The predictive qualities of earnings volatility and earnings uncertainty

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Abstract

This study examines the differential predictive power of past earnings volatility for analyst forecast errors and future returns. Past earnings volatility jointly captures two correlated, but distinct, earnings properties: time-series earnings variation and uncertainty in future earnings. To distinguish between these two earnings properties, we develop a forward-looking measure of earnings uncertainty that has a minimal mechanical link to variation in prior period earnings realizations and does not rely on analyst forecasts. Our collective results suggest that future earnings uncertainty, and not time variation in earnings, is associated with overly-optimistic future earnings expectations of equity analysts and investors. We provide the first empirical evidence on the relevance of future earnings uncertainty to analysts and investors over one-year horizons. In addition, we provide empirical evidence showing that forecast dispersion is a poor measure of earnings uncertainty.

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1. Introduction

This study investigates the predictive power of past earnings volatility to explain the forecast errors of equity analysts and investors. Past earnings volatility, defined as the standard deviation of past earnings realizations, jointly captures two distinct economic constructs: time variation in earnings and the precision with which future earnings can be estimated. By time-variation in earnings, we mean the time-series volatility in earnings realizations caused by accrual measurement errors and fundamental economic shocks (Dichev and Tang 2009). By precision, we mean how precisely future earnings as reported under GAAP can be estimated in the current period. In this study, we refer to earnings precision in terms of its inverse, earnings uncertainty, and define it as the distribution around future earnings expectations. We disentangle these two correlated economic constructs captured by past earnings volatility and determine their relative predictive power for explaining the forecast errors of equity analysts and investors.

The primary motivation for our study stems from the fact that despite a relatively extensive literature examining the consequences of past earnings volatility, prior studies have not investigated whether historical variation in earnings is relevant to analysts and investors once earnings uncertainty (the precision with which future earnings can be estimated) has been controlled. Graham et al. (2005) note executives strongly believe more volatile earnings are less predictable and less predictable earnings have negative consequences. However, as noted by Dichev and Tang (2009), it is unclear whether managers dislike past earnings volatility because they believe time-variation in earnings directly leads to more uncertain future earnings *or* if managers dislike uncertain future earnings (which happen to be correlated with a volatile past earnings stream). Carrying forward this question to the broader accounting literature, it is unclear whether variation in past earnings affects the earnings forecasts of analysts and investors after controlling for the effect of earnings uncertainty. This question is important as a primary tension in the accounting literature lies in understanding whether actions (and reactions) of analysts and investors prior studies associate with past earnings volatility are due to: i) the underlying economic uncertainty at time t, or ii) the way past earnings were reported between t-τ and t.

The primary challenge in separating the predictive power associated with time-series earnings variation from

that associated with earnings uncertainty comes from the tight connection between the two constructs. Indeed, time variation in earnings, measured by past earnings volatility, is often used to proxy for earnings uncertainty as firms with more volatile earnings processes tend to have future earnings that are more difficult to predict (e.g., Dichev and Tang 2009). At the same time, however, realized earnings variation and earnings uncertainty are not perfectly linked. For example, extreme earnings realizations will increase past earnings volatility, but may not increase the uncertainty of future earnings because extreme earnings tend to (predictably) mean revert very quickly. Further, earnings realizations from early periods will affect past earnings volatility, but may be unrelated to the predictability of future earnings since these realizations no longer convey timely information.

To distinguish the incremental predictive power of the two accounting constructs captured by past earnings volatility, earnings uncertainty and time variation in earnings, we develop a novel, firm-specific measure of earnings uncertainty that has a minimal mechanical link to time variation in earnings and is not derived from analyst earnings forecasts. Our measure builds on Barber and Lyon (1996) and Blouin et al. (2010) and uses a matched-firm expectation model to estimate future earnings and the uncertainty associated with the future earnings expectation.

Our central empirical result strongly suggests that earnings uncertainty, and not time-series earnings variation, predicts forecast errors of equity analysts and investors. Using conventional cross-sectional regressions, we find that earnings uncertainty significantly predicts future returns: controlling for size, book-to-market, accruals, and momentum, average predictive slopes for future monthly returns on earnings uncertainty are negative and three to five standard errors from zero, depending on the specification. We find similar predictive inferences, both in statistical and economic terms, on earnings uncertainty using hedge return portfolio tests and analyst forecast errors. Collectively, our empirical results suggest that earnings uncertainty, and not time-variation in earnings, has significant predictive power for the errors of analysts and investors.

In addition, we find past earnings volatility, but not earnings uncertainty, strongly predicts lower future earnings. Our results confirm the conjecture that time-variation in earnings lead to lower future earnings

(Minton, Schrand, and Walther 2002), suggesting time-variation in earnings has real effects on future firm performance. However, our evidence suggests analysts and investors understand these effects once earnings uncertainty is controlled.

Our study contributes to the accounting and finance literatures in three additional ways. First, we propose and validate a forward-looking, firm-specific measure of earnings uncertainty. Our measure requires a minimal time-series of earnings realizations, thereby minimizing the mechanical relation with past earnings volatility. In specification tests, we show that this measure is well specified in the full sample and in select subsamples of firms experiencing extreme performance. Further, in direct comparative tests, we show our uncertainty measure better estimates earnings uncertainty (more precise and less biased) compared to estimates derived from analyst forecast dispersion. Our uncertainty measure offers future researchers not only a better estimate of uncertainty, but also one available for a broader number of firms spanning a longer time-series.

Second, our results contribute to the information uncertainty and the 'low volatility' anomaly literatures (Zhang 2006; Baker et al. 2011). Prior studies in these literatures do not directly articulate the source of investor uncertainty. Rather, these literatures proxy for uncertainty using variables that jointly capture multiple types of uncertainty and future expected performance.[1] Our results suggest earnings uncertainty is a significant predictor of future returns over horizons extending at least 12 months, a result that counters the one to three month predictive relations noted in prior studies (Diether et al. 2002; Ang et al. 2006).

Third, while not the primary purpose of our study, we also contribute to the earnings prediction literature. While accounting researchers have produced an extensive set of earnings prediction models, the models are primarily derived from ordinary least squares regressions and therefore subject to the restrictions and assumptions imposed by OLS. We extend the work of Barber and Lyon (1996) and show that our nonparametric matched-firm empirical design produces superior earnings expectations relative to simpler

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[1] For example, firm size, market-to-book, forecast dispersion, realized return volatility (and other variables) have each been used as empirical proxies for information uncertainty.

random walk and analyst forecast prediction models. Barber and Lyon (1996) primarily examine operating earnings of NYSE and AMEX firms from 1977-1992 whereas we examine earnings before extraordinary items of NYSE, AMEX, and NASDAQ firms from 1968-2009.

The rest of our study proceeds as follows. Section 2 discusses prior literature and motivates our research question and empirical tests. Section 3 describes our measure of earnings uncertainty and the construction of our primary sample. Sections 4 and 5 report results from our primary empirical tests. Section 6 reports robustness tests. Section 7 concludes.

2. Research Motivation

2.1   Prior literature

Prior studies in accounting and finance have differed in their interpretation of past earnings volatility and why it is (or is not) relevant to capital market participants. Many studies interpret past earnings volatility as an empirical measure capturing value-irrelevant noise caused by measurement error in the accrual process and transitory economic shocks (e.g., Dichev and Tang 2009), linking it to a series of negative firm outcomes. These negative firm outcomes include biased analyst earnings forecasts (Dichev and Tang 2009), analyst coverage effects (Lang, Lins, and Miller 2003), higher cost of equity capital (Francis et al. 2004; 2005). Related studies find time variation in cash flows affects investment decisions, leading to lower investment and lower future earnings (Minton and Schrand 1999; Minton, Schrand and Walther 2002). Finally, similar in tenor to the volatility literatures, the earnings smoothness literature views past earnings volatility as a measure of the discretionary reporting choices made by managers to smooth reported earnings. The primary debate in the earnings smoothness literature is whether the discretionary reporting choices made by managers over time clarify or garble the informativeness of earnings (Tucker and Zarowin 2005; Jayaraman 2008; Rountree et al. 2008).[2] While the research designs and research questions vary across these (and other) studies examining past earnings volatility, the general takeaway is fairly consistent: the significant associations between past earnings

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[2] Dechow, Ge, and Schrand (2010) provide a more extensive discussion on the earnings smoothness literature within the broader context of earnings quality.

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volatility and a series of negative firm outcomes suggests that time-variation in earnings is relevant to a large set of capital market participants and an undesirable earnings attribute.

An alternative perspective suggests the precision with which future earnings can be estimated, not time-variation in earnings, is the primary economic dynamic behind the significant associations with past earnings volatility documented in prior studies. This view is emphasized in early accounting studies examining the link between accounting measures of risk and market measures of risk (Beaver, Kettler, and Scholes 1970; Rosenberg and McKibben 1973). It also is consistent with more recent studies that suggest the precision with which future earnings and cash flows can be estimated affects firm value, either because the precision of earnings estimates affects a firm's cost of capital (Easley and O'Hara 2004; Johnson 2004; Lambert, Leuz and Verrecchia 2007) or variation in investors' assessment of earnings precision affects their expectations of future earnings (Daniel, Hirshleifer and Subrahmanyam 1998; Jiang et al. 2005).

Obviously, there is significant conceptual overlap between the two interpretations of past earnings volatility. Firms with more volatile historical earnings streams will tend to have future earnings that are more uncertain. Thus, the use of past earnings volatility as an empirical proxy for uncertainty in future earnings is reasonable as the two constructs, time-variation in earnings and earnings uncertainty, are certainly positively correlated. However, the conceptual overlap between the two constructs is not complete and, in fact, the two constructs are expected to diverge from each other in predictable ways. For example, timely loss recognition associated with accounting conservatism is one reason we might observe a negative correlation between past earnings volatility and earnings uncertainty (Frankel and Litov 2009). Relatedly, large losses tend to be transitory and are associated with strong earnings reversals in the subsequent period. Nonetheless, large one-time losses will lead to higher past earnings volatility, though not necessarily high earnings uncertainty (especially the earlier in the time-series the one-time loss is recognized). Another example is noted by Kothari et al. (2002), who find research and development expenditures are positively associated with earnings volatility even though R&D leads to predictably higher future earnings (Lev and Sougiannis 1996).

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Understanding whether the combination of past economic shocks and manager reporting choices, which lead to higher time-variation in earnings, affect the earnings forecasts of analysts and investors *incremental* to contemporaneous economic uncertainty that affects how precisely future GAAP earnings can be estimated serves as the primary motivation for our study. An extensive literature suggests financial reporting choices have significant consequences that are incremental to the economic performance captured by earnings, i.e., the earnings quality literature. However, because past earnings volatility is a joint function of past economic shocks and measurement errors inherent in the accrual system, and each of these elements is likely correlated to future earnings uncertainty, prior studies have been unable to convincingly determine whether the consequences associated with past earnings volatility are due to underlying economic uncertainty at time *t* or uncertainty caused over time by the accounting process.

In the subsequent sections, we briefly discuss the two modal empirical variables used in prior studies to proxy earnings uncertainty: past earnings volatility and analyst forecast dispersion. We discuss the strengths and weaknesses of each variable and then propose a potential alternative empirical proxy for earnings uncertainty. We highlight its empirical costs and benefits relative to past earnings volatility and analyst forecast dispersion. We then provide our empirical predictions.

2.2   The relation between past earnings volatility and earnings uncertainty

If a firm's earnings process is reasonably stable, then past earnings volatility (as measured by variation in a time series of realizations) will be a precise and unbiased estimate of uncertainty in future earnings. However, to the extent each earnings realization in the time-series is not equally informative of the underlying future earnings process of the firm, past earnings volatility will not proxy for earnings uncertainty. Further, as noted by Frankel and Litov (2009), some accounting conventions such as conservatism will lead to more volatile earnings process while at the same time (possibly) producing less uncertain future earnings. Accordingly, we expect that past earnings volatility is positively correlated with earnings uncertainty for the average firm. However, for any given firm, the strength and sign of these associations could vary significantly.

2.3   The relation between analyst forecast dispersion and earnings uncertainty

The dominant empirical measure of earnings uncertainty in the accounting and finance literature is dispersion in analyst forecasts.[3] Advantages to using analyst forecast dispersion to proxy for earnings uncertainty include the fact that dispersion is a direct function of an earnings expectation model (i.e., it represents a distribution around an expected value, the consensus forecast), it is not a mechanical function of prior period earnings realizations, and earnings expectations are routinely updated in response to news.

Nonetheless, the use of analyst forecasts has several costs. Analyst forecasts are only available in machine readable format for relatively large, mature firms and coverage is relatively sparse for even large firms prior to 1990. Second, analyst earnings forecasts are not consistently defined across firms or even across firms in the same industry as analysts exclude line items inconsistently (Brown and Larocque 2012). Third, analyst forecasts are biased, although the direction of the bias is context-specific which leads to more empirical complications.[4] Consideration of these biases is important since earnings uncertainty represents the second moment of earnings; thus, proxies for earnings uncertainty will only be as good as the empirical proxies for the first moment (i.e., the earnings expectation). Finally, as McNichols and O'Brien (1997) and Diether et al. (2002) point out, the analysts' incentives to cover a firm may directly affect both the consensus forecast and the dispersion. For example, analysts are much more likely to drop the coverage of a firm they view negatively than to formally issue that negative forecast. Performance-related censoring of the available forecasts can lead to optimistic biases in earnings forecasts and understated estimates of earnings uncertainty for poorly performing firms. While the optimistic earnings expectation bias is well documented, whether forecast dispersion is an unbiased estimate of earnings uncertainty has not been directly examined in prior studies.

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[3] Analyst forecast dispersion is sometimes also referred to as opinion divergence (Diether et al 2002). Alternative measures of earnings uncertainty based on forecast dispersion exist in the literature. Barron, Kim, Lim, and Stevens (1998) suggest a measure that decomposes forecast dispersion into an uncertainty component and an information asymmetry component. Sheng and Thevenot (2011) suggest an uncertainty measure based on a GARCH model. We do not directly consider these alternative measures in our study as the BKLS model imposes a significant look-ahead bias in its design by requiring the earnings realization to compute earnings uncertainty. The empirical design of Sheng and Thevenot requires a significant time-series of forecasts (20+ years of earnings estimates per firm).

[4] For example, analyst forecasts tend to be optimistically biased early in the fiscal period, pessimistically biased by the end of the fiscal period. Analyst forecasts tend to be optimistically biased for "growth" firms, pessimistically biased for "value" firms.

2.4   Motivation for a pure earnings uncertainty measure

The above discussion provides suggestive intuition as to why it is difficult to determine whether predictive relations noted in prior studies on past earnings volatility or forecast dispersion are due to the time variation in earnings, analyst coverage and forecast biases, or simply due to current economic uncertainty. In addition, if time variation in earnings affects analyst forecasts, then forecast dispersion could also jointly capture dynamics associated with time-series earnings variation and economic uncertainty, further convoluting any analysis.

To directly distinguish the predictive power of earnings uncertainty from time-variation in earnings, we need to develop an empirical estimate of earnings uncertainty with a minimal mechanical relation to past earnings realizations and one that does not require analyst forecasts. Specifically, we propose an earnings uncertainty measure that builds on Barber and Lyon (1996). Barber and Lyon propose a nonparametric matched-firm approach to estimate expected operating performance. Their empirical design is based on matching firm *i* at time *t* to firms with comparable characteristics in the preceding period, yielding a firm-specific estimate of expected future operating performance.

Also produced from their empirical design, but unexplored by prior studies, is the empirical distribution of the earnings realizations in period *t* of firm *i*'s matched-firms. Specifically, since the matched-firms are grouped together because they have characteristics similar to firm *i*, differences in the matched-firms' earnings realizations represent possible earnings realizations of firm *i* in period *t*+1. Accordingly, the variance of the matched-firms' earnings realizations in period *t* can be viewed as the variance (i.e., earnings uncertainty) of firm *i*'s *t*+1 earnings as of time *t*.[5] This empirical design dovetails nicely into the concept earnings uncertainty should represent the precision that *future* earnings can be estimated (Beaver et al. 1970) while minimizing the mechanical link to time-series earnings variation – exactly what we need for our empirical tests.

As with any empirical design, there are potential costs and benefits to the matched-firm approach. From an

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[5] Blouin et al. (2010) utilize similar intuition to project the distribution of pretax income level for twenty years to estimate marginal tax rates. However, they do not project firm-specific estimates of earnings uncertainty nor explore the capital market implications for the earnings volatility literature.

empirical benefits perspective, the matched-firm process does not impose any structural relation between firm characteristics and earnings uncertainty across time or across firms. Further, the matched-firm approach is parsimonious, requiring a very limited time-series of earnings realizations and firm characteristics thereby allowing estimates of earnings uncertainty for a large subset of firms. A potential cost is the matching process requires an appropriate number of matched firms to produce an earnings distribution. Since firms with extreme characteristics could tend to have extreme earnings uncertainty, these observations may tend to be omitted from our analysis due to a lack of firms with comparable matching characteristics.

Ultimately, the relative effectiveness of a matched-firm approach to estimating earnings uncertainty is an empirical question. While the matched-firm approach produces unbiased earnings expectations in the Barber and Lyon (1996) sample, their sample was limited to operating earnings of NYSE and AMEX firms between 1977 and 1992. Our sample includes NASDAQ firms, examines a much longer time-series (1968-2010), and focuses on earnings before extraordinary items. Accordingly, the increased sample breadth and time-series may prove difficult to produce a parsimonious matching procedure that produces unbiased estimates across the broad cross-section of firms and also across stratified subsamples of firms experiencing extreme performance.

In the subsequent section, we propose and perform a series of specification tests to assess the validity of our earnings uncertainty measure. If these tests suggest that our earnings uncertainty variable is reasonably well-specified, we will be able to directly test the incremental predictive power of earnings uncertainty against time-series variation in earnings (as captured by past earnings volatility).

III.   Sample selection and variable measurement

3.1   Sample Selection

Our primary sample is drawn from the population of all firms listed in the Compustat Annual Industrial and Research files. Since the primary variables of interest are earnings uncertainty and past earnings volatility, our sample spans fiscal year ends 1968:06 – 2011:05. We define earnings as earnings before extraordinary items (IB), scaled by average total assets (AT). We further reduce the sample to firms traded on the NYSE, AMEX,

and NASDAQ (CRSP exchange code 1, 2, 3), nonfinancial firms (SIC codes 6000-6999 per CRSP), firms with CRSP share codes equal to 10, 11 and 12 and firms with non-missing earnings in t and $t+1$. Our primary sample is comprised of all firms meeting the above criteria and have a calculable earnings uncertainty value or a past earnings volatility measure, yielding 152,710 firm year observations.

3.2   Earnings uncertainty measurement

Our empirical design is based on the matched-firm expectation model of Barber and Lyon (1996). Similar to their empirical design, we use observable earnings realizations of comparable firms to form an expectation of future earnings. In addition, and new to the accounting literature, we also use those same observable earnings realizations to form an estimate of the uncertainty surrounding the earnings expectation. Since the earnings realizations of the comparable firms are observable at t, our empirical design does not impose a look-ahead bias nor are the earning expectations (or uncertainty estimates) mechanically linked to those in prior periods.

For each firm i at time t, we use as matched-firms all firms of similar size, earnings, and one-year earnings change in years t-5 to t-1. Specifically, each firm i is matched to firms in years t-5 to t-1 that are in the same NYSE-based total asset portfolio. The first portfolio comprises all firms with total assets below the 10th NYSE-based asset percentile; all remaining firms fall in the second portfolio. Within each size portfolio, firm i is subsequently matched to firms with comparable earnings and one-year earnings change. Consistent with prior studies, we define earnings as earnings before extraordinary items scaled by average assets (Dichev and Tang 2009). We define firms with comparable earnings (one-year earnings change) to firm i at time t as those firms whose t-τ earnings and t-τ one-year change in earnings are no more or less than 0.5 percent of firm i's earnings and one-year earnings change in fiscal year t. This matching process yields, for each firm i, a set of firms with comparable earnings performance observable at time t.[6]

For each of the matched firms, we compute the change in earnings between t-τ and t-τ+1. To reduce the mechanical effect extreme earnings changes in a matched-firm can have on estimates of earnings uncertainty,

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[6] For example, IWKS (F/Y/E 1997) had earnings of 0.076, change in earnings of 0.032, and total assets below the 10th NYSE total asset percentile. All firms with total assets below the 10th NYSE total asset decile in fiscal years 1992-1996, with earnings between 0.071 and 0.081 and one-year change in earnings between 0.027 and 0.037 serve as IWKS's matched-firms. (In our sample, $IWKS_{1997}$ had 20 matched firms).

we discard matched-firms with extreme performance, defined as one-year change in earnings greater in absolute magnitude than 50% of total assets.[7] We use the average change in earnings across matched-firms as firm i's expected earnings change between t and $t+1$. We use the standard deviation of the realized earnings changes of the matched firms as a measure of firm i's earnings uncertainty around its $t+1$ earnings expectation. We require at least five matches for each firm to compute this characteristic.

We repeat the matching procedure detailed above for all firms without at least five matches. Unmatched firms tend to be those with more extreme current earnings or one-year earnings changes. For these firms, we utilize a percentile-based matching procedure and use all firms within the same t-τ size portfolio whose t-τ earnings and t-τ earnings change are between 80% and 120% of firm i's earnings and one-year earnings change in fiscal year t.[8]

As a result of our matched-firm expectation model, for each firm i, we have an expectation of $t+1$ earnings *and* an estimate of the uncertainty surrounding each earnings expectation. Note, the matching process should minimize concerns that the expectations and uncertainty estimates are mechanically affected by time-variation in earnings: the earnings expectations and uncertainty estimates are simply based on current year earnings and one-year earnings changes, estimable without any look-ahead bias and updated annually.

4   Empirical results

4.1   Descriptive Statistics

Table 1 reports descriptive statistics for firms in our primary sample. We annually winsorize all current-year summary statistics with the exception of total assets rank and firm-number matches at the 1st and 99th percentiles. Results are largely in line with prior studies on earnings volatility. Panel A shows summary statistics for earnings uncertainty that are similar to those of past earnings volatility, however, earnings uncertainty values tend to be a bit larger and available for roughly 400 more firms per year than past earnings

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[7] This screen has a minimal effect on the average number of matched firms per firm (less than 1 percent).
[8] For example, ALGI (F/Y/E 1996) had earnings of 0.114, change in earnings of -0.082, and total assets below the 10th NYSE total asset percentile. All firms with total assets below the 10th NYSE percentile in fiscal years 1991-1995, earnings between 0.091 and 0.137, and one-year change in earnings between -0.066 and -0.098 serve as ALGI's matched-firms. (In our sample, ALGI$_{1996}$ had 28 matches).

Table 1
Summary Statistics
This table reports cross-sectional summary statistics. Panel A reports the time-series average of the annual cross-sectional mean (Avg.), standard deviation (Std.), 1st percentile (1st.), 50th percentile (50th), 99th percentile (99th), and number of observations (Obs.). The sample spans firms with fiscal year ends between 1968:06 and 2011:05, except for analyst forecast dispersion (Disp.), which spans 1983:06-2011:05. Panel B reports the time-series average of the annual cross-sectional correlations, with Pearson product moment correlations reported below the diagonal, and Spearman rank correlations reported above the diagonal. All variables are annually winsorized at the 1st and 99th percentile with the exception of Matches and Size.

Panel A: Average Descriptive Statistics

Variable	Description	Avg.	Std.	1st	50th	99th	Obs.
EU_t	Earnings uncertainty	0.069	0.047	0.015	0.054	0.217	3,351.8
$EV_{t-4,t}$	Past earnings volatility	0.065	0.081	0.003	0.036	0.484	2,941.0
$Disp_t$	Analyst forecast dispersion	0.164	0.191	0.002	0.102	1.140	1,543.4
Matches	Number of firm matches for EU	64.84	100.00	5.00	32.35	414.05	3,351.8
$Size_t$	NYSE-based total asset decile	2.88	2.62	1.00	1.26	10.00	3,551.4
BM_t	Log book-to-market	-0.44	0.80	-2.87	-0.36	1.32	3,408.5

Panel B: Average Cross-sectional Correlations

Variable	Description	EU_t	$EV_{t-4,t}$	$Disp_t$	BM_t	ME_t
EU_t	Earnings uncertainty	-	0.59	0.07	-0.07	-0.54
$EV_{t-4,t}$	Past earnings volatility	0.54	-	0.17	-0.15	-0.44
$Disp_t$	Standard deviation of analyst EPS estimates	0.10	0.13	-	0.23	0.15
BM_t	Log book-to-market	-0.14	-0.25	0.18	-	-0.27
ME_t	Log market value of equity	-0.46	-0.34	0.12	-0.25	-

EU_t	Earnings uncertainty as defined in section 3.1
$EV_{t-4,t}$	Past earnings volatility computed as the standard deviation of earnings before extraordinary items (IB) scaled by average total assets (AT) between t-4 and t.
$Disp_t$	Standard deviation of analyst annual EPS forecasts from summary file, (1983:06 – 2011:05)
Matches	Number of matched firms to derive the earnings uncertainty estimates
$Size_t$	Firm size, reported as NYSE-based total asset decile breakpoints
BM_t	Natural log of book to market, book value (Compustat) and market equity (CRSP) as of fiscal year end t.
ME_t	Natural log of market equity per CRSP as of the last day of fiscal year t.

volatility and 1,800 more firms per year than analyst forecast dispersion. Panel B provides a correlation matrix for key variables and results again are largely in line with prior studies. As expected, earnings uncertainty, forecast dispersion, and past earnings volatility are each positively correlated with each other, although significant independent variation in each variable exists.[9] Earnings uncertainty and past earnings volatility are each negatively associated with firm size and book-to-market. Consistent with Johnson (2004), we note that

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[9] For example, the Pearson correlation of 0.54 implies that EU_t only explains about 30% of the cross-sectional variation in $EV_{t-4,t}$.

forecast dispersion is positively associated with book-to-market, whereas past earnings volatility and earnings uncertainty are negatively correlated with book-to-market. This result suggests forecast dispersion may be differentially associated with expected future growth and/or risk.

The summary statistics suggest our measure of earnings uncertainty shares similar characteristics to past earnings volatility and forecast dispersion, but is distinct in its own right. However, table 1 does not provide empirical confirmation that our measure of uncertainty proxies for actual uncertainty at time t. Empirical confirmation on the veracity of our empirical earnings uncertainty estimate is critical for us to distinguish the incremental predictive power of time-variation in earnings from earnings uncertainty. We formally examine its veracity in the next section.

4.2   Specification tests of cross-sectional earnings uncertainty

To assess how well our earnings uncertainty measure proxies for actual earnings uncertainty at time t, relative to past earnings volatility and analyst forecast dispersion, we annually regress realized earnings volatility on our earnings uncertainty measures. We define realized earnings volatility as the absolute value of the difference between realized earnings and expected earnings. Similar specification tests have been used to examine how well current period return characteristics proxy for future return volatility (Schwert 1989).

Table 2 reports the results from specification regressions across two time horizons (1968-2010; 1991-2010) and across multiple subsets of firms that share characteristics known to be associated with extreme earnings (e.g., B/M, accruals, size). The closer the intercept (γ_0) is to 0.0 and the slope (γ_1) is to 1.0, the better the respective variable proxies for actual earnings uncertainty at time t. In addition, since estimates of earnings uncertainty are a direct function of the expectation of future earnings, we also report average cross-sectional intercepts (β_0) and slopes (β_1) from annual regressions of actual earnings regressed on expected earnings. Both sets of t-statistics are based on the variability in the time-series slope estimates and incorporate a Newey-West (1987) correction with five lags to control for possible autocorrelation in the slope estimates.

Table 2
Annual cross-sectional specification regressions: 1968-2010
This table reports the time-series average intercepts and slopes from the following annual cross-sectional regressions:

Panel A:	Panel B:	Panel C:
$Real\_Vol = \gamma_0 + \gamma_1 EU + e$	$Real\_Vol = \gamma_0 + \gamma_1 EV + e$	$Real\_Vol = \gamma_0 + \gamma_1 Disp + e$
$Earn_{t+1} = \beta_0 + \beta_1 E_t[Earn_{t+1}] + e$	$Earn_{t+1} = \beta_0 + \beta_1 Earn_t + e$	$EPS_{t+1} = \beta_0 + \beta_1 + AF_t + e$

Real_Vol is defined in each panel as the absolute value of unexpected earnings. In panel A, unexpected earnings is the difference between realized earnings and expected earnings from the matched-firm expectation model; in panel B, unexpected earnings is the difference between realized earnings and current earnings; in panel C, unexpected earnings is the difference between the consensus analyst EPS estimate and realized EPS, per the unadjusted I/B/E/S summary file (month 4 of fiscal year t+1). Analyst forecasts and EPS realizations are adjusted to account for stock splits occurring between forecast date and announcement date. Since analyst forecast data is not available until 1976, we only report results for the 1991-2010 sample. All independent variables are winsorized at the 1st and 99th percentile. To minimize the look-ahead bias, future earnings values used in panels A and B are winsorized between -1.0 and 1.0. In panel C, we trim unexpected EPS realizations greater than 50% of market equity (~ 1% of sample). All other variables defined in table 1.

Sample	FM slopes	Full Sample 1968-2010					Late Sample 1991-2010				
		γ_0	γ_1	β_0	β_1	Obs.	γ_0	γ_1	β_0	β_1	Obs.
Panel A: Earnings Uncertainty											
All	Avg.	0.000	0.839	-0.005	0.967	3340	-0.004	0.952	-0.006	0.945	3848
stocks	FM t-stat	(0.11)	(14.87)	(-2.28)	(60.15)		(-1.82)	(29.86)	(-1.72)	(91.03)	
Low	Avg.	0.001	0.883	-0.003	0.938	636	-0.005	1.010	-0.002	0.873	748
dWC$_t$.	FM t-stat	(0.49)	(13.34)	(-0.99)	(27.13)		(-1.74)	(25.80)	(-0.37)	(52.31)	
High	Avg.	0.008	0.827	-0.017	0.960	656	0.003	0.984	-0.018	0.936	756
dWC$_t$	FM t-stat	(3.70)	(10.95)	(-4.08)	(48.29)		(1.44)	(35.76)	(-3.24)	(67.49)	
Low	Avg.	0.007	0.912	-0.004	1.000	617	0.003	1.035	0.003	0.967	705
BM	FM t-stat	(3.36)	(15.79)	(-0.71)	(36.54)		(1.12)	(33.45)	(0.38)	(57.47)	
High	Avg.	0.008	0.670	-0.013	0.871	668	0.006	0.796	-0.020	0.822	784
BM	FM t-stat	(2.59)	(10.62)	(-3.38)	(29.24)		(1.02)	(19.35)	(-3.80)	(41.46)	
Tiny	Avg.	0.004	0.817	-0.009	0.960	1814	-0.001	0.957	-0.011	0.934	2130
	FM t-stat	(1.71)	(11.74)	(3.00)	(47.88)		(-0.22)	(29.03)	(-2.71)	(83.52)	
Panel B: Past Earnings Volatility											
All	Avg.	0.025	0.606	-0.005	0.781	2930	0.039	0.505	-0.010	0.757	3348
stocks	FM t-stat	(4.62)	(12.65)	(-1.58)	(42.16)		(10.44)	(9.33)	(-4.18)	(77.90)	
Low	Avg.	0.034	0.702	-0.001	0.730	576	0.056	0.558	-0.006	0.697	667
dWC$_t$	FM t-stat	(4.18)	(10.31)	(-0.13)	(28.54)		(16.19)	(9.41)	(-1.44)	(49.07)	
High	Avg.	0.036	0.491	-0.021	0.802	524	0.053	0.429	-0.029	0.767	612
dWC$_t$	FM t-stat	(5.59)	(14.93)	(-4.51)	(42.91)		(14.21)	(9.67)	(-7.33)	(75.85)	
Low	Avg.	0.045	0.552	-0.003	0.801	534	0.072	0.417	-0.006	0.784	634
BM	FM t-stat	(4.45)	(9.91)	(-0.75)	(39.85)		(22.43)	(8.52)	(-0.94)	(61.63)	
High	Avg.	0.024	0.674	-0.014	0.690	609	0.036	0.606	-0.025	0.618	699
BM	FM t-stat	(4.58)	(14.47)	(-2.69)	(20.04)		(5.46)	(8.74)	(-4.66)	(28.04)	
Tiny	Avg.	0.039	0.556	-0.013	0.770	1465	0.061	0.443	-0.024	0.751	1742
	FM t-stat	(4.74)	(11.03)	(-2.76)	(38.14)		(13.17)	(8.83)	(-7.65)	(76.70)	
Panel C: Forecast Dispersion											
All	Avg.						0.094	3.022	-0.318	1.162	2255
stocks	FM t-stat						(3.28)	(12.98)	(-10.73)	(90.88)	
Low	Avg.						0.129	2.333	-0.235	1.133	335
dWC$_t$	FM t-stat						(2.99)	(6.63)	(-5.53)	(28.86)	
High	Avg.						0.101	3.962	-0.365	1.173	417
dWC$_t$	FM t-stat						(1.05)	(3.43)	(-11.05)	(17.31)	
Low	Avg.						0.001	4.137	-0.304	1.255	440
BM	FM t-stat						(0.02)	(5.73)	(-6.38)	(30.62)	
High	Avg.						0.199	2.177	-0.385	1.129	281
BM	FM t-stat						(5.39)	(6.09)	(-10.05)	(36.66)	
Tiny	Avg.						0.224	1.074	-0.165	1.012	767
	FM t-stat						(10.96)	(27.42)	(-4.86)	(156.86)	

Several empirical patterns from table 2 are worth noting. First, focusing on the All Stocks sample (shaded across all three panels), the average intercepts (γ_0) and slopes (γ_1) in panel A suggest our matched-firm earnings uncertainty measure is relatively well-specified. The average slopes on earnings uncertainty are 0.839 in the full sample and 0.952 in the latter-sample. Further, in the latter half of the sample (years 1991-2010), the slope on earnings uncertainty is statistically indistinguishable from 1.0 with a much smaller standard error (relative to the full sample), suggesting that our uncertainty measure performs better in the latter part of the sample. Finally, the average intercepts on earnings uncertainty are small and statistically indistinguishable from zero, suggesting that our earnings uncertainty measure is unbiased.

In contrast, the average slopes and intercepts on past earnings volatility (shaded rows in panel B) suggest that past earnings volatility poorly proxies for earnings uncertainty. Focusing on the comparison of shaded rows across panels A and B, the slopes (γ_1) in panel B are significantly lower and the intercepts (γ_0) are significantly larger in absolute magnitude relative to those reported in in panel A. Further, the difference in slopes and intercepts across panels A and B grows in the latter part of the full sample, suggesting that past earnings volatility is becoming less similar to earnings uncertainty over time.

Interestingly, the slopes on forecast dispersion (panel C) suggest that forecast dispersion poorly proxies for earnings uncertainty at time t.[10] Again, focusing on the full sample (shaded rows in panel C), forecast dispersion has an average predictive slope of 3.02 that is more than 8 standard errors away from 1.0. Perhaps more disheartening is the positive and significant intercept (0.09; t-stat 3.28). This result suggests forecast dispersion significantly understates earnings uncertainty. To the best of our knowledge, panel C offers the first empirical evidence on the veracity of analyst forecast dispersion as a proxy for actual uncertainty at time t.

As an additional robustness check, the remaining, unshaded rows in table 2 show how well our earnings uncertainty measure performs across select subsets of firms relative to past earnings volatility and forecast

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[10] Since reliable forecast data does not exist over the full sample, we report specification test results for forecast dispersion only in the latter sample. Results are qualitatively similar if we include forecast dispersion observations beginning in 1976.

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dispersion. Firms are sorted annually into high or low quintiles based on book-to-market and change in working capital. 'Tiny' firms are those with total assets below the 10th NYSE-based total asset percentile. Inferences are largely consistent to those reported in the shaded rows.

In sum, table 2 makes two important points. First, our matched-firm measure of earnings uncertainty is reasonably well-specified on average and in select samples of firms experiencing extreme performance. Second, forecast dispersion poorly proxies for earnings uncertainty. The forecast dispersion result is important given the wide-spread belief in the accounting and finance literature suggesting forecast dispersion captures future earnings uncertainty (Clement et al. 2003; Johnson 2004).

4.3   The predictive power of earnings volatility and earnings uncertainty for future earnings

Prior studies have shown that past earnings volatility has predictive power for future earnings (Minton, Schrand, and Walther 2002; Dichev and Tang 2009). A subtle but important consideration in distinguishing the predictive power of past earnings volatility from earnings uncertainty is to determine if our earnings uncertainty variable predicts future earnings. Distinct from past earnings volatility, if our earnings uncertainty variable is well-specified, it should *not* be associated with future earnings once expected earnings are controlled. As a final specification test of our matched-firm earnings uncertainty variable, we regress future earnings on expected future earnings and earnings uncertainty. If our earnings uncertainty variable captures actual future earnings uncertainty, and not an economic dynamic predictive of future performance, we should find no relation between our earnings uncertainty variable and future earnings. We test this formally in table 3.

Similar to table 2, we provide results for the full time-series and the latter half of the time-series.[11]   As a calibration exercise, in model 2 we regress future earnings on current earnings and past earnings volatility to calibrate our results with those of Minton, Schrand and Walther (2002). Consistent with their results, we find a strong negative relation between future earnings and past earnings volatility. This result suggests past earnings

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[11] For brevity, we do not report results across the subsamples of firms experiencing extreme performance as reported in table 2. Inferences are qualitatively identical in the subsamples to that reported in the full sample.

Table 3
Annual cross-sectional specification regressions: 1968-2010
This table reports the time-series average intercepts and slopes from the following annual cross-sectional regressions:

Model 1: $Earn_{t+1} = \gamma_0 + \gamma_1 E_t[Earn_{t+1}] + \gamma_2 EU_t + e$

Model 2: $Earn_{t+1} = \gamma_0 + \gamma_1 Earn_t + \gamma_2 EV_{t-4,t} + e$

Model 3: $EPS_{t+1} = \gamma_0 + \gamma_1 E_t[EPS_{t+1}] + \gamma_2 Disp_t + e$

In model 1, expected earnings and earnings uncertainty is from the matched-firm expectation model as described in section 3.2; in model 2, $Earn_t$ is earnings before extraordinary items scaled by average total assets; in model 3, expected earnings is the consensus analyst EPS estimate per the unadjusted I/B/E/S summary file (month 4 of fiscal year t) and Disp is the standard deviation in the forecasts. EPS realizations are adjusted to account for stock splits occuring between forecast date and announcement date. Since analyst forecast data is not available until 1976, we only report results for the 1991-2010 sample. All independent variables are winsorized at the 1st and 99th percentile. To minimize the look-ahead bias, realized values of $Earn_{t+1}$ are winsorized between -1.0 and 1.0; for analyst forecasts, we trim unexpected EPS realizations greater than 50% of market equity (~ 1% of sample) *t*-statistics are adjusted for possible autocorrelation (Newey-West , 5 lags).

	FM slopes	Full Sample 1968-2010				Late Sample 1991-2010			
		γ_0	γ_1	γ_2	Obs.	γ_0	γ_1	γ_2	Obs.
Model									
1	Avg.	-0.001	0.946	-0.044	3340	0.001	0.918	-0.075	3848
	FM t-stat	(-0.49)	(54.64)	(-0.95)		(0.156)	(38.10)	(-1.11)	
2	Avg.	0.007	0.735	-0.168	2930	0.004	0.702	-0.173	3348
	FM t-stat	(3.63)	(31.11)	(-7.35)		(1.35)	(39.54)	(-7.81)	
3	Avg.					-0.306	1.154	0.057	2255
	FM t-stat					(-12.23)	(87.52)	(0.14)	

volatility is informative of future profitability incremental to expected earnings. In model 1, we regress future earnings on expected earnings and our earnings uncertainty variable. In contrast to the slope on past earnings volatility, the slope on earnings uncertainty is significantly smaller (in absolute magnitude) and statistically indistinguishable from zero. Finally, model 3 reports the predictive power of forecast dispersion for future earnings, controlling for expected earnings (consensus EPS). Model 3 confirms analysts are optimistically biased (γ_0 = -0.306; t-statistic -12.23), although the bias does not lead to forecast dispersion having incremental predictive power for future earnings to the consensus forecast.

In summary, the evidence reported in tables 2 and 3 suggests our earnings uncertainty variable is a reasonably well-specified estimate of uncertainty in future earnings. Across the broad sample, the latter sample period, and select subsamples of firms, we find specification slopes of approximately 1.0 and intercepts that are approximately 0.0. Results also cast doubt on the veracity of forecast dispersion as a meaningful measure of uncertainty, especially in firms experiencing extreme performance. While our earnings uncertainty measure is presumably imperfect, it more precisely estimates realized volatility (smaller standard errors) relative to past

earnings volatility and forecast dispersion and should provide a powerful measure to distill the predictive power of time-series variation in earnings from earnings uncertainty as it relates to the forecast errors of equity analysts and investors.

V.   Predictive power of earnings uncertainty

5.1   The relation between analyst forecast errors, past earnings volatility, and earnings uncertainty

Our first set of tests aims to distill the relative predictive power of earnings uncertainty from that of time-series variation in earnings focuses relating to analyst forecast errors. Tension for this empirical investigation comes from prior research suggesting that analysts do not understand the implications of past earnings volatility for future earnings (Dichev and Tang 2009). Specifically, Dichev and Tang show that analysts fail to recognize that earnings are less persistent for firms with high past earnings volatility. Unexplored by Dichev and Tang, but important to the accounting literature, is determining whether the forecast bias is due to the time-series variation in earnings or the underlying uncertainty surrounding future earnings. If our earnings uncertainty variable subsumes the predictive power of past earnings volatility for forecast errors, it suggests that time-series variation in earnings does not significantly affect analyst forecasts. Rather, analyst forecasts are affected by the fundamental uncertainty that affects their estimates of future earnings.

To distill these two competing explanations from each other formally, we examine the predictive power of past earnings volatility and earnings uncertainty for forecast errors across two specifications. In the first specification (table 4, models 1-3), we regress analyst forecast errors on past earnings volatility, earnings uncertainty, and some conventional control variables (prior period forecast error, size, book-to-market). If time-series variation in earnings affects analyst forecasts, we should find a significantly negative association between past earnings volatility and forecast errors. However, if the negative association found in prior studies is due to the positive correlation between time-variation in earnings and earnings uncertainty, we should find a strong negative slope on earnings uncertainty and an insignificant slope on past earnings volatility in model 3.

Analyst forecast errors are computed as the difference between the consensus analyst earnings forecast from

the summary unadjusted I/B/E/S file as of month 4 minus actual earnings. Thus, $FE_{i,t+1}$ equals the consensus earnings per share forecasts minus actual earnings per share ($FE_{i,t+1}=E_t[EPS_{i,t+1}]-EPS_{i,t+1}$). Consistent with prior literature, we scale analyst earnings forecasts by market value of equity at the beginning of the period (fiscal year end *t*) and begin our analysis of forecast errors in fiscal year 1977. Regression slopes are pooled and t-statistics are clustered by firm (gvkey) and year (fyear).[12]

Empirical results are reported in table 4. In regressions 1 and 2, we find strong negative relations between analyst forecast errors and earnings uncertainty (1) and past earnings volatility (2). The slopes are strong in both specifications, but significantly larger for earnings uncertainty. In model 3, we directly test the explanatory power of past earnings volatility and earnings uncertainty for analyst forecast errors. The purpose of this test is to determine if the significant slopes on past earnings volatility in model 1 is due to time-series variation in earnings or earnings uncertainty. In model 3 we find a strong negative slope on earnings uncertainty while past earnings volatility has very little incremental explanatory power.[13] This result suggests that earnings uncertainty is strongly predictive of future forecast errors (or that any predictive power of past earnings volatility for forecast errors stems from its correlation with earnings uncertainty, not time-variation in earnings).

In our second specification (table 4, models 4-6), we test the interactive effects of earnings uncertainty on how efficiently analysts update their forecasts conditional on their most recent error. Building on the findings of Dichev and Tang (2009), we are interested in determining whether earnings uncertainty or time-series variation in earnings (as captured by past earnings volatility) is significantly associated with the autocorrelation structure of forecast errors. If analysts fail to appreciate the persistence of earnings in firms with high earnings uncertainty, we expect a negative interactive effect between the recent forecast error and earnings uncertainty.

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[12] Qualitatively identical inferences result from Fama-MacBeth annual cross-sectional regressions with t-statistics that are Newey-West adjusted.

[13] The difference in slopes in model 3 on past earnings volatility (-0.018) and earnings uncertainty (-0.249) are statistically different (*p-value <0.01*).

Table 4
Predicting analyst forecast errors, 1983-2010
This table reports the predictive relation between earnings uncertainty (EU_t), past earnings volatility ($EV_{t-4,t}$), and future analyst forecast errors (FE_{t+1}). Specifically, we regress future forecast errors on earnings uncertainty, past earnings volatility, and other control variables for years ends 1977:06 – 2011:05. Analyst forecast errors (FE_{t+1}) are computed as the difference between the actual EPS in fiscal year t+1 minus consensus analyst annual EPS forecast for t+1 as of the fourth month of fiscal year t+1 per the I/B/E/S unadjusted summary file. Actual EPS realizations are adjusted for splits that occur between the forecast date and the announcement date. Forecast errors are scaled by price as of the beginning of t+1. Regression slopes are pooled and standard errors are clustered by firm (gvkey) and year (fyear). All explanatory variables defined as in prior tables and winsorized annually. Forecast errors (FE_{t+1}) are trimmed as in prior tables.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.008	-0.004	0.016	0.006	-0.005	0.014
t	(0.78)	(-0.42)	(1.59)	(0.73)	(-0.60)	(7.38)
EU_t	-0.212		-0.249	-0.271		-0.317
t	(-3.63)		(-3.52)	(-4.33)		(-4.20)
$EV_{t-4,t}$		-0.087	-0.018		-0.110	-0.001
t		(-3.09)	(-1.19)		(-3.86)	(-0.08)
FE_t	0.527	0.595	0.574	0.717	0.674	0.748
t	(7.68)	(8.35)	(8.06)	(7.42)	(7.70)	(7.39)
EU_t x FE_t				-3.444		-4.292
t				(-3.72)		(-4.40)
$EV_{t-4,t}$ x FE_t					-1.714	1.051
t					(-2.03)	(1.27)
BM_t	-0.009	-0.009	-0.010	-0.009	-0.009	-0.011
t	(-3.01)	(-2.63)	(-2.98)	(-3.07)	(-2.61)	(-3.05)
ME_t	0.000	0.001	-0.001	0.000	0.001	-0.000
t	(0.56)	(1.17)	(-0.53)	(1.33)	(1.59)	(-0.02)
Obs.	61,389	53,876	51,423	61,389	53,876	51,423

However, if it is the time-series variation in earnings that explains the negative interaction noted by Dichev and Tang, the interaction of past earnings volatility and the most recent forecast error should still explain future forecast errors after controlling for earnings uncertainty.

The results from models 4-6 confirm the predictive power of earnings uncertainty. Consistent with the idea that past earnings volatility is a weak proxy for earnings uncertainty, model 4 shows a much stronger predictive main and interactive effect on earnings uncertainty relative to past earnings volatility in model 5. Further, model 6 shows that the explanatory power of earnings uncertainty subsumes that of past earnings volatility.

We interpret the results from table 4 as suggestive that time-series variation in earnings, as captured by past

earnings volatility, is not misinterpreted by analysts *per se*. Rather, past earnings volatility is correlated with earnings uncertainty and it is earnings uncertainty, not time-series variation in earnings that leads to forecast errors. This result is consistent with the notion that earnings uncertainty leads to systematic forecast biases. However, as is well established in the accounting literature, analyst forecasts are subject to many biases and the actions of analysts may not proxy for the actions of investors. Accordingly, in the next section we test whether the actions of investors (as proxied by future return patterns) are associated with earnings uncertainty in a direction and relative magnitude consistent with those of analysts.

5.2   The relation between future returns, past earnings volatility, and earnings uncertainty

To date, prior studies have failed to find that past earnings volatility or earnings uncertainty predict future returns, especially over annual time periods (Zhang 2006; Frankel and Litov 2009; McInnis 2010).[14] However, as suggested above, this lack of a significant empirical relation could be due to the fact that empirical proxies based on a time-series of earnings realizations jointly capture the effects of prior period economic shocks, accrual estimation errors, and fundamental uncertainty in next period's earnings. Since each of these constructs is different, empirical measures that jointly capture the constructs could mask the true predictive power of the individual constructs.

Prior studies examining the effect of information uncertainty predict, but do not explicitly show, that earnings uncertainty should be negatively associated with future returns. For example, Jiang et al. (2005) define information uncertainty in terms of "value ambiguity, or the degree to which a firm's value can be reasonably estimated by even the most knowledgeable investors at reasonable costs." Interestingly, Jiang et al. do not examine direct measures of earnings uncertainty, choosing instead to proxy for information uncertainty using indirect proxies such as firm age and implied equity duration. Zhang (2006) examines forecast dispersion (among other proxies for uncertainty), but fails to find a significant relation between future returns and forecast dispersion over an annual period.

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[14] One exception to this claim is Minton, Schrand, and Walther (2002) who find that fitted values from an earnings prediction model that include past earnings volatility can be used to form a profitable trading strategy.

The purpose of the subsequent tables is to examine the predictive power of earnings uncertainty for future returns. The primary advantage of our earnings uncertainty variable compared to forecast dispersion (Zhang 2006) or firm characteristics thought to be correlated with earnings uncertainty (Zhang 2006; Jiang et al. 2005), is that our variable more precisely maps into the economic construct of earnings uncertainty. If we find that our earnings uncertainty variable predicts future returns on an annual basis, it would be the first empirical evidence that we are aware of that shows long-horizon valuation consequences of earnings uncertainty.

To test if investor expectations are affected by earnings uncertainty directionally similar to analysts, we regress future monthly returns against our earnings uncertainty measure and other firm characteristics known to be associated with future returns using conventional Fama and Macbeth (1973) regressions in table 5. We report empirical results for two sets of firms. Models 1-3 report the average regression slopes, *t*-statistics and sample sizes from 504 monthly cross-sectional regressions, 1969:05–2011:04 for all firms with a share price greater than $5 as of the last day of trading in the fourth month of year *t*+1. In models 4-6, we report regression results for the sample of firms with estimates of either earnings uncertainty or forecast dispersion, 1984:05–2011:04. The analysis reported in models 4-6 calibrates the economic and statistical significance of our earnings uncertainty measure against the more commonly used forecast dispersion measure (Diether et al. 2002; Zhang 2006). All variables with the exception of future returns are winsorized monthly at the 1st and 99th percentile. All explanatory variables are updated once per fiscal year with the exception of return momentum, which is updated monthly.

In general, inferences from the regression slopes reported in models 1-3 of table 5 are in line with the contention that earnings uncertainty is positively associated with overly-optimistic future earnings expectations. Slope coefficients on earnings uncertainty are strongly negative with slopes approximately 3.0 standard errors from zero across specifications 1 and 2. In specification 3, we substitute the coefficient of variation for earnings uncertainty. The coefficient of variation scales earnings uncertainty by the absolute value of expected earnings, thereby preventing firms with extreme earnings (and generally higher earnings volatility)

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Table 5
Cross-sectional regressions of future monthly returns on earnings uncertainty, 1969 – 2011
This table reports average slopes from cross-sectional regressions of future monthly stock returns (in %) on earnings uncertainty (EU_t), past earnings volatility ($EV_{t-4,t}$), log transform of earnings uncertainty scaled by absolute value of expected earnings (cEU_t), log transform of analyst forecast dispersion scaled by absolute value of average analyst forecast of EPS ($cDisp_t$), and other firm characteristics (the regression intercepts are omitted from the table). All predictor variables are winsorized monthly at their 1st and 99th percentiles. Predictor variables are updated once per year, four months after the end of the firm's prior fiscal year with the exception of momentum, which is updated monthly. For month j, Mom_t is equal to the natural log of the cumulative return from month j-12 to j-2. dWC_t is equal to the change in non-cash, non-debt working capital, scaled by average assets. BM_t is the natural log of book value minus the natural log of market value at fiscal year end. ME_t is the nature log of market value of equity per CRSP on the last day of trading in month 4 of t+1. The sample includes all nonfinancial firms on CRSP and Compustat with nonmissing data for future returns with share prices greater than or equal to $5 as of the last day of trading in month 4, t+1. Monthly returns include any delisting return. t-statistics are based on the time-series variability in the slope estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
	1969:05 – 2011:04			1984:05 – 2011:04		
EU_t	-3.050	-2.442				
t	(-2.81)	(-2.77)				
$EV_{t-4,t}$		-1.443				
t		(-1.45)				
cEU_t			-0.115	-0.097		-0.074
t			(-4.57)	(-4.17)		(-3.29)
$cDisp_t$					-0.087	-0.060
t					(-1.64)	(-1.14)
dWC_t	-2.077	-1.918	-2.058	-1.755	-1.613	-1.904
t	(-7.81)	(-7.54)	(-7.91)	(-5.62)	(-4.62)	(-5.10)
Mom_t	1.034	0.912	1.021	0.861	0.799	0.701
t	(5.52)	(4.85)	(5.38)	(3.88)	(3.36)	(2.94)
BM_t	0.224	0.173	0.296	0.303	0.184	0.203
t	(3.45)	(2.84)	(3.87)	(3.26)	(1.73)	(1.93)
ME_t	-0.051	-0.063	-0.046	-0.006	-0.008	-0.014
t	(-1.65)	(-2.15)	(-1.36)	(-0.16)	(-0.16)	(-0.29)
Obs.	2382	2031	2382	2593	1874	1714

from disproportionately populating the extremes of the earnings uncertainty distribution.[15] Inferences with respect to coefficient of variation are consistent to those reported in model 1, albeit significantly stronger with a negative slope on the scaled earnings uncertainty variable that is more than 4.5 standard errors from zero.

In models 4-6, we directly compare the predictive power of our measure of earnings uncertainty against that derived from forecast dispersion. Diether et al. (2002) show that forecast dispersion scaled by the absolute

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[15] Minton and Schrand (1999) and Minton, Schrand, and Walther (2002) both measure volatility using this form of the coefficient of variation.

value of expected earnings is negatively associated with future returns. While Diether et al. suggest that their forecast dispersion measure captures opinion divergence across investors, others have interpreted forecast dispersion as capturing earnings uncertainty (Johnson 2004; Zhang 2006). Accordingly, models 4-6 provide a direct test of the incremental predictive power of our earnings uncertainty measure against one derived from forecast dispersion.

Results show that our earnings uncertainty measure largely subsumes the predictive power of forecast dispersion for future returns. Perhaps surprising to some, our results show that forecast dispersion is a weak predictor of future returns over an annual period. In fact, however, these results agree with those in Diether et al. and Zhang (2006).[16] These results also agree with our fundamental premise that better estimates of the first moment (future earnings) produce better estimates of the second moment of earnings (future earnings uncertainty), which lead to more precise inferences on the predictive power of earnings uncertainty.

5.3   The relation between contemporaneous returns and change in earnings uncertainty

To further explore the valuation consequences of earnings uncertainty, we examine the relation between the one-year change in earnings uncertainty and one-year equity returns. The purpose of these tests is to examine the other side of the earnings uncertainty relation with equity returns. That is, if high earnings uncertainty is negatively associated with future returns due to overly-optimistic earnings expectations, then changes in earnings uncertainty should be positively associated with contemporaneous period returns. We test this formally across two distinct specifications in table 6.

In models 1-3 of table 6 we annually regress annual buy-and-hold returns (t-1, t) on the contemporaneous one-year change in earnings uncertainty, lagged uncertainty, and a series of conventional control variables. Consistent with prior literature, we expect positive slopes on one-year earnings change, lagged earnings, book-to-market, and a negative slope on lagged size. If earnings uncertainty is positively associated with the forecast

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[16] Diether et al. report similar results in their lagged forecast analysis (Figure 1; pp. 2131). Note hedge returns are statistically indistinguishable from zero at approximately four months. Zhang (2006) also finds insignificant hedge returns when forecast dispersion is used to proxy for uncertainty and only updated once a year (table 2; pp. 114).

optimism of investors, then we expect positive slopes on one-year change in earnings uncertainty and lagged earnings uncertainty.

Average slopes on the control variables are in line with expectations. Model 1 notes positive slopes on earnings change, lagged earnings, and book-to-market and a negative slope on lagged size. Consistent with earnings uncertainty affecting investor expectations, models 2 and 3 note positive slopes on the one year change in earnings uncertainty in both specifications (2,3) and on lagged earnings uncertainty in (3).

In models 4-6, we examine the predictive power of change in earnings uncertainty on the so-called intangible returns. Introduced by Daniel and Titman (2006), intangible returns are interpreted as the component of realized returns that is unrelated (orthogonal) to contemporaneous realized accounting performance. If earnings uncertainty explains equity returns because it affects investors' expectations of future earnings, and not due to its relation with realized accounting performance, then a predictive relation between intangible returns by change in earnings uncertainty will offer powerful corroborative evidence to that noted in models 1-3.

For simplicity, we define intangible returns as the logarithmic change in market to book between t-1 and t (see Fama and French 2008).[17] Explanatory variables remain the same as models 1-3. Similar to models 1-3, we expect a positive relation between intangible return and book-to-market and a negative relation with firm size as these variables jointly capture variation in earnings expectations and firm risk. Importantly, we expect an insignificant relation between intangible returns and earnings since intangible returns are unrelated to accounting-based performance. Finally, to the extent that earnings uncertainty is positively associated with investor expectations of future earnings, we expect a positive relation between intangible returns and the change in earnings uncertainty.

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[17] Fama and French (2008, p. 2985, equation 7) propose a simpler empirical design to measure intangible returns than Daniel and Titman (2006). Specifically, intangible return $= \log(BM_{t-1}) - \log(BM_t)$

Table 6
Cross-sectional regressions of contemporaneous annual returns on changes in earnings uncertainty
Models 1-3 report the average slopes and t-statistics from cross-sectional regressions of annual returns between fiscal year end t-1 and t regressed on change in earnings uncertainty, lagged earnings uncertainty, and other firm characteristics. The annual return begins in the first month of fiscal year t and the sample spans 1968 - 2010. Models 4-6 report the average slopes and t-statistics from cross-sectional regressions of annual intangible returns between t-1 and t. We define intangible returns as in Fama and French (2008), equal to one year change in the natural log of market-to-book (log MB_t – logMB_{t-1}). The explanatory variables are defined as follows: BM_t, ME_t, EU_t are as defined in previous tables. $Earn_{t-1}$. is equal to earnings before extraordinary items (IB) scaled by average total assets (AT). All explanatory variables are annually winsorized at the 1st and 99th percentile. t-statistics incorporate a Newey-West correction of 5 lags to control for possible autocorrelation in the slopes.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dep. Var: Total Return			Dep. Var: Intangible Return		
$\Delta EU_{t-1,t}$		0.726	1.125		0.529	0.926
t		(2.56)	(5.06)		(2.06)	(3.69)
EU_{t-1}			0.825			0.833
t			(3.62)			(5.33)
$\Delta Earn_{t-1,t}$	3.697	3.842	3.921	1.253	1.365	1.44
t	(4.36)	(4.31)	(4.50)	(1.70)	(1.75)	(1.88)
$Earn_{t-1}$	1.276	1.304	1.495	0.205	0.229	0.400
t	(3.67)	(3.64)	(4.78)	(0.56)	(0.61)	(1.17)
BM_{t-1}	0.088	0.088	0.098	0.202	0.201	0.212
t	(5.52)	(5.49)	(6.85)	(21.17)	(21.34)	(21.35)
ME_{t-1}	-0.031	-0.031	-0.024	0.006	0.005	0.012
t	(-3.74)	(-3.73)	(-3.31)	(1.03)	(1.06)	(2.26)
Obs.	2738	2738	2738	2709	2709	2709

Results in models 4-6 are line with our expectations. These relations suggest that as the uncertainty about a firm's future earnings process increases, *ceteris paribus*, a firm's market-to-book ratio will tend to increase for reasons unrelated to expected growth, risk, or realized earnings.

6 Robustness Tests

6.1 Portfolio returns

Table 7 examines the relation between future monthly returns and earnings uncertainty from a portfolio perspective. Because earnings uncertainty and forecast dispersion are strongly associated with size and book-to-market, and these characteristics also predict returns, our portfolios are formed based on the component of earnings uncertainty that is orthogonal to our control variables. That is, each month we regress earnings uncertainty or its coefficient of variation on our control variables (size, B/M, momentum, and accruals) and

Table 7

Average returns on uncertainty-sorted portfolios

This table reports average monthly returns (in %) for three sets of uncertainty-sorted portfolios, formed based on (1) earnings uncertainty (EU*), (2) earnings uncertainty scaled by the absolute value of expected future earnings (cEU*), and (3) forecast dispersion scaled by the absolute value of consensus EPS (cDisp*). Low–High is the average return on quintile 1 minus quintile 5. Portfolios are equal-weighted and formed monthly. Accounting data comes from Compustat and market data come from CRSP. The sample includes all nonfinancial firms on CRSP and Compustat with nonmissing data for current returns, and EU* or Disp*.

Portfolio	1969:05 – 2011:04			1983:05 – 2011:04		
	EU*	cEU*		EU*	cEU*	Disp*
Low	1.20	1.31		1.18	1.24	1.08
2	1.18	1.19		1.14	1.15	1.09
3	1.15	1.10		1.09	1.06	0.98
4	1.08	1.02		1.05	0.97	0.95
High	0.99	0.98		0.90	0.94	0.86
Low–High	0.21	0.33		0.28	0.30	0.22
FM t-stat	(2.36)	(5.42)		(2.19)	(4.43)	(1.30)

form portfolios based on the residuals from this regression. This design choice allows us isolate the component of uncertainty unrelated to the control variables and calibrate its nonparametric relation to future returns.

Consistent with prior empirical tables, we report results for earnings uncertainty over the full 504 month sample (1969:05–2011:04) and the 324 month later sample for forecast dispersion (1984:05-2011:04). The empirical relations noted in table 7 agree with those of table 5. Average monthly hedge returns over the full sample are 0.21 and 0.33 per month for portfolios (1) and (2), each significantly different than zero. Over the later sample, we find similar, albeit slightly weaker results. We investigate the cause of this drop in predictive power in the next section.

6.2   Time-series analysis

Accounting and finance researchers tend to focus on the sign and statistical significance from a time-series average of cross-sectional regressions to confirm whether a firm characteristic is associated with future returns. Since Fama-Macbeth slopes and *t*-statistics are functions of equal-weighted averages computed over the sample period, they are sensitive to extreme realizations. Further, as conventionally reported, the FM slopes and *t*-statistics tell us very little about whether a relation is getting stronger or weaker over the time period.

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Accordingly, it is possible that the negative relation between future returns and earnings uncertainty is a relic of a very strong early-period relation and does not reflect more recent period dynamics.

As a final robustness test on the predictive relation of earnings uncertainty and future returns, we plot the time-series variation in the 10-year rolling average FM slopes on explanatory variables in figure 1. The primary purpose of this analysis is to examine whether the average slopes on earnings uncertainty change over time or are sensitive to certain subperiods of the full sample.

Figure 1 reports plots of the 10-year rolling average of the monthly slopes from model 1 of table 5. We exclude size and B/M from the plot because their slope magnitudes are very different and the time-series variation in the slopes of the other control variables is not the primary interest of this study (however, these variables are still used as explanatory variables). Since our future return series begins in 1969:05, the time-series plots span 1979:04 to 2011:04.
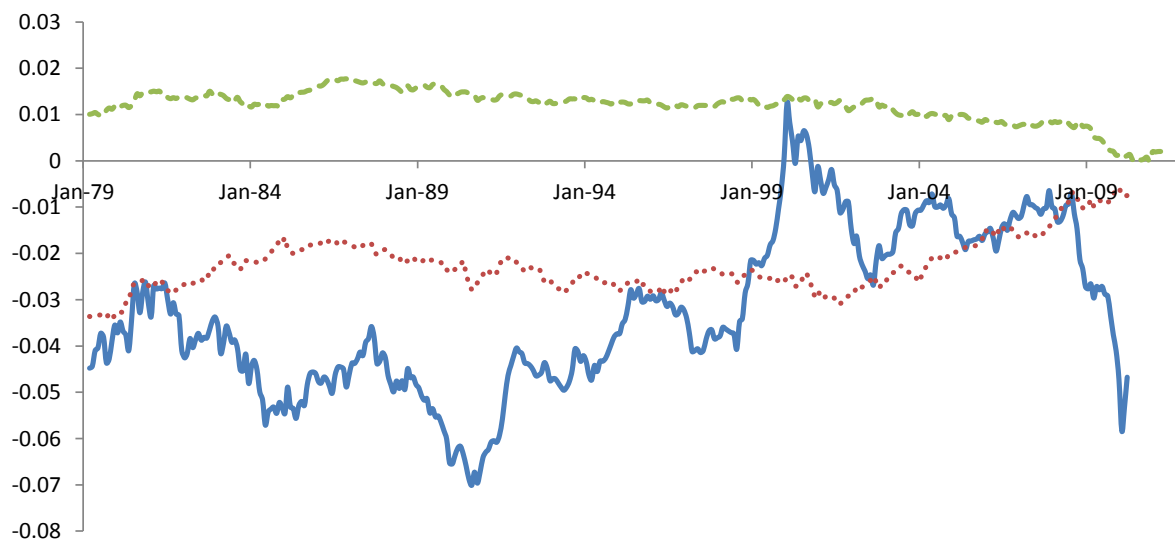

Figure 1: 10-year rolling slope estimates, 1979-2010
dWC (⋯); Mom (---); EU (─)
The figure plots ten-year rolling average (120 months) of Fama-Macbeth slopes from regressing future returns (in %) on earnings uncertainty (EU), book-to-market, momentum, size, and working capital accruals (Model 1, table 5). Slope averages on book-to-market and size are omitted from figure, but included as control variables in regression.

Figure 1 shows that the slopes on accruals and momentum tend to shrink over time, but their 10 year rolling average tend to lie completely below or above the x-axis. The decline in slopes on momentum and accruals suggest that past estimates on these characteristics tend to overestimate the current predictive significance of these variables and are consistent with prior studies (Green, Hand, Soliman 2011; Lewellen 2013).

In contrast to the slopes on the control variables, there is no apparent decline in the rolling slope average on earnings uncertainty (although the slopes are more volatile). We do, however, note a severe positive spike on the earnings uncertainty slopes in late 1999, early 2000. A similar result is noted in Diether et al. where they note the behavior of high dispersion stock strongly reverse in 2000 from the predictive patterns of years 1983-1999 (pp. 2127). In untabulated analysis, we find that this spike is concentrated in microcap NASDAQ firms between 1999:11 – 2000:02. In particular, there were an above average number of high uncertainty firms realizing monthly returns well in excess of 200% in this four month period.

6.3   Alternative Specification Discussion

Our research design groups firms based on summary characteristics prior studies have found to have strong relations with earnings predictability. The simplicity of the matching process we employ to derive our measure of earnings uncertainty could elicit an almost endless list of alternative matching criteria. However, while matching firms on increasingly more precise firm characteristics may produce more precise earnings expectations, it will also tend to exclude many more firms. The more firms excluded from the primary sample of firms, the higher the likelihood our inferences could be biased (by the exclusion of firms), thereby decreasing the generalizability of our results to a broad cross-section of firms. Without explicitly reporting the details, we can report our empirical results are robust to alternative matching criteria based on earnings and firm size. Specifically, varying the definition of 'comparable' earnings performance by reasonable amounts has little effect on our empirical results.

7   Conclusion

This study examines the predictive power of past earnings volatility. We hypothesize that past earnings volatility jointly captures two distinct economic dynamics: time-series variation in earnings and earnings uncertainty. Due to the tight connection between the two dynamics, prior empirical studies have been unable to distill the predictive power of earnings uncertainty from that associated with time-series variation in earnings. We develop a new measure of future earnings uncertainty based on a matched-firm empirical design. We show that our earnings uncertainty variable is a well specified estimate of actual uncertainty and dominates those based on time-variation in earnings realizations and analyst forecast dispersion. Collectively, our empirical results strongly and consistently suggest that earnings uncertainty, and not time-series variation in earnings, leads to overly-optimistic future earnings forecasts of equity analysts and investors.

Our results contribute along several dimensions of accounting research. First, we show that earnings uncertainty has a strong (negative) predictive relation for analyst forecast errors and future returns. Prior studies examining information uncertainty have hypothesized, but have not empirically documented, that earnings uncertainty should be associated with overly-optimistic forecasts. An obvious alternative explanation for this 'no-result' finding from prior studies is that earnings uncertainty does not affect firm valuation, consistent with the existence of influential market agents arbitraging away pricing inefficiencies (Diamond and Verrecchia 1987). Our study is the first to show that uncertainty in future earnings is value-relevant and that this relevance comes from its relation with future earnings expectations. Further, in contrast to Diether et al. (2002) and Ang et al. (2006) who show relatively short horizon predictive power for future returns, our evidence suggests a more persistent negative relation that holds for at least one year.

Second, we build from the work of Blouin, Core, and Guay (2010) and offer firm-specific proxy for future earnings uncertainty. Blouin et al. note that the level of taxable earnings does not follow a random-walk, which can lead to questionable inferences on the value of the debt-tax shield when past earnings volatility is used as a proxy for future earnings uncertainty. We extend their empirical model to profitability and propose a firm-specific (rather than portfolio-level) measure of earnings uncertainty. While our matched-firm earnings

uncertainty variable is presumably imperfect, specification tests suggest it is a much better proxy for earnings uncertainty than past earnings volatility or forecast dispersion.

Finally, we believe our study has implications for future research along several dimensions. Time-series variation in earnings has been used to explain variation in investment policies (Minton and Schrand 1999), firm valuation (Rountree et al. 2008), and earnings quality (Dechow and Dichev 2002; Leuz et al. 2003). As noted above, time-series variation in earnings is positively correlated with future earnings uncertainty, but the connection is not perfect and cross-sectional variation in the predictive power of these two constructs probably exists across different firm types. Future research could (and should) examine differences in the predictive power of earnings uncertainty and time-series variation in earnings in these settings.

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