

An Evaluation of Accounting-Based Measures of Expected Returns

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ABSTRACT: We develop an empirical method that allows us to evaluate the reliability of an expected return proxy via its association with realized returns even if realized returns are biased and noisy measures of expected returns. We use our approach to examine seven accounting-based proxies that are imputed from prices and contemporaneous analysts' earnings forecasts. Our results suggest that, for the entire cross-section of firms, these proxies are unreliable. None of them has a positive association with realized returns, even after controlling for the bias and noise in realized returns attributable to contemporaneous information surprises. Moreover, the simplest proxy, which is based on the least reasonable assumptions, contains no more measurement error than the remaining proxies. These results remain even after we attempt to purge the proxies of their measurement error via the use of instrumental variables and grouping. We provide additional evidence, however, that demonstrates that some proxies are reliable when the consensus long-term growth forecasts are low and/or when analysts' forecast accuracy is high.

Keywords: *cost of capital; expected rate of return; earnings forecasts; residual income valuation; measurement error.*

I. INTRODUCTION

We develop an empirical approach for evaluating the reliability of estimates of the expected rate of return on equity capital. We use our approach to examine seven accounting-based proxies that are imputed from prices and contemporaneous

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analysts' earnings forecasts.¹ We show that for the entire cross-section of firms, none of these proxies has a positive association with realized returns after controlling for changes in expectations about future cash flows and future discount rates. Moreover, a naïve measure of expected return (the inverse of price to forward earnings) contains no more, and often less, measurement error than the remaining proxies. We provide additional evidence, however, that demonstrates that some proxies *are* reliable when the consensus long-term growth forecasts are low and/or when analysts' forecast accuracy is high.

Similar to the majority of studies in the empirical asset-pricing literature, our inferences about the reliability of a particular expected return proxy are based on its association with realized returns. However, unlike these studies, we assume that realized returns are biased and noisy measures of expected returns. This assumption is motivated by evidence presented in Elton (1999) and Fama and French (2002). These authors demonstrate that "information surprises," which cause realized returns to differ from expected returns, do not cancel out over time or across firms.² We show that these information surprises are also correlated with expected returns. Taken together, these observations imply that simple regressions of realized returns on expected return proxies yield spurious inferences because of omitted correlated variables bias.

In light of the above, we adopt an approach that explicitly takes into account the bias and noise in realized returns. Our approach is based on the linear return decomposition developed by Vuolteenaho (2002), who demonstrates that information surprises equal the change in expectations about future cash flows (i.e., cash flow news) less the change in expectations about future discount rates (i.e., return news). Hence, he provides a theoretical foundation for a regression of realized returns on proxies for expected returns, cash flow news, and return news. The coefficients from this regression serve as our initial source of evidence about the reliability of the expected return proxies.

A problem with basing our inferences on the regression coefficients discussed above is that the estimates of these coefficients are affected by errors in variables bias. Because we cannot observe expectations and changes in expectations, all of the regressors (i.e., the expected return proxy, the cash flow news proxy, and the return news proxy) are measured with error. The sign and magnitude of the bias attributable to measurement error is generally unknown when more than one variable in a multivariate regression contains measurement error (e.g., Rao 1973). However, the return decomposition demonstrates that if the components of realized returns are measured without error, then the estimates of the slope coefficients in a regression of realized returns on expected returns, cash flow news, and return news are unambiguously equal to 1. Thus, the bias in the coefficients corresponding to our empirical proxies is well defined. This, in turn, implies that we can modify the econometric method described in Garber and Klepper (1980) and Barth (1991) to develop

¹ Examples of studies that use accounting-based expected return proxies to evaluate the cross-sectional determinants of expected returns include: Chen et al. (2004), Dhaliwal et al. (2003), Gebhardt et al. (2001), Francis et al. (2003), Gode and Mohanram (2003), Hail (2002), Hail and Leuz (2004), Hribar and Jenkins (2004), and Lee et al. (2003). We illustrate our method by examining variants of several of the expected return proxies used in these studies. However, our method can be used to evaluate any expected return proxy including those based on forecasts of dividends and prices (e.g., Botosan 1997; Botosan and Plumlee 2002; Brav et al. 2004; Francis et al. 2004).

² Elton (1999, 1199) states: "The use of average realized returns as a proxy for expected returns relies on a belief that information surprises tend to cancel out over the period of a study and realized returns are therefore an unbiased measure of expected returns. However, I believe there is ample evidence that this belief is misplaced." Fama and French (2002) provide evidence that suggests the abnormally large equity premium observed during the post-war era was attributable to information surprises that took the form of consistent downward revisions in expected future discount rates. We elaborate on these issues in Section II.

rankings of measurement error variances of the expected return proxies that serve as our second source of evidence about their reliability.

Our empirical results suggest that, for the entire cross-section of firms, the accounting based proxies we evaluate are not reliable estimates of the expected rate of return on equity capital. None of the proxies has a positive association with realized returns even after we control for changes in expectations about future cash flows and future discount rates. Moreover, the measurement error variance of a naïve proxy based on the price-to-forward-earnings ratio is never greater, and often lower, than the error variances of the remaining proxies. These results are robust. For example, we evaluate the effectiveness of two commonly used methods for mitigating measurement error: instrumental variables, and grouping. Neither of these approaches lead to improvements in the associations between the expected return proxies and realized returns, nor do they affect the ordering of the measurement error variances (i.e., the measurement error variance of the naïve proxy is no different from the error variances of the remaining proxies).

Further analyses, however, demonstrate that certain proxies are reliable for some subsets of the data. First, we show that the reliability of the proxies is decreasing in the magnitude of consensus long-term earnings growth rate, and that an analog of the measure of expected returns used by Claus and Thomas (2001) is a reliable proxy for a subsample of firms with low consensus long-term growth forecasts. We also demonstrate that when *ex post* analysts' forecasts errors are low, all of the proxies have a positive association with expected returns. Combining these two sets of results with the fact that *ex post* forecast errors are increasing in analysts' long-term growth forecasts leads us to draw two conclusions: (1) the lack of reliability for the general cross-section is partially attributable to low-quality analysts' forecasts, and (2) the consensus long-term earnings growth rate is a useful *ex ante* indicator of reliability (the higher the forecasted growth, rate the lower the reliability).

We contribute to the accounting and finance literatures in three ways. First, we develop an empirical approach for drawing unbiased inferences about an expected return proxy from its association with realized returns even if realized returns are biased and noisy. Second, we provide evidence suggesting that in most circumstances the expected return proxies we evaluate are unreliable. This implies that there is a need for further research on the development of accounting-based measures of expected returns, and that extant evidence based on the proxies we evaluate should be interpreted with caution. Finally, we provide evidence consistent with the notion that the apparent lack of reliability of our expected return proxies is partially attributable to the quality of analysts' earnings forecasts, which suggests that further study of the determinants of analysts' forecast errors is warranted.³

Two other studies explicitly aimed at evaluating the reliability of accounting-based measures of expected returns are Botosan and Plumlee (2005) and Guay et al. (2003). Botosan and Plumlee (2005) rank measures of expected returns by comparing coefficients from regressions of expected return proxies on assumed risk factors (e.g., CAPM beta, equity market value, leverage, etc.). While this approach has intuitive appeal, it requires that the researcher make the implicit assumption that the risk factors evaluated are correct and exhaustive, which is unlikely. As discussed in Section II, the return decomposition that serves as the foundation for our tests is based on a tautology: that is, our analyses are based

³ Like other studies (e.g., Abarbanell and Bushee 1997; Francis et al. 2000) that document large valuation errors when analysts' forecasts are used in valuation, we are unable to distinguish between two possible explanations for the measurement error in the expected return proxies: (1) errors in the forecasts, and (2) the restrictive assumptions underlying the implementations of the valuation models used to obtain the estimates of the expected rate of return.

on a fully specified model of the relation between an expected return proxy and *true* expected return.

The approach adopted by Guay et al. (2003) is similar to ours as they also evaluate the relation between various expected return proxies and realized returns. There is a crucial difference between our study and theirs, however; we include cash flow news and return news proxies in our regressions, whereas they do not. In particular, the evidence presented in Guay et al. (2003) is based on simple regressions of realized return on the expected return proxy. Hence, as discussed above, the associations they document are likely to be biased measures of the relation between the expected return proxies and true expected return. In Section IV, we provide evidence that bias of this nature exists and is non-trivial.

The remainder of the paper unfolds in the following manner. In the next two sections we describe our empirical method, discuss our proxies of interest, and describe our sample. Our main empirical results are presented in Section IV. The results of our instrumental variables analyses, grouping analyses, and analyses of the relation between the reliability of the expected return proxies and analyst long-term growth forecasts are discussed in Section V. We provide concluding comments in Section VI.

II. EMPIRICAL METHOD

We begin by describing Vuolteenaho's (2002) linear decomposition of realized return into three components: expected return, cash flow news, and return news. Vuolteenaho's (2002) decomposition forms the basis of a linear regression of realized return on the proxies for its components. After discussing this regression we describe how measurement error in the regressors leads to bias in the regression coefficients. Finally, we describe the manner in which we refine the method discussed in Garber and Klepper (1980) and Barth (1991) so that we can isolate the portion of the coefficient bias that is solely attributable to the measurement error in the expected return proxy.

The Components of Realized Returns

Vuolteenaho (2002) demonstrates that firm i 's realized, continuously compounded return for year $t+1$, r_{it+1} , can be decomposed into three components: (1) expected return, er_{it+1} , (2) changes in expectations about future cash flows (cash flow news, cn_{it+1}), and (3) changes in expectations about future discount rates (return news, rn_{it+1}). In particular:

$$r_{it+1} \approx er_{it+1} + cn_{it+1} - rn_{it+1}. \quad (1)$$

In Equation (1) expectations underlying er_{it+1} are formed at the end of year t , whereas cn_{it+1} and rn_{it+1} reflect revisions in expectations occurring during year $t+1$.⁴ A detailed description of Vuolteenaho's (2002) return decomposition, which is similar to the well-known return decomposition developed by Campbell (1991), is provided in Appendix A. Empirical proxies for expected return, er_{it+1} , cash flow news, cn_{it+1} , and return news, rn_{it+1} , are described in Section III.

Three observations about Equation (1) warrant mentioning. First, Equation (1) is derived from a tautology; hence, our analyses do not rely on implicit or explicit assumptions about investor rationality, the nature of market equilibrium, transactions costs, etc. Second, the linear return decompositions developed by Campbell (1991) and Vuolteenaho (2002)

⁴ In Equation (1) the negative sign on return news, rn_{it+1} , reflects the fact that, *ceteris paribus*, increases in future discount rates lead to a decrease in contemporaneous price and, thus, realized return, r_{it+1} , is lower than expected return, er_{it+1} .

are well accepted. For example, a number of studies in finance use variations of Equation (1) as a means of evaluating the determinants of realized returns (comprehensive literature reviews can be found in Campbell et al. [1997, Chapter 7] and Cochrane [2001, Chapter 20]). Finally, since Equation (1) reflects the effect of changes in expectations about future cash flows and future discount rates on realized returns, it provides a direct means of dealing with Elton's (1999) argument that information surprises cause realized returns to be a biased and noisy measure of expected returns.

The third point is especially pertinent to our study. Bias in realized returns implies that the estimate of the slope coefficient taken from a simple regression of realized returns on expected returns is also biased. If changes in expectations about future cash flows (discount rates) are associated with contemporaneous expected returns, the coefficient on expected returns will be affected by correlated omitted variables bias. This is quite plausible. For example, an explanation for the equity premium puzzle is that during the post-war period the U.S. (and other Western nations) experienced an unprecedented run of "good luck."⁵ Hence, the expected future rate of return required by investors as compensation for holding the market portfolio steadily declined (i.e., economy-wide m_{it+1} was negative), which, per Equation (1), caused the *realized* equity premium to be consistently larger than expected.⁶ This, in turn, led to higher than expected realized returns on individual stocks. Moreover, the magnitude of the bias at the individual stock level was arguably increasing in the covariance between a stock's return and the return on the market portfolio. It follows that changes in expectations about future discount rates (i.e., m_{it+1}) were correlated with both realized and expected returns (i.e., r_{it+1} and er_{it+1}), and the coefficient on er_{it+1} is biased if m_{it+1} is omitted from the regression.⁷

The Regression Based on Vuolteenaho's (2002) Return Decomposition

We begin our analyses by estimating the following regression for each expected return proxy:

$$r_{it+1} = \alpha_{0t+1} + \alpha_{1t+1} \times e\hat{r}_{it+1} + \alpha_{2t+1} \times c\hat{n}_{it+1} + \alpha_{3t+1} \times r\hat{n}_{it+1} + \varepsilon_{it+1}. \quad (2)$$

In Equation (2) $e\hat{r}_{it+1}$, $c\hat{n}_{it+1}$, and $r\hat{n}_{it+1}$ represent the expected return proxy, the cash flow news proxy, and the proxy for *negative* return news (i.e., $-1 \times rn_{it+1}$), which we refer to as the return news proxy. The expected return proxies, the cash flow news proxies, and the return news proxies are described in Section III. If these empirical proxies are measured *without* error, α_{1t+1} , α_{2t+1} , and α_{3t+1} are equal to 1 and α_{0t+1} is equal to 0. Hence, one means of evaluating a particular measure of expected returns is to conduct a test of the difference between α_{1t+1} and 1. Unfortunately, these tests do not lead to clear-cut inferences; because we are unable to observe expectations or revisions in expectations, each of the regressors in Equation (2) contains error, which implies the bias in a particular regression coefficient is a complex function of the measurement errors in *all* of the regressors (e.g., Rao 1973). To circumvent this problem we use a refinement of the approach discussed in Garber and

⁵ See Cochrane (2001, Chapter 21, 460–462) for a discussion of the equity premium puzzle. The discussion under the heading "Luck and a Lower Target" is particularly relevant.

⁶ Fama and French (2002) provide specific evidence of this phenomenon.

⁷ A similar argument can be made for the inclusion of cn_{it+1} in the regression. In particular, if changes in expectations about future cash flows are correlated with investment opportunities, which, in turn, are correlated with expected returns, cn_{it+1} will be correlated with both realized and expected return. Berk et al. (1999) develop a model in which firms' optimal investment choices are associated with expected returns.

Klepper (1980) and Barth (1991) to isolate the portion of the bias in α_{1t+1} that is solely attributable to the measurement error in $e\hat{r}_{it+1}$.

Measurement Error Analysis

In this subsection we describe the intuition underlying the method we use to isolate the portion of the bias in α_{1t+1} that is solely attributable to measurement error in $e\hat{r}_{it+1}$. Appendix B contains a rigorous description of our econometric approach, which is centered on the following regression:

$$v_{Cit+1} = \delta_{0t+1} + \delta_{1t+1} \times \epsilon_{1it+1}^A + \delta_{2t+1} \times \epsilon_{2it+1}^A + \delta_{3t+1} \times \epsilon_{3it+1}^A + \mu_{it+1}. \quad (3)$$

In Equation (3) v_{Cit+1} equals the difference between firm i 's observed, realized return for year $t+1$, and the sum of the empirical measures of its components (i.e., $v_{Cit+1} = r_{it+1} - e\hat{r}_{it+1} - c\hat{n}_{it+1} - r\hat{n}_{it+1}$); thus, v_{Cit+1} equals the combined measurement error in our empirical proxies. Each regressor (i.e., ϵ_{1it+1}^A , ϵ_{2it+1}^A , and ϵ_{3it+1}^A) essentially equals the adjusted error from a regression of one of the proxies on the remaining two (e.g., ϵ_{1it+1}^A is obtained by regressing $e\hat{r}_{it+1}$ on $c\hat{n}_{it+1}$ and $r\hat{n}_{it+1}$). Hence, each regression coefficient in Equation (3) measures the relation between the error in a particular proxy and the combined error in all the proxies. The expression for the regression coefficient corresponding to ϵ_{1it+1}^A , which we refer to as the "noise variable," is:⁸

$$\begin{aligned} \delta_{1t+1} = & \sigma^2(v_{1it+1}) + \{\sigma(v_{1it+1}, v_{2it+1}) + \sigma(v_{1it+1}, v_{3it+1})\} + \{\sigma(er_{it+1}, v_{2it+1}) \\ & + \sigma(er_{it+1}, v_{3it+1})\}. \end{aligned} \quad (4)$$

In Equation (4) $\sigma^2(v_{1it+1})$ is the variance of the measurement error in the expected return proxy, $\sigma(v_{1it+1}, v_{2it+1})$ denotes the covariance between the measurement error in $e\hat{r}_{it+1}$ and the measurement error in $c\hat{n}_{it+1}$, $\sigma(v_{1it+1}, v_{3it+1})$ is the covariance between the measurement error in $e\hat{r}_{it+1}$ and the measurement error in $r\hat{n}_{it+1}$, $\sigma(er_{it+1}, v_{2it+1})$ is the covariance between true expected return and the measurement error in $c\hat{n}_{it+1}$, and $\sigma(er_{it+1}, v_{3it+1})$ is the covariance between true expected return and the measurement error in $r\hat{n}_{it+1}$. If the covariance terms are constant across expected return proxies, then variation across proxies in the noise variable is solely attributable to variation in the measurement error in the expected return proxies (i.e., $\sigma^2(v_{1it+1})$). This implies that the expected return proxy with the smallest noise variable contains the least measurement error and is the most reliable. Hence, we begin our measurement error analyses by estimating Equation (3) for each of the expected return proxies of interest.

A problem with using the noise variables to rank our expected return proxies is that it is unlikely that the covariance terms shown in Equation (4) are constant across expected return proxies. Because each of our measures of the expected rate of return is based on a unique set of assumptions about dividends, future earnings growth, and terminal profitability, it is likely that the relation between the error in each proxy and the errors in the remaining independent variables is also unique. This implies that inferences based on the relative magnitudes of the different estimates of the noise variable may not provide a

⁸ As shown in Appendix B, the expressions for δ_{2t+1} and δ_{3t+1} are similar to the expressions for δ_{1t+1} . Given that our primary interest relates to the measurement error in the expected return proxies, we choose to focus the discussion in the body of the paper on δ_{1t+1} .

meaningful basis for inferring the relative magnitudes of $\sigma^2(v_{1it+1})$. To circumvent this problem we refine the econometric approach developed by Garber and Klepper (1980) and Barth (1991) and estimate “modified noise variables.”⁹

$$\delta_{1t+1}^M = \sigma^2(v_{1it+1}) - \{\sigma(er_{it+1}, cn_{it+1}) + \sigma(er_{it+1}, rn_{it+1})\} \\ - \{\sigma(v_{1it+1}, cn_{it+1}) + \sigma(v_{1it+1}, rn_{it+1})\}. \quad (5)$$

In Equation (5) $\sigma(er_{it+1}, cn_{it+1}) + \sigma(er_{it+1}, rn_{it+1})$ equals the covariance between true expected return and the sum of true cash flow news and true return news.

Two observations regarding the modified noise variables are pertinent. First, while there is reason to believe $\sigma(er_{it+1}, cn_{it+1}) + \sigma(er_{it+1}, rn_{it+1})$ is not equal to zero, it involves only the true values of the constructs, which implies it is constant across proxies. Hence, if differences in $\sigma(v_{1it+1}, cn_{it+1}) + \sigma(v_{1it+1}, rn_{it+1})$ are second order, which is a reasonable assumption, differences in the modified noise variables are primarily attributable to differences in the measurement error variances of the proxies (i.e., $\sigma^2(v_{1it+1})$).¹⁰ Second, δ_{1t+1}^M is not a function of the measurement errors in the cash flow news and return news proxies (i.e., v_{1it+1} and v_{2it+1}). This implies that rankings based on δ_{1t+1}^M are unaffected by risk-related measurement errors in cn_{it+1} and rn_{it+1} .

Summary

To summarize, bias and noise attributable to information surprises imply that simple regressions of realized returns on expected return proxies yield spurious inferences that are attributable to omitted correlated variables. Hence, we include measures of cash flow news and return news in our regressions (i.e., Equation (2)). However, because all of the regressors in Equation (2) contain measurement error, the regression coefficient corresponding to the expected return proxy is not a clear-cut indicator of the reliability of this proxy. To overcome this problem we use a refinement of the method described in Garber and Klepper (1980) and Barth (1991) to estimate the measurement error variances.

III. EMPIRICAL PROXIES AND SAMPLE CONSTRUCTION

Accounting-Based Measures of Expected Return

In this section we provide a brief overview of the seven expected return proxies we evaluate, each of which is imputed from prices and contemporaneous earnings forecasts. Our first proxy is based on the assumption that expected cum-dividend aggregate earnings for the next two years are valuation sufficient. Hence, it essentially equals the inverse of the price-to-forward-earnings ratio. For this reason we refer to it as r_{pe} . The purpose of including r_{pe} in our analyses is to provide a naïve benchmark (based on restrictive assumptions about future earnings growth).¹¹

Our next four expected return proxies are each derived from the finite-horizon version of the earnings, earnings growth model developed by Ohlson and Juettner-Nauroth (2003) and described in Easton (2004):

⁹ The refinements are described in Appendix B.

¹⁰ Two observations support the assumption that differences in $\sigma(v_{1it+1}, cn_{it+1}) + \sigma(v_{1it+1}, rn_{it+1})$ across expected return proxies are second order: (1) there is no reason to believe errors in our ability to measure expectations at time t are correlated with revisions in true expectations occurring during time $t+1$, and (2) even if this correlation is non-zero, there is no reason to believe its magnitude differs across proxies.

¹¹ To be precise, the valuation model underlying r_{pe} relies on the assumption that after year $t+2$ cum-dividend aggregate earnings grow at a rate equal to the cost of capital.

$$\begin{aligned}
 P_{it} &= \frac{eps_{it+1}}{r} + \frac{eps_{it+2} + r \times dps_{it+1} - (1 + r) \times eps_{it+1}}{r \times (r - \Delta agr)} \\
 &= \frac{eps_{it+1}}{r} + \frac{agr_{it+1}}{r \times (r - \Delta agr)}.
 \end{aligned} \tag{6}$$

In Equation (6) P_{it} is price at the end of year t , $eps_{it+\tau}$ is the year t forecast of year $t+\tau$ earnings per share, dps_{it+1} is the year t forecast of dividends paid in year $t+1$, r is the expected rate of return, and Δagr is a growth rate. Following Easton (2004), we refer to the difference between expected year-two cum-dividend accounting earnings (i.e., $eps_{it+2} + r \times dps_{it+1}$) and normal accounting earnings that would be expected given earnings of period one (i.e., $(1 + r) \times eps_{it+1}$) as “abnormal growth in earnings” or agr_{it+1} . Hence, Δagr equals the perpetual rate of change in abnormal growth in earnings beyond the forecast horizon.

The first proxy derived from Equation (6) embeds the assumption that no dividends are paid in year $t+1$ and that Δagr equals 0. As shown in Easton (2004), this proxy is equal to the square root of the inverse of the PEG ratio; hence, we refer to it as r_{peg} .¹² Relaxing the assumption that dps_{it+1} is equal to 0 yields a modified version of the PEG ratio and a proxy we refer to as r_{mpeg} .¹³ A criticism of r_{peg} and r_{mpeg} is that the assumption of constant abnormal growth in earnings is too restrictive. Gode and Mohanram (2003) avoid this criticism by assuming Δagr is a cross-sectional constant equal to the difference between the risk-free rate of interest and 3 percent. We refer to their proxy as r_{gm} . Easton (2004), on the other hand, simultaneously estimates r and Δagr for portfolios of stocks allowing for cross-sectional variation in Δagr . We refer to his proxy as $r_{\Delta agr}$.¹⁴

Our final two measures of expected return are derived from the residual income valuation model. We refer to the first of these two proxies as r_{ct} because it is based on the work of Claus and Thomas (2001). Claus and Thomas (2001) assume that earnings grow at the analysts’ consensus long-term growth rate until year $t+5$. They assume earnings after year $t+5$ grow at the rate of inflation, which is set equal the risk-free rate less 3 percent. The second proxy derived from the residual income model is based on the work of Gebhardt et al. (2001); hence, we refer to it as r_{gls} . Gebhardt et al. (2001) use actual earnings forecasts to develop estimates of return on equity for year $t+1$ and $t+2$. They assume that accounting return on equity linearly fades to the historical industry median between years $t+3$ and $t+12$, and remains constant thereafter.¹⁵

Finally, note that all of our expected return proxies reflect continuous compounding. In particular, the value of $e\hat{r}_{it+1}$ for a particular set of assumptions equals $\ln(1 + r)$, where r is the discount rate implied by the corresponding valuation model. The valuation models underlying each of the expected return proxies and details of their calculation are provided in Table 1.

¹² The PEG ratio, which is equal to the PE ratio divided by the short-term earnings growth rate, is a common means of comparing stocks in analysts’ reports.

¹³ Since I/B/E/S does not provide forecasts of dividends, we assume dps_{t+1} equals dps_t (i.e., dividends per share paid in year t).

¹⁴ This method simultaneously estimates the expected rate of return and the growth rate for a portfolio of firms that have similar PEG ratios. Assigning these estimates of the expected rate of return to each firm in the portfolio introduces measurement error. However, it allows us to avoid having to make *ad hoc* assumptions about Δagr .

¹⁵ While both r_{ct} and r_{gls} are based on the residual income valuation model, as discussed above, each reflects different assumptions about the manner in which *ROE* evolves after year $t+2$. Our empirical results demonstrate that these differences in assumptions lead to significant differences in the statistical properties of the two proxies. For example, as shown in Table 3, the correlation between r_{ct} and r_{gls} is less than 0.50.

TABLE 1
Summary of Empirical Proxies, Data Sources, and Sample Construction

$e\hat{r}_{it+1}$	Expected Return Proxies	
	Valuation Model	Comments
r_{pe}	$P_{it} = \frac{eps_{it+1} + r \times dps_{it} + eps_{it+2}}{(1+r)^2 - 1}$	
r_{peg}	$P_{it} = \frac{eps_{it+2} - eps_{it+1}}{r^2}$	
r_{mpeg}	$P_{it} = \frac{eps_{it+2} + r \times dps_{it} - eps_{it+1}}{r^2}$	
r_{gm}	$P_{it} = \frac{eps_{it+1}}{r} + \frac{eps_{it+2} + r \times dps_{it} - (1+r) \times eps_{it+1}}{r \times (r - \Delta agr)}$	Δagr is the contemporaneous yield on a ten-year government bond less 3 percent.
$r_{\Delta agr}$	$P_{it} = \frac{eps_{it+1}}{r} + \frac{eps_{it+2} + r \times dps_{it} - (1+r) \times eps_{it+1}}{r \times (r - \Delta agr)}$	r and Δagr are estimated simultaneously via the approach discussed in Easton (2004).
r_{ct}	$P_{it} = bps_{it} + \sum_{\tau=1}^4 \frac{(ROE_{it+\tau} - r) \times bps_{it+\tau-1}}{(1+r)^\tau} + \frac{(ROE_{it+5} - r) \times bps_{it+4} \times (1+\gamma)}{(r-\gamma) \times (1+r)^4}$	$ROE_{it+\tau} = eps_{it+\tau}/bps_{it+\tau-1}$. $eps_{it+\tau} = eps_{it+2} \times (1 + ltg_i)^{\tau-2} \forall \tau > 2$. ltg_i is the I/B/E/S consensus forecast of the growth rate in earnings per share. $bps_{it+\tau} = bps_{it+\tau-1} + eps_{it+\tau} \times (1 - K)$. For profitable firms $K = \max(0, \min(dps_{it}/eps_{it}, 1))$. For loss firms $K = \max(0, \min(dps_{it}/(.06 \times bps_{it}), 1))$. γ is the contemporaneous yield on a ten-year government bond less 3 percent. We solve for r via an iterative procedure.
r_{gls}	$P_{it} = bps_{it} + \sum_{\tau=1}^{11} \frac{(ROE_{it+\tau} - r) \times bps_{it+\tau-1}}{(1+r)^\tau} + \frac{(ROE_{it+12} - r) \times bps_{it+11}}{r \times (1+r)^{11}}$	$ROE_{it+\tau} = eps_{it+\tau}/bps_{it+\tau-1}$ for $\tau = 1, 2$. $ROE_{it+\tau} = ROE_{it+\tau-1} - fade \forall \tau > 2$. $fade = (ROE_{it-2} - HIROE_t)/10$, $HIROE_t$ is the historical industry median ROE for all firm-years in the same industry spanning year $t-4$ through year t with positive earnings and equity book values. We use the industry definitions shown in Fama and French (1997). $bps_{it+\tau} = bps_{it+\tau-1} \times (1 + ROE_{it+\tau} - K)$. For profitable firms $K = \max(0, \min(dps_{it}/eps_{it}, 1))$. For loss firms $K = \max(0, \min(dps_{it}/(.06 \times bps_{it}), 1))$. We solve for r via an iterative procedure.

(continued on next page)

TABLE 1 (continued)

Cash Flow News Proxy, $c\hat{n}_{it+1}$, and Return News Proxy, $r\hat{n}_{it+1}$

Formula	Comments
$c\hat{n}_{it+1} = (roe_{it} - froe_{it,t}) + (froe_{it+1,t+1} - froe_{it,t+1})$ $+ \frac{\rho}{1 - \rho \times \omega_t} \times (froe_{it+1,t+2} - froe_{it,t+2})$	$roe_{it} = \ln(1 + ROE_{it})$, $ROE_{it} = eps_{it}/bps_{it-1}$. $froe_{ij,k} = \ln(1 + ROE_{ij,k})$, $ROE_{ij,k}$ denotes the forecast of return on equity for fiscal year k and is based on the consensus I/B/E/S forecast made at the end of year j . The approach we use to estimate ρ is discussed in Appendix A. ω_t is estimated on an annual basis via the pooled, cross-sectional regression shown in Equation (9).
$r\hat{n}_{it+1} = \frac{\rho}{1 - \rho} \times (e\hat{r}_{it+2} - e\hat{r}_{it+1})$	$r\hat{n}_{it+1}$ varies across expected return proxies. The approach we use to estimate ρ is discussed in Appendix A. When conducting our multivariate analyses we define return news as:
	$r\hat{n}_{it+1} = - \frac{\rho}{1 - \rho} \times (e\hat{r}_{it+2} - e\hat{r}_{it+1})$

We use continuously compounded returns; hence, the value of $e\hat{r}_{it+1}$ for a particular proxy is equal to the natural log of 1 plus the discount rate imputed from the valuation model underlying that proxy. P_{it} is the closing share price for fiscal year t per Compustat (data item 199), dps_{it} is dividends per share for year t per Compustat (data item 26), and bps_{it} (bps_{it-1}) is equity book value at the end of year t ($t-1$) per Compustat (data item 60) divided by common shares outstanding at the end of year t ($t-1$) per Compustat (data item 25). eps_{it} is reported earnings per share for year t per I/B/E/S. eps_{it+1} is the consensus earnings per share forecast for year $t+1$ per I/B/E/S. When available, we use the actual, consensus forecast for year $t+2$ as our proxy for eps_{it+2} . When actual forecasts are unavailable we use I/B/E/S forecasts of growth in earnings as the basis for developing our proxy for eps_{it+2} . We eliminate firm-years occurring before 1981 and after 1998, or that do not have a December fiscal year-end. We delete firm-years with missing or non-positive P_{it} , bps_{it} , bps_{it-1} , or common shares outstanding; with negative eps_{it+1} ; with $eps_{it+2} < eps_{it+1}$; with $lrg_i < 0$; with missing cum-dividend, continuously compounded stock return in year $t+1$ per CRSP, r_{it+1} ; with a missing cash flow news proxy, $c\hat{n}_{it+1}$; or a missing return news proxy, $r\hat{n}_{it+1}$. Finally, firm-years with values of r_{it+1} , $e\hat{r}_{it+1}$, $c\hat{n}_{it+1}$ or $r\hat{n}_{it+1}$ in the top or bottom 1/2 percentile of the annual, cross-sectional distribution are considered outliers and deleted. Our final sample consists of 15,680 firm-years.

Cash Flow News and Return News Proxies

In the Vuolteenaho (2002) return decomposition (Equation (1)), cash flow news cn_{it+1} is the component of realized returns corresponding to the change in investors' expectations about future cash flows. As shown in Appendix A, cash flow news is defined as follows:

$$cn_{it+1} = \Delta E_{t+1} \left[\sum_{\tau=1}^{\infty} \rho^{\tau-1} \times roe_{it+\tau} \right]. \quad (7)$$

In Equation (7) $\Delta E_{t+1}[\cdot]$ equals $E_{t+1}[\cdot] - E_t[\cdot]$, ρ is a number slightly less than 1, and roe is the natural log of 1 plus the accounting rate of return on equity. This equation implies that a revision in expectations about future profitability leads to a realized return that is larger (in magnitude) than expected return. The effect on realized return of a particular revision in expectations about future profitability is not, however, a cross-sectional constant. Rather, the size of the effect depends on investors beliefs about growth, which are captured by ρ . In particular, as shown in Appendix A, ρ is monotonically increasing in the price-to-dividend ratio, which is generally considered a function of future growth opportunities.¹⁶ Hence, ρ can be viewed as a "capitalization factor."

We use the following formula to estimate our cash flow news proxies:

$$\begin{aligned} c\hat{n}_{it+1} = & (roe_{it} - froe_{it,t}) + (froe_{it+1,t+1} - froe_{it,t+1}) \\ & + \frac{\rho}{1 - \rho \times \omega_t} \times (froe_{it+1,t+2} - froe_{it,t+2}). \end{aligned} \quad (8)$$

In Equation (8) $froe_{ij,k}$ denotes forecasted roe for fiscal year k and is based on the consensus forecast of eps_{ik} made in December of year j , ω_t is the expected persistence of roe as of time t .¹⁷ The manner in which we estimate ρ , which varies with the price-to-dividend ratio, is discussed in Appendix A. Our cash flow news proxy embeds the assumption that roe follows a first order autoregressive process after year $t+1$. This assumption is consistent with evidence presented in Beaver (1970), Freeman et al. (1982), and Sloan (1996).

We estimate ω_t via the following pooled cross-sectional and time-series regression:

$$roe_{it+1} = \omega_{0t} + \omega_t \times roe_{it}. \quad (9)$$

In Equation (9) τ is a number between t and $t-9$ and the sample includes all firm-years in the same Fama and French (1997) industry with requisite data in year $t-9$ through year t (i.e., for each year t we estimate ω_t using firm years between year $t-9$ and year t). Given that accounting methods, competition, and risk vary across industry, our use of an industry specific ω_t reduces the potential for bias attributable to risk-related measurement error in $c\hat{n}_{it+1}$.

¹⁶ Consider the dividend growth model $P = \frac{dps}{r - g} \Rightarrow \frac{P}{dps} = \frac{1}{r - g}$, which clearly implies the price-to-dividend ratio is increasing in the growth rate, g .

¹⁷ We include $(roe_{it} - froe_{it,t})$ in Equation (8) to capture the change in expectations that occurs in year $t+1$ upon the announcement of actual year t earnings. As discussed below, $froe_{it,t}$ is based on information that becomes publicly available on the third Thursday of the last fiscal month of year t .

In the Vuolteenaho (2002) return decomposition (Equation (1)), return news rn_{it+1} is the component of realized returns corresponding to the change in investors' expectations about future discount rates.¹⁸ As shown in Appendix A, return news is defined as follows:

$$rn_{it+1} = \Delta E_{t+1} \left[\sum_{\tau=2}^{\infty} \rho^{\tau-1} \times r_{it+\tau} \right]. \quad (10)$$

ρ has the same role in the above expression as its role in cn_{it+1} (i.e., it is a capitalization factor that allows the sensitivity of realized return to a given change in the expected discount rate to vary across stocks on the basis of variation in growth). We use the following formula to estimate our return news proxy:

$$r\hat{n}_{it+1} = \frac{\rho}{1 - \rho} \times (e\hat{r}_{it+2} - e\hat{r}_{it+1}). \quad (11)$$

That is, $r\hat{n}_{it+1}$ varies across valuation models, and embeds the assumption that changes in the discount rate are permanent (i.e., the discount rate follows a random walk). This assumption is consistent with the fact that each of our expected return proxies is the geometric average of all expected future discount rates.

Our cash flow and return news proxies are a function of analysts' forecasts, which also serve as the basis of our expected return proxies. This is unavoidable as expectations and changes in expectations are inextricably linked. For example, the expected return assigned to a particular stock is a function of the risk of the expected payoffs; hence, cn_{it+1} reflects revisions in the expectations underlying er_{it+1} . Similar logic implies that rn_{it+1} and er_{it+1} are related, which, in turn, implies $r\hat{n}_{it+1}$ varies across valuation models.

Sample Construction

Price at fiscal year-end, equity book value, dividends, and number of shares outstanding are obtained from the 1999 Compustat annual primary, secondary, tertiary, and full coverage research files. Earnings forecasts are derived from the summary 2000 I/B/E/S tape. We determine median forecasts from the available analysts' forecasts on the I/B/E/S file that is released on the third Thursday of December. We delete firms with non-December fiscal year-ends so that the market-implied discount rate and growth rate are estimated at the same point in time for each firm-year observation.¹⁹ For observations in 1995, for example, the December forecasts became available on the 21st day of the month. These data included forecasts for a fiscal year ending ten days later (i.e., December 31, 1995) and either an earnings forecast for each of the fiscal years ending December 31, 1996 and 1997 (i.e.,

¹⁸ In the context of a multifactor asset-pricing model, return news is attributable to an unforeseen change in the risk-free rate, unforeseen changes in the factor loadings (i.e., the "betas"), and unforeseen changes in the factor premiums (e.g., the market risk premium). In the instant case, a change in the risk-free rate is irrelevant because it has an equal effect on all equities; hence, it has no effect on the cross-sectional distribution of realized returns. Changes in factor loadings are relevant to the extent they vary across stocks. These changes occur because of changes in the correlation between a particular factor and stock returns, or a change in the volatility of the factor. Changes in factor premiums affect a particular equity by an amount proportionate to the corresponding factor loading for that stock. Hence, even though these changes are economy-wide, they do affect the cross-sectional distribution of realized returns. Changes in factor premiums occur because of changes in investors' appetite for risk, ability to diversify, etc.

¹⁹ While limiting our sample to firms with fiscal-years that end in December reduces the power of our tests, it is unlikely that it leads to bias; hence, our inferences are likely unaffected by this research design choice.

eps_{it+1} and eps_{it+2}) or the forecast for the fiscal year ending December 31, 1996 (i.e., eps_{it+1}) and a forecast of growth in earnings per share for the subsequent years. When available, we use the actual forecasts for the subsequent year (in this example, 1997) as our proxy for eps_{it+2} . When actual forecasts are unavailable we use I/B/E/S forecasts of growth in earnings as the basis for developing our proxy for eps_{it+2} . Realized returns for the year following the earnings forecast date (in the example, January 1, 1996 to December 31, 1996) are obtained from the Center for Research in Security Prices (CRSP) Monthly Return file.

We eliminate firm-year observations (1) prior to 1981 and after 1998 because there are very few observations with complete data in these years, (2) with missing price, dividends per share, or common shares outstanding, (3) with missing or negative book value of equity, (4) with negative eps_{it+1} , (5) with $eps_{it+2} < eps_{it+1}$, (6) with a negative consensus forecast of long-term earnings per share growth, (7) with missing cum-dividend, continuously compounded stock return in year $t+1$, (8) with a missing cash flow news proxy, or (9) with a missing return news proxy. Finally, firm-years with values of r_{it+1} , $e\hat{r}_{it+1}$, $c\hat{n}_{it+1}$, or $r\hat{n}_{it+1}$ in the top or bottom 1/2 percentile of each yearly, cross-sectional distribution are considered outliers and deleted. Our final sample consists of 15,680 firm-year observations.

IV. MAIN EMPIRICAL RESULTS

In this section we discuss the descriptive statistics, correlations, and the results of our main empirical tests. As discussed above and in Appendix B, the Vuolteenaho (2002) return decomposition pertains to continuously compounded returns; hence, we transform realized returns and each of the measures of expected return by taking the log of 1 plus the proxy of interest. Analyses of untransformed values lead to similar inferences. Descriptive statistics and correlations are based on the definition of $r\hat{n}_{it+1}$ shown in Equation (11). The value of $r\hat{n}_{it+1}$ underlying our multivariate tests is obtained from Equation (11) and is equal to:

$$- \frac{\rho}{1 - \rho} \times (e\hat{r}_{it+2} - e\hat{r}_{it+1}).$$

Descriptive Statistics

Descriptive statistics for realized returns, the expected return proxies, and the cash flow news proxy are shown on Panel A of Table 2. The median estimate of r_{pe} is 8.3 percent, which is considerably less than the median realized return of 12.2 percent. Moreover, as shown in the column titled $less_r_f$, 31 percent of the firm-years in our sample have values of r_{pe} below the contemporaneous value of the continuously compounded risk-free rate. These results suggest that r_{pe} is a downward-biased measure of expected return. However, they do not provide evidence about the cross-sectional association between r_{pe} and true expected returns, which is the pertinent issue given our research question.²⁰

²⁰ Given the expected risk premium on a stock is rarely less than zero, a high value of $less_r_f$ suggests that the average of the expected return proxy is a poor measure of mean expected returns. However, $less_r_f$ is not informative about the cross-sectional characteristics of the proxy (i.e., bias does not imply noise). Hence, in the context of our research question a high value of $less_r_f$ is not *prima facie* evidence that an expected return proxy is unreliable. Conversely, our empirical tests relate to the cross-sectional characteristics of the expected return proxies and do not shed light on whether the proxies are useful measures of mean expected returns. For example, while our evidence suggests that variation in r_{et} does not capture variation in true expected returns, we cannot conclude that the evidence presented in Claus and Thomas (2001) regarding the magnitude of the expected equity premium is unreliable.

TABLE 2
Descriptive Statistics

Panel A: Realized Returns, the Expected Return Proxies, and the Cash Flow News Proxy

	<u>Mean</u>	<u>Std</u>	<u>less-r_f</u>	<u>5th</u>	<u>25th</u>	<u>50th</u>	<u>75th</u>	<u>95th</u>
r_{it+1}	0.096	0.366	0.435	-0.551	-0.093	0.122	0.315	0.631
r_{pe}	0.088	0.034	0.310	0.041	0.065	0.083	0.107	0.152
r_{peg}	0.110	0.032	0.119	0.066	0.090	0.106	0.126	0.169
r_{mpeg}	0.122	0.032	0.026	0.081	0.100	0.116	0.137	0.181
r_{gm}	0.129	0.033	0.012	0.086	0.107	0.124	0.145	0.189
$r_{\Delta agr}$	0.128	0.029	0.005	0.094	0.110	0.122	0.138	0.178
r_{ct}	0.120	0.032	0.020	0.077	0.098	0.115	0.138	0.180
r_{gls}	0.109	0.031	0.105	0.063	0.089	0.107	0.126	0.163
$c\hat{n}_{it+1}$	-0.026	0.384	NA	-0.447	-0.151	-0.037	0.044	0.440

Panel B: The Return News Proxies

	<u>Mean</u>	<u>Std</u>	<u>5th</u>	<u>25th</u>	<u>50th</u>	<u>75th</u>	<u>95th</u>
$r\hat{n}_{it+1}$ (pe)	0.054	1.317	-1.734	-0.298	-0.036	0.265	2.204
$r\hat{n}_{it+1}$ (peg)	-0.027	1.609	-2.390	-0.336	-0.034	0.270	2.352
$r\hat{n}_{it+1}$ (mpeg)	-0.022	1.613	-2.384	-0.359	-0.042	0.297	2.383
$r\hat{n}_{it+1}$ (gm)	-0.047	1.665	-2.461	-0.377	-0.047	0.293	2.343
$r\hat{n}_{it+1}$ (Δagr)	-0.023	1.448	-2.013	-0.291	-0.036	0.233	2.043
$r\hat{n}_{it+1}$ (ct)	-0.076	1.259	-2.104	-0.359	-0.064	0.236	1.909
$r\hat{n}_{it+1}$ (gls)	0.007	0.928	-1.407	-0.274	-0.037	0.233	1.609

r_{it+1} is the realized, continuously compounded return for year $t+1$. r_{pe} is the expected return estimate imputed from the price to forward earnings model. r_{peg} is the expected rate of return implied by the PEG ratio. r_{mpeg} is the expected rate of return implied by the modified PEG ratio. r_{gm} and $r_{\Delta agr}$ are the expected return estimates imputed from Gode and Mohanram's (2003) and Easton's (2004) implementation of the Ohlson and Juettner-Nauroth (2003) model, respectively. r_{ct} and r_{gls} are the expected return estimates imputed from Claus and Thomas's (2001) and Gebhardt et al.'s (2001) implementation of the residual income valuation model, respectively. All the expected return proxies represent continuously compounded returns. $c\hat{n}_{it+1}$ is the cash flow news proxy. $r\hat{n}_{it+1}$ (xxx) is the return news proxy for model xxx. See Table 1 for further details. Mean, Std, 5th, 25th, 50th, 75th, and 95th represent the mean, standard deviation, 5th percentile, 25th percentile, median, 75th percentile, and 95th percentile, respectively. $less-r_f$ is the proportion of firm-years in which the return variable has a value less than the natural log of 1 plus the contemporaneous risk-free rate of return.

The adjustment provided by taking short-term earnings growth into account (r_{peg}) causes the median estimate of expected returns to increase to 10.6 percent and inclusion of dividends in the expected payoff (r_{mpeg}) causes the median to rise to 11.6 percent. The estimation procedure used by Gode and Mohanram (2003) relies on the assumption that abnormal growth in earnings increases after year $t+1$ and the method used by Easton (2004) leads to estimates of increases in abnormal growth in earnings that are, on average, positive. Hence, the median value of r_{gm} (12.4 percent) and $r_{\Delta agr}$ (12.2 percent) exceeds the median value of r_{mpeg} . The medians of r_{ct} and r_{gls} , which are based on the residual income valuation model, are 11.5 percent and 10.7 percent, respectively.

The median value of the cash flow news proxy ($c\hat{n}_{it+1}$) is -3.7 percent.²¹ To the extent that this measure of cash flow news is attributable to analyst optimism (e.g., Richardson et

²¹ The median (mean) value of ω_t used in the calculation of $c\hat{n}_{it+1}$ is 0.52 (0.55).

al. 2001) that is ignored by the market, the negative median value of cash flow news represents measurement error in our cash flow news proxies. Moreover, given that our expected return proxies and return news proxies are also derived from analysts' forecasts, the negative median value of cash flow news implies that these constructs are also measured with error.

Descriptive statistics for our return news proxies are shown in Panel B of Table 2. Since these estimates equal the change in the estimate of expected return over the realized return interval, they differ across the various estimates of expected returns. The median estimates of return news are consistently negative. For example, the median return news implied by the change in r_{peg} is -3.4 percent and the median return news for r_{ct} is -6.4 percent. In light of the fact that prices rose during our sample period, the decline in our expected return proxies suggests a coincident decline in the equity premium.

Correlations

Table 3, Panel A summarizes the correlations among realized returns, the expected return proxies, and the estimates of cash flow news. Pearson product moment (Spearman rank order) correlations are shown above (below) the diagonal. Correlations between our return news proxies and the remaining variables of interest are shown in Panel B. The correlations are the temporal averages of the annual cross-sectional correlations. The t-statistics are the ratio of these averages to their temporal standard errors. We focus our discussion on the Spearman correlations. The Pearson correlations lead to similar inferences.

There is a significant positive correlation between realized return and two of the expected return proxies: r_{ct} (0.073, t-statistic of 2.35) and r_{gls} (0.061, t-statistic of 1.95). None of the correlations between the remaining expected return proxies and realized returns is statistically different from zero at the 0.05 level. Moreover, three of the correlations are negative. These negative correlations imply that the cash flow news and return news components of realized returns reflect more than random measurement error, which only causes attenuation bias and has no affect the sign of the correlation.²² Rather, these correlations support the arguments we made in Section II. Specifically, true cash flow news and true return news are correlated with our expected return proxies. Hence, in order to avoid drawing spurious inferences attributable to omitted correlated variables bias it is crucial that we control for variation in cash flow news and returns news.

As expected, the correlation between realized returns and the estimate of cash flow news is positive and significant (Spearman correlation of 0.314 with a t-statistic of 16.99). The significant negative correlation between the cash flow news proxy and r_{pe} and the significant negative correlations between the cash flow news proxy and each of the estimates of expected returns derived from the abnormal growth in earnings model (i.e., Equation (6)) provide additional support for our argument that including a cash flow news proxy in our regressions is necessary in order to avoid correlated omitted variables bias. These negative correlations suggest that firms with relatively high discount rates experienced larger

²² The correlation between realized return ($r_{it+1} \approx er_{it+1} + cn_{it+1} - m_{it+1}$) and an expected return proxy $e\hat{r}_{it+1}$ equals $\frac{\sigma(er_{it+1}, e\hat{r}_{it+1}) + \sigma(cn_{it+1} - m_{it+1}, e\hat{r}_{it+1})}{\sigma(r_{it+1}) \times \sigma(e\hat{r}_{it+1})}$. If cash flow news and return news are simply random measurement error, then the second term in the numerator equals zero and the sign is equal to the sign of the first term. The sign of the first term is positive unless the covariance between true expected return and the measurement error in the expected return proxy is negative and has an absolute value greater than the variance of true expected returns. This is unlikely.

TABLE 3
Correlations among Key Variables

Panel A: Realized Returns, the Expected Return Proxies, and the Cash Flow News Proxy

	r_{it+1}	r_{pe}	r_{peg}	r_{mpeg}	r_{gm}	$r_{\Delta agr}$	r_{ct}	r_{gls}	$c\hat{n}_{it+1}$
r_{it+1}		0.048 (1.16)	-0.032 (-1.40)	0.013 (0.54)	-0.006 (-0.34)	-0.010 (-0.52)	0.050 (1.68)	0.057 (2.03)	0.243 (13.71)
r_{pe}	0.056 (1.31)		0.384 (18.98)	0.537 (15.73)	0.339 (14.93)	0.325 (17.56)	0.713 (38.29)	0.599 (33.13)	-0.039 (-2.77)
r_{peg}	-0.028 (-1.13)	0.386 (19.48)		0.892 (44.39)	0.880 (37.33)	0.866 (26.11)	0.591 (33.64)	0.415 (23.05)	-0.141 (-12.44)
r_{mpeg}	0.023 (0.85)	0.577 (18.41)	0.860 (38.84)		0.956 (60.30)	0.817 (20.10)	0.664 (39.26)	0.394 (19.52)	-0.132 (-12.94)
r_{gm}	-0.003 (-0.13)	0.351 (13.87)	0.843 (31.81)	0.936 (47.21)		0.811 (18.89)	0.567 (30.02)	0.278 (11.25)	-0.134 (-13.31)
$r_{\Delta agr}$	0.015 (-0.68)	0.360 (19.89)	0.910 (101.45)	0.807 (38.93)	0.795 (32.16)		0.498 (20.54)	0.331 (14.84)	-0.129 (-11.89)
r_{ct}	0.073 (2.35)	0.713 (40.22)	0.620 (37.09)	0.724 (59.88)	0.610 (28.21)	0.573 (38.55)		0.428 (14.13)	-0.088 (-4.55)
r_{gls}	0.061 (1.95)	0.605 (38.42)	0.471 (28.48)	0.451 (25.16)	0.317 (12.12)	0.418 (24.07)	0.470 (17.86)		0.148 (4.11)
$c\hat{n}_{it+1}$	0.314 (16.99)	-0.030 (-1.98)	-0.222 (-20.03)	-0.178 (-14.93)	-0.191 (-13.53)	-0.210 (-19.73)	-0.113 (-6.16)	0.068 (3.43)	

Panel B: Correlations among Return News Proxies, Realized Returns, the Expected Return Proxies, and the Cash Flow News Proxy

Model	Pearson Product Moment			Spearman Rank Order		
	r_{it+1}	$e\hat{r}_{it+1}$	$c\hat{n}_{it+1}$	r_{it+1}	$e\hat{r}_{it+1}$	$c\hat{n}_{it+1}$
$r\hat{n}_{it+1}$ (pe)	-0.339 (-8.97)	-0.245 (-7.79)	0.055 (2.89)	-0.429 (-14.74)	-0.291 (-6.49)	0.125 (4.81)
$r\hat{n}_{it+1}$ (peg)	-0.174 (-5.36)	-0.338 (-10.77)	0.031 (1.77)	-0.200 (-7.17)	-0.375 (-12.00)	0.123 (4.49)
$r\hat{n}_{it+1}$ (mpeg)	-0.198 (-6.36)	-0.343 (-15.79)	0.026 (1.48)	-0.264 (-10.55)	-0.387 (-18.10)	0.090 (3.84)
$r\hat{n}_{it+1}$ (gm)	-0.153 (-5.29)	-0.356 (-14.91)	0.018 (1.10)	-0.214 (-9.17)	-0.402 (-17.71)	0.075 (3.69)
$r\hat{n}_{it+1}$ (Δagr)	-0.164 (-5.92)	-0.414 (-11.64)	0.018 (1.01)	-0.174 (-7.38)	-0.434 (-16.39)	0.097 (4.17)
$r\hat{n}_{it+1}$ (ct)	-0.134 (-3.63)	-0.286 (-11.44)	0.126 (8.21)	-0.223 (-6.58)	-0.323 (-10.27)	0.251 (10.22)
$r\hat{n}_{it+1}$ (gls)	-0.444 (-12.52)	-0.240 (-9.09)	0.024 (1.44)	-0.475 (-17.03)	-0.272 (-7.55)	-0.001 (-0.03)

All correlations reflect averages of the annual correlations. t-statistics (in parentheses) equal the ratio of the correlation to its temporal standard error. Cells above (below) the diagonal of the correlation matrix shown in Panel A correspond to Pearson product moment (Spearman rank order) correlations. The rows in Panel B are the correlations between the measure of return news for a particular model and realized returns, expected returns as measured via the model of interest, and the cash flow news proxy. r_{it+1} is the realized, continuously compounded return for year $t+1$. r_{pe} is the expected return estimate imputed from the price to forward earnings model. r_{peg} is the expected rate of return implied by the PEG ratio. r_{mpeg} is the expected rate of return implied by the modified PEG ratio. r_{gm} and $r_{\Delta agr}$ are the expected return estimates imputed from Gode and Mohanram's (2003) and Easton's (2004) implementation of the Ohlson and Juettner-Nauroth (2003) model, respectively. r_{ct} and r_{gls} are the expected return estimates imputed from Claus and Thomas's (2001) and Gebhardt et al.'s (2001) implementation of the residual income valuation model, respectively. All the expected return proxies represent continuously compounded returns. $c\hat{n}_{it+1}$ is the cash flow news proxy. $r\hat{n}_{it+1}(xxx)$ is the return news proxy for model xxx.

See Table 1 for further details.

than average negative information surprises about future cash flows during the time period under study.²³

The correlation between r_{gls} and the cash flow news proxy is positive and significant, however (Spearman correlation of 0.068 with a t-statistic of 3.43). A rationale for this phenomenon is as follows. There are two essential differences between r_{gls} and the remaining expected return proxies: (1) the residual income valuation model is anchored on year t equity book value, and (2) the terminal value correction used by Gebhardt et al. (2001) is a function of historical industry median return on equity (*ROE*). Thus, compared to the remaining estimates of expected returns, the amount of cross-sectional variation in r_{gls} attributable to variation in the firm-specific book-to-market ratio and variation in industry *ROE* is relatively high. These facts are a likely explanation for the positive correlation between r_{gls} and the estimate of cash flow news: variation in our cash flow news proxy is also a function of variation in equity book value and it is possible that analysts tend to revise their optimistic forecasts of *ROE* toward the industry *ROE*.²⁴

Table 3, Panel B summarizes the Pearson and Spearman correlations among our return news proxies and realized return, the cash flow news proxy, and the corresponding estimates of expected return. As expected, the correlation between each of the estimates of return news and realized returns are significantly less than zero (all the t-statistics are less than -3.5). The correlations between the return news proxies and the corresponding proxies for expected returns are all negative and statistically significant. These results are consistent with a decline in the equity premium during our sample period. As discussed in Section II, if the equity premium fell during the sample period, then stocks with high betas (and, thus, high expected returns) experienced larger than average downward revisions in expected future discount rates (i.e., m_{it+1}).²⁵ Hence, in order to avoid drawing spurious inferences attributable to omitted variables bias, it is crucial we include a proxy for return news in our regressions.

Multivariate Analyses

Results pertaining to our multivariate tests are shown in Tables 4 and 5. The regression coefficients shown in these tables are the temporal averages of the regression coefficients obtained from annual cross-sectional regressions. The t-statistics are computed via the approach described in Fama and MacBeth (1973).

Summary statistics from the estimation of the regression of realized returns on the empirical measures of its components (expected return, cash flow news, and return news)—Equation (2)—are presented in Table 4 for each of the expected return proxies. The estimates of the coefficient α_1 on the expected return proxies are negative for each of the regressions except the regression based on r_{ct} , and this estimate is not statistically different from zero. Moreover, untabulated results demonstrate that all of the estimates of α_1 are

²³ These correlations are also consistent with the notion that analysts' forecasts are too extreme in the sense that high forecasts are too high and low forecasts are too low. For example, if year zero analysts' forecasts are too high (too low), the implied discount rate will be biased upward (downward) and analysts' forecast errors and revisions will be negative (positive).

²⁴ We test this conjecture by estimating annual regressions of each expected return proxy on the contemporaneous book-to-market ratio and historical industry *ROE*. The average, untabulated R^2 s from these regressions are: r_{pe} 0.135, r_{peg} 0.027, r_{mpeg} 0.045, r_{gm} 0.029, $r_{\Delta agr}$ 0.026, r_{ct} 0.05, and r_{gls} 0.225. These results support our conjecture for two reasons: (1) the highest average R^2 is obtained in the regression involving r_{gls} , and (2) the average R^2 is higher when the correlation between the expected return proxy and the cash flow news proxy is higher.

²⁵ Alternatively, these negative correlations may be attributable to measurement error in our proxies. For example, a decline in analyst optimism may have occurred during our sample period, or extremely high (low) forecasts may be followed by larger than average downward (upward) revisions.

TABLE 4
Multivariate Analyses for Annual Portfolios

Regression: $r_{it+1} = \alpha_{0t+1} + \alpha_{1t+1} \times e\hat{r}_{it+1} + \alpha_{2t+1} \times c\hat{n}_{it+1} + \alpha_{3t+1} \times r\hat{n}_{it+1} + \varepsilon_{it+1}$

$e\hat{r}_{it+1}$	α_0	α_1	α_2	α_3	R^2
r_{pe}	0.16 (5.33)	-0.54 (-1.46)	0.29 (5.28)	0.10 (10.36)	0.22
r_{peg}	0.19 (6.26)	-0.67 (-2.81)	0.26 (5.59)	0.04 (6.43)	0.12
r_{mpeg}	0.15 (4.02)	-0.36 (-1.20)	0.27 (5.67)	0.05 (7.11)	0.13
r_{gm}	0.16 (4.90)	-0.40 (-1.75)	0.26 (5.67)	0.04 (5.98)	0.11
$r_{\Delta agr}$	0.20 (6.16)	-0.70 (-2.70)	0.26 (5.70)	0.04 (6.41)	0.11
r_{ct}	0.09 (1.98)	0.10 (0.25)	0.30 (5.09)	0.05 (4.29)	0.13
r_{gls}	0.24 (7.91)	-1.15 (-4.21)	0.29 (5.52)	0.19 (13.52)	0.30

Separate regressions are estimated for each of the 18 annual cross-sections of data. Parameter estimates equal the average of the annual regression coefficients. t-statistics (in parentheses) equal the ratio of the parameter estimates to their temporal standard errors. R^2 is the mean R^2 from the annual regressions. $e\hat{r}_{it+1}$, $c\hat{n}_{it+1}$, $r\hat{n}_{it+1}$, and r_{it+1} represent the expected return proxy, the cash flow news proxy, the return news proxy and the realized, continuously compounded return for year $t+1$. r_{pe} is the expected return estimate imputed from the price to forward earnings model. r_{peg} is the expected rate of return implied by the PEG ratio. r_{mpeg} is the expected rate of return implied by the modified PEG ratio. r_{gm} and $r_{\Delta agr}$ are the expected return estimates imputed from Gode and Mohanram's (2003) and Easton's (2004) implementation of the Ohlson and Juettner-Nauroth (2003) model, respectively. r_{ct} and r_{gls} are the expected return estimates imputed from Claus and Thomas's (2001) and Gebhardt et al.'s (2001) implementation of the residual income valuation model, respectively. All the expected return proxies represent continuously compounded returns.

See Table 1 for further details.

significantly less than 1 at the 0.01 level. These results suggest there is a considerable amount of measurement error in each of the expected return proxies. On the other hand, as discussed in Section II and Appendix B, the observed bias in α_1 may be attributable to other factors; hence, the need for additional analyses. As expected, the estimates of the coefficients on $c\hat{n}_{it+1}$ and $r\hat{n}_{it+1}$ are significantly positive. For example, for the regression based on r_{gls} , the estimate of the coefficient on $c\hat{n}_{it+1}$ is 0.29 (t-statistic of 5.52) and the estimate of the coefficient on $r\hat{n}_{it+1}$ is 0.19 (t-statistic of 13.52). Nonetheless, untabulated results demonstrate that these estimates are also significantly less than one, which implies that these constructs are also measured with error.

The results of estimating Equation (3) for each of our return proxies are shown in Table 5. Before proceeding with a discussion of the regression coefficients it is interesting to note that Equation (3) explains a considerable portion of the cross-sectional variation in the

TABLE 5
Multivariate Analyses for Annual Portfolios

Regressions: $v_{Cit+1} = \delta_{0t+1} + \delta_{1t+1} \times \varepsilon_{1it+1}^A + \delta_{2t+1} \times \varepsilon_{2it+1}^A + \delta_{3t+1} \times \varepsilon_{3it+1}^A + \mu_{it+1}$

$$v_{Cit+1}^M = \delta_{0t+1} + \delta_{1t+1}^M \times \varepsilon_{1it+1}^A + \delta_{2t+1} \times \varepsilon_{2it+1}^A + \delta_{3t+1} \times \varepsilon_{3it+1}^A + \mu_{it+1}$$

Model	Unmodified Noise Variables (v_{Cit+1} is the regressand)					Modified Noise Variables (v_{Cit+1}^M is the regressand)				
	δ_0	δ_1	δ_2	δ_3	R^2	δ_0	δ_1^M	δ_2	δ_3	R^2
pe	0.161 (5.33)	0.0076 (9.42)	0.132 (3.65)	1.214 (6.36)	0.94	0.161 (5.33)	0.0005 (1.42)	0.132 (3.65)	1.214 (6.36)	0.94
peg	0.189 (6.26)	0.0152 (7.70)	0.136 (4.01)	2.098 (7.89)	0.96	0.189 (6.26)	0.0012 (5.92)	0.136 (4.01)	2.098 (7.89)	0.96
mpeg	0.153 (4.02)	0.0142 (8.07)	0.139 (4.03)	2.093 (7.85)	0.96	0.153 (4.02)	0.0008 (3.76)	0.139 (4.03)	2.093 (7.85)	0.96
gm	0.162 (4.90)	0.0161 (7.99)	0.142 (4.08)	2.284 (8.32)	0.96	0.162 (4.90)	0.0010 (5.31)	0.142 (4.08)	2.284 (8.32)	0.96
Δ agr	0.203 (6.16)	0.0144 (8.02)	0.143 (4.30)	1.712 (8.71)	0.95	0.203 (6.16)	0.0008 (5.02)	0.143 (4.30)	1.712 (8.71)	0.96
ct	0.087 (1.98)	0.0070 (9.48)	0.106 (2.91)	1.130 (7.30)	0.93	0.087 (1.98)	0.0003 (1.25)	0.106 (2.91)	1.130 (7.30)	0.93
gls	0.239 (7.91)	0.0081 (9.28)	0.150 (4.02)	0.552 (7.77)	0.90	0.239 (7.91)	0.0004 (1.61)	0.150 (4.02)	0.552 (7.77)	0.91

Separate regressions are estimated for each of the 18 annual cross-sections of data. Parameter estimates equal the average of the annual regression coefficients. t-statistics (in parentheses) equal the ratio of the parameter estimates to their temporal standard errors. R^2 is the mean R^2 from the annual regressions.

$v_{Cit+1} = r_{it+1} - e\hat{r}_{it+1} - c\hat{n}_{it+1} - r\hat{n}_{it+1}$, where $e\hat{r}_{it+1}$, $c\hat{n}_{it+1}$, $r\hat{n}_{it+1}$, and r_{it+1} represent the expected return proxy, the cash flow news proxy, the return news proxy and the realized, continuously compounded return for year $t+1$. All the expected return proxies represent continuously compounded returns. See Table 1 for further details.

$$v_{Cit+1}^M = v_{Cit+1} - \{\sigma(e\hat{r}_{it+1}, c\hat{n}_{it+1}) + \sigma(e\hat{r}_{it+1}, r\hat{n}_{it+1})\} \times \varepsilon_{1it+1}^A$$

$$\varepsilon_{1it+1}^A = \frac{-\varepsilon_{1it+1} - \beta_{10t+1}}{\sigma^2(\varepsilon_{1it+1})}, \varepsilon_{2it+1}^A = \frac{-\varepsilon_{2it+1} - \beta_{20t+1}}{\sigma^2(\varepsilon_{2it+1})}, \text{ and } \varepsilon_{3it+1}^A = \frac{-\varepsilon_{3it+1} - \beta_{30t+1}}{\sigma^2(\varepsilon_{3it+1})}$$

$\sigma(e\hat{r}_{it+1}, c\hat{n}_{it+1})$ ($\sigma(e\hat{r}_{it+1}, r\hat{n}_{it+1})$) is the covariance between the expected return proxy and the cash flow news (return news) proxy. The β , ε , and $\sigma^2(\varepsilon)$ terms shown above are taken from the following first-stage regressions:

$$e\hat{r}_{it+1} = \beta_{10t+1} + \beta_{11t+1} \times c\hat{n}_{it+1} + \beta_{12t+1} \times r\hat{n}_{it+1} + \varepsilon_{1it+1}$$

$$c\hat{n}_{it+1} = \beta_{20t+1} + \beta_{21t+1} \times e\hat{r}_{it+1} + \beta_{22t+1} \times r\hat{n}_{it+1} + \varepsilon_{2it+1}$$

$$r\hat{n}_{it+1} = \beta_{30t+1} + \beta_{31t+1} \times e\hat{r}_{it+1} + \beta_{32t+1} \times c\hat{n}_{it+1} + \varepsilon_{3it+1}$$

The regression coefficients relating to the measurement error variance of $e\hat{r}_{it+1}$ are:

$$\delta_{1it+1} = \sigma^2(v_{1it+1}) + \{\sigma(v_{1it+1}, v_{2it+1}) + \sigma(v_{1it+1}, v_{3it+1})\} + \{\sigma(er_{it+1}, v_{2it+1}) + \sigma(er_{it+1}, v_{3it+1})\}$$

$$\delta_{1t+1}^M = \sigma^2(v_{1it+1}) - \{\sigma(er_{it+1}, c\hat{n}_{it+1}) + \sigma(er_{it+1}, r\hat{n}_{it+1})\} - \{\sigma(v_{1it+1}, c\hat{n}_{it+1}) + \sigma(v_{1it+1}, r\hat{n}_{it+1})\}$$

$\sigma^2(v_{1it+1})$ is the measurement error variance of the expected return proxy, $\sigma(v_{1it+1}, v_{2it+1})$ ($\sigma(v_{1it+1}, v_{3it+1})$) is the covariance between the measure error in the expected return proxy and the measurement error in the cash flow news (return news) proxy, $\sigma(er_{it+1}, v_{2it+1})$ ($\sigma(er_{it+1}, v_{3it+1})$) is the covariance between true expected returns and the measurement error in the cash flow news (return news) proxy, $\sigma(er_{it+1}, c\hat{n}_{it+1})$ ($\sigma(er_{it+1}, r\hat{n}_{it+1})$) is the covariance between true expected returns and true cash flow news (return news), and $\sigma(v_{1it+1}, c\hat{n}_{it+1})$ ($\sigma(v_{1it+1}, r\hat{n}_{it+1})$) is the covariance between the measurement error in the expected return proxy and true cash flow news (return news).

combined measurement error in our estimates of expected returns (i.e., v_{Cit+1}).²⁶ For example, the R^2 based on r_{gls} is 0.90. This implies the return decomposition developed by Vuolteenaho (2002) provides a useful characterization of the components of realized returns.

Turning to the regression coefficients, two implications are immediate. First, all of the expected return proxies contain statistically significant measurement error. For example, the proxy with the highest measurement error variance is r_{gm} (δ_1 of 0.0161, t-statistic of 7.99). Second, while r_{ct} contains the least measurement error (δ_1 of 0.007, t-statistic of 9.48), the simplest proxy, r_{pe} , has only a slightly higher measurement error variance (δ_1 of 0.0076, t-statistic of 9.42). Moreover, untabulated results demonstrate that the measurement error in r_{pe} is not significantly greater than the measurement error in r_{ct} or any of the remaining proxies.²⁷

Inferences based on variation in δ_1 are predicated on the assumption that the correlations between the measurement error in our expected return proxies and the measurement error in the remaining proxies are the same for each of the expected return proxies. As discussed in Section II this assumption may not be valid. Thus, we evaluate the modified noise variables. The results of these analyses are summarized on the right-hand side of Table 5.

The expected return proxy with the lowest estimate of δ_1^M is r_{ct} (0.0003, t-statistic of 1.25). However, the coefficient on r_{ct} is only slightly less than the estimate of δ_1^M pertaining to r_{pe} (0.0005, t-statistic of 1.42), and the difference between these two coefficients is statistically insignificant (untabulated t-statistic of 0.99). Moreover, the coefficient on r_{pe} is smaller than each of the coefficients on the remaining proxies except r_{gls} , and the coefficient on r_{gls} is not statistically different from the coefficient on r_{pe} .

Sensitivity Analyses

The results presented in Tables 4 and 5 are striking. None of the expected return proxies we evaluate has a statistically positive association with realized return even though we control for information surprises attributable to changes in expectations about future cash flows and future discount rates. Further, none of the proxies has less measurement error than the simplest proxy, r_{pe} , which is based on a restrictive set of assumptions about future growth and profitability. Taken together these results suggest the proxies we evaluate are unreliable. Given the provocative nature of this conclusion, we discuss the (untabulated) results of three sets of robustness checks.

In our first set of robustness checks we evaluate the sensitivity of our results to assumptions about ρ . The results shown in Tables 4 and 5 are based on the assumption that ρ varies with the price-to-dividend ratio; however, it is possible that ρ varies for other risk-related reasons. To alleviate this concern we re-estimate the regressions underlying Tables 4 and 5 using values of ρ that vary with: (1) size (equity market value), and (2) the debt-to-equity ratio.²⁸ Results based on these robustness checks are similar to the results shown

²⁶ The untabulated means (medians) of v_{Cit+1} for the expected return proxies are: r_{pe} 0.09 (0.03), r_{peg} -0.01 (0.01), r_{mpeg} -0.02 (-0.02), r_{gm} -0.05 (-0.03), $r_{\Delta agr}$ -0.03 (-0.01), r_{ct} -0.07 (-0.03), and r_{gls} 0.02 (0.01). These amounts suggest that, for several of the expected return proxies, the average (median) combined measurement error is nontrivial. They are not, however, informative about the cross-sectional characteristics of the proxies as bias does not imply noise.

²⁷ The measurement error in r_{pe} is significantly *lower* than the measurement error in all of the expected return proxies derived from the abnormal growth in earnings model (i.e., Equation (6)). To illustrate how we test the difference between δ_1 for two expected return proxies, consider r_{pe} and r_{peg} . We begin by calculating annual differences between the value of δ_1 pertaining to r_{pe} and the value of δ_1 pertaining to r_{peg} . Next, we calculate the mean and standard error of these annual differences, and form t-statistics by taking the ratio of these two numbers.

²⁸ We use an approach similar to the approach shown in Appendix B to estimate different values of ρ for size (debt-to-equity) quintiles.

in Tables 4 and 5. We also obtain similar results to those shown in Tables 4 and 5 when, as per Vuolteenaho (2002), we assume ρ is equal to 0.967 for all firm-year observations.

In our second set of robustness checks we evaluate whether our results are attributable to extreme observations. We begin by re-estimating Equation (2) via rank regressions, which yield inferences similar to those based on the results shown on Table 4.²⁹ Rank regressions cannot be used to estimate δ_1 and δ_1^M ; hence, to evaluate the sensitivity of our estimates of the measurement error in each proxy we re-estimate δ_1 and δ_1^M after deleting firm-years with values of r_{it+1} , $e\hat{f}_{it+1}$, $c\hat{n}_{it+1}$, or $r\hat{n}_{it+1}$ in the top or bottom fifth percentile of the annual cross-sectional distribution.³⁰ This modification does not change our inferences.

Finally, we evaluate the robustness of our Fama and MacBeth (1973) t-statistics by calculating t-statistics on precision weighted regression coefficients. Specifically, we divide each annual coefficient by its contemporaneous standard error, and calculate t-statistics by dividing the mean of the precision weighted coefficients by their temporal standard errors. These t-statistics are similar to those shown on Tables 4 and 5.

V. INSTRUMENTAL VARIABLES, GROUPING, AND LONG-TERM GROWTH PARTITIONS

Two common approaches for dealing with measurement error are: (1) instrumental variables, and (2) grouping. In this section we examine the effect these methods have on the reliability of the expected return proxies. Our motivation for this analysis is two-fold. First, if instrumental variables or grouping mitigates the measurement error in the expected return proxies, business practitioners and researchers can use these methods as the basis for developing estimates of expected return. Second, these methods provide an additional means of evaluating the robustness of the results discussed in Section IV. In particular, we demonstrate that for each expected return proxy the estimate of α_1 from Equation (2) is not statistically positive even after we attempt to purge the proxy of its measurement error. In addition, r_{pe} continues to perform as well as less simple proxies.³¹

In this section we also examine how our results vary with the magnitude of analysts' forecasts of long-term growth and with the magnitude of analysts' *ex post* forecast errors. Consistent with La Porta (1996) and Frankel and Lee (1998) we demonstrate a positive association between analysts' forecasts of the long-term earnings growth rate, ltg_i , and errors in analysts' forecasts of earnings. Next, by combining evidence about the variation in α_1 and δ_1^M across partitions of the data formed on the basis of ltg_i with evidence about the variation in α_1 and δ_1^M across partitions of the data formed on the basis of *ex post* analysts' forecast errors, we demonstrate that: (1) the results documented in Section IV are attributable to errors in the earnings forecasts underlying our estimates of expected return, and (2) ltg_i is a useful *ex ante* indicator of forecast quality. This evidence is useful for three reasons. First, it sheds light on potential future research opportunities (e.g., development of better earnings forecast models or statistical approaches to purge the error from analysts'

²⁹ Ranks are determined separately for each annual cross-section and the t-statistics pertaining to the rank regressions are estimated via the Fama and MacBeth (1973) procedure.

³⁰ Valid comparisons of δ_1 (δ_1^M) across expected return proxies can only be drawn if the same set of observations underlies each estimate of δ_1 (δ_1^M). Hence, for the purposes of this robustness check we discard observations with values of $e\hat{f}_{it+1}$ or $r\hat{n}_{it+1}$ in the top or bottom fifth percentile for *any* of the expected return proxies when estimating δ_1 (δ_1^M) for a *particular* expected return proxy. This leads to a considerably smaller sample size of 8,748 firm-year observations.

³¹ We also evaluate a proxy, r_{avg} , which equals the average of r_{pe} , r_{peg} , r_{mpeg} , r_{gm} , r_{dagr} , r_{cr} , and r_{gls} . Untabulated results demonstrate that the estimate of α_1 corresponding to r_{avg} is negative, and r_{avg} does not have a lower measurement error variance than r_{pe} .

forecasts).³² Second, this evidence provides researchers with guidance regarding the reliability of the expected return proxies in different empirical settings. For instance, researchers should be particularly careful when interpreting evidence about the cross-sectional determinants of the expected return proxies when this evidence is based on a sample that primarily consists of high ltg_i firms. Finally, we show that for observations in the bottom third of the distribution of ltg_i , r_{ct} contains very little measurement error, which suggests this proxy is a reliable measure of expected returns for a nontrivial subset of our sample.³³

Instrumental Variables

We implement the instrumental variables procedure in the following manner. First, each of the expected return proxies is regressed on instruments that are for the purposes of these analyses assumed to be correlated with true expected return but uncorrelated with the measurement error. Next, the fitted values from the instrumental variables regression are evaluated in the same manner as the underlying expected return proxies.

We select the following instruments: CAPM beta, market capitalization, the ratio of equity book value to equity market value, the standard deviation of past returns, and industry type. Before discussing the empirical results pertaining to the instrumental variables analysis, we briefly motivate our choice of instruments.

Well-known theoretical results developed by Sharpe (1964), Lintner (1965), and Mossin (1966) suggest that beta is an appropriate measure of systematic risk. Our firm-year estimates of beta, $BETA_{it}$, are derived from regressions of monthly returns on contemporaneous excess returns (i.e., market return less the yield on a one-month treasury bill) where the data are drawn from the 60-month period prior to the earnings forecast date. Malkiel and Xu (1997) focuses on total risk as measured by the variance of returns. We use the standard deviation of the daily returns occurring during the year leading up to the forecast date, SD_{it} , as our measure of total risk. A variety of studies (e.g., Banz 1981; Fama and French 1992) document a negative association between size and realized returns suggesting that market capitalization as of the earnings forecast date, $SIZE_{it}$, is a potential proxy for risk. Consistent with Fama and French (1992) and Berk et al. (1999), we use the ratio of the book value of common equity to the market value of common equity at the earnings forecast date, BM_{it} , as another measure of risk. Finally, a number of papers (e.g., Fama and French 1997; Gebhardt et al. 2001) show that the equity premium differs across industries. Similar to Gebhardt et al. (2001) we use the average of the firm-specific estimates of expected return, IND_{it} , as our proxy for industry type (industry classifications are the same as those in Fama and French [1997]).

The results of estimating regressions of each of the expected return proxies on the four risk proxies ($BETA_{it}$, SD_{it} , $SIZE_{it}$, and BM_{it}) are shown on the left-hand side of Table 6. For all of the expected return proxies other than r_{pe} and r_{ct} the estimates of the coefficients on $BETA_{it}$ and SD_{it} are positive (the coefficient on $BETA_{it}$ is not statistically significant in the r_{mpg} and r_{gls} regressions). Contrary to expectations, the estimates of the coefficient on $SIZE_{it}$ are not significantly less than zero (at the 0.05 level) for all proxies other than r_{pe} (-0.000 with a t-statistic of -3.77). A possible explanation for these results is that the I/B/E/S sample on which our analyses are based tends to include larger firms. Finally, all of the proxies except r_{ct} have a positive and statistically significant association with BM_{it} .

³² For example, Guay et al. (2003) provide evidence consistent with the notion that measurement error in accounting based estimates of the expected rate of return is partially attributable to sluggishness in analysts updating of earnings forecasts.

³³ Inferences based on the results obtained from the use of instrumental variables, grouping, ltg_i partitions, and partitions based on analysts' forecast errors are not sensitive to the robustness checks discussed in Section IV.

TABLE 6
Instrumental Variables (IV) Regressions

Regressions:

$$e\hat{r}_{it+1} = \theta_{0t} + \theta_{1t} \times BETA_{it} + \theta_{2t} \times SD_{it} + \theta_{3t} \times SIZE_{it} + \theta_{4t} \times BM_{it} + \psi_{it} \quad (\text{IV Regression One})$$

$$e\hat{r}_{it+1} = \theta_{0t} + \theta_{1t} \times BETA_{it} + \theta_{2t} \times SD_{it} + \theta_{3t} \times SIZE_{it} + \theta_{4t} \times BM_{it} + \theta_{5t} \times IND_{it} + \psi_{it} \quad (\text{IV Regression Two})$$

$e\hat{r}_{it+1}$	Regression One (excluding <i>IND</i>)						Regression Two (including <i>IND</i>)						
	θ_{0t}	θ_{1t}	θ_{2t}	θ_{3t}	θ_{4t}	R^2	θ_{0t}	θ_{1t}	θ_{2t}	θ_{3t}	θ_{4t}	θ_{5t}	R^2
r_{pe}	0.096 (12.27)	-0.005 (-2.15)	-0.419 (-3.55)	-0.000 (-3.77)	0.023 (8.53)	0.16	0.002 (0.77)	-0.001 (-0.96)	-0.051 (-0.87)	0.000 (3.53)	0.016 (6.89)	0.905 (75.46)	0.42
r_{peg}	0.083 (28.94)	0.010 (5.20)	0.716 (12.37)	-0.000 (-0.34)	0.008 (4.62)	0.13	-0.003 (-2.05)	0.006 (5.63)	0.531 (13.03)	-0.000 (-2.39)	0.007 (4.48)	0.843 (44.43)	0.27
r_{mpeg}	0.112 (21.24)	0.002 (1.15)	0.175 (2.15)	0.000 (0.55)	0.013 (6.81)	0.07	-0.002 (-0.76)	0.002 (2.26)	0.211 (4.07)	0.000 (0.90)	0.010 (5.83)	0.916 (51.27)	0.21
r_{gm}	0.117 (24.17)	0.003 (3.33)	0.304 (4.57)	0.000 (1.45)	0.010 (5.34)	0.06	-0.001 (-0.54)	0.002 (3.60)	0.250 (5.14)	0.000 (0.33)	0.008 (5.05)	0.914 (48.45)	0.17
$r_{\Delta agr}$	0.111 (32.41)	0.006 (4.66)	0.452 (7.95)	-0.000 (-0.69)	0.008 (5.09)	0.09	0.003 (1.44)	0.004 (5.25)	0.349 (8.37)	-0.000 (-2.00)	0.007 (4.86)	0.862 (44.50)	0.19
r_{ct}	0.126 (15.55)	-0.001 (-0.51)	0.058 (0.56)	-0.000 (-0.93)	-0.004 (-1.96)	0.08	0.002 (0.53)	0.001 (0.52)	0.149 (2.15)	0.000 (2.11)	-0.006 (-2.89)	0.969 (46.54)	0.26
r_{gls}	0.096 (14.43)	0.002 (1.28)	0.190 (1.92)	0.000 (1.38)	0.021 (9.95)	0.17	-0.007 (-3.20)	0.002 (3.25)	0.128 (1.73)	0.000 (2.16)	0.019 (9.23)	0.924 (74.14)	0.40

Separate regressions are estimated for each of 18 annual cross-sections of data. Parameter estimates equal the average of the annual regression coefficients. t-statistics (in parentheses) are the ratio of the parameter estimates to their temporal standard errors. R^2 is the average of the annual R^2 statistics. *BETA* is the capital asset pricing model beta estimated over the 60 months prior to the end of year t , *SD* is the standard deviation of daily returns in year t , *SIZE* is the market capitalization at the end of year t , *BM* is the ratio of the book value of common equity to the market value of common equity at the end of year t , and *IND* is the mean at the end of year t of the expected return proxies across firms in the same industry group. r_{pe} is the expected return estimate imputed from the price to forward earnings model. r_{peg} is the expected rate of return implied by the PEG ratio. r_{mpeg} is the expected rate of return implied by the modified PEG ratio. r_{gm} and $r_{\Delta agr}$ are the expected return estimates imputed from Gode and Mohanram's (2003) and Easton's (2004) implementation of the Ohlson and Juettner-Nauroth (2003) model, respectively. r_{ct} and r_{gls} are the expected return estimates imputed from Claus and Thomas's (2001) and Gebhardt et al.'s (2001) implementation of the residual income valuation model, respectively.

All the expected return proxies represent continuously compounded returns.

See Table 1 for further details.

It is evident from the results in the right-hand side of Table 6 that industry type captures much of the variation in the expected returns proxies. For example, the estimate of the coefficient on IND_{it} for the regression where the dependent variable is r_{ct} is 0.969 with a t-statistic of 46.54. Nonetheless, the coefficients on $BETA_{it}$, SD_{it} , $SIZE_{it}$, and BM_{it} are essentially unchanged with the exception that r_{pe} and r_{ct} are positively associated with $SIZE_{it}$ after IND_{it} is included in the regression.

As shown on Table 7, the fitted values taken from the instrumental variables regressions have lower measurement error variances (i.e., δ_1^M) than the raw proxies. On the other hand, only r_{ct} has a fitted value with a lower measurement error variance than the fitted value of r_{pe} , and untabulated results demonstrate that this difference is only statistically significant when the fitted values are taken from regressions that include IND_{it} (t-statistic of 3.55). Moreover, none of the estimates of α_1 shown on Table 7 are statistically greater than zero. Hence, even after attempting to purge the proxies of their measurement error via instrumental variables, we continue to find little evidence supporting an argument that the proxies we evaluate are reliable measures of expected returns.

Several studies (e.g., Botosan and Plumlee 2005; Gebhardt et al. 2001; Gode and Mohanram 2003) use coefficients from regressions of proxies for expected returns on various risk factors (or correlations between proxies for expected returns and risk factors) as means of ranking expected returns proxies. It is evident from the coefficient estimates on the right-hand side of Table 6 that the expected return proxy that is *best* according to the criteria adopted by these authors is r_{peg} . Specifically, in the r_{peg} regression, the t-statistic for the estimated coefficients on $BETA_{it}$ and SD_{it} (5.63 and 13.03, respectively) are higher than the corresponding t-statistics in the other regressions, the estimate of the coefficient on $SIZE_{it}$ is negative (t-statistic of -2.39), and the coefficients on BM_{it} and IND_{it} are highly significant. Nonetheless, the evidence in Table 7 demonstrates that r_{peg} is one of the *worst* proxies as it has the highest δ_1^M and one of the lowest estimates of α_1 . In other words, ranking expected returns on the basis of correlations with potential risk factors may lead to erroneous conclusions.

Grouping

The instrumental variables procedure combines variables that are, under the maintained hypothesis, expected to be correlated with expected returns. Grouping, on the other hand, focuses on each variable separately. We group observations into annual portfolios of 10 based on variables designed to minimize the within portfolio variation in the construct of interest (e.g., beta) and maximize the variation across portfolios.³⁴ All analyses that are conducted at the firm-specific level are repeated using portfolio averages (i.e., average realized return, average expected return, average cash flow news, and average return news).

The results of our portfolio level analyses shown in Table 8 lead to inferences that are similar to those based on the results shown in Tables 4, 5, and 7. In particular, none of the estimates of α_1 taken from Equation (2) is statistically greater than zero. Moreover, the rankings of δ_1^M pertaining to the portfolio averages of the expected return proxies are, by and large, similar to the rankings of δ_1^M pertaining to the firm-specific estimates. There is one exception, however: the simplest expected return proxy, r_{pe} , does not have the lowest

³⁴ Analyses based on portfolios of size 20 lead to similar inferences. Nonetheless, it is possible that the use of even larger portfolios leads to a significant reduction in measurement error. Unfortunately, we do not have sufficient degrees of freedom to reliably evaluate this assertion; hence, we cannot make definitive statements about the reliability of the proxies at the portfolio level. Furthermore, we cannot assess the accuracy of estimates of the expected rate of return that are specifically designed for large portfolios of observations (such as, Easton et al. 2002; O'Hanlon and Steele 2000).

TABLE 7
Multivariate Analyses for Annual Portfolios Using Fitted Estimates of Expected Returns
from Instrumental Variables (IV) Regressions

Regressions:

$$r_{it+1} = \alpha_{0t+1} + \alpha_{1t+1} \times e\hat{r}_{it+1} + \alpha_{2t+1} \times c\hat{n}_{it+1} + \alpha_{3t+1} \times r\hat{n}_{it+1} + \varepsilon_{it+1}$$

$$v_{Cit+1}^M = \delta_{0t+1} + \delta_{1t+1}^M \times \varepsilon_{1it+1}^A + \delta_{2t+1} \times \varepsilon_{2it+1}^A + \delta_{3t+1} \times \varepsilon_{3it+1}^A + \mu_{it+1}$$

Model	α_1		δ_1^M	
	IV Regression One	IV Regression Two	IV Regression One	IV Regression Two
pe	-1.40 (-1.63)	-0.69 (-1.16)	0.0001 (0.79)	0.0003 (1.11)
peg	-3.49 (-3.23)	-1.77 (-2.58)	0.0005 (3.59)	0.0006 (3.87)
mpeg	-2.89 (-1.54)	-1.38 (-1.53)	0.0002 (2.28)	0.0003 (2.21)
gm	-7.36 (-3.19)	-1.79 (-2.09)	0.0002 (3.02)	0.0003 (2.98)
Δ agr	-4.69 (-2.09)	-2.76 (-2.62)	0.0003 (3.20)	0.0004 (3.34)
ct	0.00 (0.00)	0.84 (1.13)	-0.0001 (-1.28)	-0.0001 (-0.40)
gls	-2.31 (-3.22)	-1.19 (-2.52)	0.0003 (3.87)	0.0005 (2.83)

Separate regressions are estimated for each of the 18 annual cross-sections of data. Parameter estimates equal the average of the annual regression coefficients. t-statistics (in parentheses) equal the ratio of the parameter estimates to their temporal standard errors. R^2 is the mean R^2 from the annual regressions.

$v_{Cit+1} = r_{it+1} - e\hat{r}_{it+1} - c\hat{n}_{it+1} - r\hat{n}_{it+1}$, where $e\hat{r}_{it+1}$, $c\hat{n}_{it+1}$, $r\hat{n}_{it+1}$, and r_{it+1} represent the predicted expected return proxy taken from the following instrumental variables regressions:

$$e\hat{r}_{it+1} = \theta_{0t} + \theta_{1t} \times BETA_{it} + \theta_{2t} \times SD_{it} + \theta_{3t} \times SIZE_{it} + \theta_{4t} \times BM_{it} + \psi_{it} \quad (\text{IV Regression One})$$

$$e\hat{r}_{it+1} = \theta_{0t} + \theta_{1t} \times BETA_{it} + \theta_{2t} \times SD_{it} + \theta_{3t} \times SIZE_{it} + \theta_{4t} \times BM_{it} + \theta_{5t} \times IND_{it} + \psi_{it}$$

(IV Regression Two)

In the above regressions $BETA$ is the capital asset pricing model beta estimated over the 60 months prior to the end of year t , SD is the standard deviation of daily returns in year t , $SIZE$ is the market capitalization at the end of year t , BM is the ratio of the book value of common equity to the market value of common equity at the end of year t , and IND is the mean at the end of year t of the expected return proxies across firms in the same industry group.

The cash flow news proxy, the return news proxy, and the realized, continuously compounded return for year $t+1$. All the expected return proxies represent continuously compounded returns.

See Table 1 for further details.

$$v_{Cit+1}^M = v_{Cit+1} - \{\sigma(e\hat{r}_{it+1}, c\hat{n}_{it+1}) + \sigma(e\hat{r}_{it+1}, r\hat{n}_{it+1})\} \times \varepsilon_{1it+1}^A$$

$$\varepsilon_{1it+1}^A = \frac{-\varepsilon_{1it+1} - \beta_{10t+1}}{\sigma^2(\varepsilon_{1it+1})}, \varepsilon_{2it+1}^A = \frac{-\varepsilon_{2it+1} - \beta_{20t+1}}{\sigma^2(\varepsilon_{2it+1})}, \text{ and } \varepsilon_{3it+1}^A = \frac{-\varepsilon_{3it+1} - \beta_{30t+1}}{\sigma^2(\varepsilon_{3it+1})}$$

(continued on next page)

TABLE 7 (continued)

$\sigma(e\hat{r}_{it+1}, c\hat{n}_{it+1})$ ($\sigma(e\hat{r}_{it+1}, r\hat{n}_{it+1})$) is the covariance between the expected return proxy and the cash flow news (return news) proxy. The β , ε , and $\sigma^2(\varepsilon)$ terms shown above are taken from the following first-stage regressions:

$$\begin{aligned} e\hat{r}_{it+1} &= \beta_{10t+1} + \beta_{11t+1} \times c\hat{n}_{it+1} + \beta_{12t+1} \times r\hat{n}_{it+1} + \varepsilon_{1it+1} \\ c\hat{n}_{it+1} &= \beta_{20t+1} + \beta_{21t+1} \times e\hat{r}_{it+1} + \beta_{22t+1} \times r\hat{n}_{it+1} + \varepsilon_{2it+1} \\ r\hat{n}_{it+1} &= \beta_{30t+1} + \beta_{31t+1} \times e\hat{r}_{it+1} + \beta_{32t+1} \times c\hat{n}_{it+1} + \varepsilon_{3it+1} \end{aligned}$$

The regression coefficients relating to the measurement error variance of $e\hat{r}_{it+1}$ are:

$$\delta_{it+1}^M = \sigma^2(v_{it+1}) - \{\sigma(er_{it+1}, cn_{it+1}) + \sigma(er_{it+1}, m_{it+1})\} - \{\sigma(v_{it+1}, cn_{it+1}) + \sigma(v_{it+1}, m_{it+1})\}$$

$\sigma^2(v_{it+1})$ is the measurement error variance of the expected return proxy, $\sigma(er_{it+1}, cn_{it+1})$ ($\sigma(er_{it+1}, m_{it+1})$) is the covariance between true expected returns and true cash flow news (return news), and $\sigma(v_{it+1}, cn_{it+1})$ ($\sigma(v_{it+1}, m_{it+1})$) is the covariance between the measurement error in the expected return proxy and true cash flow news (return news).

measurement error variance (i.e., δ_1^M) when portfolios are formed on the basis of the book-to-market ratio.

Long-Term Growth Partitions

First, for each annual cross-section of data we partition observations into three groups: (1) bottom third of the distribution of ltg_i (low ltg_i), (2) middle third of the distribution of ltg_i , (medium ltg_i), and (3) top third of the distribution of ltg_i , (high ltg_i). Second, we calculate descriptive statistics for each of the ltg_i partitions for ltg_i and the absolute value of the difference between firm i 's actual return on equity in year $t+2$ and the forecast as of year t of firm i 's year $t+2$ return on equity ($|FE_ROE_i|$). As shown in Panel A of Table 9, $|FE_ROE_i|$ is increasing in ltg_i . For example, the mean of $|FE_ROE_i|$ for observations in the low ltg_i is 5 (7) percent lower than the mean of $|FE_ROE_i|$ for observations in the medium (high) ltg_i partition, and the untabulated t-statistic for this difference is -6.26 (-8.95).³⁵ These results are consistent with those shown in Frankel and Lee (1998) and La Porta (1996), and imply that ltg_i is a reasonable *ex ante* proxy for *ex post* forecast errors.

Second, for each proxy we estimate α_1 and δ_1^M via Fama and MacBeth (1973) regressions for each of the three ltg_i partitions. Taken together with the descriptive statistics shown on Panel A of Table 9, the regression results shown on Panel B of Table 9, imply that there is a positive association between the reliability of the expected return proxies and the quality of analysts' earnings forecasts. In particular, as ltg_i increases, α_1 declines and δ_1^M increases for four of the seven proxies (r_{pe} , r_{mpeg} , $r_{\Delta agr}$, and r_{ct}). Moreover, estimates of α_1 for firm-years with low ltg_i are positive for all of the proxies except r_{gls} . It is also pertinent that, for the low ltg_i partition, the estimate of α_1 corresponding to r_{ct} is statistically greater than zero (t-statistic of 3.04) and r_{ct} has a statistically lower measurement error variance (i.e., δ_1^M)

³⁵ The mean of $|FE_ROE_i|$ for observations in the medium ltg_i partition is 2 percent lower than the mean of $|FE_ROE_i|$ for observations in the high ltg_i partition, and the untabulated t-statistic for this difference is -3.18 . Moreover, as shown in Panel A of Table 9, $|FE_ROE_i|$ is monotonically increasing in ltg_i for all percentiles of $|FE_ROE_i|$, and all of the t-statistics (untabulated) associated with these differences are greater than 3 in absolute value with the exception of the t-statistic pertaining to the difference between the 95th percentile of $|FE_ROE_i|$ for firms in the medium ltg_i partition and the 95th percentile of $|FE_ROE_i|$ for firms in the high ltg_i partition. The t-statistics equal the mean of the annual differences divided by their standard error. Finally, the untabulated Pearson (Spearman) correlation between ltg_i and $|FE_ROE_i|$ is 0.13 (0.25) with a t-statistic of 6.41 (17.46).

TABLE 8
**Multivariate Analyses for Annual Portfolios Using Averages from Portfolios of 10 Formed on the Basis of Beta,
the Standard Deviation of Monthly Returns, Market Capitalization, and the Book-to-Market Ratio**

Regressions:

$$r_{it+1} = \alpha_{0t+1} + \alpha_{1t+1} \times e\hat{r}_{it+1} + \alpha_{2t+1} \times c\hat{n}_{it+1} + \alpha_{3t+1} \times r\hat{n}_{it+1} + \varepsilon_{it+1}$$

$$v_{Cit+1}^M = \delta_{0t+1} + \delta_{1t+1}^M \times \varepsilon_{1it+1}^A + \delta_{2t+1} \times \varepsilon_{2it+1}^A + \delta_{3t+1} \times \varepsilon_{3it+1}^A + \mu_{it+1}$$

Model	α_1				δ_1^M			
	BETA Portfolios	SD Portfolios	SIZE Portfolios	BM Portfolios	BETA Portfolios	SD Portfolios	SIZE Portfolios	BM Portfolios
pe	-0.11 (-0.18)	0.01 (0.02)	-0.82 (-1.60)	-2.34 (-4.42)	-0.0001 (-0.84)	-0.0001 (-1.27)	0.0001 (2.03)	0.0007 (5.95)
peg	-0.76 (-1.37)	-1.61 (-2.74)	-1.05 (-2.32)	-1.31 (-3.34)	0.0003 (3.29)	0.0005 (3.77)	0.0003 (4.99)	0.0003 (7.32)
mpeg	-0.10 (-0.23)	-0.53 (-0.76)	-0.88 (-1.76)	-1.78 (-3.39)	0.0001 (1.51)	0.0001 (1.54)	0.0002 (3.76)	0.0004 (6.12)
gm	-0.49 (-1.15)	-1.18 (-2.09)	-1.00 (-2.28)	-1.48 (-3.40)	0.0002 (2.98)	0.0003 (2.67)	0.0002 (5.06)	0.0004 (5.79)
Δ agr	-1.05 (-1.61)	-1.88 (-2.24)	-1.09 (-2.07)	-2.08 (-4.27)	0.0002 (2.95)	0.0003 (3.19)	0.0002 (4.44)	0.0003 (6.13)
ct	0.48 (0.88)	0.52 (0.77)	-0.74 (-1.22)	-0.36 (-0.50)	0.0000 (-0.16)	0.0000 (-0.22)	0.0001 (1.90)	0.0001 (1.66)
gl	-0.38 (-0.89)	-0.95 (-1.66)	-1.02 (-2.98)	-1.88 (-5.17)	0.0000 (0.04)	0.0001 (1.03)	0.0002 (2.70)	0.0003 (4.42)

(continued on next page)

TABLE 8 (continued)

Separate regressions are estimated for each of the 18 annual cross-sections of data. Parameter estimates equal the average of the annual regression coefficients. t-statistics (in parentheses) equal the ratio of the parameter estimates to their temporal standard errors. R^2 is the mean R^2 from the annual regressions.

$v_{Cit+1} = r_{it+1} - e\hat{r}_{it+1} - c\hat{n}_{it+1} - m\hat{n}_{it+1}$, where $e\hat{r}_{it+1}$, $c\hat{n}_{it+1}$, $m\hat{n}_{it+1}$, and r_{it+1} represent the portfolio average of the expected return proxy, the cash flow news proxy, the return news proxy, and realized, continuously compounded return for the year $t+1$. Portfolios of 10 are formed by ranking the variables on the basis of the variable of interest: CAPM beta (*BETA*), standard deviation of returns (*SD*), market capitalization (*SIZE*), and book-to-market (*BM*). All the expected return proxies represent continuously compounded returns.

See Table 1 for further details.

$$v_{Cit+1}^M = v_{Cit+1} - \{\sigma(e\hat{r}_{it+1}, c\hat{n}_{it+1}) + \sigma(e\hat{r}_{it+1}, m\hat{n}_{it+1})\} \times \varepsilon_{1it+1}^A$$

$$\varepsilon_{1it+1}^A = \frac{-\varepsilon_{1it+1} - \beta_{10t+1}}{\sigma^2(\varepsilon_{1it+1})}, \varepsilon_{2it+1}^A = \frac{-\varepsilon_{2it+1} - \beta_{20t+1}}{\sigma^2(\varepsilon_{2it+1})}, \text{ and } \varepsilon_{3it+1}^A = \frac{-\varepsilon_{3it+1} - b_{30t+1}}{\sigma^2(\varepsilon_{3it+1})}$$

$\sigma(e\hat{r}_{it+1}, c\hat{n}_{it+1})$ ($\sigma(e\hat{r}_{it+1}, m\hat{n}_{it+1})$) is the covariance between the expected return proxy and the cash flow news (return news) proxy. The β , ε , and $\sigma^2(\varepsilon)$ terms shown above are taken from the following first-stage regressions:

$$e\hat{r}_{it+1} = \beta_{10t+1} + \beta_{11t+1} \times c\hat{n}_{it+1} + \beta_{12t+1} \times m\hat{n}_{it+1} + \varepsilon_{1it+1}$$

$$c\hat{n}_{it+1} = \beta_{20t+1} + \beta_{21t+1} \times e\hat{r}_{it+1} + \beta_{22t+1} \times m\hat{n}_{it+1} + \varepsilon_{2it+1}$$

$$m\hat{n}_{it+1} = \beta_{30t+1} + \beta_{31t+1} \times e\hat{r}_{it+1} + \beta_{32t+1} \times c\hat{n}_{it+1} + \varepsilon_{3it+1}$$

The regression coefficients relating to the measurement error variance of $e\hat{r}_{it+1}$ are:

$$\delta_{1it+1}^M = \sigma^2(v_{1it+1}) - \{\sigma(er_{it+1}, cn_{it+1}) + \sigma(er_{it+1}, mn_{it+1})\} - \{\sigma(v_{1it+1}, cn_{it+1}) + \sigma(v_{1it+1}, mn_{it+1})\}$$

$\sigma^2(v_{1it+1})$ is the measurement error variance of the expected return proxy, $\sigma(er_{it+1}, cn_{it+1})$ ($\sigma(er_{it+1}, mn_{it+1})$) is the covariance between true expected returns and true cash flow news (return news), and $\sigma(v_{1it+1}, cn_{it+1})$ ($\sigma(v_{1it+1}, mn_{it+1})$) is the covariance between the measurement error in the expected return proxy and true cash flow news (return news).

than r_{pe} (untabulated t-statistic of 2.29). Hence, for a nontrivial subset of our sample, r_{ct} appears to be a reliable proxy for expected returns.

Finally, in order to provide further insights regarding the association between analysts' forecast errors and the reliability of the expected return proxies, we partition the data into thirds on the basis of $|FE_ROE_i|$ and estimate α_1 and δ_1^M for each partition. The results of this analysis, which are shown on Panel C of Table 9, support the notion that there is a strong, positive association between the quality of analysts' forecasts and the reliability of the proxies. In particular, as $|FE_ROE_i|$ increases, α_1 declines and δ_1^M increases. Moreover, for firm-years with low $|FE_ROE_i|$ estimates of α_1 are positive for all of the proxies (the estimates for r_{mpeg} , r_{gm} , and r_{ct} are statistically significant), and estimates of δ_1^M are not statistically different from zero. While $|FE_ROE_i|$ is unobservable at time t and, thus, cannot

TABLE 9
Associations between the Long-Term Earnings Growth Rate (ltg_i), Absolute Forecast Errors ($|FE_ROE_i|$), and Reliability of Expected Return Proxies

Panel A: Descriptive Statistics of ltg_i and $|FE_ROE_i|$ by ltg_i Partitions

	<u>Mean</u>	<u>Std</u>	<u>5th</u>	<u>25th</u>	<u>50th</u>	<u>75th</u>	<u>95th</u>
ltg_i							
Low ltg_i	0.085	0.024	0.037	0.073	0.093	0.100	0.120
Medium ltg_i	0.138	0.021	0.110	0.120	0.135	0.150	0.180
High ltg_i	0.241	0.086	0.150	0.180	0.215	0.280	0.400
$ FE_ROE_i $							
Low ltg_i	0.103	0.259	0.003	0.016	0.043	0.106	0.328
Medium ltg_i	0.153	0.388	0.006	0.027	0.063	0.142	0.487
High ltg_i	0.173	0.378	0.010	0.041	0.089	0.179	0.483

Panel B: Regression Analyses by ltg_i Partitions

$$r_{it+1} = \alpha_{0t+1} + \alpha_{1t+1} \times e\hat{r}_{it+1} + \alpha_{2t+1} \times c\hat{n}_{it+1} + \alpha_{3t+1} \times r\hat{n}_{it+1} + \epsilon_{it+1}$$

$$v_{Cit+1}^M = \delta_{0t+1} + \delta_{1t+1}^M \times \epsilon_{1it+1}^A + \delta_{2t+1} \times \epsilon_{2it+1}^A + \delta_{3t+1} \times \epsilon_{3it+1}^A + \mu_{it+1}$$

<u>Model</u>	<u>α_1</u>			<u>δ_1^M</u>		
	<u>Low ltg_i</u>	<u>Medium ltg_i</u>	<u>High ltg_i</u>	<u>Low ltg_i</u>	<u>Medium ltg_i</u>	<u>High ltg_i</u>
pe	0.27 (0.65)	-0.50 (-1.74)	-1.82 (-4.12)	0.0004 (1.17)	0.0008 (2.95)	0.0011 (2.84)
peg	0.16 (0.48)	-0.25 (-0.67)	-1.34 (-3.40)	0.0009 (3.22)	0.0008 (4.13)	0.0010 (4.93)
mpeg	0.35 (0.99)	-0.24 (-0.62)	-1.20 (-2.89)	0.0006 (2.28)	0.0008 (3.94)	0.0009 (4.19)
gm	0.24 (0.81)	0.02 (0.04)	-0.94 (-2.26)	0.0009 (3.18)	0.0009 (4.17)	0.0009 (4.48)
Δagr	0.20 (0.61)	-0.46 (-1.34)	-1.44 (-3.49)	0.0006 (2.38)	0.0007 (5.13)	0.0008 (5.16)
ct	1.31 (3.04)	0.44 (0.97)	-0.85 (-1.40)	0.0001 (0.27)	0.0002 (0.73)	0.0005 (1.64)
gls	-0.79 (-2.16)	-0.97 (-4.30)	-2.43 (-4.66)	0.0008 (2.30)	0.0004 (2.00)	0.0000 (0.02)

(continued on next page)

TABLE 9 (continued)

Panel C: Regression Analyses by $|FE_ROE_i|$ Partitions
$$r_{it+1} = \alpha_{0t+1} + \alpha_{1t+1} \times e\hat{r}_{it+1} + \alpha_{2t+1} \times c\hat{n}_{it+1} + \alpha_{3t+1} \times r\hat{n}_{it+1} + \varepsilon_{it+1}$$

$$v_{Cit+1}^M = \delta_{0t+1} + \delta_{1t+1}^M \times \varepsilon_{1it+1}^A + \delta_{2t+1} \times \varepsilon_{2it+1}^A + \delta_{3t+1} \times \varepsilon_{3it+1}^A + \mu_{it+1}$$

Model	α_1			δ_1^M		
	Low $ FE_ROE_i $	Medium $ FE_ROE_i $	High $ FE_ROE_i $	Low $ FE_ROE_i $	Medium $ FE_ROE_i $	High $ FE_ROE_i $
pe	0.41 (1.41)	-0.22 (-0.63)	-1.19 (-2.30)	-0.0002 (-0.47)	0.0000 (0.06)	0.0015 (2.92)
peg	0.57 (1.34)	-0.36 (-1.14)	-1.18 (-3.19)	0.0000 (0.00)	0.0008 (3.13)	0.0024 (6.69)
mpeg	0.98 (2.96)	-0.05 (-0.13)	-0.98 (-2.54)	-0.0003 (-1.53)	0.0004 (1.62)	0.0021 (6.17)
gm	0.76 (2.32)	-0.19 (-0.68)	-0.93 (-2.66)	-0.0001 (-0.75)	0.0006 (2.93)	0.0023 (6.98)
Δ agr	0.60 (1.39)	-0.38 (-1.09)	-1.18 (-2.69)	-0.0001 (-0.34)	0.0005 (2.48)	0.0020 (5.57)
ct	1.25 (4.06)	1.01 (2.52)	-0.43 (-0.76)	-0.0003 (-1.39)	-0.0003 (-1.50)	0.0007 (2.28)
gls	0.22 (0.79)	-0.93 (-2.88)	-1.72 (-3.59)	0.0000 (0.07)	0.0004 (1.61)	0.0003 (1.10)

ltg_i ($|FE_ROE_i|$) partitions are formed each year by sorting the data into thirds on the basis of the consensus analyst forecast of the long-term growth in earnings, ltg_{it} (the absolute value of the difference between actual ROE_{it+2} and the forecast as of year t of ROE_{it+2} , $|FE_ROE_i|$). Low ltg_i ($|FE_ROE_i|$), medium ltg_i ($|FE_ROE_i|$), and high ltg_i ($|FE_ROE_i|$) denote observations with values of ltg_i ($|FE_ROE_i|$) in the bottom, middle, and top third of the distribution, respectively. Mean, Std, 5th, 25th, 50th, 75th, and 95th represent the mean, standard deviation, 5th percentile, 25th percentile, median, 75th percentile, and 95th percentile, respectively. Separate annual cross-sectional regressions are estimated for each partition. Parameter estimates equal the average of the annual regression coefficients. t-statistics (in parentheses) equal the ratio of the parameter estimates to their temporal standard errors. R^2 is the mean R^2 from the annual regressions.

$v_{Cit+1} = r_{it+1} - e\hat{r}_{it+1} - c\hat{n}_{it+1} - r\hat{n}_{it+1}$, where $e\hat{r}_{it+1}$, $c\hat{n}_{it+1}$, $r\hat{n}_{it+1}$, and r_{it+1} represent the expected return proxy, the cash flow news proxy, the return news proxy and realized, continuously compounded return for the year $t+1$. All the expected return proxies represent continuously compounded returns. See Table 1 for further details.

$$v_{Cit+1}^M = v_{Cit+1} - \{\sigma(e\hat{r}_{it+1}, c\hat{n}_{it+1}) + \sigma(e\hat{r}_{it+1}, r\hat{n}_{it+1})\} \times \varepsilon_{1it+1}^A$$

$$\varepsilon_{1it+1}^A = \frac{-\varepsilon_{1it+1} - \beta_{10t+1}}{\sigma^2(\varepsilon_{1it+1})}, \varepsilon_{2it+1}^A = \frac{-\varepsilon_{2it+1} - \beta_{20t+1}}{\sigma^2(\varepsilon_{2it+1})}, \text{ and } \varepsilon_{3it+1}^A = \frac{-\varepsilon_{3it+1} - \beta_{30t+1}}{\sigma^2(\varepsilon_{3it+1})}$$

$\sigma(e\hat{r}_{it+1}, c\hat{n}_{it+1})$ ($\sigma(e\hat{r}_{it+1}, r\hat{n}_{it+1})$) is the covariance between the expected return proxy and the cash flow news (return news) proxy. The β , ε , and $\sigma^2(\varepsilon)$ terms shown above are taken from the following first-stage regressions:

$$e\hat{r}_{it+1} = \beta_{10t+1} + \beta_{11t+1} \times c\hat{n}_{it+1} + \beta_{12t+1} \times r\hat{n}_{it+1} + \varepsilon_{1it+1}$$

$$c\hat{n}_{it+1} = \beta_{20t+1} + \beta_{21t+1} \times e\hat{r}_{it+1} + \beta_{22t+1} \times r\hat{n}_{it+1} + \varepsilon_{2it+1}$$

$$r\hat{n}_{it+1} = \beta_{30t+1} + \beta_{31t+1} \times e\hat{r}_{it+1} + \beta_{32t+1} \times c\hat{n}_{it+1} + \varepsilon_{3it+1}$$

The regression coefficients relating to the measurement error variance of $e\hat{r}_{it+1}$ are:

$$\delta_{1t+1}^M = \sigma^2(v_{1it+1}) - \{\sigma(er_{it+1}, cn_{it+1}) + \sigma(er_{it+1}, rn_{it+1})\} - \{\sigma(v_{1it+1}, cn_{it+1}) + \sigma(v_{1it+1}, rn_{it+1})\}$$

$\sigma^2(v_{1it+1})$ is the measurement error variance of the expected return proxy, $\sigma(er_{it+1}, cn_{it+1})$ ($\sigma(er_{it+1}, rn_{it+1})$) is the covariance between true expected returns and true cash flow news (return news), and $\sigma(v_{1it+1}, cn_{it+1})$ ($\sigma(v_{1it+1}, rn_{it+1})$) is the covariance between the measurement error in the expected return proxy and true cash flow news (return news).

be used on an *ex ante* basis, these results remain pertinent as they imply that the development of better approaches for forecasting earnings or statistical models of analysts' forecast errors are fruitful research opportunities.

VI. SUMMARY AND CONCLUSIONS

We develop an empirical approach that allows us to evaluate the reliability of an expected return proxy from its association with realized returns even if realized returns are biased and noisy measures of expected returns. Our results suggest that, for the entire cross-section of firms, the seven accounting-based proxies we consider are not reliable measures of expected returns. None of the proxies has a positive association with realized returns even after controlling for the bias and noise in realized returns attributable to contemporaneous information surprises. Moreover, the simplest model, which is based on the least reasonable assumptions *ex ante*, yields an estimate of expected returns that contains no more measurement error than the remaining proxies. These results are robust as they remain descriptive even after we attempt to purge the proxies of their measurement error via the use of instrumental variables and grouping.

Further analyses, however, demonstrate that certain proxies are reliable for nontrivial subsets of the data. First, we show that the reliability of the proxies is decreasing in the magnitude of consensus analysts' long-term earnings growth rate, and that r_{ct} (the proxy inspired by Claus and Thomas [2001]) is a reliable proxy for firms with low consensus long-term growth forecasts. We also demonstrate that when *ex post* analysts' forecasts errors are low, all of the proxies have a positive association with expected returns. Combining these two sets of results with the fact that *ex post* forecast errors are increasing in analysts' long-term growth forecasts leads us to conclude that the consensus long-term earnings growth rate is a useful *ex ante* indicator of reliability.

This study has three implications for future research. First, the approach we describe can be extended and used in other contexts. For example, development of alternative proxies for cash flow news and return news will improve researchers' ability to draw direct insights about the association between an expected return proxy and true expected returns. This, in turn, will ameliorate the need for the more complex analyses of measurement error variances. In addition, the identity of the model of market equilibrium that best characterizes the risk-return trade-off is of significant interest to many, and our approach provides a means of evaluating models of expected returns suggested by asset-pricing theory.

Second, given the general lack of reliability of the proxies we evaluate, the extant evidence in the accounting and finance literatures based on these proxies should be interpreted with caution. In addition, further research on approaches for imputing reliable estimates of expected returns from contemporaneous prices appears warranted. Finally, by demonstrating a link between the apparent lack of reliability of the proxies we evaluate and the quality of analysts' forecasts, we provide direction for future research—development of better approaches for forecasting earnings or statistical models of analysts' forecast errors appear fruitful.

APPENDIX A

Linear Decomposition of Realized Returns and Estimation of ρ

In this appendix we describe Vuolteenaho's (2002) linear return decomposition, which serves as the foundation for our empirical tests. We also describe the statistical procedure we use to estimate ρ .

Vuolteenaho's (2002) Linear Return Decomposition

We begin by noting the following identities:

$$1 \equiv (1 + ROE_{it+1})^{-1} \times \left(\frac{B_{it+1} + D_{it+1}}{B_{it}} \right) \quad (\text{A.1})$$

$$1 \equiv (1 + R_{it+1})^{-1} \times \left(\frac{M_{it+1} + D_{it+1}}{M_{it}} \right). \quad (\text{A.2})$$

In Equations (A.1) and (A.2) ROE_{it+1} equals E_{it+1}/B_{it} , E_{it+1} is earnings at time $t+1$, B_{it} is equity book value at the end of period t , D_{it+1} is dividends paid during period $t+1$, R_{it+1} is stock return for period $t+1$ and M_{it} is equity market value at the end of period t . We assume clean surplus accounting; hence, Equation (A.1) is an identity (i.e., $B_{it+1} + D_{it+1} \equiv B_{it} + E_{it+1}$).

Dividing each side of Equations (A.1) and (A.2) by D_{it} , rearranging, and taking logs we obtain the following expressions for the ratio of equity book value to dividends and the price to dividend ratio:

$$\begin{aligned} (b_{it} - d_{it}) &= \ln(B_{it}) - \ln(D_{it}) \\ &= \ln\left(\frac{B_{it}}{D_{it}}\right) \equiv \ln(e^{b_{it+1}-d_{it+1}} + 1) + \Delta d_{it+1} - roe_{it+1} \end{aligned} \quad (\text{A.3})$$

$$\begin{aligned} (m_{it} - d_{it}) &= \ln(M_{it}) - \ln(D_{it}) \\ &= \ln\left(\frac{M_{it}}{D_{it}}\right) \equiv \ln(e^{m_{it+1}-d_{it+1}} + 1) + \Delta d_{it+1} - r_{it+1}. \end{aligned} \quad (\text{A.4})$$

In Equations (A.3) and (A.4) lower case letters denote natural logs, Δd_{it+1} is the natural log of dividend growth at time $t+1$ (i.e., $d_{it+1} - d_{it} = \ln(D_{it+1}/D_{it})$), roe_{it+1} denotes the natural log of 1 plus ROE_{it+1} and r_{it+1} denotes realized, continuously compounded returns for time $t+1$. Equation (A.4) illustrates that the price to dividend ratio is increasing in future dividend growth but decreasing in the future discount rate. An analogous interpretation holds for Equation (A.3).

While Equations (A.3) and (A.4) are identities, they are also nonlinear (i.e., they are both functions of logged expressions). Hence, they cannot be directly converted into a linear expression for the natural log of the book-to-market ratio, which is necessary for the development of linear decomposition of realized returns. To derive a linear expression for the natural log of the book-to-market ratio, we approximate Equations (A.3) and (A.4) by taking Taylor expansions of $\ln(e^{m_{it+1}-d_{it+1}} + 1)$ and $\ln(e^{b_{it+1}-d_{it+1}} + 1)$ about the point $e^{\lambda \times (b-d) + (1-\lambda) \times (m-d)}$ (λ is a number between 0 and 1 and $m-d$ and $b-d$ denote unconditional means). Next, we subtract the approximation of Equation (A.4) from the approximation of Equation (A.3). This yields the following linear approximation of the natural log of the book-to-market ratio:

$$\begin{aligned} (b_{it} - m_{it}) &\approx \frac{e^{\lambda \times (b-d) + (1-\lambda) \times (m-d)}}{1 + e^{\lambda \times (b-d) + (1-\lambda) \times (m-d)}} \times (b_{it+1} - m_{it+1}) + r_{it+1} - roe_{it+1} \\ &= \rho \times (b_{it+1} - m_{it+1}) + r_{it+1} - roe_{it+1}. \end{aligned} \quad (\text{A.5})$$

In Equation (A.5) ρ is a number slightly less than 1. To understand ρ better it is useful to assume λ equals 0, in which case $\rho = \frac{e^{(m-d)}}{1 + e^{(m-d)}} = \frac{M/D}{1 + M/D} = \frac{M}{D + M}$, which implies that ρ is bounded between 0 and 1, and is increasing in the price-to-dividend ratio.

Assuming $\lim_{T \rightarrow \infty} \rho^{T+1} \times (b_{it+T} - m_{it+T}) = 0$ and iterating Equation (A.5) forward, yields the following approximate expression for the natural log of the book-to-market ratio:

$$(b_{it} - m_{it}) \approx \sum_{\tau=1}^{\infty} \rho^{\tau-1} \times r_{it+\tau} - \sum_{\tau=1}^{\infty} \rho^{\tau-1} \times roe_{it+\tau}. \quad (\text{A.6})$$

Equation (A.6) illustrates that the book-to-market ratio is increasing in future discount rates (i.e., prices are low when expected future discount rates are high) and decreasing in future accounting returns (i.e., prices are high when expected profitability is high).

Finally, we obtain a linear approximation of realized returns by evaluating the change in expectations of Equation (A.6) from t to $t+1$ and rearranging.³⁶

$$\begin{aligned} r_{it+1} &\approx E_t[r_{it+1}] + \Delta E_{t+1} \left[\sum_{\tau=1}^{\infty} \rho^{\tau-1} \times roe_{it+\tau} \right] - \Delta E_{t+1} \left[\sum_{\lambda=2}^{\infty} \rho^{\lambda-1} \times r_{it+\lambda} \right] \\ &= er_{it+1} + cn_{it+1} - rn_{it+1}. \end{aligned} \quad (\text{A.7})$$

In Equation (A.7) $E_t[\cdot]$ is the conditional expectation operator and $\Delta E_{t+1}[\cdot]$ equals $E_{t+1}[\cdot] - E_t[\cdot]$. Equation (A.7) illustrates the components of realized returns. In particular, changes in expected future *roe* (i.e., cash flow news, cn_{it+1}) and changes in expected discount rates (i.e., return news, rn_{it+1}) cause realized returns, r_{it+1} , to differ from expected returns, er_{it+1} . Hence, in order to draw meaningful inferences about the reliability of a particular measure of expected returns, we must control for cash flow news and return news.

Estimation of ρ

We estimate ρ for five portfolios—four equal-size portfolios are formed on the magnitude of the price-to-dividend ratio and a fifth portfolio includes all non-dividend-paying stocks. Because ρ is a function of the unconditional (i.e., long-run) price-to-dividend ratio, we set it equal to the median of the annual estimates of ρ_t obtained from the following pooled, cross-sectional regression equation, which is obtained by rearranging Equation (A.5):

$$(b_{it} - m_{it} - r_{it+1} + roe_{it+1}) = \rho_{0t} + \rho_t \times (b_{it+1} - m_{it+1}). \quad (\text{A.8})$$

In Equation (A.8) τ is a number between t and $t-9$ and the sample includes all firm-years in the same price-to-dividend portfolio with requisite data in year $t-9$ through year t (i.e., for each year t we estimate ρ_t using firm years between year $t-9$ and year t).

³⁶ Equation (A.6) implies that: $0 = \Delta E_{t+1}[b_{it} - m_{it}] = \Delta E_{t+1} \left[\sum_{\tau=1}^{\infty} \rho^{\tau-1} \times roe_{it+\tau} \right] - \Delta E_{t+1} \left[\sum_{\lambda=1}^{\infty} \rho^{\lambda-1} \times r_{it+\lambda} \right]$,

which equals $\Delta E_{t+1} \left[\sum_{\tau=1}^{\infty} \rho^{\tau-1} \times roe_{it+\tau} \right] - \left\{ (r_{it+1} - E_t[r_{it+1}]) + \Delta E_{t+1} \left[\sum_{\lambda=2}^{\infty} \rho^{\lambda-1} \times r_{it+\lambda} \right] \right\}$. This, in turn, implies Equation (A.7). It also implies that cash flow news relates to changes in expectations about all future *roe* (i.e., $t+1, t+2, \dots$), whereas return news relates only to changes in expectations about discount rates pertaining to years occurring *after* year $t+1$.

The values of ρ for the different price-to-dividend portfolios are: (1) non-dividend-paying stocks $\rho = 0.988$, (2) fourth quartile of price-to-dividend ratio for dividend paying stocks (i.e., the quartile with the highest price-to-dividend ratio): $\rho = 0.957$, (3) third quartile of price-to-dividend ratio for dividend-paying stocks: $\rho = 0.921$, (4) second quartile of price to dividend for dividend-paying stocks: $\rho = 0.927$, and (5) first quartile of price-to-dividend ratio for dividend-paying stocks: $\rho = 0.924$.

APPENDIX B

Statistical Approach for Estimating Measurement Error Variances

As discussed in Section II of the main text, the bias in the estimates of α_{1t+1} obtained from Equation (2) does not provide clear evidence about the relative measurement error in a particular expected return proxy. To understand better the bias in α_{1t+1} it is helpful to consider the following re-expression of Equation (1) from the main text:

$$\begin{aligned} r_{it+1} &\approx er_{it+1} + cn_{it+1} - rn_{it+1} \\ &= (e\hat{r}_{it+1} - v_{1it+1}) + (c\hat{n}_{it+1} - v_{2it+1}) + (r\hat{n}_{it+1} - v_{3it+1}) \\ &= e\hat{r}_{it+1} + c\hat{n}_{it+1} + r\hat{n}_{it+1} + (-v_{1it+1} - v_{2it+1} - v_{3it+1}) \\ &= \hat{r}_{it+1} + v_{Cit+1}. \end{aligned} \quad (\text{B.1})$$

In Equation (B.1) v_{1it+1} , v_{2it+1} , and v_{3it+1} denote the measurement error in $e\hat{r}_{it+1}$, $c\hat{n}_{it+1}$, and $r\hat{n}_{it+1}$, respectively. Recall, $r\hat{n}_{it+1}$, which we refer to as the return news proxy, is the negative of return news (i.e., $-rn_{it+1}$). We assume the measurement error in a particular proxy is uncorrelated with the true underlying construct, but may be correlated with the true values of the other constructs and the measurement errors in the remaining proxies. While we are primarily interested in v_{1it+1} , it is unobservable. However, we can use the combined measurement error, v_{Cit+1} , to evaluate the extent to which v_{1it+1} contributes to the bias in α_{1t+1} . Results presented in Rao (1973), Garber and Klepper (1980), and Barth (1991) demonstrate that v_{Cit+1} and the bias in α_{1t+1} are related in the following manner:

$$\begin{aligned} v_{Cit+1} &= \alpha_{0t+1} - \text{Bias}(\alpha_{1t+1}) \times e\hat{r}_{it+1} - \text{Bias}(\alpha_{2t+1}) \times c\hat{n}_{it+1} - \text{Bias}(\alpha_{3t+1}) \\ &\quad \times r\hat{n}_{it+1} + \varepsilon_{it+1} \\ &= \alpha_{0t+1} + \left(\frac{\eta_{1t+1}}{\sigma^2(\varepsilon_{1it+1})} - \frac{\beta_{21t+1} \times \eta_{2t+1}}{\sigma^2(\varepsilon_{2it+1})} - \frac{\beta_{31t+1} \times \eta_{3t+1}}{\sigma^2(\varepsilon_{3it+1})} \right) \times e\hat{r}_{it+1} \\ &\quad + \left(\frac{\eta_{2t+1}}{\sigma^2(\varepsilon_{2it+1})} - \frac{\beta_{11t+1} \times \eta_{1t+1}}{\sigma^2(\varepsilon_{1it+1})} - \frac{\beta_{32t+1} \times \eta_{3t+1}}{\sigma^2(\varepsilon_{3it+1})} \right) \times c\hat{n}_{it+1} \\ &\quad + \left(\frac{\eta_{3t+1}}{\sigma^2(\varepsilon_{3it+1})} - \frac{\beta_{12t+1} \times \eta_{1t+1}}{\sigma^2(\varepsilon_{1it+1})} - \frac{\beta_{22t+1} \times \eta_{2t+1}}{\sigma^2(\varepsilon_{2it+1})} \right) \times r\hat{n}_{it+1} + \varepsilon_{it+1}. \end{aligned} \quad (\text{B.2})$$

In Equation (B.2) the β and $\sigma^2(\varepsilon)$ are the slope coefficients and residual variances obtained from the set of regressions shown in Equation (B.3):

$$\begin{aligned} e\hat{r}_{it+1} &= \beta_{10t+1} + \beta_{11t+1} \times c\hat{n}_{it+1} + \beta_{12t+1} \times r\hat{n}_{it+1} + \varepsilon_{1it+1} \\ c\hat{n}_{it+1} &= \beta_{20t+1} + \beta_{21t+1} \times e\hat{r}_{it+1} + \beta_{22t+1} \times r\hat{n}_{it+1} + \varepsilon_{2it+1} \\ r\hat{n}_{it+1} &= \beta_{30t+1} + \beta_{31t+1} \times e\hat{r}_{it+1} + \beta_{32t+1} \times c\hat{n}_{it+1} + \varepsilon_{3it+1}. \end{aligned} \quad (\text{B.3})$$

η_{1t+1} , η_{2t+1} , and η_{3t+1} are functions of the variances of the measurement errors in $e\hat{r}_{it+1}$, $c\hat{n}_{it+1}$, and $r\hat{n}_{it+1}$, respectively. Hence, we refer to the η terms as “noise variables.” The relation between the noise variables and the covariance structure of the measurement errors is:

$$\begin{aligned} -\eta_{1t+1} &= \sigma^2(v_{1it+1}) + \{\sigma(v_{1it+1}, v_{2it+1}) + \sigma(v_{1it+1}, v_{3it+2})\} \\ &\quad + \{\sigma(er_{it+1}, v_{2it+1}) + \sigma(er_{it+1}, v_{3it+1})\} \\ -\eta_{2t+1} &= \sigma^2(v_{2it+1}) + \{\sigma(v_{2it+1}, v_{1it+1}) + \sigma(v_{2it+1}, v_{3it+1})\} \\ &\quad + \{\sigma(cn_{it+1}, v_{1it+1}) + \sigma(cn_{it+1}, v_{3it+1})\} \\ -\eta_{3t+1} &= \sigma^2(v_{3it+1}) + \{\sigma(v_{3it+1}, v_{1it+1}) + \sigma(v_{3it+1}, v_{2it+1})\} \\ &\quad + \{\sigma(rn_{it+1}, v_{1it+1}) + \sigma(rn_{it+1}, v_{2it+1})\}. \end{aligned} \quad (B.4)$$

In Equation (B.4) $\sigma^2(v_{1it+1})$, $\sigma^2(v_{2it+1})$, and $\sigma^2(v_{3it+1})$ denote the variance of the measurement error in $e\hat{r}_{it+1}$, $c\hat{n}_{it+1}$, and $r\hat{n}_{it+1}$, respectively. The terms in the first set of braces correspond to covariances between the measurement errors in the proxies (e.g., $\sigma(v_{1it+1}, v_{2it+1})$ is the covariance between the measurement error in $e\hat{r}_{it+1}$ and the measurement error in $c\hat{n}_{it+1}$). The terms in the second set of braces after the equal sign correspond to covariances between true, unobservable constructs and measurement errors in the proxies (e.g., $\sigma(er_{it+1}, v_{2it+1})$ is the covariance between true expected return and the measurement error in $c\hat{n}_{it+1}$).

Equations (B.2) through (B.4) demonstrate that the difference between one and α_{1t+1} is a complex function of the covariance structure of the independent variables and the covariance structure of their measurement errors. Hence, this difference is not solely attributable to measurement error in the expected return proxy (i.e., v_{1it+1}). However, we can use Equations (B.2) through (B.4) to infer the portion of the bias in α_{1t+1} that is attributable to v_{1it+1} . We follow the two-stage process described in Barth (1991).

In the *first stage* we estimate the regressions shown in Equation (B.3). Next, we combine the regression coefficients, residuals, and residual variances from these regressions to develop a set of constructs that are used as the regressors in the following *second stage* regression, which is obtained by rearranging Equation (B.2):

$$\begin{aligned} v_{Cit+1} &= \eta_{0t+1} + (-\eta_{1t+1}) \times \left(\frac{\epsilon_{1it+1} - \beta_{10t+1}}{\sigma^2(\epsilon_{1it+1})} \right) + (-\eta_{2t+1}) \\ &\quad \times \left(\frac{-v_{2it+1} - \beta_{20t+1}}{\sigma^2(\epsilon_{2it+1})} \right) + (-\eta_{3t+1}) \times \left(\frac{-\epsilon_{3it+1} - \beta_{30t+1}}{\sigma^2(\epsilon_{3it+1})} \right) \\ &\quad + \mu_{it+1} \\ &= \delta_{0t+1} + \delta_{1t+1} \times \epsilon_{1it+1}^A + \delta_{2t+1} \times \epsilon_{2it+1}^A + \delta_{3t+1} \times \epsilon_{3it+1}^A + \mu_{it+1}. \end{aligned} \quad (B.5)$$

Note each of the regressors in Equation (B.5) is a function of a particular error term from one of the regressions shown in Equation (B.3). Hence, we refer to these regressors as adjusted errors (e.g., the regressor that is a function of ϵ_{1it+1} is referred to as ϵ_{1it+1}^A).

Ranking on the basis of δ_{1t+1} embeds the assumption that $\{\sigma(v_{1it+1}, v_{2it+1}) + \sigma(v_{1it+1}, v_{3it+1})\}$ and $\{\sigma(er_{it+1}, v_{2it+1}) + \sigma(er_{it+1}, v_{3it+1})\}$ are constant across expected return proxies, which may not be descriptive. To circumvent this problem we refine the regression

shown in Equation (B.5) by replacing the regressand (i.e., v_{Cit+1}) with v_{Cit+1}^M , which is defined as:

$$v_{Cit+1}^M = v_{Cit+1} - \{\sigma(e\hat{r}_{it+1}, c\hat{n}_{it+1}) + \sigma(e\hat{r}_{it+1}, r\hat{n}_{it+1})\} \times \varepsilon_{1it+1}^A. \quad (\text{B.6})$$

In Equation (B.5) $\sigma(e\hat{r}_{it+1}, c\hat{n}_{it+1})$ denotes the covariance between the expected return proxy of interest and the cash flow news proxy, and $\sigma(e\hat{r}_{it+1}, r\hat{n}_{it+1})$ is the covariance between the expected return proxy and the return news proxy. The coefficient on ε_{1it+1}^A obtained via estimation of Equation (B.6) is:³⁷

$$\begin{aligned} \delta_{1t+1}^M &= -\eta_{1t+1} - \{\sigma(e\hat{r}_{it+1}, c\hat{n}_{it+1}) + \sigma(e\hat{r}_{it+1}, r\hat{n}_{it+1})\} \\ &= \sigma^2(v_{1it+1}) - \{\sigma(er_{it+1}, cn_{it+1}) + \sigma(er_{it+1}, rn_{it+1})\} \\ &\quad - \{\sigma(v_{1it+1}, cn_{it+1}) + \sigma(v_{1it+1}, rn_{it+1})\}. \end{aligned} \quad (\text{B.7})$$

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³⁷ To derive the expression for δ_{1t+1}^M we begin by re-expressing the sum of the covariance between the expected return and cash flow news proxies and the covariance between the expected return and return news proxies:

$$\begin{aligned} \sigma(e\hat{r}_{it+1}, c\hat{n}_{it+1}) + \sigma(e\hat{r}_{it+1}, r\hat{n}_{it+1}) &= \sigma(er_{it+1} + v_{1it+1}, cn_{it+1} + v_{2it+1}) + \sigma(er_{it+1} + v_{1it+1}, rn_{it+1} + v_{3it+1}) \\ &= \sigma(er_{it+1}, cn_{it+1}) + \sigma(er_{it+1}, rn_{it+1}) + \sigma(er_{it+1}, v_{2it+1}) + \sigma(er_{it+1}, v_{3it+1}) \\ &\quad + \sigma(v_{1it+1}, cn_{it+1}) + \sigma(v_{1it+1}, rn_{it+1}) + \sigma(v_{1it+1}, v_{2it+1}) + \sigma(v_{1it+1}, v_{3it+1}). \end{aligned}$$

Next, using the definition of $-\eta_{1t+1}$ shown in Equation (B.4), we arrive at the following expression for δ_{1t+1}^M :

$$\begin{aligned} \delta_{1t+1}^M &= -\eta_{1t+1} - \{\sigma(e\hat{r}_{it+1}, c\hat{n}_{it+1}) + \sigma(e\hat{r}_{it+1}, r\hat{n}_{it+1})\} \\ &= \sigma^2(v_{1it+1}) - \{\sigma(er_{it+1}, cn_{it+1}) + \sigma(er_{it+1}, rn_{it+1})\} - \{\sigma(v_{1it+1}, cn_{it+1}) + \sigma(v_{1it+1}, rn_{it+1})\}. \end{aligned}$$

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