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Earnings Smoothness, Average Returns, and Implied Cost of Equity Capital

John McInnis
The University of Texas at Austin

ABSTRACT: Despite a belief among corporate executives that smooth earnings paths lead to a lower cost of equity capital, I find no relation between earnings smoothness and average stock returns over the last 30 years. In other words, owners of firms with volatile earnings are not compensated with higher returns, as one would expect if volatile earnings lead to greater risk exposure. Although prior empirical work links smoother earnings to a lower implied cost of capital, I offer evidence that this link is driven primarily by optimism in analysts' long-term earnings forecasts. This optimism yields target prices and implied cost of capital estimates that are systematically too high for firms with volatile earnings. Overall, the evidence is inconsistent with the notion that attempts to smooth earnings can lead to a lower cost of equity capital.

Keywords: *cost of capital; earnings smoothness; asset pricing; analyst forecasts.*

Data Availability: *Data are available from commercial vendors.*

I. INTRODUCTION

In an influential survey article, Graham et al. (2005) report that corporate executives express a strong desire to report smooth earnings paths, holding cash flow volatility constant. Surprisingly, executives also indicate a willingness to sacrifice long-term value to achieve smoother earnings. A primary motivation offered for such behavior is that executives believe that investors perceive firms with smoother earnings to be less risky, and thus demand a lower expected return, or cost of equity capital. In this study, I use asset-pricing tests—common in financial economics—to assess the relation, if any, between earnings smoothness and expected returns.

Though prior empirical work in accounting has linked smoother earnings to a lower implied cost of equity capital (Francis et al. 2004; Verdi 2006), I re-examine the issue for three reasons. First, theoretical support for the notion that smoother earnings lead to a lower

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cost of equity capital is mixed. Second, inferences in prior research are based primarily on an association between earnings smoothness and cost of capital estimates imputed from Value Line analysts' forecasted target prices. In short, these studies find that analysts *expect* firms with smoother earnings to experience lower future returns than firms with volatile earnings. Given the importance of the research question, it is critical to seek corroborative evidence from alternative methodologies. Most asset-pricing studies in financial economics evaluate whether a variable is linked to expected returns by examining its relation with average realized stock returns. I use asset-pricing regressions to test whether firms with smoother earnings do in fact experience actual lower future returns. In this manner, I can benchmark analysts' expectations of future share price appreciation against realized outcomes in the equity market.

Finally, Core et al. (2008) subject another accounting attribute—accrual quality—to asset-pricing tests and find no evidence that is a separately priced ''risk factor,'' even though implied cost of capital tests indicate it is. This study investigates whether a similar pattern exists for earnings smoothness and, if so, seeks to explain why different methodologies yield different results.

My empirical tests yield the following findings. First, I find no relation between earnings smoothness (defined as earnings volatility relative to cash flow volatility) and average stock returns from 1975 to 2006. Earnings smoothness, in isolation or combined with other risk proxies, has no ability to explain average returns, either at the firm or the portfolio level. Thus, there is no evidence that owners of firms with volatile earnings are rewarded with higher average stock returns.

Second, I offer evidence that the link between implied cost of equity capital and earnings smoothness results primarily from optimistic bias in analysts' long-term earnings projections. Specifically, I document a positive association between optimism in analysts' earnings forecasts and earnings volatility. This optimistic bias in forecasted earnings yields projected future stock prices, and thus implied cost of equity capital estimates, that are systematically too high for firms with volatile earnings. Finally, I show that a substantial portion of the relation between optimism in analysts' earnings forecasts and earnings volatility can be explained by analysts' mis-weighting of prior earnings changes when predicting future earnings changes.

This study contributes to the extant literature in at least three ways. First, the asset-pricing evidence does not support the apparently widely held belief among corporate executives that smoother earnings can lower cost of equity capital. This study is the first of which I am aware to examine smoothness and average stock returns, and its findings should interest managers, investors, and researchers. Second, this study is the first to reconcile differences in results from asset-pricing and implied cost of capital tests. Specifically, the evidence helps explain why implied cost of capital estimates based on projected target prices are correlated with earnings smoothness, but actual stock returns are not. This analysis is important not just for the present study, but may also explain why a similar phenomenon is observed with other accounting attributes, such as accrual quality (Core et al. 2008). Finally, this study contributes to a growing literature that raises concerns over cross-sectional inferences from implied cost of capital tests (Easton and Sommers 2007; Ogneva et al. 2007). Findings highlight the importance of ensuring that the association between implied cost of equity capital and the variable of interest is not driven by biased input variables (e.g., earnings forecasts).

These findings are subject to two important caveats. First, I use *ex post*, realized stock returns to proxy for expected returns in the asset-pricing analysis. In addition to expected

returns, realized returns are comprised of information surprises (news about future cash flows or discount rates). In supplementary analysis, I find no evidence that information surprises compromise inferences from the asset-pricing tests. Nevertheless, since true information surprises are unobservable, I cannot completely dismiss them as a confounding factor in the analysis. Thus, while the asset-pricing tests are inconsistent with a relation between smoothness and cost of equity capital, they do not necessarily offer unequivocal evidence that there is no relation. Second, tests that examine the link between earnings smoothness and cost of equity capital are actually joint tests of two hypotheses: (1) smoother earnings reduce some form of information risk, and (2) this information risk is priced. Failure to document a link between average returns and earnings smoothness casts doubt on at least one hypothesis, but it does not provide evidence as to which hypothesis may be incorrect.

II. PRIOR LITERATURE

The literature on earnings smoothing is vast, dating back to the 1960s. I briefly review only two strands of this literature. Since the extent to which one believes smoother earnings can reduce cost of capital often hinges on normative judgments, I discuss this area of the literature first. Second, I discuss analytical and empirical work that links smoother earnings to cost of capital.

Smooth Earnings: Benefits and Drawbacks

Disagreement exists in the literature as to whether smoothness is a desirable property of accounting earnings. Barnea et al. (1975) argue that smoother earnings allow outsiders to better predict future earnings, and Chaney and Lewis (1995) construct a model based on Spence's (1973) signaling theory in which income smoothing is used by "high-quality" firms to signal their type. Beidleman (1973) asserts that smoothing is useful for internal budgeting and in reducing perceived riskiness among outsiders. Other authors, however, cast earnings smoothing in a less favorable light. Leuz et al. (2003) view earnings smoothing as a device used by insiders to obfuscate their consumption of private control benefits. Bhattacharya et al. (2003) contend that smoothing leads to greater earnings "opacity," while Myers et al. (2007) offer evidence that firms use income smoothing as an earnings management tool to maintain artificially long strings of increasing EPS.

Earnings Smoothing and Cost of Capital—Analytical Work

In traditional asset-pricing theory, only systematic, undiversifiable risks affect expected returns. This framework casts doubt on any association between firm-specific earnings volatility and cost of capital.[1] In the CAPM, for example, idiosyncratic return volatility is not priced because it does not affect the variance of a well-diversified portfolio. Similar logic can be applied to earnings volatility. By holding a diversified portfolio of stocks, investors can lay claim to a stream of earnings that is much "smoother" that any of its components. In short, portfolio theory suggests firms need not smooth out idiosyncratic "blips" in their earnings, since investors can do this themselves.

Some studies, however, argue for a link between earnings smoothness and cost of capital. Trueman and Titman (1988) develop a model in which firms smooth earnings to

[1] I focus on cost of equity capital only, not cost of debt capital or total cost of capital. For convenience, I use the terms cost of equity capital and cost of capital interchangeably.

reduce their perceived probability of bankruptcy, thereby lowering borrowing rates. The model does not address cost of equity capital directly, however, and does not allow for investor diversification across multiple securities as in the CAPM. Easley and O'Hara (2004) construct a model in which uninformed investors demand a risk premium for securities when they lack information *vis-à-vis* informed investors. The authors argue this ''information risk'' is undiversifiable. So, to the extent income smoothing reduces information asymmetry, smoother earnings may be associated with a lower cost of equity capital. However, given the above discussion, the effect of earnings smoothness on information asymmetry remains unclear. If smoothness facilitates the predictability of future earnings or cash flows, or helps signal the underlying economic ''type'' of a firm, information asymmetry could be attenuated. On the other hand, if earnings smoothness plays primarily an obfuscatory role that leads to greater reporting opacity, information asymmetry could be exacerbated.

Furthermore, recent research by Lambert et al. (2008, 2007) challenges the notion that information risk, as modeled by Easley and O'Hara (2004), is even priced in equilibrium, suggesting instead that it can be diversified away by investors. They contend that better quality financial reporting (which smoothing, for the reasons listed above, may or may not facilitate) can directly reduce cost of capital, but only through a firm's CAPM beta.

Finally, Goel and Thakor (2003) model a setting in which earnings volatility benefits informed investors at the expense of uninformed investors, because the latter demand a risk premium to stay in the market. Firms respond by smoothing earnings to reduce perceived volatility, but these smoothing attempts are unwound by the market due to rational expectations and have no effect on cost of capital in equilibrium.

Earnings Smoothing and Cost of Capital—Empirical Evidence

The most direct empirical evidence of a link between cost of capital and earnings smoothness comes from Francis et al. (2004). They examine seven accounting attributes, one of which is earnings smoothness, and find a reliably negative association between the smoothness of earnings and implied cost of capital estimates based on forecasts of future stock prices and dividends provided by Value Line. In essence, the findings of Francis et al. (2004) indicate Value Line analysts *expect* firms with volatile earnings to earn higher future stock returns than firms with smooth earnings. As a robustness check, Francis et al. (2004) document a negative relation between earnings smoothness and the earnings-based MPEG cost of capital estimate derived in Easton (2004). They also offer evidence that earnings smoothness (along with other attributes) serves as the basis for a mimicking-portfolio risk factor that is priced in equilibrium, but Core et al. (2008) object to their methodology. I discuss this issue in more detail in the next section.

Verdi (2006) extends Francis et al. (2004) using principal components analysis and replicates their main results using Value Line-based cost of capital estimates. However, the relation between cost of capital and earnings smoothness reverses in sign and becomes insignificant when he uses a cost of capital estimate derived by Gebhardt et al. (2001). Finally, Bhattacharya et al. (2003) relate three country-level measures of earnings manipulation, one of which is earnings smoothing, to country-level cost of capital measures. Using cost of capital estimates from dividend yields, they find that countries with smoother earnings have a *higher* cost of capital, but this relation becomes insignificant when they use an international factor-pricing model to measure cost of capital. Since earnings smoothness

per se is not the focus of their study, Bhattacharya et al. (2003) offer no reasons for their differing results.[2]

In summary, the literature on earnings smoothness does not yield a consensus as to whether it (1) represents a beneficial or desirable attribute of financial reporting, or more importantly (2) affects cost of equity capital. Moreover, there is no evidence as to whether earnings smoothness is related to average realized stock returns at the firm or portfolio level, which is a common test used in much of financial economics to judge candidate risk factors. The next section explains how the current study can help to fill this void in the literature.

III. ASSET-PRICING TESTS

To test the hypothesis that smoother earnings are associated with a lower cost of equity capital, I first employ standard asset-pricing tests that relate earnings smoothness to average realized stock returns. Realized returns are, tautologically, a function of two things: expected returns and information surprises (Campbell 1991). The expected return component derives from the discount rate (i.e., cost of capital) investors apply to a stock's expected payoffs at the beginning of the return period. Information surprises represent changes in investors' expectations of future payoffs and required discount rates during the return period. Assuming rational pricing, information surprises are zero in expectation and unpredictable through time. Thus, average realized returns, across firms and over time, proxy for expected returns.

While this methodology has been standard practice in finance over the last 30 years, it has two potential shortcomings. First, even if information surprises are mean zero, they can have substantial variance, particularly at the individual-stock level. This adds noise to the analysis and could lead to low power tests (Botosan and Plumlee 2005). I address this concern in the next section by grouping stocks into portfolios to help mitigate the effects of firm-specific noise. Second, information surprises may not be mean zero over the sample period, yielding a biased proxy for expected returns (Elton 1999). Fama and French (2002), for example, offer evidence that the average return on the S&P index was "a lot higher than expected" over the last 50 years, due to discount rate shocks. However, even if the average return across all stocks is higher than expected over the sample period, inferences from cross-sectional asset-pricing tests are still valid. As Francis et al. (2004, 1002) note, bias in realized returns will confound inferences in asset-pricing tests only if it is correlated cross-sectionally with variable of interest. I discuss this issue in more detail in Section V.

Data

Data for the asset-pricing tests come from the intersection of the CRSP Monthly Stock File and the Compustat Industrial Annual File, obtained through Wharton Research Data Services (WRDS). The sample period runs from 1/1/75 to 12/31/06. I begin in 1975 because this marks the first year that Value Line implied cost of capital estimates can be obtained (Brav et al. 2005; Francis et al. 2004). To remain in the sample, I require a firm-month to have non-missing return data on CRSP and non-missing values for the Compustat accounting variables described below. In total, the asset-pricing sample contains 682,435 firm-month observations for 6,076 unique firms.

[2] Other studies, such as Hunt et al. (2000) and Thomas and Zhang (2006), relate earnings smoothness to price multiples such P/E. While these studies can speak to the valuation implications of smooth earnings in general, they cannot speak to cost of capital effects directly, since discount rate and expected cash flow effects are difficult (if not impossible) to disentangle using price multiples.

Empirical Methodology and Results

To investigate whether more volatile earnings are associated with higher stock returns, I first run the following cross-sectional regression every month from 1/1/75 to 12/31/06:

$$R_i - R^f = \alpha + \beta_1 Smooth_i + \beta_2 Beta_i + \beta_3 Size_i + \beta_4 BM_i + \varepsilon_i. \quad (1)$$

R_i is the raw monthly stock return for firm i, stated as a percentage. R^f is the return on the one-month T-bill obtained from WRDS. *Smooth* is the decile rank of a firm-year's earnings smoothness measure. I measure earnings smoothness as the standard deviation of net income (scaled by average total assets) divided by the standard deviation of cash flows from operations (scaled by average total assets). Thus, higher values of this variable indicate more earnings volatility. Scaling by cash flow volatility measures the extent to which accrual accounting has smoothed out the underlying volatility of the firm's operations. The smoothness measure is calculated at the annual level over rolling ten-year windows ending in the current fiscal year.[3] I define earnings smoothness in this manner to be consistent with prior research (Francis et al. 2004; Leuz et al. 2003) and because it corresponds closely to the construct described by executives in the Graham et al. (2005) survey.

I also include other standard factors in the model. *Beta* is the slope coefficient from the regression of a firm's monthly raw returns on the monthly value-weighted market return over a rolling five-year window ending in the current fiscal year. *Size* is the natural log of market value of equity, measured at the end of the current fiscal year. *BM* is the natural log of the ratio of book value of equity to market value of equity, measured at the end of the current fiscal year. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For example, a December-year-end firm gets a new smoothness, *Beta*, *Size*, and *BM* measure the following April.[4]

Panel A of Table 1 reports time-series averages of the parameters from the 384 monthly regressions in Equation (1). Standard errors are calculated from the time-series variation in these parameters. This methodology, developed by Fama and MacBeth (1973), ensures the reported t-statistics account for cross-sectional correlation in the error terms in Equation (1). Estimates from Table 1 indicate that earnings smoothness is not associated with average realized stock returns, either in isolation (t = 0.70) or in conjunction with *Beta*, *Size*, and *BM* (t = 0.47). Also, *Beta* is not associated with average returns, while *Size* (*BM*) is negatively (positively) related to average returns over the sample period, consistent with extant work in financial economics (e.g., Fama and French 1992). Results are similar if the raw, rather than the ranked, value of earnings smoothness is used instead.

Panels B and C of Table 1 report descriptive statistics along with univariate correlations between *Smooth* and the other covariates in Equation (1). Firms with volatile earnings tend to be smaller, have higher betas, and lower book-to-market ratios than firms with smooth earnings. The correlations are modest, however, so earnings smoothness does not appear to be "swamped" by the other covariates. In short, cross-sectional tests provide no support for the notion that stockholders of firms with volatile earnings are compensated with higher average returns.

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[3] Requiring a ten-year window to estimate earnings smoothness restricts the sample to typically larger, more successful firms, as Francis et al. (2004) note, and limits the extent to which the findings can be generalized. However, notions of a "smooth" or "volatile" earnings stream lose meaning in the absence of a sufficient time-series.

[4] I provide further variable construction details in the table footnotes.

TABLE 1
Cross-Sectional Regression of Monthly Returns on Earnings Smoothness

Panel A: Regression Results

	Intercept	*Smooth*	*Beta*	*Size*	*BM*	R^2
Estimate	**1.15**	0.013				0.005
t-stat	(5.15)	(0.70)				
Estimate	**1.841**	0.006	0.076	**−0.132**	**0.241**	0.035
t-stat	(6.72)	(0.47)	(0.51)	(−3.06)	(3.62)	

Panel B: Descriptive Statistics for Full Sample

Variable	Mean	5th	25th	Median	75th	95th
Smoothness Measure	0.652	0.178	0.369	0.592	0.878	1.299
Beta	1.016	0.112	0.607	0.981	1.356	2.091
Size	5.184	1.754	3.520	5.068	6.745	8.974
BM	−0.415	−1.724	−0.860	−0.376	0.084	0.781
Ret	1.122	−17.660	−5.653	0.094	6.599	21.868

Panel C: Univariate Correlations with Smoothness Measure

Beta	*Size*	*BM*
0.155	−0.106	−0.029

For each month, from 1/1/75 to 12/31/06, the cross-section of excess realized returns is regressed on the variables listed above. Results are reported in Panel A. Monthly excess returns are measured in percentages and are calculated as the raw stock return less the risk-free rate. The raw stock return is obtained from the CRSP monthly stock file and the risk-free rate is the return on the one-month T-bill obtained from the Fama-French files at WRDS. *Smooth* is the decile rank of a firm-years' smoothness measure, which is calculated from the Compustat Industrial Annual File as the time-series standard deviation of net income before extraordinary items (#18) (scaled by average total assets (#6)) divided by the standard deviation of cash flows (scaled by average total assets) over the ten previous years ending in the current fiscal year. Cash flows equal net income less accruals. Accruals are the change in current assets (#4) minus the change in cash (#1) minus the change in current liabilities (#5) plus the change in ST debt (#34) minus depreciation (#14), scaled by average total assets. The smoothness measure is calculated at the annual level over rolling ten-year windows ending in the current fiscal year. Decile ranking is performed monthly. *Beta* is the slope coefficient from the regression of a firm's monthly raw returns on the monthly value-weighted market return (from the CRSP monthly index file) over a rolling five-year window ending in the current fiscal year. I require at least 18 monthly returns over the rolling five-year interval to calculate *Beta*. *Size* is the natural log of market value of equity from Compustat (#25 * #199), measured at the end of the current fiscal year. *BM* is the natural log of the ratio of book value of equity to market value of equity (log(#60) less *Size*), measured at the end of the current fiscal year. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For example, a December year-end firm gets a new *Smooth*, *Beta*, *Size*, and *BM* measure each April. Parameter estimates are time-series averages of the parameters from the 384 monthly cross-sectional regressions. t-statistics are calculated from the standard errors of these monthly averages. Panel B contains descriptive statistics and Panel C contains univariate correlations between *Smooth* and *Beta*, *Size*, and *BM*. Throughout the table, parameter estimates significant at the 5 percent level or lower (two-tailed) are bolded.

One criticism of these cross-sectional tests is that realized returns are noisy, particularly at the firm level. That is, firm-specific news may be so vast as to swamp any pattern that exists in realized returns related to earnings smoothness. To deal with this concern, I perform portfolio time-series regressions in the tradition of Black et al. (1972). Each month, from 1/1/75 to 12/31/06, I group firms into ten portfolios based upon the latest decile

rank of their earnings smoothness measure, estimating the following time-series regression for each portfolio:

$$R_{pt} - R_t^f = \alpha + \beta_1(R^M - R^f)_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_i. \quad (2)$$

R_{pt} is the value-weighted return on portfolio p ($p = 1$ through 10) for month t. $R^M - R^f$ is the monthly excess return on the value-weighted market return from CRSP. *SMB* (Small minus Big) is the excess monthly return of small firms over big firms, and *HML* (High minus Low) is the excess monthly return of high *BM* firms over low *BM* firms. *SMB* and *HML* were created by Fama and French (1993), who argue that the slopes on these variables in Equation (2) proxy for an asset's exposure to underlying risk factors—such a shifts in investors' future investment opportunities (Merton 1973)—that is compensated in average returns. This claim remains controversial, however.[5]

Regardless of whether the reader believes Equation (2) captures a rational, equilibrium pricing model, it is useful in this study for two reasons. First, grouping firms into portfolios reduces a substantial portion of the idiosyncratic variation in returns observed at the firm level. For example, the average portfolio time-series standard deviation of excess returns in my sample is 67 percent lower than the average firm-level standard deviation of returns (untabulated). Thus, utilizing portfolios reduces a considerable amount of the firm-specific "noise" in realized returns and produces a more stable return variable from which to identify any pattern related to earnings smoothness.

Second, if earnings smoothness is indeed a "risk factor" compensated in average returns, and this factor is orthogonal to any *Beta*, *Size*, or *BM* effects, then one should observe generally increasing estimates of α in Equation (2) as the portfolios progress from smooth to volatile earnings. The reason is that α represents the portion of an asset's average return in excess of that predicted by the asset's sensitivity to the risk factors in the model. If a factor model is properly specified (that is, if there are no omitted risk factors), then the estimated αs should be zero (Black et al. 1972; Cochrane 2001, Chap. 12). If, however, the model omits a risk factor, then portfolios with greater exposure to that factor will have a greater portion of average excess returns left unexplained (i.e., a higher α).

Panel A of Table 2 presents the results of the ten time-series portfolio regressions, along with an additional hedge portfolio regression. The hedge portfolio goes long (short) in portfolio 10 (1), and measures the monthly difference in returns between firms with the most volatile earnings and firms with the smoothest earnings. In Model 1, I include only an intercept to provide a sense of the average realized monthly return for each portfolio. There does not appear to be a clear, increasing trend in average returns from the smoothest to the most volatile earnings portfolios. Thus, there does not appear to be a link between earnings smoothness and average returns, even on a univariate basis. The hedge portfolio intercept indicates that firms in the most volatile earnings decile earn about six basis points more a month in excess returns than firms in the smoothest earnings decile, but this difference is not statistically different from zero ($t = 0.38$).

Model 2 includes all of the variables from Equation (2). Now, none of the intercepts are significantly different from zero at the 5 percent level (two-sided). The hedge portfolio actually earns an average negative monthly return, inconsistent with the notion that more volatile earnings lead to a higher risk premium, but this difference is insignificant as well ($t = -0.71$). The nearly monotonic loadings on $R^M - R^f$, *SMB*, and *HML* across portfolios

[5] Some authors, for example, claim the ability of *BM* to predict future returns is related not to sensitivity to some underlying risk factor, but rather to investor irrationality (see Lakonishok et al. 1994).

TABLE 2
Time-Series Regressions of Monthly Portfolio Returns on the Fama-French Three Factors

Panel A: Portfolio Regressions

	Smoothest Earnings							Most Volatile Earnings			Hedge
Portfolio Number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**10 − 1**
Model 1											
Intercept (α)	**1.012**	**1.014**	**1.064**	**1.108**	**1.074**	**0.969**	**1.023**	**1.057**	**1.040**	**1.074**	0.062
t-stat	**(4.53)**	**(4.58)**	**(4.59)**	**(4.62)**	**(4.51)**	**(3.98)**	**(4.01)**	**(4.02)**	**(3.60)**	**(3.43)**	(0.38)
Model 2											
Intercept (α)	0.074	0.094	0.107	0.139	0.101	0.011	0.066	0.089	0.038	−0.019	−0.092
t-stat	(0.93)	(1.26)	(1.45)	(1.91)	(1.33)	(0.15)	(0.94)	(1.06)	(0.39)	(−0.17)	(−0.71)
$R^M - R^f$	**0.951**	**0.939**	**0.969**	**0.993**	**0.995**	**1.006**	**1.027**	**1.012**	**1.078**	**1.140**	**0.190**
t-stat	**(49.05)**	**(51.59)**	**(53.9)**	**(56.09)**	**(53.64)**	**(56.62)**	**(60.55)**	**(49.16)**	**(45.32)**	**(42.11)**	**(5.97)**
SMB	**0.325**	**0.338**	**0.403**	**0.428**	**0.402**	**0.425**	**0.483**	**0.563**	**0.618**	**0.728**	**0.404**
t-stat	**(12.89)**	**(14.29)**	**(17.25)**	**(18.6)**	**(16.67)**	**(18.4)**	**(21.9)**	**(21.07)**	**(20.02)**	**(20.69)**	**(9.78)**
HML	**0.421**	**0.387**	**0.381**	**0.354**	**0.378**	**0.314**	**0.242**	**0.234**	**0.169**	**0.203**	**−0.218**
t-stat	**(14.71)**	**(14.42)**	**(14.36)**	**(13.52)**	**(13.79)**	**(11.96)**	**(9.65)**	**(7.69)**	**(4.82)**	**(5.09)**	**(−4.64)**
R^2	0.88	0.90	0.91	0.92	0.91	0.92	0.93	0.91	0.90	0.89	0.42

Panel B: Hypothesis Test

GRS Test for Model 2

Ho	**Ha**	**p**
all α = 0	all α ≠ 0	0.24

For each month, from 1/1/75 to 12/31/06, all firm-years in the sample are sorted into ten deciles based upon their earnings smoothness measure. See Table 1 for a description of how earnings smoothness is measured. Portfolios of stocks are then formed for each earnings smoothness decile. Model 1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e., the average excess returns for each portfolio over the sample period). Excess returns equal the value-weighted return on the portfolios less the risk-free rate. Model 2 reports the parameter estimates from a regression of the portfolio excess returns on the three Fama-French factors. Parameter estimates significant at the 5 percent level or lower (two-tailed) are bolded. $R^M - R^f$ is excess return on the value-weighted market portfolio. *SML* is the value-weighted size-mimicking portfolio return. *HML* is the value-weighted BM-mimicking portfolio return. R^M, R^f, *SMB*, and *HML* are obtained directly from Wharton Research Data Services via Ken French's website. Monthly returns are measured in percentages. The GRS test (see Gibbons et al. 1989) is a test of whether all intercepts in Model 2 are jointly equal to 0.

are consistent with the univariate correlations from Table 1. Firms with smoother earnings are bigger, have lower CAPM betas, and are more likely to be "value" firms than firms with volatile earnings.[6] Panel B of Table 2 reports the Gibbons et al. (1989) test, which indicates that the null hypothesis that all intercepts in Model 2 are jointly zero cannot be rejected (p = .24). This evidence, combined with the fact that all intercepts in Model 2 are individually insignificant and the R^2s are generally at 90 percent or better, indicates that the three-factor model of Fama and French (1993) fares quite well in pricing the test portfolios.

The findings in Tables 1 and 2 are robust to a variety of alternative specifications. These include replacing *Smooth* with earnings volatility not scaled by cash flow volatility, estimating *Smooth* over a shorter window, measuring *Smooth* using quarterly earnings, separating *Smooth* into innate versus discretionary or "managed" components, adjusting *Smooth* for differences across industries, considering the pricing effects of smooth, increasing earnings, backing out one-time special items, controlling for trended earnings growth, using annual cross-section regressions, and using equal weighted returns in the portfolio tests.

As a final test, I examine whether earnings smoothness, as a potential "risk factor," augments the three-factor model in Equation (2). If earnings smoothness is truly a risk factor, then assets that co-vary more strongly with a portfolio designed to mimic exposure to this risk factor should command a higher risk premium and earn higher returns. To this end, for each month I construct a factor-mimicking portfolio called *VMS* (Volatile minus Smooth) by subtracting the value-weighted return of stocks in the lowest three deciles from the value-weighted return on stocks in the highest three deciles of earnings smoothness. I then conduct time-series regressions of the form:

$$R_{it} - R_t^f = \alpha + \beta^{Rm-Rf}(R^M - R^f)_t + \beta^{SMB}SMB_t + \beta^{HML}HML_t + \beta^{VMS}VMS + \varepsilon_i. \tag{3}$$

Panel A of Table 3 contains average parameter estimates from firm-specific regressions across 5,336 firms with at least 18 monthly return observations over the sample period. Standard errors are based on variation in the parameters across firms. This procedure leads to inflated t-statistics since because is likely strong cross-correlation in the slope coefficients across firms. However, I do not draw any inferences from Panel A, so I make no correction for this bias. The results in Panel A are qualitatively similar to those of Francis et al. (2004, Table 10). They interpret the positive and significant loading on *VMS* as indicating that earnings smoothness is a priced risk factor. Core et al. (2008) take issue with this interpretation and argue that a positive and significant loading in Equation (3) is insufficient evidence to indicate that a factor is priced. For example, the loading on the market factor in Panel A is positive and significant; there is strong correlation between individual stock returns and the market portfolio. This correlation does not imply, however, that the CAPM is true and that market risk is priced. The central prediction of the CAPM is that assets with a higher β^{Rm-Rf} should earn a higher return. Analogously, if earnings smoothness is a priced risk factor, then assets with a higher β^{VMS} should earn a higher return.

To test for this relation, I first estimate the factor loadings (i.e., the βs) in Equation (3) at the portfolio level to mitigate the errors-in-variables problem that arises from firm-specific estimation (Black et al. 1972; Fama and MacBeth 1973). Core et al. (2008) use a similar

[6] In untabulated tests, I regress, at the portfolio level, average (unranked) smoothness measures on average *Beta*, *Size*, and *BM*. The adjusted R^2 is roughly 22 percent, leaving 78 percent of the variation in earnings smoothness across portfolios unexplained. Still, this orthogonal component is not compensated in average returns, as evidenced in Tables 1 and 2.

TABLE 3
Average Returns and Earnings Smoothness "Factor Loadings"

Panel A: Average Firm-Specific Factor Loadings

	Intercept	$R^M - R^f$	*SMB*	*HML*	*VMS*	R^2
Estimate	**0.193**	**0.891**	**0.698**	**0.349**	**0.425**	0.24
t-stat	**(5.99)**	**(70.00)**	**(40.54)**	**(19.11)**	**(15.53)**	

Panel B: Average Factor Loadings across 25 Portfolios Sorted on B/M and Smoothness

	Intercept	$R^M - R^f$	*SMB*	*HML*	*VMS*	R^2
Estimate	**0.091**	**1.003**	**0.493**	**0.390**	0.088	0.87
t-stat	**(4.06)**	**(123.77)**	**(12.34)**	**(6.04)**	(1.08)	

Panel C: Monthly Cross-Sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	β_{RM-Rf}	β_{SMB}	β_{HML}	β_{VMS}	R^2
Estimate	0.332	0.203	**0.885**	0.337	0.001	0.47
t-stat	(0.57)	(0.36)	**(2.60)**	(1.57)	(0.01)	

Each month, from 1/1/75 to 12/31/06, I construct a factor-mimicking portfolio called *VMS* (Volatile minus Smooth) by subtracting the value-weighted return of stocks in the lowest three deciles from the value-weighted return on stocks in the highest three deciles of earnings smoothness. See Table 1 for a description of how earnings smoothness and stock returns are measured, and definitions of $R^M - R^f$, *SMB*, and *HML*. Panel A presents average coefficients across 5,336 firm-specific, time-series regressions of excess monthly returns on the three Fama-French factors plus *VMS*. t-statistics are calculated from the standard errors of the average parameters. Panel B presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the three Fama-French factors plus *VMS*. The 25 portfolios are created by sorting stocks into quintiles based on B/M and earnings smoothness each month. t-statistics are calculated from the standard errors of the average parameters. Panel C presents average coefficients from 384 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e., the slope coefficients from the regressions in Panel B). t-statistics are calculated from the standard errors of the average monthly parameter estimates. Parameter estimates significant at the 5 percent level or lower (two-tailed) are bolded.

approach. Each month I sort firms (independently) into quintiles based on earnings smoothness and *BM*, forming 25 portfolios from the intersection of these sorts. Sorting on earnings smoothness ensures sufficient variation in the variable of interest among the test assets; sorting on *BM* produces variation in average returns, thereby giving the model in Equation (3) something to explain.

Panel B of Table 3 provides average parameters estimates across 25 portfolio-specific, time-series estimations of Equation (3). Note in this panel that the average loading on *VMS* is now insignificant (t = 1.08). To test whether higher loadings on *VMS* lead to higher returns, I estimate the following cross-sectional regression for every month:

$$R_{pt} - R_t^f = \alpha + \delta_1\beta_p^{Rm-Rf} + \delta_2\beta_p^{SMB} + \delta_3\beta_p^{HML} + \delta_4\beta_p^{VMS} + \varepsilon_i. \quad (4)$$

In Equation (4), the βs from the time-series portfolio regressions reported in Panel B of Table 3 are used as covariates to explain cross-sectional variation in the 25 portfolio returns. Panel C reports the time-series average of the parameters from the 384 monthly regressions, along with Fama-Macbeth t-statistics. The loading on β_{VMS} is quite small and insignificant (t = 0.01), providing no support for earnings smoothness as an incrementally priced risk factor. The loading on β_{SMB} is positive and significant at the 5 percent level (t = 2.60),

while the loading on β_{HML} is positive but insignificant (t = 1.57). One limitation of the analysis in Table 3 is that the portfolio loadings in Panel B are likely measured more noisily than characteristics like *Size*, *BM*, or *Smooth*, such that measurement error could bias the coefficients in Panel C toward zero (note the insignificant loading on β_{HML}). However, it is worth noting that the characteristic-based tests in Tables 1 and 2 do not support earnings smoothness as a priced risk factor either.

In summary, I find no discernable relation between earnings smoothness and average stock returns over the past 30 years. Tables 1 through 3 indicate that earnings smoothness has no ability to explain variation in average returns, either as a characteristic at the firm or portfolio level or as the basis for a mimicking portfolio in a factor model. Why, then, are smoother earnings strongly associated with a lower implied cost of capital using Value Line estimates? One explanation is that Value Line analyst estimates are systematically optimistic, a possibility I explore in the next section. Another possibility is that *ex ante* Value Line estimates are correct on average, but information surprises contaminate the asset-pricing tests over the last 30 years. I discuss this possibility in Section V.

IV. IMPLIED COST OF CAPITAL TESTS

In this section, I examine the Value Line input variables used to generate implied cost of capital estimates. Specifically, I benchmark Value Line projections against actual realizations to see why Value Line analysts expect (implicitly at least) a relation between stock returns and earnings smoothness when none seems to exist over the sample period. I first provide some background on Value Line and briefly discuss data sources. I then lay out the empirical methodology and results.

Background

Value Line is an equity research firm that provides no brokerage or investment banking services. Their primary product is the Investment Survey, which is distributed weekly to subscribers. The Investment Survey contains historical financial information, as well as projections of future items such as stock prices, earnings, and dividends for more than 1,700 firms. Brav et al. (2005) use projected stock price and dividend information from the Value Line Investment Survey to impute cost of capital. I discuss their procedure in more detail below. These estimates from Brav et al. (2005) serve as the dependent variable that Francis et al. (2004) link to earnings smoothness.

Data

The data used in this section come from a variety of sources. For the period 1975–2001, I obtain implied cost of capital estimates directly from Alon Brav's website.[7] For the period 1989–2001, I obtain the Estimates and Projections file directly from Value Line. This data set contains the projections of future stock prices, earnings, and dividends from the Investment Survey that underlie the implied cost of capital estimates of Brav et al. (2005).[8] The intersection of these two data sets comprises the primary sample for this section, which I refer to as the "projections subsample." I also obtain data from the Compustat, CRSP, and I/B/E/S files as I describe below. Overall, the projections subsample contains 9,105 observations for 1,365 firms over the period 1989–2001.

[7] http://www.duke.edu/~brav/.

[8] Unfortunately, the Estimates and Projections file obtained from Value Line only contains data on firms that Value Line deems as currently active and/or still covers. To mitigate a potential survivorship problem, I hand-collect data from the hard copy Investment Survey for 2,078 firm-years that have *CoC* estimates from Brav et al. (2005) but are not in the Estimates and Projections file over the sample period.

Empirical Methodology and Results

I begin by replicating the main findings of Francis et al. (2004) using the cost of capital estimates from Brav et al. (2005). They estimate cost of capital from the following expression:

$$(1 + CoC)^4 = \frac{TP}{P} + \frac{DIV\left[\frac{(1 + CoC)^4 - (1 + g)^4}{CoC - g}\right]}{P}, \tag{5}$$

where *TP* is the estimate of four-year ahead stock price, *DIV* is the estimate of next year's dividends per share, *g* is the estimated annual growth rate of dividends per share, and *P* is the stock price per share nine days before publication date of the analyst's projections in the Investment Survey. Estimated implied cost of capital is the value of *CoC* that equates both sides of Equation (5). Following Francis et al. (2004), I estimate the following cross-sectional regression every year from 1975 to 2001:

$$CoC_i = \alpha + \beta_1 Smooth_i + \beta_2 Beta_i + \beta_3 Size_i + \beta_4 BM_i + \varepsilon_i, \tag{6}$$

where *Smooth* is the annual decile rank of a firm's earnings smoothness measure and *Beta*, *Size*, and *BM* are defined as before. CoC_i is the estimated cost of capital from Equation (5) and is stated as a percentage. Panel A of Table 4 presents the average parameter estimates, along with Fama-Macbeth t-statistics (adjusted with a Newey and West [1987; Newey-West] correction for autocorrelation at four lags), from the annual regressions in Equation (6). I present estimates for the entire period 1975–2001, as well as the period 1989–2001 covered by the projections subsample. The results are very similar to Table 5 in Francis et al. (2004). They report a coefficient of 0.125 on *Smooth*, while I find a coefficient in Panel A of 0.143 (t = 4.96) for the full period. Thus, I confirm the primary findings of Francis et al. (2004) regarding earnings smoothness.

To see why firms with volatile earnings have a higher implied *CoC* than firms with smooth earnings, I turn to the projections subsample. Value Line analysts calculate four-year target prices (*TP*) by forecasting future EPS four years beyond the current year and multiplying this figure by a forecasted price-to-earnings (P/E) ratio (Brav et al. 2005; Courteau et al. 2006).[9] The implication of this calculation by Value Line is a point perhaps overlooked by prior implied cost of capital research. Value Line markets the Investment Survey as tool for investors to pick stocks. Firms with high target prices relative to current prices are viewed as "good buys," with high forecasted earnings growth (presumably that the market has not noticed). To the researcher, though, this spread between current price and forecasted price in Equation (5) is treated as a compensation for risk (i.e., a higher expected return or cost of capital). To the extent that Value Line is overly optimistic in their earnings and target price forecasts for some firms, however, the resulting implied cost of capital estimates derived from Equation (5) will be upwardly biased. To test for this bias, I benchmark these forecasted variables against their actual realizations, and relate any differences to earnings smoothness. Specifically, I define the following variables:

[9] Value Line confirms this methodology on their website. Visit: http://www.valueline.com/ed_vlpage.html and click on item 6. In untabulated analysis, I find that the Pearson (Spearman) in-sample correlation between projected target prices and the product of forecasted EPS and forecasted P/E is 0.93 (0.98).

TABLE 4
Earnings Smoothness and Implied Cost of Capital from Value Line Estimates

Panel A: Cross-Sectional Regressions of Annual Implied Cost of Capital Estimates on Earnings Smoothness

	Intercept	*Smooth*	*Beta*	*Size*	*BM*	R^2
Years: 1975–2001						
Estimate	**21.453**	**0.143**	**3.632**	**−0.671**	**2.542**	0.20
t-stat	(12.10)	(4.96)	(6.77)	(−3.34)	(4.60)	
Years: 1989–2001						
Estimate	**20.100**	**0.163**	**3.962**	**−1.113**	**1.793**	0.25
t-stat	(20.66)	(5.04)	(5.93)	(−19.77)	(4.08)	

Panel B: Average Expected and Actual Values for Value Line Input Variables by Earnings Smoothness Decile: 1989–2001

Smoothness Decile	n	Expected Dividends	Expected Price Appreciation	Actual Price Appreciation	Expected Earnings	Actual Earnings	Earnings Forecast Error	Expected P/E Ratio	Actual P/E Ratio	P/E Forecast Error
Smooth			*TP/P*	*AP*	*FEPS*	*AEPS*	FE^{EPS}	*FPE*	*APE*	FE^{PE}
1	931	0.136	1.641	1.622	0.117	0.079	0.038	14.778	21.382	−6.592
2	918	0.125	1.663	1.616	0.118	0.083	0.035	14.678	19.353	−4.537
3	946	0.116	1.676	1.667	0.118	0.083	0.036	14.881	18.520	−3.517
4	892	0.123	1.647	1.597	0.116	0.078	0.038	15.020	18.764	−3.697
5	915	0.131	1.678	1.585	0.119	0.077	0.042	15.008	19.176	−4.069
6	898	0.114	1.698	1.554	0.120	0.074	0.046	15.040	19.606	−4.459
7	918	0.090	1.754	1.736	0.123	0.078	0.045	15.223	20.208	−4.904
8	902	0.078	1.779	1.648	0.124	0.071	0.053	15.390	18.767	−3.306
9	898	0.097	1.766	1.624	0.123	0.070	0.053	15.820	20.421	−4.582
10	887	0.082	1.860	1.688	0.128	0.061	0.067	15.631	21.316	−5.549

(*continued on next page*)

TABLE 4 (continued)

Panel A presents coefficients estimates from annual cross-sectional regressions of implied cost of capital estimates on the variables listed above. Implied cost of capital estimates are based on projected target prices and dividends from Value Line (see Brav et al. 2005) and are obtained directly from Alon Brav's website. Implied cost of capital estimates are measured in percentages, stated on an annual basis, and are averaged over a 12-month period ending four months after the end of the fiscal year. *Smooth* is the decile rank (sorted annually) of a firm-years' earnings smoothness measure. See Table 1 for details as to the calculation of earnings smoothness, *Beta*, *Size*, and *BM*. The first regression presents parameter estimates from the 27-year period from 1975 to 2001, while the second regression covers the 13-year period from 1989 to 2001. Parameter estimates are time-series averages of the parameters from the annual cross-sectional regressions. t-statistics are calculated from the standard errors of these annual averages, adjusted for a Newey-West correction at four lags. Parameter estimates significant at the 5 percent level or lower (two-tailed) are bolded.

Panel B presents mean values (by earnings smoothness deciles) of the forecasted and realized values of the input variables that underlie the implied cost of capital estimates used in Panel A. Data is obtained from the Value Line Estimates and Projections File for the period 1989–2001. Expected dividends are Value Line analysts' forecasts of future dividends over the four-year forecast horizon, scaled by *P*, the stock price (from CSRP) nine days before the publication date of the analysts' report. See Equation (5) in the study for more details. *TP* is the midpoint of the range of four-year-ahead target stock price forecasted by Value Line. *FEPS* is the forecasted four-year-ahead *EPS*, scaled by *P*. *AEPS* is the actual four-year-ahead earnings (obtained from I/B/E/S), divided by forecasted four-year-ahead shares outstanding, scaled by *P*. FE^{EPS} is *EPS* forecast error, which equals *FEPS* minus *AEPS*. *FPE* is the forecasted four-year-ahead P/E ratio, calculated as (*TP*/*P*)/*FEPS*. *APE* is the actual four-year-ahead P/E ratio, calculated as actual four-year-ahead price per share divided by *AEPS* * *P*. Actual four-year-ahead price is calculated as future total market value of equity four years after the third month subsequent to the end of the current fiscal year, scaled by forecasted four-year-ahead shares outstanding. FE^{PE} is the P/E forecast error and equals *FPE* minus *APE*. *AP* is actual share price appreciation, which equals *APE* * *AEPS*. All variables from the Estimates and Projections File are averaged over a 12-month period ending four months after the end of the fiscal year.

$FEPS$ = forecasted four-year-ahead EPS, scaled by P, the current stock price;
$AEPS$ = actual four-year-ahead earnings, divided by forecasted four-year-ahead shares outstanding, scaled by P;
FE^{EPS} = EPS forecast error, calculated as $FEPS - AEPS$;
FPE = forecasted four-year-ahead P/E ratio, calculated as $(TP/P)/FEPS$;
APE = actual four-year-ahead P/E ratio, calculated as actual four-year-ahead price per share divided by $AEPS * P$. Actual four-year-ahead price is calculated as future market value of equity four years after the third month subsequent to the end of the current fiscal year, scaled by forecasted four-year-ahead shares outstanding;
FE^{PE} = P/E forecast error, calculated as $FPE - APE$; and
AP = actual price appreciation, equal to $AEPS \times APE$.

Three methodological details merit discussion before proceeding. First, the Estimates and Projections File from Value Line does not report actual annual four year-ahead earnings in a consistent and reliable fashion. As a result, I obtain actual earnings from I/B/E/S. This approach seems reasonable because both I/B/E/S and Value Line exclude from reported earnings nonrecurring items analysts did not intend to forecast.

Second, of the 9,105 observations in the sample, 1,017 do not have available four-year-ahead stock return or earnings data. Excluding these observations from the analysis could induce a potential survivorship bias. Specifically, because non-survivors have relatively poor future returns and earnings prior to their exit from the sample (untabulated), excluding these observations leads to an upward bias in average future returns and profitability. To the extent that firms with more volatile earnings drop out of the sample at a disproportionate rate, this pattern could bias the results in favor of finding a positive relationship between earnings volatility and future returns or earnings.[10] This problem could be particularly acute over a four-year period, especially when benchmarked against asset-pricing tests, which require only all available future monthly returns up to 12 months.

To mitigate this potential bias, I do the following: If a stock stops trading prior to the end of the four-year cumulation window, then I multiply its last available market value of equity by the delisting return (if available) from CRSP.[11] I then reinvest the proceeds in an equally weighted portfolio (rebalanced monthly) of firms in the same earnings smoothness decile. I calculate the portfolio returns excluding dividends, so as to capture only stock price appreciation. The value of the proceeds at the end of the accumulation window serves as the future market value of equity used to calculate APE and AP. If a firm is missing four-year ahead actual EPS from I/B/E/S, then I impute this value. Specifically, I multiply the last available value of actual EPS by the appropriately compounded earnings growth rate for the firm's earnings smoothness decile. I also conduct the analysis without this survivorship correction (i.e., by just examining four-year survivors) to assess its impact on my findings. I find inferentially similar results, so it appears that survivorship is not an overriding concern in this setting. Nevertheless, the tabled results that follow include this correction, as I feel it is methodologically appropriate.

Third, I winsorize the variables TP/P, $FEPS$, $AEPS$, and APE at the top and bottom 1 percent of their distributions each year to mitigate the influence of extreme observations.

[10] The proportion of non-survivors in the smoothest (most volatile) earnings decile is 8.5 (13.5) percent. The correlation between smoothness decile rank and the proportion of non-survivors in each decile is 0.84 ($p < .01$).
[11] Following Sloan (1996), if the delisting return is missing but the delisting code indicates a forced delisting or liquidation, I assume a delisting return of −100 percent.

Brav et al. (2005) winsorize Value Line target prices in generating their *CoC* estimates, so I winsorize *TP* and *FEPS* for consistency. I winsorize *AEPS* and *APE* since outliers in the raw, price scaled EPS distribution produce extreme actual P/E values. Note that winsorizing *AEPS* and *APE* also implicitly winsorizes actual share appreciation, *AP*. Results are inferentially similar if I delete the top and bottom 1 percent of the variables above each year, or if I make no adjustment for outliers.

Panel B of Table 4 presents mean values, by earnings smoothness decile, of the forecasted and actual variables underlying the implied *CoC* estimates. The third column lists the average expected dividend component of implied *CoC* − the second term on the RHS of Equation (5). This value decreases as earnings become more volatile, while the other component of implied *CoC*, expected share price appreciation (*TP/P*), increases almost monotonically. Thus, expected price appreciation alone drives the positive relation between *Smooth* and implied *CoC*. However, while expected price appreciation increases nearly monotonically across smoothness deciles, actual price appreciation (*AP*) is relatively flat, consistent with the asset-pricing tests in the previous section. As a sensitivity check, I repeat the asset-pricing analysis in Tables 1 and 2 using the projections subsample and find similar results for the smoothness measure.

Forecasted EPS (*FEPS*) in Panel B of Table 4 also increases with earnings volatility, while actual EPS (*AEPS*) appears to decrease. The positive gap between *FEPS* and *AEPS* indicates that earnings forecasts are too optimistic, across the board, for all firms. But as earnings become more volatile, the gap grows, and earnings forecast errors (FE^{EPS}) get larger (i.e., more optimistic). Finally, the last three columns in Panel B of Table 4 report mean values of the P/E variables (*FPE*, *APE*, and FE^{PE}) by smoothness decile. While *FPE* increases nearly monotonically with earnings volatility, no clear pattern emerges for *APE* and FE^{PE}.

Table 4 yields two important takeaways. First, the association between *Smooth* and implied *CoC* is driven exclusively by expected share price appreciation (*TP/P*). Second, the relation between *Smooth* and actual price appreciation (*AP*) appears weak, while the relation between *Smooth* and earnings forecast errors (FE^{EPS}) appears quite strong. This evidence implies that optimism in analysts' expectations of future EPS yields target prices that are systematically too high for firms with volatile earnings. These target prices are ultimately not achieved, explaining why firms with volatile earnings have higher implied *CoC*s, but do not earn higher returns, than firms with smooth earnings.

To investigate this possibility further, I first examine whether the univariate patterns in Panel B of Table 4 hold up in a multivariate framework that controls for *Beta*, *Size*, and *BM* effects. To do so, I estimate the following cross-sectional regressions each year:

$$DepVar_i = \alpha + \beta_1 Smooth_i + \beta_2 Beta_i + \beta_3 Size_i + \beta_4 BM_i + \varepsilon_i, \tag{7}$$

where the covariates are defined as before and $DepVar_i$ is, separately, AP_i, FE^{EPS}, and FE^{PE}. Panel A of Table 5 presents the average coefficient estimates from the annual regressions in Equation (7). Due to the overlapping nature of the data (i.e., annual regressions with four-year cumulation windows), all t-statistics in this section are based on Fama-Macbeth standard errors, adjusted for autocorrelation with a Newey-West correction up to four lags.[12]

[12] General practice for Newey-West estimation is to use a lag length equal to the smallest integer greater than $T^{.25}$ (Greene 2003, 267). With $T = 13$, this implies a lag length of 2. I repeat all of the subsequent analysis using a lag length equal to 2, and a lag length equal to 0 (i.e., no adjustment). I also repeat the analysis using pooled regressions and clustering standard errors on industry and firm. Results are inferentially similar.

TABLE 5
Earnings Smoothness and Input Variables for Value Line Implied Cost of Capital Estimates

Panel A: Annual Cross-Sectional Regressions of Actual Four-Year Price Appreciation and Forecast Errors on Earnings Smoothness

	Dependent Variable		
	Actual Price Appreciation	**Earnings Forecast Error**	**P/E Forecast Error**
	AP	FE^{EPS}	FE^{PE}
Smooth	0.003	**0.003**	−0.006
t-stat	(0.45)	**(3.92)**	(−0.05)
Beta	0.235	**0.026**	1.408
t-stat	(1.55)	**(6.98)**	(1.74)
Size	−0.055	**−0.009**	−0.268
t-stat	(−1.67)	**(−5.52)**	(−0.56)
BM	−0.047	**0.020**	**1.182**
t-stat	(−0.60)	**(5.36)**	**(2.03)**

Panel B: Decomposition of the Relation between Earnings Smoothness and Four-Year Expected Share Price Appreciation

	Dependent Variable								
	Expected Price Appreciation	=	**Actual Price Appreciation**	+	**Earnings Bias**	+	**P/E Bias**	+	**Interaction**
	TP/P	=	***AP***	+	$FE^{EPS} * FCPE$	+	$FE^{PE} * FCEPS$	+	$-(FE^{EPS} * FE^{PE})$
Smooth	**0.014**		0.003		**0.032**		−0.002		−0.019
t-stat	**(5.40)**		(0.45)		**(4.06)**		(−0.13)		(−1.54)
Beta	**0.357**		0.235		**0.404**		0.04		**−0.322**
t-stat	**(5.18)**		(1.55)		**(4.90)**		(0.34)		**(−3.15)**
Size	**−0.09**		−0.055		**−0.135**		−0.024		**0.125**
t-stat	**(−10.58)**		(−1.67)		**(−5.20)**		(−0.45)		**(3.39)**
BM	**0.110**		−0.047		**0.18**		−0.038		0.015
t-stat	**(3.68)**		(−0.60)		**(3.82)**		(−0.49)		(0.11)

Panel A provides average parameter estimates from annual regressions of four-year actual price appreciation (*AP*), earnings forecast error (FE^{EPS}), and P/E forecast error (FE^{PE}) on earnings smoothness and control variables. See Table 4 for variable definitions. Panel B provides average parameter estimates from annual regressions of the components of four-year expected price appreciation (*TP/P*) on earnings smoothness and control variables. These regressions decompose the slope coefficients from the *TP* regressions into the four components listed above. See the Appendix for details of the decomposition. Parameter estimates are time-series averages of the parameters from the annual cross-sectional regressions over the 13-year period from 1989 to 2001. t-statistics are calculated from the standard errors of these annual averages, adjusted with a Newey-West (1987) correction for autocorrelation up to four lags. Parameter estimates significant at the 5 percent level or lower (two-tailed) are bolded.

The results in Panel A of Table 5 confirm the univariate findings in Table 4. The relation between *Smooth* and actual price appreciation is insignificant (t = 0.45).[13] *Smooth* is strongly correlated with FE^{EPS} (t = 3.92) as are the other covariates, while there is no significant relation between *Smooth* and FE^{PE} (t = −0.05).

To assess the impact of earnings optimism on the relation between *Smooth* and expected share price appreciation (*TP/P*) more formally, I decompose *TP/P* into four components:

$$\frac{TP}{P} = \underbrace{(AP)}_{\text{Actual Price Appreciation}} + \underbrace{(FE^{EPS} * FPE)}_{\text{Earnings Bias}} + \underbrace{(FE^{PE} * FEPS)}_{\text{P/E Bias}} - \underbrace{(FE^{EPS} * FE^{PE})}_{\text{Interaction Effect}}. \tag{8}$$

The Appendix explains the derivation of this decomposition. Equation (8) demonstrates that expected price appreciation can be decomposed into actual price appreciation, plus bias in forecasted earnings (ignoring any bias in forecasted P/E), plus bias in forecasted P/E (ignoring any bias in forecasted earnings), minus the interaction of EPS and P/E bias. The interaction term measures the joint effect of EPS and P/E bias and is necessary because the middle two terms ignore error in forecasted P/E and earnings, respectively. The Appendix provides a simple numerical example.

Equation (8) allows me to decompose the relation between *Smooth* and *TP/P* into these four components as well, using OLS regression. Specifically, the slope coefficients from regressing *TP/P* on the covariates in Equation (7) simply equal the sum of the slope coefficients from four separate regressions with the four components in Equation (8) serving as dependent variables.[14]

So, in the following regression:

$$TP/P_i = \alpha + \beta_1 Smooth_i + \beta_2 Beta_i + \beta_3 Size_i + \beta_4 BM_i + \varepsilon_i, \tag{9}$$

the βs simply equal the sum of the βs from the following four regressions:

$$\begin{aligned} APi_i &= \alpha + \beta_1 Smooth_i + \beta_2 Beta_i + \beta_3 Size_i + \beta_4 BM_i + \varepsilon_i \\ (FE^{EPS} * FPE)_i &= \alpha + \beta_1 Smooth_i + \beta_2 Beta_i + \beta_3 Size_i + \beta_4 BM_i + \varepsilon_i \\ (FE^{PE} * FEPS)_i &= \alpha + \beta_1 Smooth_i + \beta_2 Beta_i + \beta_3 Size_i + \beta_4 BM_i + \varepsilon_i \\ -(FE^{EPS} * FE^{PE})_i &= \alpha + \beta_1 Smooth_i + \beta_2 Beta_i + \beta_3 Size_i + \beta_4 BM_i + \varepsilon_i. \end{aligned} \tag{10}$$

[13] Surprisingly, in Panel A of Table 5, while *Size* is negatively related to future returns at the 10 percent level (one-sided; t = −1.67) as expected, the loading on *BM* is insignificant (t = −0.60), while the loading on *Beta* is positive and significant at 10 percent on a one-sided basis (t = 1.55). Upon further investigation, three factors explain why these results differ from the asset-pricing tests. First, using an unwinzorized return metric increases the significance on Size. Second, I perform cross-sectional monthly return regressions—using returns without dividends—in Equation (1) for the projections subsample from 1989–2001. I find very similar results to those reported in the Appendix. When I use returns with dividends (as I do in Table 1), results are the same except *Beta* loses significance. Thus, measuring returns with or without dividends affects the loading on *Beta*. Finally, Brav et al. (2005) note that Value Line tends not to cover small, high *BM* firms. This is where the *BM* effect is the strongest (Loughran 1997). When I expand the sample to all firms in the asset-pricing sample over the same time period, *BM* becomes positive and significant.

[14] To see this, let y be a dependent variable that can be decomposed into i components such that $y = \Sigma_i y_i$. The vector of OLS coefficients is then given by: $[X'X]^{-1}X'y = [X'X]^{-1}X'\Sigma_i y_i = \Sigma_i[X'X]^{-1}X'y_i$.

Panel B of Table 5 provides estimates from the five regressions in Equations (9) and (10). The first row indicates that the positive coefficient relating Smooth to *TP/P*, 0.014 (t = 5.40), is driven primarily by the coefficient relating *Smooth* to bias in forecasted EPS, 0.032 (t = 4.06), consistent with Panel A. As earnings become more volatile, analysts' earnings forecasts become more optimistic. Actual price appreciation and bias in P/E forecast play a small role, and both coefficients individually are insignificantly different from zero. The coefficient on the interaction term, −0.019, is insignificant (t = −1.54) at the 5 percent level.[15] Results for the remaining variables in Panel B are generally similar, with earnings bias and, to some extent, the interaction term playing significant roles in relating these variables to expected price appreciation.

In summary, I conclude from Tables 4 and 5 that bias in analysts' long-term earnings forecasts is the main driver of the association between earnings smoothness and implied cost of capital. As earnings become more volatile, earnings projections become more optimistic, producing target prices that are too high and never achieved. Thus, while Value Line analysts may expect firms with volatile earnings to earn higher returns, this future price appreciation does not materialize over the sample period.

Why is Earnings Optimism Increasing in Earnings Volatility?

Prior research finds that analysts mis-weight the persistence of prior earnings changes when predicting future earnings changes. For example, Easterwood and Nutt (1999) demonstrate that analysts' under-react to large prior earnings decreases and over-react to large prior earnings increases, yielding forecasts of future earnings that are optimistic on average. Firms with volatile earnings naturally have larger prior earnings increases and decreases than firms with smooth earnings. Thus, I conjecture that the large prior earnings changes of volatile earnings firms, combined with analysts' general mis-weighting of prior earnings changes, produce optimism in future earnings forecasts that is increasing in earnings volatility.

To test this conjecture, I adopt a framework similar to Easterwood and Nutt (1999). Define $CEPS_{t-5\rightarrow t-1}$ as the change in earnings per share from year t–5 to $t-1$, scaled by price at the end of year $t-1$. Further, let D be an indicator variable equal to 1 if $CEPS_{t-5\rightarrow t-1}$ is negative, and 0 otherwise. Finally, consider the following regression equations:

$$FEPS_{t+4} - AEPS_t = \lambda + \delta_1 D + \delta_2 CEPS_{t-5\rightarrow t-1} + \delta_3(D * CEPS_{t-5\rightarrow t-1}) + \varepsilon; \tag{11}$$

$$AEPS_{t+4} - AEPS_t = \alpha + \beta_1 D + \beta_2 CEPS_{t-5\rightarrow t-1} + \beta_3(D * CEPS_{t-5\rightarrow t-1}) + \tau; \tag{12}$$

$$\begin{aligned} FEPS_{t+4} - AEPS_{t+4} = {} & (\lambda - \alpha) + (\delta_1 - \beta_1)D + (\delta_2 - \beta_2)CEPS_{t-5\rightarrow t-1} \\ & + (\delta_3 - \beta_3)(D * CEPS_{t-5\rightarrow t-1}) + (\varepsilon - \tau). \end{aligned} \tag{11) − (12) = (13}$$

[15] Since ($FE^{EPS} * FE^{PE}$) is positive (negative) when FE^{PE} and FE^{EPS} have identical (different) signs, the coefficient on the interaction term can be interpreted as the extent to which variation in the independent variables increases or decreases the likelihood that FE^{EPS} and FE^{PE} will share the same sign.

Equation (11) measures the implicit weights, δ_2 and δ_3, that analysts place on positive and negative prior earnings changes when predicting future four-year earnings changes. Equation (12) measures the "true" relation between actual earnings changes and past earnings changes.[16] Equation (13), the difference between Equations (11) and (12), measures the differences in the weights used by analysts to predict future earnings from the empirical weights. Thus, Equation (13) indicates that, by regressing FE^{EPS} on past earnings changes, one can estimate the extent to which analysts mis-weight prior earnings changes when predicting future earnings changes. If analysts over-react to positive prior earnings changes, then $\delta_2 - \beta_2$ will be positive. If analysts under-react to negative prior earnings changes, then the sum of $\delta_2 - \beta_2$ and $\delta_3 - \beta_3$ will be negative.

Panel A of Table 6 reports average parameters from annual estimates of the regressions in Equation (13) for the Value Line sample. I report estimates for the full sample and for firms in the upper (more volatile) and lower (less volatile) three earnings smoothness deciles. Across all specifications, the coefficient on $CEPS_{t-5\rightarrow t-1}$ is significantly positive, and the coefficient on $D * CEPS_{t-5\rightarrow t-1}$ is significantly negative. In addition, the sum of these two coefficients is significantly negative ($p < 0.01$, untabulated). These findings are consistent with those of Easterwood and Nutt (1999): analysts over(under) react to positive (negative) prior earnings changes. Note that this mis-weighting is present in both smooth and volatile earnings firms.

Can such a finding help explain why analysts' long-term earnings forecasts are more optimistic for firms with volatile earnings? To answer this question, I focus on the subsample of observations in the upper (more volatile) and lower (less volatile) three earnings smoothness deciles. I create an indicator variable, *VOL*, equal to 1 if the observation is in the upper, or more volatile, deciles, and 0 if it is in the lower, or smoother, deciles. In Panel B of Table 6, I regress FE^{EPS} on *VOL*, and separately, on *VOL* and the covariates in Equation (13). These regressions estimate the extent to which analysts' mis-weighting of prior earnings changes can explain the difference in mean FE^{EPS} between the firms with the smoothest and most volatile earnings. The first regression indicates that firms in the most volatile earnings deciles have EPS forecast errors that are higher than firms in the smoothest earnings deciles by 2.2 percent ($t = 4.77$) of equity market value. The second regression indicates that this difference shrinks by almost 70 percent, to 0.7 percent, and becomes insignificant ($t = 1.42$) once prior earnings changes are considered. In short, prior positive and negative earnings changes are correlated with both *VOL* and FE^{EPS}, and their mis-weighting by analysts explains an economically and statistically significant fraction of the difference in FE^{EPS} between volatile and smooth earnings firms.

V. WEIGHING THE EVIDENCE

This study provides evidence that: (1) earnings smoothness is not linked to average returns over the last 30 years, and (2) the relationship between earnings smoothness and implied cost of capital from Value Line is driven by forecast errors in future earnings estimates. One interpretation of this evidence is that earnings smoothness is not a factor compensated in equity cost of capital, and the Value Line implied cost of capital estimates are contaminated by analyst optimism. Another possibility is that *ex post* average returns are

[16] Easterwood and Nutt (1999) actually split prior earnings changes into quartiles and find evidence of analyst mis-weighting in quartiles 1 and 4 (extreme positive or negative changes). In my sample, I find some evidence of mis-weighting even in intermediate quartiles (untabulated). For this reason, and to simplify the analysis, I just examine positive and negative changes in general.

TABLE 6
The Relation between Future Earnings Forecast Errors and Past Earnings Changes

Panel A: Regression of Four-Year Earnings Forecast Error on Positive and Negative Prior Four-Year Earnings Changes

	Intercept	*D*	*CEPS*	*D * CEPS*	R^2	n
Full Sample						
Estimate	**0.028**	**0.011**	**0.319**	**−0.549**	0.055	9114
t-stat	**(8.26)**	**(3.48)**	**(6.05)**	**(−7.58)**		
Smooth Earnings Firms						
Estimate	**0.02**	**0.016**	**0.424**	**−0.700**	0.086	2797
t-stat	**(5.24)**	**(3.30)**	**(4.00)**	**(−4.33)**		
Volatile Earnings Firms						
Estimate	**0.032**	0.016	**0.298**	**−0.504**	0.077	2690
t-stat	**(9.97)**	(3.17)	**(4.05)**	**(−7.04)**		

Panel B: The Role of Past Earnings Changes in Explaining the Difference in Average Earnings Forecast Errors between Volatile and Smooth Earnings Firms

	Intercept	*VOL*	*D*	*CEPS*	*D * CEPS*	R^2	n
Estimate	**0.036**	**0.022**				0.02	5487
t-stat	**(7.46)**	**(4.77)**					
Estimate	**0.024**	0.007	**0.015**	**0.319**	**−0.545**	0.083	5487
t-stat	**(6.92)**	1.42	**(3.67)**	**(7.05)**	**(−9.13)**		

Panel A presents results from annual regressions of FE^{EPS} on the variables above, using data from the Value Line Estimates and Projections sample in Tables 4 and 5. FE^{EPS} is defined in Table 4. *CEPS* is the change in net income before extraordinary items per Compustat (#data18) from year *t*–5 to year *t*–1, scaled by market value of equity at the end of year *t*–1. *D* is an indicator variable equal to 1 if *CEPS* is negative, and 0 otherwise. Results are presented for the full sample, as well as firms in the lowest three (smoothest) and highest three (most volatile) earnings smoothness deciles. See Table 1 for details on the earnings smoothness measure.

Panel B uses just observations in the upper and lower three earnings smoothness deciles. *VOL* is an indicator variable equal to 1 if an observation is in the highest three (most volatile) earnings smoothness deciles, and 0 if it is in the lowest three (smoothest) earnings smoothness deciles. Parameter estimates are time-series averages of the parameters from the annual cross-sectional regressions over the 13-year period from 1989 to 2001. t-statistics are calculated from the standard errors of these annual averages, adjusted with a Newey-West (1987) correction for autocorrelation up to four lags. Parameter estimates significant at the 5 percent level or lower (two-tailed) are bolded.

confounded by information surprises over the sample period. Note that the information surprises would have to be correlated in the cross-section with earnings smoothness (Francis et al. 2004). Perhaps, due to chance, firms with more volatile earnings had a disproportionate run of "bad luck" over the sample period, reporting lower earnings (i.e., negative "cash flow" surprises) and thus realizing lower stock returns than analysts and investors were expecting. This possibility would also explain why Value Line analysts appeared, *ex post*, to be overly optimistic in their earnings projections.

I conduct two different tests to evaluate the effects of cash flow surprises on the asset-pricing tests. For brevity, I do not table them here (the results are available upon request). First, I include a future earnings surprise measure as a control variable in the asset-pricing regression from Table 1, following the methodology of Ogneva (2009), who argues that information surprises confound the analysis in Core et al. (2008). The future earnings surprise is measured as actual earnings minus expected earnings, where the latter is based on a statistical model, with prior-year stock returns and earnings as predictor variables.

Second, I exclude all return-months in which a firm announced future quarterly earnings from the asset-pricing tests. By excluding future announcement months, I decrease the likelihood that future information surprises related to earnings news bias the statistical tests. The results of these tests are inferentially similar to those reported in Tables 1 and 2. Unfortunately, neither of these tests is definitive. The statistical model may measure cash flow surprises with error. In addition, cash flow shocks or discount rate shocks could contaminate realized returns in periods other than earnings announcement months. In short, because investors' expectations are unobservable, true information surprises can never be precisely measured. Thus, while I find no evidence that information surprises compromise inferences from the asset-pricing tests, I cannot completely dismiss them as a confounding factor.

As to the reasonableness of Value Line analyst earnings projections, I find in untabulated results that firms with more volatile earnings have relatively lower average *current* earnings in addition to the lower average future earnings documented in Table 4, Panel B. This pattern of relatively low current earnings, relatively low future earnings, yet relatively high future earnings forecasts for firms with volatile earnings (see Table 4, Panel B) seems more consistent with undue optimism in analyst forecasts than with a chance result driven by unexpected shocks to future earnings. The mis-weighting evidence in Table 6 supports this conclusion as well.

In sum, the asset-pricing evidence indicates there has been no return premium to holding volatile earnings stocks over the last 30 years. The implied cost of capital tests indicate that analyst optimism creates a mechanical link between earnings volatility and implied cost of equity capital. The inferences drawn from this evidence likely hinge on the reader's prior beliefs as to the efficacy of asset-pricing tests. If one is suspicious that information surprises during the sample period compromise asset-pricing tests, then evidence that analyst bias contaminates implied cost of capital measures need not imply that earnings smoothness has no bearing on cost of equity capital. If, however, the reader believes that average returns over the sample period are a reasonable proxy for expected returns, the evidence casts doubt on the notion that smoothness is a priced source of risk.

VI. ACCRUAL QUALITY AND ANALYST OPTIMISM

In Table 7, I provide evidence that accrual quality—the residual variance from a regression of accruals on temporally adjacent cash flows—is systematically related to optimism in Value Line's long-term earnings forecasts. Panel A demonstrates that earnings forecast errors increase monotonically across accrual quality deciles (i.e., as accrual quality gets worse), and Panel B indicates that this relation continues to hold after controlling for *Beta*, *Size*, and *BM*. Given that Francis et al. (2004) document that accrual quality and earnings smoothness are highly correlated constructs, this result is perhaps not surprising. However, it does shed light on a puzzle in the literature. Core et al. (2008) find no evidence that accrual quality is a priced risk factor, even though this variable is strongly related to implied cost of capital using Value Line estimates. Table 7 suggests that optimism in Value Line's earnings projections may drive this relation, just as it drives the relation between earnings smoothness and implied cost of capital.

VII. CONCLUSION

The projected target prices of Value Line analysts indicate that they expect firms with volatile earnings to experience greater future stock price appreciation than firms with smooth earnings, creating a negative relation between imputed cost of capital and earnings smoothness. Evidence from the U.S. stock market indicates no such pattern, however. I find

TABLE 7
Accrual Quality and Value Line Four-Year Earnings Forecast Errors

Panel A: Average Four-Year Earnings Expectations versus Actual Earnings by Accrual Quality Decile

Accrual Quality Decile	n	Expected Earnings	Actual Earnings	Earnings Forecast Error
Smooth		*FEPS*	*AEPS*	FE^{EPS}
1	909	0.099	0.087	0.012
2	903	0.105	0.078	0.027
3	886	0.112	0.075	0.037
4	899	0.118	0.085	0.033
5	887	0.122	0.083	0.040
6	896	0.122	0.078	0.044
7	890	0.125	0.077	0.048
8	865	0.130	0.074	0.057
9	866	0.135	0.060	0.075
10	826	0.141	0.059	0.082

Panel B: Annual Cross-Sectional Regressions of Earnings Forecast Error on Accrual Quality (*AQ*)

	AQ	*Beta*	*Size*	*BM*
Estimate	**0.005**	**0.016**	**−0.005**	**0.025**
t-stat	**(8.61)**	**(6.01)**	**(−3.10)**	**(6.11)**

Panel A lists mean values of expected earnings, actual earnings, and forecast errors by accrual quality deciles for the Value Line Estimates and Projections File from 1989–2001. Accrual quality is estimated as the residual variance from firm-level regressions of working capital accruals (accruals plus depreciation) on current, one-year back, and one-year ahead operating cash flows. Accruals and cash flows are defined in Table 1. See Table 4 for details on the additional variables.

Panel B contains average parameter estimates from annual cross-sectional regressions of earnings forecast error (FE^{EPS}) on the decile ranking of accrual quality (*AQ*), as well as *Beta*, *Size* and *BM*. See Table 1 for details as to the construction of the latter three variables. t-statistics are calculated from the standard errors of annual averages, adjusted with a Newey-West (1987) correction for autocorrelation up to four lags. Parameter estimates significant at the 5 percent level or lower (two-tailed) are bolded.

no relation between earnings smoothness and average stock returns over the last 30 years. I offer evidence that the inverse relation between earnings smoothness and implied cost of capital results primarily from optimistic bias in analysts' long-term earnings projections. Specifically, a positive correlation between earnings volatility and earnings optimism yields target prices, and thus implied cost of capital estimates, that are too high for firms with volatile earnings. These findings are important because they call into question the wisdom of smoothing earnings to achieve a lower risk premium, particularly if such actions sacrifice economic value. While smoother earnings may have other benefits, I find no evidence that smoother earnings are associated with a lower return premium. This study also highlights the need to control for biased input variables in studies that use implicit cost of capital estimates, which should be of interest to a variety of researchers.

A number of recent studies investigate the reliability of implied cost of capital estimates (Botosan and Plumlee 2005; Easton and Monahan 2005; Guay et al. 2006). While this study contributes to that literature, I view the evidence neither as a general indictment of

implied cost of capital tests nor as a general endorsement of asset-pricing tests. The appropriate methodology for a given study will obviously vary with the research question and setting. In some studies, for example, due to limited sample sizes or data availability, asset-pricing tests may not be feasible. In general, however, when both methodologies are available, the desire for convergent evidence across differing methodologies provides a justification for using both (Campbell and Fiske 1959). In this vein, I view asset pricing and implied cost of capital tests as complementary.

APPENDIX
DECOMPOSITION OF EXPECTED SHARE PRICE APPRECIATION

Noting that Value Line target prices are calculated from forecasts of future earnings multiplied by forecasted P/E ratios, TP/P can be decomposed as follows:

$$\begin{aligned}
\frac{TP}{P} &= (FEPS * FPE) \\
&= (AEPS + FE^{EPS}) * (APE + FE^{PE}) \\
&= (AEPS * APE) + (FE^{EPS} * FPE) + (AEPS * FE^{PE}) \\
&= (AEPS * APE) + (FE^{EPS} * FPE) + ((FEPS - FE^{EPS}) * FE^{PE}) \\
&= (AEPS * APE) + (FE^{EPS} * FPE) + (FEPS * FE^{PE}) - (FE^{PE} * FE^{EPS}) \\
&= (AP) + (FE^{EPS} * FPE) + (FEPS * FE^{PE}) - (FE^{PE} * FE^{EPS})
\end{aligned}$$

See Table 4 for variable definitions.

To fix ideas, consider the following simple numerical example. Let forecasted target price (*TP*) equal \$45 per share, current stock price equal \$20 per share (*P*), forecasted earnings per share equal \$3.00, and forecasted P/E (*FCPE*) equal 15. Further, let the actual stock price turn out to be \$35, with actual EPS equal to \$2.50, implying an actual P/E (*APE*) of 14. The decomposition works out as:

$$\begin{aligned}
\frac{TP}{P} &= (FEPS * FPE) \\
\frac{45}{20} &= \left(\frac{3.00}{20} * 15\right) \\
&= (AEPS + FE^{EPS}) * (APE + FE^{PE}) \\
&= \left(\frac{2.50 + .50}{20}\right) * (14 + 1) \\
&= (AP) + (FE^{EPS} * FPE) + (FEPS * FE^{PE}) - (FE^{PE} * FE^{EPS}) \\
&= \left(\frac{2.50 * 14}{20}\right) + \left(\frac{.50 * 15}{20}\right) + \left(\frac{3.00 * 1}{20}\right) - \left(\frac{.50 * 1}{20}\right) \\
&= \left(\frac{35}{20}\right) + \left(\frac{7.50}{20}\right) + \left(\frac{3.00}{20}\right) - \left(\frac{.50}{20}\right)
\end{aligned}$$

The interaction term is needed since multiplying by *FCPE* in the second term and *FCEPS* in the third term (both of which are themselves too high) overstates the true effect of EPS and P/E forecast bias.

REFERENCES

Barnea, A., J. Ronen, and S. Sadan. 1975. The implementation of accounting objectives: An application to extraordinary items. *The Accounting Review* 50 (January): 58–68.

Beidleman, C. R. 1973. Income smoothing: The role of management. *The Accounting Review* 48 (October): 653–667.

Bhattacharya, U., H. Daouk, and M. Welker. 2003. The world price of earnings opacity. *The Accounting Review* 78 (July): 641–678.

Black, F., M. Jensen, and M. Scholes. 1972. *The Capital Asset Pricing Model: Some Empirical Tests.* Studies in the Theory of Capital Markets. New York, NY: Praeger.

Botosan, C. A., and M. Plumlee. 2005. Assessing alternative proxies for the expected risk premium. *The Accounting Review* 80 (January): 21–53.

Brav, A., R. Lehavy, and R. Michaely. 2005. Using expectations to test asset pricing models. *Financial Management* 34 (Autumn): 31–64.

Campbell, D., and D. Fiske. 1959. Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological Bulletin* 56 (March): 81–105.

Campbell, J. 1991. A variance decomposition for stock returns. *The Economic Journal* 101 (March): 157–179.

Chaney, P. K., and C. M. Lewis. 1995. Earnings management and firm valuation under asymmetric information. *Journal of Corporate Finance* 1 (April): 319–345.

Cochrane, J. 2001. *Asset Pricing*. Princeton, NJ: Princeton University Press.

Core, J., W. Guay, and R. Verdi. 2008. Is accruals quality a priced risk factor? *Journal of Accounting and Economics* 46 (September): 2–22.

Courteau, L., J. Kao, T. O'Keefe, and G. D. Richardson. 2006. Relative accuracy and predictive ability of direct valuation methods, price to aggregate earnings method, and a hybrid approach. *Accounting and Finance* 46 (October): 553–575.

Das, S., C. B. Levine, and K. Sivaramakrishnan. 1998. Earnings predictability and bias in analysts' earnings forecasts. *The Accounting Review* 73 (April): 277–294.

Dechow, P. M., and I. D. Dichev. 2002. The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review* 77 (Supplement): 35–59.

Easley, D., and M. O'Hara. 2004. Information and the cost of capital. *The Journal of Finance* 59 (August): 1553–1583.

Easterwood, J. C., and S. R. Nutt. 1999. Inefficiency in analysts' earnings forecasts: Systematic misreaction or systematic optimism? *The Journal of Finance* 54 (October): 1777–1797.

Easton, P. 2004. PE Ratios, PEG Ratios, and estimating the implied expected rate of return on equity capital. *The Accounting Review* 79 (January): 73–95.

———, and S. Monahan. 2005. An evaluation of accounting based measures of expected returns. *The Accounting Review* 80 (March): 501–538.

———, and G. Sommers. 2007. Effect of analysts' optimism on estimates of the expected rate of return implied by earnings forecasts. *Journal of Accounting Research* 45 (December): 983–1015.

Elton, E. J. 1999. Expected return, realized return, and asset pricing tests. *The Journal of Finance* 54 (August): 1199–1220.

Fama, E. F., and J. D. MacBeth. 1973. Risk, return, and equilibrium: Empirical tests. *The Journal of Political Economy* 81 (May–June): 607–636.

———, and K. R. French. 1992. The cross-section of expected stock returns. *The Journal of Finance* 47 (June): 427–465.

———, and ———. 1993. Common risk factors in the returns on bonds and stocks. *Journal of Financial Economics* 33: 3–56.

———, and ———. 2002. The equity premium. *The Journal of Finance* 57 (April): 637–659.

Francis, J., R. LaFond, P. M. Olsson, and K. Schipper. 2004. Costs of equity and earnings attributes. *The Accounting Review* 79 (October): 967–1010.

Gebhardt, W. R., C. M. C. Lee, and B. Swaminathan. 2001. Toward an implied cost of capital. *Journal of Accounting Research* 39 (June): 135–176.

Gibbons, M. R., S. A. Ross, and J. Shanken. 1989. A test of the efficiency of a given portfolio. *Econometrica* 57 (September): 1121–1152.

Goel, A. M., and A. V. Thakor. 2003. Why do firms smooth earnings? *The Journal of Business* 76 (January): 151–192.

Greene, W. H. 2003. *Econometric Analysis*. 5th edition. Englewood Cliffs, NJ: Prentice Hall, Inc.

Guay, W., S. Kothari, and S. Shu. 2006. Properties of implied cost of capital using analysts' forecasts. Working paper, University of Pennsylvania.

Graham, J. R., C. R. Harvey, and S. Rajgopal. 2005. The economic implications of corporate financial reporting. *Journal of Accounting and Economics* 40 (December): 3–73.

Hunt, A., S. Moyer, and T. Shevlin. 2000. Earnings volatility, earnings management and equity value. Unpublished manuscript, University of Washington.

Lakonishok, J., A. Shleifer, and R. W. Vishny. 1994. Contrarian investment, extrapolation, and risk. *The Journal of Finance* 49 (December): 1541–1578.

Lambert, R., C. Leuz, and R. Verrecchia. 2007. Accounting information, disclosure, and the cost of capital. *Journal of Accounting Research* 45 (May): 385–420.

———, ———, and ———. 2008. Information asymmetry, information precision, and the cost of capital. Working paper, University of Pennsylvania.

Leuz, C., D. Nanda, and P. D. Wysocki. 2003. Earnings management and investor protection: an international comparison. *Journal of Financial Economics* 69: 505–527.

Loughran, T. 1997. Book-to-market across firm size, exchange, and seasonality: Is there an effect? *Journal of Financial and Quantitative Analysis* 32 (September): 249–268.

Merton, R. C. 1973. An intertemporal capital asset pricing model. *Econometrica* 41 (September): 867–887.

Myers, J., L. Myers, and D. Skinner. 2007. Earnings momentum and earnings management. *Journal of Accounting, Auditing and Finance* 22 (Spring): 249–284.

Newey, W. K., and K. D. West. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55 (May): 703–708.

Ogneva, M., K. R. Subramanyam, and K. Raghunandan. 2007. Internal control weakness and cost of equity: Evidence from SOX Section 404 disclosures. *The Accounting Review* 82 (October): 1255–1298.

———. 2009. Accrual quality and expected returns: The importance of controlling for cash flow shocks. Working paper, Stanford University.

Sloan, R. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71 (July): 289–315.

Spence, A. M. 1973. Job market signaling. *The Quarterly Journal of Economics* 87 (August): 355–374.

Thomas, J. K., and H. Zhang. 2006. Another look at P/E ratios. Working paper, Yale School of Management.

Trueman, B., and S. Titman. 1988. An explanation for accounting income smoothing. *Journal of Accounting Research* 26 (Supplement): 127–139.

Verdi, R. 2006. Information environment and the cost of equity capital. Working paper, Massachusetts Institute of Technology.