
Zero Surprise Portfolio with 1,037 Observations

Panel C
High Dispersion Subset n = 11,020
Zero Surprise Portfolio with 503 Observations
Figure 3’
Distributions of Returns Versus Price-Scaled Earnings Surprise
Portfolios of 500 Observations Except Zero Surprise Portfolio
Partitioned on Dispersion from Prior Year

Panel A’
Low Dispersion Subset n = 9,893
Zero Surprise Portfolio with 1,530 Observations

Panel B’
Medium Dispersion Subset n = 9,904
Zero Surprise Portfolio with 961 Observations

Panel C’
High Dispersion Subset n = 9,900
Zero Surprise Portfolio with 574 Observations
Figure 3
Distributions of Returns Versus Price-Scaled Earnings Surprise
Portfolios of 500 Observations Except Zero Surprise Portfolio
Partitioned on Absolute Earnings Surprise Magnitude Averaged over Preceding 4 Years

Panel A''
Low Earnings Surprise Subset n = 11,905
Zero Surprise Portfolio with 1,658 Observations

Panel B''
Medium Earnings Surprise Subset n = 11,901
Zero Surprise Portfolio with 955 Observations

Panel C''
High Earnings Surprise Subset n = 11,902
Zero Surprise Portfolio with 659 Observations
Relative areas of plot symbols represent sample size relative to the sample size of the unrestricted range of earnings surprises. For example, for the low dispersion subset, the sample size in the 0.0025 range is 89.4% of that for the unrestricted range. Similarly, for the medium dispersion subset, the sample size in the 0.0025 range is 69.8% of that for the unrestricted range. For the high dispersion subset, the sample size in the 0.0025 range is 30.0% of that for the unrestricted range. See Table 4 for exact sample sizes.
Table A1
Estimates of ERCs by Subsets of Earnings Surprise Magnitude As An Ex Post Precision Proxy, Contemporaneous Forecast Dispersion As An Ex Post Precision Proxy, and Adaptation Option Group

\[ \text{CAR} = \beta_0 + \beta_1 \text{ES} + \varepsilon \]

<table>
<thead>
<tr>
<th>Ex Post Precision: ES Magnitude</th>
<th>Adaptation Option Group</th>
<th>Column A: High Ex Ante Precision Proxied By Contemporaneous Dispersion</th>
<th>Column B: Medium Ex Ante Precision Proxied By Contemporaneous Dispersion</th>
<th>Column C: Low Ex Ante Precision Proxied By Contemporaneous Dispersion</th>
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<td>( \beta_1 )</td>
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<td>3.36</td>
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<td>Losses</td>
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<td>0.11</td>
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<tr>
<td>Large Profits</td>
<td>3,211</td>
<td>0.00</td>
<td>7.99</td>
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<tr>
<td>Medium Profits</td>
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<td>8.79</td>
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<td>5.77</td>
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<tr>
<td>Large Profits</td>
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<td>17.35</td>
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<td>14.17</td>
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<tr>
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<td>Losses</td>
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<td>12.89</td>
<td>***</td>
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<tr>
<td>Large Profits</td>
<td>3,128</td>
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<td>26.01</td>
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<tr>
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<td>-0.01</td>
<td>16.11</td>
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<td>16.46</td>
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<tr>
<td>Large Profits</td>
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<td>34.52</td>
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<td>19.46</td>
<td>***</td>
</tr>
</tbody>
</table>

*** Significantly greater than zero at p=0.01
** Significantly greater than zero at p=0.05
* Significantly greater than zero at p=0.10

*** Significantly less than \( \beta_1 \) for large profit forecast group at p=0.01
** Significantly less than \( \beta_1 \) for large profit forecast group at p=0.05
* Significantly less than \( \beta_1 \) for large profit forecast group at p=0.10
Figure A1
Adaptation Option Relation for Individual Observations
Market Value / Lagged Book Value versus Earnings Forecast / Lagged Book Value
Figure A2
Stylized ERC Predictions Using Table 4 and Figure 4 (Panels A to C below) and Actual ERCs From Table A1 (Panels D to F below)
ERCs By Magnitude of Earnings Surprise, Dispersion Subset, and Adaptation Group

Panel A: Predictions For Low Dispersion Subset
Panel B: Predictions For Medium Dispersion Subset
Panel C: Predictions For High Dispersion Subset
Panel D: Actual Results For Low Dispersion Subset
Panel E: Actual Results For Medium Dispersion Subset
Panel F: Actual Results For High Dispersion Subset