Analysts' estimates of cost of equity capital*

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Abstract

We explore a large sample of analysts' estimates of cost of equity capital (CoE) revealed in analysts' reports to evaluate their determinants and ability to capture expected stock returns. We find that the CoE estimates strongly predict future stock returns and are significantly related to beta, size, book-to-market ratio, leverage and short-term return reversals but not to profitability, investments or other return predictors. These estimates also incrementally predict future returns after controlling for known return predictors. Consistent with financial distress being a risk factor, analysts appear to increase their CoE estimates following negative earnings news. Finally, based on a pair-wise comparison of CoE estimates with alternative expected return proxies (estimated from CAPM, Fama-French factor models or implied cost of capital models), we find that CoE estimates tend to be least noisy. We conclude that analysts' CoE estimates are meaningful proxies of expected stock returns and, where available, are a useful alternative to commonly used expected return proxies.

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1. Introduction

Analysts play a key role in financial markets by processing information and providing several data outputs to aid market participants' decisions. Highlighting the importance of such data, a vast literature evaluates a number of outputs provided by analysts, including their earnings forecasts, cash flow forecasts, target prices, stock recommendations and industry recommendations and generally concludes that analysts provide useful information to investors.[1] However, little is known about a critical input to analysts' valuation models, namely cost of equity capital (CoE). While academics have dedicated significant time and effort to better understand the fundamental determinants of costs of capital, little empirical evidence exists on the determinants of discount rates employed by analysts, an important set of information intermediaries in capital markets. This study fills this gap by conducting a large scale examination of whether analysts' estimates of CoE are meaningful, and if so what known risk proxies and firm characteristics are associated with these estimates.

Based on the previously documented usefulness of analysts' other outputs, it may be tempting to conclude that analysts' CoE estimates also contain useful information. However, a key difference precludes such a conclusion. In contrast to earnings and others forecasts whose veracity is revealed ex-post by comparing forecast values to their corresponding actuals, no such assessment is possible for analysts' CoE estimates. CoE are not directly observable, hindering measurement of their estimation errors and the attendant scrutiny of these estimates

1 The conclusion that analysts' outputs are useful is by no means unanimous. For instance, while stock markets have been shown to react to analysts' forecast revisions to earnings forecasts (e.g., Griffin, 1976; Givoly and Lakonishok, 1979; Elton et al., 1981), analysts' long-term growth forecasts are found to be overly optimistic with little predictive power for realized growth rates over longer horizons (e.g., La Porta, 1996; Chan et al., 2003; Barniv et al., 2009). Also, while Womack (1996) finds stock markets to immediately react to information in analyst's recommendations, Altinkilc and Hansen (2009) find revisions to recommendations are associated with economically insignificant mean price reactions. Similarly, while Barber et al. (2001) document that purchasing (selling short) stocks with the most (least) favorable consensus recommendations yield abnormally high stock returns, Bradshaw (2004) and Barniv et al. (2012) find that stock recommendations are either insignificantly or negatively associated with future stock returns.

by market participants. This also severely restricts an analyst's ability to learn from their past estimation errors. These limitations are likely to cap the benefits and rewards to an analyst from providing more accurate CoE estimates, lowering their incentives to expend time or effort on estimating a firm's CoE relative to that spent on more clearly assessable outcomes, such as earnings forecasts.

Consistent with analysts' expending little effort on their CoE estimates, studies have shown that analysts' discount rate estimates suffer from significant execution errors and questionable choices. By analyzing 120 analysts' reports against a theoretically-motivated valuation template, Green et al. (2016) found that estimates of Weighted Average Cost of Capital (WACC) vary substantially across analysts and that when computing WACC, a large proportion of analysts use unreasonably high risk-free rates, market risk premium or ignore the costs of debt. Based on face-to-face interviews with analysts and managing directors, they conclude that such valuation errors partly reflect genuine mistakes, but also partly the fact that analysts are not directly compensated for being textbook correct in their valuations. Similarly, based on a detailed survey of the methods used by analysts to compute discount rates, Mukhlynina and Nyborg (2016) point out that nearly half their respondents incorrectly compute WACC. These findings raise the possibility that there is little systematic or meaningful about the choice of analysts' CoE estimates. Mukhlynina and Nyborg (2016) further corroborate this in their quote from a survey respondent:

> *"There seem to be lots of academics asking how analysts in the real world use CAPM or calculate the cost of capital. The answer is, people don't waste time on this."*

In contrast to these concerns, researchers and practitioners often view analysts as sophisticated information agents who revise their forecasts to communicate new information to investors.

For example, based on survey evidence, Graham, Harvey and Rajgopal (2005) note that CEOs consider analysts to be one of the most important groups influencing a firm's stock price. Baker, Nofsinger and Weaver (2002) note that analyst reports are the primary source of information for most buy-side investors. Further, Mikhail, Walther and Willis (2007) show that both large and small investors trade on analyst reports. Lys and Sohn (1990) show that analysts' earnings forecasts are informative even if preceded by the forecasts of other analysts. These suggest that CoE estimates of analysts may also be informative to stock market investors and be good measures of expected stock returns, reflecting analysts' superior understanding of firm-, industry- and macro-level data.

Also, while analysts' CoE estimates can suffer from execution errors and questionable choices, it is unclear whether these concerns are large enough to render their estimates useless, or to outweigh their potential benefits relative to alternative expected-return proxies. Ultimately, this is an empirical issue that we investigate by relating analysts' CoE estimates to previously identified risk characteristics and return predictor variables as well as to future stock returns. Additionally, we evaluate the responsiveness of these estimates to firm-specific news and contrast their performance as a proxy for expected stock returns relative to commonly employed alternatives.

There would be little need to evaluate analysts' CoE estimates if there was complete agreement on the most appropriate asset pricing model and the approach for its practical implementation, as in that case, the CoE estimates would be fully deterministic. While the theoretical literature has developed a variety of asset pricing models, each with its own distinct formulation for expected returns, there is little consensus on which of these is most accurate or most appropriate for measuring CoE. Moreover, there is no clear guidance on the practical implementation of these models (such as on measurement of factor loadings and risk premium), inducing discordance in the measurement of CoE in practice. These raise questions about the approach and return factors that analysts choose for their measurement of CoE.

If as noted earlier, analysts expend little effort on CoE estimation, then their estimates could be noisy, ad-hoc and reflect very little, if any, systematic information. The diverging views on asset pricing theories and the ambiguity on implementation of CoE models could also limit the systematic information reflected in analysts' CoE estimates, if these uncertainties drive analysts to base their estimates on atheoretical or heuristic approaches. For instance, instead of using asset pricing models, an analyst may back out her CoE estimate as the rate needed in a valuation model to justify a pre-determined target price or stock recommendation. Thus, an analyst with a strong "buy" instinct based on narrative analysis, might opt for a lower CoE estimate in the valuation model, to more effectively persuade clients about her stock recommendation. Informal discussions with analysts confirm that such an atheoretical approach is not uncommon in practice.

Alternatively, analysts could ground their CoE estimation model in theory and prior empirical evidence, but employ off-the-cuff adjustments and consider return factors in their model irrespective of whether these factors unambiguously represent risk. So, without necessarily relying on a specific asset pricing model, an analyst might adjust their CoE to be larger for high growth firms and to be smaller for more profitable or smaller firms. Such heuristic views of analysts' CoE estimates are supported by the survey evidence of Block (1999), Pinto et al. (2016) and Bancel and Mittoo (2009), who find that a sizable proportion of surveyed analysts claim to ignore financial theories and rely on their judgment to estimate discount rates.[2] For example, Pinto et al. (2016) find that about half of the surveyed analysts and portfolio managers

[2] Bradshaw (2004) also provides evidence confirming heuristic choices by analysts. Comparing valuations obtained from different models with analysts' stock recommendations, he concludes that analysts' recommendations are more correlated with heuristic valuations than with theoretically correct present value models.

use a judgmentally determined hurdle rate in their valuation models. In this case, even though the chosen return factors are ad hoc and their loadings entirely judgmental, one could still find a systematic relation between the CoE estimates and the return factors.

We report several interesting findings based on our analysis of 18,129 CoE estimates parsed out of analyst reports covering the period 2001 to 2015. These CoE estimates are systematically related to a firm's beta, book-to-market, size, leverage and short-term return reversals, but unrelated to profitability, investments, price momentum and idiosyncratic volatility. Our evidence suggests that analysts rely on the original Fama-French three factors, but in addition adjust the discount rates for leverage and short-term return reversal. These findings are partly consistent with the recent survey results of Mukhlynina and Nyborg (2016) and Pinto et al. (2015), who document that around three-quarters of their respondents claim to regularly use CAPM for estimating discount rates. However, less than 5% of their respondents claim to use the Fama-French three-factor model, and Mukhlynina and Nyborg (2016) report that less than half their respondents regularly adjust CoE for a firm's leverage.

Based on regression of future stock returns on CoE estimates, we find that analysts' CoE estimates are positively related to future realized returns, consistent with these estimates reflecting expected stock returns. Since realized returns consist of expected returns and information surprises, specifically cash flow news, we verify that this relation is not driven by CoE estimates capturing future cash flow information. We re-estimate the above regression after including analyst forecast errors for the leading four quarters as additional controls and continue to find the same relation. This provides corroborative evidence that the link between CoE estimates and realized returns are better explained as arising from its relation to the expected returns component rather than the cash flow component of realized returns.

Additional analyses reveal that the predictive ability of CoE estimates for future returns holds even after controlling for firm characteristics and risk factors that prior studies commonly use to predict stock returns. This is surprising, as it indicates that analysts' CoE estimates are not only good proxies for stock expected returns but contain information about expected stock returns that are incremental to those in commonly employed risk proxies. Although not the focus of this study, we speculate that this greater predictive ability is because analysts measure risk-factor loadings better than researchers. By focusing on a relatively small set of firms, analysts are better positioned to consider both qualitative and quantitative information in their risk computations, and to more carefully incorporate the outcomes of off-balance sheet transactions, hedging activities, cross-border trading, litigation and regulations. These aspects are much harder for a researcher to incorporate in their risk proxies and estimated risk loadings for a large sample.

We next examine whether analysts revise their CoE estimates around earnings announcements. The purpose of this test is two-fold. First, it helps shed light on whether and to what extent analysts actively incorporate firm-specific news into their cost of equity estimation. Such an examination can provide corroborative evidence on whether analysts' CoE estimates are grounded in reliable information or are merely speculative.

Analysts are known to revise their earnings forecasts and stock recommendations soon after earnings announcements, to reflect the newly disclosed information. This raises the question of whether analysts also revise their CoE estimates based on recently disclosed earnings news. Second, the analysis helps evaluate the conjecture in Hecht and Vuolteenaho (2006) that earnings news conveys information not only about expected cash flows but also about a stock's expected returns. Using the Campbell (1991) return decomposition approach, Hecht and Vuolteenaho (2006) document that earnings contain information about both cash-flows and expected-return news at the individual stock level. Specifically, they report that higher realizations of earnings are associated with increases in expected returns.

Hecht and Vuolteenaho's (2006) conclusions crucially depend on the Campbell (1991) decomposition clearly identifying discount rate news and cash flow news components of stock returns. Chen and Zhao (2009) point out that the Campbell (1991) approach can lead to biased inferences due to measurement errors, which arise from backing out cash flow news as a residual. The Campbell (1991) approach is also problematic for use around earnings announcements as it assumes that markets are efficient; an assumption the literature on post-earnings-announcement drift casts doubt on (e.g., Ball and Brown, 1968; Bernard and Thomas, 1989).

By studying changes to analysts' CoE estimates around earnings announcements, we are able to provide an alternative test of the Hecht and Vuolteenaho (2006) conjecture. Our analysis reveals a non-linear relationship between earnings news and analyst' CoE estimates. We find that analysts increase their CoE estimates for firms announcing large negative earnings surprises, but do not adjust their estimates for firms with non-negative news. This finding is not predicted by any known asset pricing theory, but is consistent with Fama and French's (1996) assertion that distress risk, with which negative earnings are associated, is a priced risk factor.[3] To the extent that the analysts' CoE estimates are good proxies for stock market investors' unobserved expected returns, this finding has two implications for prior findings. First, the documented asymmetrically larger stock price responses to negative earnings news (e.g., Skinner and Sloan, 2002 and Williams, 2015) may in part be due to market participants adjusting their discount rates in response to negative earnings surprises. Second, the negative

[3] Vassolou and Xing (2004) provide empirical evidence that distress risk is a systematic risk factor priced in the cross-section of equity returns.

stock return drift following poor earnings announcements reflects the net effect of post-announcement expected return changes and the under-reaction to cash flows news.

Finally, we evaluate the performance of CoE estimates as a proxy for expected stock returns relative to other popular proxies for expected returns (viz., the implied costs of capital and proxies obtained from an empirical implementation of CAPM, Fama-French three- and five-factor models). Several studies have examined the implied costs of capital (ICC) computed by using analysts' earnings forecasts as inputs to an accounting-based valuation model (viz, Ohlson and Juettner-Nauroth, 2005) and then inverting the valuation model. While some studies have claimed these ICC measures to be a good proxy for time-varying expected returns (e.g., Pastor et al., 2008; Frank and Shen, 2016), significant concerns remain against their veracity as a proxy for expected returns (e.g., Easton and Monahan, 2005; Guay, Kothari and Shu, 2011). Compared to ICC measures, analysts' CoE estimates are likely to be less noisy as the former crucially depend on researchers' choice of valuation model, terminal growth rate assumptions, etc. We, therefore, empirically benchmark the analysts' CoE estimates against the ICC measures and the discount rates obtained from CAPM and Fama-French models to evaluate the relative precision of these alternative proxies. Employing the pair-wise comparison approach of Lee et al. (2017), we find that the CoE estimates tend to have the lowest measurement errors for longer-term expected returns, indicating that, where available, analysts' CoE estimates are a worthy alternative to commonly used proxies.

We make several contributions to the literature. To the best of our knowledge, this is the first study to provide a systematic large-scale evaluation of analyst's CoE estimates. Studies evaluating analysts' discount rates do so, at best, in an indirect manner by examining implied costs of equity capital, i.e., the discount rates implied by market prices and analysts' earnings forecasts. However, such estimates fare poorly in their correlations with future realized returns and are known to suffer from measurement errors, particularly those related to stock mispricing and sluggish analyst forecast updates (e.g., Easton and Monahan, 2005; Guay, Kothari and Shu, 2011).

This study can also potentially contribute to empirical asset pricing tests, where the lack of observable discount rates used by market participants is a perennial concern. These tests typically use implied costs of capital or future returns as proxies for the market's expected returns (Botosan, 1997; Gebhardt, Lee, and Swaminathan, 2001; Claus and Thomas, 2001). By focusing on the observed CoE estimates of an important set of market participants, viz. analysts, our results suggest that relying on these estimates as proxies for expected stock returns is a reasonable alternative. However, although analysts' CoE estimates may play a useful role as a cost of capital proxy, they are, like ICC estimates, restricted to sub-samples of firms for which the data are available.

This study focuses exclusively on analysts' revealed cost of equity estimates. Analysts who use unreasonable or instinct-driven discount rates may choose to not explicitly state their discount rates to avoid public scrutiny of their estimates. Thus, our conclusions may not be applicable to cases where analysts do not disclose their CoE estimates or to firms without analyst following, and caution is required in extrapolating our results to these settings. Our analyses, as is the case for the extensive literature focusing on analysts' earnings forecasts, should be viewed as conditional on analysts deciding to reveal their estimates.

The remainder of the paper is structured as follows. Section 2 presents the research methodology and Section 3 describes the data extraction process. We present the results in Section 4 and conclude in Section 5.

2. Research Design

Following traditional empirical asset pricing research such as Fama and French (1992), we first study the relation between analysts' CoE estimates and future stock returns. Previous studies (Fama and French, 1992) suggest that cross-sectional differences in the realized stock return reflect systematic variation in ex ante expected returns, based on the belief that unexpected price changes tend to cancel out over the sample period. Accordingly, if analyst CoE estimates are meaningful, we expect that the cross-sectional differences in future realized returns to be associated with cross-variation in CoE. To test this, we use the following panel regression:

$$Future\ Returns_{it} = \propto + \beta_1 * CoE_{ibt} + \gamma_i + \mu_t + \vartheta_b + \varepsilon_{it} \tag{1}$$

where CoE_{ibt} is the cost of equity capital extracted from an analyst report for firm *i* in quarter *t* by brokerage house *b*. $Future\ Returns_{it}$ is the 360-day buy and hold returns following the date of the analyst report. We include firm-fixed effects, calendar quarter-fixed effects based on analyst report date and broker-fixed effects to subsume time invariant firm and brokerage characteristics and market-wide effects and cluster standard errors at the industry level. We also report results based on clustering at the industry and year levels to account for potential correlations in returns across industries and over time.

Including firm-fixed effects in the regression forces identification to be based on within-firm variations in stock returns and analysts' CoE. While this mitigates omitted correlated variables concerns, it could also lower the power of the tests if expected returns are largely time invariant. Hence, in unreported analyses, we test the robustness of the results to exclude the fixed effects, and we find an even stronger association between CoE estimates and future returns than those reported here.

In the next analysis we attempt to identify the firm characteristics most closely associated with analysts' CoE estimates, based on the premise that expected returns must be associated with certain risk proxies, as Botoson et al. (2011) found, and should reveal the asset pricing models that analysts rely most upon. Such evidence could also corroborate the survey-based findings in Pinto et al (2015) and Mukhlynina and Nyborg (2016) on the process used by analysts to compute discount rates.

To identify the firm characteristics that analysts' CoE estimates emphasize and to study the relation between CoE estimates and risk characteristics, we run the following OLS regression:

$$COE_{ibt} = \propto + \sum_{z=1}^{n} \beta_z * Risk\ Characteristic_z + \gamma_i + \mu_t + \vartheta_b + \varepsilon_{i,t} \quad (2)$$

where *Risk Characteristic$_z$* represents a vector of variables that have been shown in the literature to be determinants of equity returns. Multi-collinearity issues can arise if a large number of return predictors are included, so we restrict our attention to the more commonly used return predictor variables (Fama and French, 2015; Hou, Xue and Zhang, 2015). Based on the five-factor Fama and French (2015) model, we include market beta (Fama and MacBeth, 1973; Fama and French, 1992), size (Banz, 1981; Fama and French, 1992, 2015), book-to-market equity (Fama and French, 1992; Lakonishok et al., 1994; Fama and French, 2015), investments (Titman et al., 2004; Fama and French, 2006, 2015) and profitability (Balakrishnan et al., 2010; Novy-Marx, 2013; Fama and French, 2015). We also consider characteristics that capture momentum (Jegadeesh and Titman, 1993), short-term reversals (Jegadeesh, 1990), leverage (Bhandari, 1988; Fama and French 1992) and idiosyncratic volatility (Ang et al., 2006, 2009; Hou and Loh, 2011). The empirical computations of these variables are presented in Appendix I.

We do not control for analysts-specific characteristics in our analyses, as we lose a large number of observations when we attempt to merge our CoE estimates with specific analyst reports in IBES. In general, there are significant differences in reports carried by IBES (where analysts voluntarily enter their forecasts) and by Thomson Reuters-Thomson One database (our source for analyst reports). Rogers (2017) and Call et al. (2016) also point out to systematic errors in IBES database, which could affect our matching.

To explore how analysts' CoE estimates react to earnings news, we regress changes in CoE estimates around an earnings announcement on the earnings news released at the announcement. Specifically, we estimate the following model:

$$\Delta CoE_{ibt} = \propto + \beta_1 Ernsurp_{it} + \sum_{j=2}^{n} \beta_j * Z_j + \gamma_i + \mu_t + \vartheta_b + \varepsilon_{it} \qquad (3)$$

where ΔCoE is the CoE estimate obtained from a report disclosed on day t in a post-earnings-announcement period (defined as days 0 to +45 relative to an earnings announcement date) minus the corresponding CoE estimate for the firm disclosed in a pre-earnings-announcement period (i.e., days -1 to -45 around an earnings announcement date). *Ernsurp* is analysts' forecast error revealed at the earnings announcement. This analysis requires the same brokerage firm to have provided CoE estimates in both the pre- and post- periods following an earnings announcement, which reduces the sample size significantly. This restriction, however, enables a cleaner measurement of analysts' CoE responses around an earnings announcement.

Ernsurp is measured as the actual reported earnings per share for the firm-quarter from IBES less the median of analysts' latest estimates scaled by the stock price of the firm at the beginning of the quarter. To avoid losing observations if data on specific analyst's earnings forecasts are unavailable, we estimate *Ernsurp* using the median consensus forecasts.

We control for risk and other firm characteristics in the regressions by including the variables (Z_j) considered in Equation (2) as additional controls. Untabulated analyses reveal that our qualitative results are unaffected by including changes in these variables in addition to their levels. The regressions also include time- and brokerage-fixed effects and cluster standard errors at the industry level. As the COE variable is in changes and *Ernsurp* captures news, we do not additionally consider firm fixed effects.

3. Data and Sample

We obtain CoE estimates from analyst reports in the *Thomson Reuters-Thomson One* database that were filed between January 1, 2001 and December 31, 2015. Rather than download all analyst reports (2.8 million), we search for those with tables of contents containing the phrase "cost of equity" and restrict the geography to "United States."[4] As measurement errors can result from backing out CoE estimates for analysts who reveal Weighted Average Costs of Capital estimates, we restrict our analysis to only those who directly state their CoE estimates. All non-broker, industry or economy reports are removed from the search criteria. This search produces 31,632 equity reports, which we then download and use textual analysis to extract the cost of equity measure.

Extracting the cost of equity measure from unstructured analyst reports is challenging. First, these reports are in PDF format and do not have a uniform structure. The cost of equity measure is not provided in the same location in every report. In fact, a report may not even contain a cost of equity measure even though our initial search identifies this report, as an analyst may mention "cost of equity" as a part of her qualitative discussion without providing a numerical value. Similarly, it is not possible to extract the number when presented within tables that have been pasted as images in the PDF.

To parse out the CoE estimates, we first extract the sentence where we observe the phrase "cost of equity." Next, we attempt to extract the numerical values by matching the sentence to a pre-identified set of patterns. We examine, across a variety of reports, the patterns that analysts

[4] Downloads from Thomson Reuters-Thomson One are restricted by fair usage policy. Our searches in the database are not case sensitive.

tend to follow when providing this measure. We manually examine 500 equity analyst reports across different brokerages and years and identify the repeated patterns, which are commonly found in reports from large brokerages. For example, analysts may report "cost of equity capital rate of x%" or use the phrase "using x% as the cost of equity…." We identify 36 such patterns. We then apply a textual analysis program to use these patterns to extract COE measures. However, even where the patterns match, there could be noise. For example, confidently extracting cost of equity from the phrase "an increase in our cost of equity assumption to 9.14% from 8.64%" is difficult for the program. Similarly, it would be wrong to use the number from the phrase "our downside case assuming very low growth no terminal value and a high cost of equity is $20." Thus, we look through the extracted numbers and remove cases where the numbers are meaningless. Through this process, we can extract cost of equity figures from 20,129 analyst reports. The missed reports either do not provide the cost of equity in one of the identified patterns or do not provide a number.

We merge the extracted analyst CoE estimates with daily *CRSP* data and *IBES* data using the ticker information provided in the analyst reports. Although this task is more straightforward than the extraction of the cost of equity because tickers appear at the top of every report, there is still variation across reports as to where and how the analysts present the ticker information. For example, analysts may provide either the exchange ticker or the Bloomberg ticker. We thus lose 2000 firm-year observations in this matching process. We then have a sample of 18,129 observations with CoE estimates for our primary tests. The sample spans 9,910 unique firm-quarter observations, 2,095 unique firms and 193 unique brokerages. For the tests that examine changes in cost of equity estimates around earnings announcement, the number of observations used is 2,466. Table 1 summarizes our sample selection procedure.

Table 2 provides descriptive statistics on the data. All variables except returns are winsorized at 1% and 99%.[5] The extracted CoE estimates from analyst reports have a mean (median) of 10.57% (10.0%) and range from 5.20% to 20.60%. To provide a reference, we compare the descriptive statistics for our main sample containing the extracted CoE estimates ("CoE sample") with the IBES sample for the same period (2001-2015). By comparing firm characteristics across the CoE sample and IBES sample, we observe a significant difference in means and medians of all variables with the exception of *MOMENTUM*. The mean annual stock returns for the CoE sample is 15.4%, which is significantly more than the 8.8% for the IBES sample. The CoE sample comprises of firms that are larger, with higher beta and lower book-to-market ratios. These firms also have better performance, both in terms of accounting profitability and stock return, but also have lower idiosyncratic volatility. The firms in the CoE sample also make lower investments than those in the full IBES sample. These systematic differences in the characteristics of firms in the CoE and IBES samples highlight that analysts do not randomly select firms to reveal their CoE estimates, and indicate the need for caution in extrapolating results from firms with CoE estimates disclosed to the wider population of firms covered by analysts.

4. Results and Discussion

4.1. Analyst cost of equity capital estimates and risk proxies

To check whether analysts' CoE estimates meaningfully capture investors' expected returns, we correlate their CoE estimates to ex-post realized returns. If analysts' estimates do a good job of capturing expected returns, we expect these to be positively be related to future realized returns. Thus, for each CoE estimate, we track the stock returns in the 360 calendar days following the corresponding analysts' report release date. We then sort all observations based

[5] All of our inferences continue to hold when we alternatively Winsorize the variables at 1.5% or 2% on either side.

on analysts' CoE estimates into three portfolios (top 30%, mid 40% and bottom 30%) and analyze the average returns for the three CoE-sorted portfolios.

From Table 3, Panel A, we observe a monotonic relation between the analyst CoE estimates and average realized returns across the portfolios. The average returns for the bottom 30% of CoE estimates is 9.4%, which increases to 16.3% for the mid-CoE portfolio and further to 21.5% for the portfolio with the highest CoE. In contrast, the average CoE varies from 8.2% from the lowest CoE portfolio to 13.7% for the highest CoE portfolio. The greater spread across portfolios of average realized returns is possibly because these contain greater measurement errors than analysts' CoE estimates, which is an issue we address later. An F-test of the null hypothesis that the average realized returns are equal across the portfolios is strongly rejected.

As an alternative approach to uncovering the relationship between CoE estimates and future stock returns, we regress the 1-year returns following each analyst report release date on the analysts' CoE estimate. The results, reported in Table 3, Panel B, reveal a strong positive correlation. The coefficient on analysts' CoE estimates is 3.326 (Column 1), suggesting that the ex-post realized returns are three times the analysts' CoE estimates for our sample period. When we replace the continuous CoE estimate with a rank variable for the three CoE sorted portfolios, we obtain a coefficient of 6.260, suggesting that expected portfolio returns increase by 6.26% as one moves from the lowest to the highest CoE portfolio. We also obtain consistent results when we replace the CoE ranks with an indicator variable for the middle and top-CoE portfolios. The indicator variable for bottom portfolio is subsumed by firm fixed effects. The average portfolio return for the top-CoE portfolio is higher by 12.5% and the mid-CoE portfolio by 7.4% than the bottom CoE-portfolio. These coefficients, which reflect the average portfolio returns adjusted for firm-, time- and brokerage-specific averages, are in line with the average raw returns reported in Panel A of Table 3. These findings show that analysts' CoE estimates have the ability to discriminate stock portfolios based on their average future returns. In untabulated tests, we find similar results if we perform the analyses using firm-level average CoE estimates instead of using individual analyst-level CoE estimates and conduct the analyses using firm-level observations.

The coefficient of 3.326 in Column (1) implies that for every 1% increase in CoE estimate the realized returns increase by 3%, which is surprising as the coefficient should be 1 if realized returns and CoE estimates are unbiased estimates of stock's expected returns. The large coefficient, which is significantly different from 1, is either due to analysts consistently underestimating CoE values or due to extreme measurement noise in individual stock returns. The measurement noise explanation is particularly potent as some stocks have annual returns in excess of 1000%. We thus repeat the above analysis using a portfolio-level approach that mitigates the effects of influential observations. Specifically, we form 25 portfolios each quarter based on the CoE values and, for each portfolio-quarter, then calculate the averages of realized returns and CoE. We then regress the average portfolio returns on average CoE estimates.[6]

The results presented in Column (4) of Table 3 suggest that the coefficient on CoE is 1.2 and is not statistically different from 1. The significant decline in coefficient in this portfolio-analysis confirms that individual stock returns contain significant measurement errors, affecting the CoE coefficients. This result confirms that analysts' CoE estimates are unbiased predictors of stocks' expected returns, as reflected in their future realized returns.[7]

The use of the realized returns as a proxy for expected returns relies on the assumption that information surprises tend to cancel out over the period of the study. However, it has been

[6] Portfolio-level regressions include portfolio and time fixed effects and cluster the standard errors at the portfolio level.
[7] As an alternative approach to controlling for extreme stock returns, we Winsorize individual stock returns at +100% and -100%. The coefficient on CoE from this modification is 1.3 (t-stat = 4.29) and we cannot reject the null that this coefficient is significantly different from 1.0.

argued that this assumption may not hold in the data (Elton, 1999), raising the possibility that the above findings could reflect that analysts' CoE estimates are correlated with stock mispricing. That is, since realized returns reflect cash flow news apart from information about expected returns, mispricing of future cash flows would lead to ensuing cash flow news becoming predictable and CoE estimates being correlated with such cash flow news. We therefore repeat the above analyses after including the earnings surprises for the leading four quarters from the date of the analyst report, based on evidence in many empirical asset pricing studies that stock mispricings are often corrected at subsequent earnings announcements (e.g., Bernard and Thomas, 1989; Sloan, 1996).

If the relation between CoEs and realized future returns are driven by stock mispricing, then we expect to find the coefficient on CoE estimates to be attenuated in regressions that control for four-quarters-ahead earnings surprises. Contrary to this expectation, the results presented in Column (5) of Table 3 Panel B suggest that the coefficient on CoE increases in magnitude from that in Column (1) and is more statistically significant. This finding is consistent with the explanation that forward-looking forecast errors mitigate measurement errors in realized returns. Overall, our findings suggest that analysts' CoE estimates are good proxies for expected returns as reflected in future realized returns.

To identify the firm characteristics that analysts use in their computations of CoE, we regress analysts' CoE estimates on firm characteristics. As Table 4 illustrates, CoE estimates are greater for firms with higher beta, which is consistent with the predictions of the CAPM. The coefficient on beta is 0.5 (t-statistic = 4.43) in Column (1) and this decreases further to 0.4 in Columns (2) and (3) when other firm characteristics are controlled for.[8] The positive coefficient

[8] We do not attempt to interpret the magnitude of the coefficient on beta for a variety of reasons. First, the regressions include firm fixed effects, so the beta coefficients capture only the time-varying effects of firms' beta on CoE estimate variation. Inclusion of year fixed effects in the regressions also subsumes the market risk premium. Finally, the magnitude of the beta coefficient is also affected by number of analysts using the CAPM

on beta is largely in line with the survey evidence in Muklynina and Nyborg (2016), who document that 76% of their surveyed analysts almost always or always use the CAPM.

Other than beta, analysts' CoE estimates also reflect the effects of book-to-market ratio, size, leverage and 1-month lagged returns. The significant coefficients on book-to-market ratio and on size are interesting, as the survey of Muklynina and Nyborg (2016) suggests that less than 5% of their respondents use the Fama-French three factor model. In line with other empirical evidence, analysts' estimates of expected returns are positively correlated with book-to-market ratio and negatively with firm-size. The coefficient on book-to-market is 1.3 and that on size is -0.11. The coefficient on leverage is significantly positive with a value of 1.25. The positive coefficient suggests that analysts view more levered firms as more risky. The coefficient on lagged returns is negative, indicating that analysts tend to view stocks with good stock returns in the lagged month as less risky.

These findings indicate that analysts weigh firm characteristics that have been suggested to be proxies for risk. The signs of the coefficients are also consistent with those predicted by theory or intuition. Thus, even if analysts rely on judgmental or subjective approaches to estimating CoE they seem to treat firms that are smaller, have more leverage and growth opportunities as more risky. However, analysts do not appear to consider other firm characteristics, shown in the literature to be useful in predicting future returns, as relevant for their CoE computations. Specifically, they do not give significant weight to idiosyncratic volatility, return on assets, growth in total assets and prior 11-month returns, as indicated by the insignificant coefficients on all these variables. Analysts may therefore not consider a variable as relevant for CoE estimation merely because it predicts future returns.

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and Fama-French models and the proportion of analysts updating their discount rate computations to reflect concurrent changes in betas and market risk premiums.

4.2. *Cost of equity capital and future returns*

A natural question is whether analysts' CoE estimates are related to future returns because they reflect firm characteristics known to be related to future returns, or if their CoEs contain information incremental to those in known return predictors. We address this by repeating the regression of future returns on analysts' CoE as in Equation (1), but additionally control for known return-predictors. The results from this extended regression model are presented in Table 5.

Interestingly, we find that analysts' CoE estimates are significantly positively related to 1-year-ahead stock returns even after controlling for return predictors. The coefficient on CoE estimates is 3.280 when only beta is controlled for in the regressions. This is comparable to the coefficient observed in Table 3, Panel B and indicates that the inclusion of beta has little effect on the magnitude of the coefficient. The coefficient on CoE estimates decreases to 2.293 when additional return predictors are included, but the statistical significance remains intact. Column (4) presents the results from an analysis at the portfolio level similar to the previous approach shown in Column (4) of Table 3. We find that the coefficient is 1.198 and is close to the corresponding coefficient value of 1.221 in Column (4) of Table 3.

The significant coefficient on CoE estimates suggest that analysts have better information about expected returns than what is calculated based on popular asset pricing models. This is surprising, as analysts themselves often claim to rely only on available asset pricing models (e.g., Mukhlynina and Nyborg, 2016), raising questions about the source of their superior ability to compute expected returns. Identifying this source is beyond the scope of the study, but we speculate that analysts may better estimate risk loadings than researchers, who estimate risk loadings from past data using statistical tools. As analysts typically follow only a handful of firms, they can incorporate both quantitative and qualitative information into their estimates. For example, analysts can more carefully consider qualitative information on risk that is disclosed in firms' 10-K and 8-K filings. They can also draw on additional information sources that are forward looking and cover industry or market-wide occurrences, such as strategic announcements, management forecasts, industry reports, scheduled macroeconomic announcements, press articles, etc. These allow analysts to consider the macro context while evaluating riskiness. They can also make relevant adjustments to incorporate the off-balance sheet and hedging activities of a firm. While stock returns, from which statistical estimates of risk loadings are typically obtained, also reflect such information, it is difficult to structure models that capture variations in risk exposures from such activities.

The coefficients on the control variables are generally consistent with the literature. In line with Fama and French (1992), we find an insignificant coefficient for beta, suggesting that it has little explanatory power for future returns. Further, firm-size and one-month-lagged returns are found to be significantly negatively related to future returns and significantly positively related to book-to-market.

Momentum has an insignificant negative coefficient in the regression, which appears inconsistent with the positive coefficient shown in previous literature for sample periods ending in the early 2000s. In untabulated analyses we checked this by repeating the regression (without the CoE estimate) for the sample period 1970 to 2000, and obtained results consistent with previous studies, indicating that the lack of significance is specific to our sample period.

Overall, our results so far consistently demonstrate that analysts' CoE estimates are good proxies for expected stock returns. There is little evidence to suggest that these estimates are uninformative or noisy figures, which could be the case if the CoE estimates were reverse engineered to support the pre-determined stock recommendations of analysts, for example.

4.3. Do earnings announcements convey discount rate news?

Analysts often revise their reports and recommendations around earnings announcements, so a natural question is whether they also revise their CoE estimates in response to earnings releases. We test this by estimating Equation (3), which regresses changes in CoE estimates around an earnings announcement on earnings news released in that announcement. In contrast to earlier analyses based on CoE estimate levels, the current analysis examines how changes in CoE estimates around earnings announcements are related to earnings news.

To compute changes in CoE estimates, we require a brokerage firm to have revealed their CoE both in a pre-earnings-announcement period, defined as 45 days prior to IBES earnings announcement date, and in a post-announcement period, defined as 45 days after the earnings announcement. Imposing this requirement reduces the number of observations in the sample to 2,466. We alternatively computed changes in CoE estimates at the firm-level as the difference in average analyst CoE estimate from the pre-announcement to the post-announcement period. These firm-level analyses are based on 2,208 observations.

We compute earnings news or earnings surprises as analysts' forecast errors relative to the latest median consensus estimate prior to the earnings announcement, scaled by stock price at the beginning of the quarter for which earnings are announced (*Ernsurp*). Consistent with the treatment of other accounting variables, we winsorize *Ernsurp* at 1% and 99% levels. We also consider earnings news using the earnings estimate of the same analysts as those whose changes in CoE are analyzed. This decreases the sample even further in untabulated analyses but does not qualitatively alter the results.

To allow for potential non-linearity in the relation between *ΔCoE* and *Ernsurp*, we sort all observations into terciles based on *Ernsurp* being in the highest 30%, mid 40% or the lowest 30% and include interactive indicator variables for each tercile group (namely, *Ernsurp_HIGH, Ernsurp_MID and Ernsurp_LOW*). Panel A of Table 6 presents univariate statistics for the variables in Equation (3). The average *ΔCOE* is 0.02 percentage points with the changes ranging from -2.0 to +2.6 percentage points. The average *Ernsurp* is 0.005 for the highest Ernsurp tercile, zero for the middle tercile and -0.007 for the lowest tercile.

The results from estimating Equation (3) at the analyst level are presented in Table 6, Panel B and those based on firm-level analysis are given in Table 6, Panel C. From Column (1) of Panel B, where *Ernsurp* is included linearly, we find a negative coefficient on *Ernsurp* that is marginally significant. The coefficient turns insignificant when other control variables are included in the regression. The insignificant coefficient contrasts with the results reported in Hecht and Vuolteenaho (2006), who find poor earnings growth decreases a firm's expected returns, based on a linear regression between earnings growth and the negative of expected-returns news.

When we allow the coefficient on *Ernsurp* to vary across the *Ernsurp*-terciles, we continue to find the coefficient to be insignificant for the high and mid-terciles. For the lowest tercile, however, the coefficient on *Ernsurp* is significantly negative, suggesting that analysts increase the expected returns for firms with large negative earnings news. While we are not aware of any asset pricing models that predict a negative relation between discount rates and negative earnings news, this finding is in line with the arguments of Fama and French (1996) and the findings of Vassolou and Xing (2004) that distress risk is a priced risk factor, as financial distress is typically preceded by periods of negative earnings news.

The coefficient on *Ernsurp*Ernsurp_Low* is -4.793 (t-statistics = -2.116) when all control variables are included in the regression, implying that a one standard deviation decrease in *Ernsurp* of 0.023 for this group decreases analysts' CoE estimates by 11 basis points. For comparison, the average CoE estimate for this group is 11.0%.

The results in Table 6, Panel B from the firm-level analyses are qualitatively similar to those based on analyst-level analyses. The coefficient on *Ernsurp* is statistically insignificant in a linear specification (Columns (1) and (2)), but when the coefficient is allowed to vary across Ernsurp terciles it is significantly negative for the lowest Ernsurp group alone.

The coefficient on control variables in the regressions in both Panels A and B are generally insignificant. Only the level of leverage (*LEV*) is consistently significant (at the 5% level or better) in both panels and has a significantly positive coefficient, which is consistent with the view that more levered firms are perceived to be more risky..

4.3 Comparing CoE estimates with alternative expected return proxies

We next benchmark analysts' CoE estimates with other expected return proxies (ERPs) in terms of their relative ability to reflect the true, but unobserved, expected returns of a firm. This analysis is in the spirit of Easton and Monahan (2005), Guay, Kothari and Shu (2011) and Lee, So and Wang (2017). We implement this test following the approach in Lee et al. (2017), who provide a framework for comparing the performance of alternative ERPs based on relative variances of each ERP's measurement error—i.e., the error of an ERP relative to a firm's true but unobservable expected returns. The intuition behind their model is that the variance of the true (but unobserved) expected returns is constant across alternative ERPs and is cancelled out by differencing variances of measurement errors across alternative ERPs. Thus, although the measurement errors of a given ERP are not observable, the difference in variance of measurement errors across alternative ERPs is estimable and can be used to evaluate the performance of the ERPs. Lee et al. (2017) also show that the optimal performance of expected return proxies could vary depending on whether the focus is on its cross-sectional evaluation (cross-sectional variation in ERPs should reflect the cross-sectional variation in firms' expected returns) or time-series evaluation (the time-series variation in a firm's ERP should reflect variations in its expected returns over time). Accordingly, we examine both these dimensions in ascertaining the performance of analysts' CoE estimates.

Prior studies offer several alternative proxies for expected rates of return for individual equities. We compare the CoE estimates from analyst reports with eight benchmark ERPs: three factor-based expected return proxies (CAPM, the Fama and French (1993) three-factor model and the Fama and French (2015) five-factor model) and five implied cost of capital estimates (ICC estimates from Gebhardt, Lee and Swaminathan's (2001) model, Claus and Thomas' (2001) model, Easton's (2004) model, Ohlson and Juettner-Nauroth's (2005) model or a composite estimate computed as simple average of the above four ICC estimates).

As in Lee et al. (2017), we first compute time-series error variance (*TSVar*) for each of the expected return proxies as follows:

$$TSVar_i = Var_i\left(\widehat{er}_{i,t}\right) - 2Cov_i\left(r_{i,t+1}, \widehat{er}_{i,t}\right) \tag{4}$$

where $Var_i\left(\widehat{er}_{i,t}\right)$ is the time-series variance of a given ERP for firm *i*, and $Cov_i\left(r_{i,t+1}, \widehat{er}_{i,t}\right)$ is the time-series covariance between a given ERP and realized returns for firm *i* in period *t+1*. For each firm *i*, we then compute a pair-wise difference between $TSVAR_i$ for analysts' CoE estimates and that for each of the eight benchmark ERPs. We then evaluate whether the cross-sectional averages for each of the eight series of differences are significantly different from zero.

We conduct the cross-sectional ERP comparisons analogously, where the cross-sectional error variance for each ERP and year *t* ($CSVar_t$) is computed from the cross-sectional variance of the ERP and the cross-sectional covariance between the ERP and realized stock returns in period *t+1*. We then evaluate whether the time-series averages of the difference in $CSVAR_t$ for analysts' CoE estimates with the benchmark ERPs are significantly different from zero. All else equal, ERPs with lower error variances ($TSVAR_i$ or $CSVAR_t$) are deemed to be of higher quality.

We report results from tests that measure realized returns over three alternative windows (monthly, quarterly and annual) beginning the day of the analyst report in which a CoE estimate is disclosed. This enables us to ascertain the relative performance of analysts' CoE estimates as a proxy for expected returns at different horizons. Examining longer windows is particularly important for our study because analyst CoE estimates are likely to reflect their longer-term view of a firm's expected returns.[9]

For each CoE estimate in our sample, we calculate the corresponding benchmark ERPs using data available as of the corresponding analyst report date *t*. For the factor-based models (CAPM and Fama-French factor models), we first estimate factor loadings using daily returns from CRSP and the Fama and French factors over the period *t-1* to *t-360*. We then use the estimated factor loadings and the Fama and French daily factors for day *t* to compute the expected return.[10] The calculations of the ICC estimates replicates the approach used in previous studies (Gebhardt, Lee and Swaminathan, 2001; Claus and Thomas, 2001; Easton, 2004; Ohlson and Juettner-Nauroth, 2005) and is discussed in Appendix II. Consistent with our earlier analysis, we Winsorize estimated factor loadings, ICC estimates and measurement error variances at 1% and 99% levels.

The results from the analysis of differences in $TSVAR_i$ and in $CSVAR_t$ are presented in Table 7, Panels A and B respectively. Each entry presents the average difference in measurement error variance for the CoE estimate and the variance error for a benchmark ERP. A significantly

[9] As our ERP proxies are computed at a monthly frequency, cross-sectional analyses based on quarterly or annual returns could be affected by overlapping returns. We therefore report Newey-West adjusted t-statistics in cross-sectional analyses based on quarterly or annual returns.

[10] Daily Fama-French factors data are from Ken French's website. Analyst forecasts used in computation of ICC proxies are obtained from I/B/E/S.

negative value indicates that the CoE estimate has a lower measurement error variance, and is therefore of a higher quality relative to the benchmark ERP, and vice-versa.

When using monthly realized returns, we find that the CoE estimates perform worse than the factor-based asset pricing models but better than all of the ICC estimates.[11] However, when the measurement horizon for realized returns is lengthened, the superiority of factor-based asset pricing models diminishes. In analyses based on quarterly returns, the CoE estimates performance is similar to the factor-based models. When the return measurement is further extended to yearly, the CoE estimates outperform almost all benchmark ERPs, indicating that analysts' CoE estimates are better proxies for expected returns, particularly over long horizons.

The cross-sectional variances shown in Table 7 Panel B continue to provide similar conclusions. When realized returns are measured at a monthly-level, the CoE estimates perform worse than the factor model but better than the ICC models. However, the advantage of factor models declines as the return measurement period is extended. When realized returns are measured over a year, the CoE estimates perform at least as well as the factor-based ERPs, but continue to perform better than the implied costs of capital estimates.

Collectively, these findings suggest that CoE estimates from analyst reports tend to be more accurate measures of a firm's long-run expected stock returns.

5. Conclusions

We explore a large sample of analysts' estimates of CoE with a view to understanding whether the estimates fairly reflect expected stock returns and their determinants. We also evaluate the relative performance of CoE estimates as a proxy for expected returns relative to the implied costs of capital in addition to those obtained from factor models. We find that analysts' CoE

[11] Our results are not directly comparable to Lee et al. (2017) due to differences in sample composition.

estimates strongly predict future stock returns, consistent with them being good proxies for expected returns. When we examine the firm characteristics that analysts weight in their CoE computations, we find that analysts primarily reflect firm beta, book-to-market ratios and firm size, suggesting that their CoE estimates are in line with the Fama-French 3-factor asset pricing model. They further appear to adjust their CoE estimates for leverage and short-term return reversals, but do not seem to weigh profitability or investments in their CoE estimates, possibly because these factors have been discovered only during our sample period and there is a lag before the factors are adopted in practice. Also, the Fama and French (2015) five-factor asset pricing model was only published at the end of our sample period. Interestingly, we also find little evidence that analysts emphasize other return predictors such as momentum in their CoE estimates, indicating that they do not adjust their CoE estimates for a variable simply because it is related to future returns.

When we investigate whether analysts' CoE estimates have incremental predictive power for future returns over other known predictors, we find the estimates to be positively related to future returns. We also find that analysts increase their CoE estimates following a firm's revelation of negative earnings news. No significant adjustments are observed for firms that report earnings in excess of or close to analysts' earnings expectations. The change in CoE estimates for firms with poor earnings news is consistent with the assertions of Fama and French (1996) that distress risk is a priced risk factor, as financial distress is typically preceded by periods of negative earnings news. Finally, when we compare measurement errors in CoE estimates with measurement errors in other proxies for expected stock returns, we find CoE estimates tend to have a lower noise. This is particularly true for expected returns measured over longer-horizons.

Our findings suggest that analysts' CoE estimates are good proxies for expected stock returns. Several empirical asset pricing tests are hampered by the lack of observability of discount rates and typically rely upon realized stock returns to capture expected stock returns. We contribute by suggesting that analysts' revealed discount rates can be a useful alternative proxy for expected stock returns. However, like research that relies on analysts' earnings forecasts and implied costs of capital, a clear limitation of this proxy is that the CoE estimates are not revealed for all stocks and by all analysts. Therefore, caution is required in extrapolating findings from this sample to instances where analysts CoE estimates are unavailable.

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Appendix I

This appendix describes the measurements of firm characteristics just prior to an analyst releasing his/her report on the firm. Data for accounting variables, number of shares outstanding and stock price at the end of the fiscal quarter are obtained from Compustat. Daily stock returns and value-weighted market returns are from CRSP daily files.

Variable name	Variable Definition
CoE_{ibt}	Analyst's cost of equity estimate revealed by brokerage *b* in their report for firm i and period *t*. This variable is extracted from analyst research reports downloaded from Thomson One.
$Ernsurp_t$	Analysts' earnings forecast errors for quarter q that immediately precedes the analyst report on date t, measured as $(act_q - medest_q)/prc_q$, where *act* is the actual reported earnings per share for quarter q, *medest* is the latest median analyst estimate prior to earnings announcement and *prc* is the end of quarter q's stock price. *act* and *medest* are obtained from IBES and *prc* is from Compustat.
RETURNS	Stock returns, estimated as the buy-and-hold returns from day 0 to day +360 relative to analyst report release date (day 0).
$BETA_t$	Firm specific beta, obtained from regression of daily stock returns in the six months (i.e., calendar days *t*-180 to *t*-3) prior to analyst's report release date (day 0) on value-weighted market returns.
$MCAP_t$	Market Capitalization, computed as natural log of number of shares outstanding multiplied by stock price at end of fiscal quarter preceding analyst's report release date.
BTM_t	Book-To-Market Ratio, defined as ratio of book value of equity to market value of equity at end of fiscal quarter preceding analyst's report release date.
LEV_t	Leverage, defined as the ratio of long term debt + debt in current liabilities to total assets. All variables are measured at the end of the fiscal quarter preceding analyst's report release date.
$IDIO\_VOL_t$	Idiosyncratic Volatility is computed as $(1-R^2)/R^2$, where R^2 is estimated from the regression of excess daily stock returns on the three Fama-French factors over days t-90 to t-7 relative to the analyst's report release date (day 0).
MOM_t	Momentum, defined as the buy-and-hold stock returns over an 11-month period ending two calendar months prior to the month of analyst report release.
LAG_RETURN_t	Stock return in the calendar month immediately preceding the analyst report release month.
PROFITABILITY	Operating profitability, measured as revenues minus cost of goods sold, minus selling, general and administrative expenses, minus interest expense all divided by book equity. All variables are taken the fiscal quarter just preceding analyst's report release date.
INVESTMENTS	Investments made by firm, measured as the percentage growth in total assets over the four quarters ending in the most recent fiscal quarter prior to analyst's report release date.

Appendix II. Implied cost of equity capital models

We estimate implied costs of capital using the following four models:

Model	Equation used to estimate implied costs of capital (r_{ICC})	Model-specific assumptions
CT MODEL: Claus and Thomas (2001):	$$P_t = bv_t + \sum_{k=1}^{T} \frac{(eps_{t+k} - r_{CT} * bv_{t+k-1})}{(1 + r_{CT})^k} + \frac{(eps_{t+T} - r_{CT} * bv_{t+T-1})(1+g)}{(r_{CT} - g)(1 + r_{CT})^T}$$	• For first five years, residual income (= $eps_{t+k} - r_{CT} * bv_{t+k-1}$) is computed using analysts' earnings per share forecasts • From t=5, residual income is assumed to perpetually grow at the one-year ahead inflation rate.
GLS MODEL: Gebhardt, Lee and Swaminathan (2001):	$$P_t = bv_t + \sum_{k=1}^{T} \frac{(eps_{t+k} - r_{GLS} * bv_{t+k-1})}{(1 + r_{GLS})^k} + \frac{(eps_{t+T+1} - r_{GLS} * bv_{t+T})}{r_{GLS} * (1 + r_{GLS})^T}$$	• For first three years, residual income (= $eps_{t+k} - r_{GLS} * bv_{t+k-1}$) is computed using analysts' earnings per share forecasts. • For subsequent nine years, residual income is computed assuming the firm's return on equity (ROE) linearly reverts to the industry median ROE. The industry median ROE is calculated for each industry-year using all firms with available data over the prior three years. The industry categorization is based on Campbell (1996). • From t=12, the growth rate for residual income is set to zero.
OJN MODEL: Ohlson and Juettner-Nauroth (2005):	$$P_t = \frac{d_{t+1}}{(r_{OJN} - g_l)} + \frac{eps_t(g_s - g_l)}{r_{OJN}(r_{OJN} - g_l)}$$	
MPEG MODEL: Easton (2004):	$$P_t = \frac{r_{MPEG} * d_{t+1} + eps_{t+2} - eps_{t+1}}{r_{MPEG} * r_{MPEG}}$$	

Where,

P_t is the market price of a firm's stock three months after end of fiscal year *t.* The three-month lag allows prices to fully reflect year *t* information.

bv_t is the book value per share at the end of fiscal year t.

eps_{t+i} is the expected earnings per share for fiscal year t+i (i>0) using either explicit analyst forecasts or derived from analysts' growth forecasts.

g is the terminal perpetual growth rate. We assume this to be the one-year ahead inflation.

g_s and g_l are the expected short-term and long-term growth rates in OJN model. Following Gode and Mohanram (2003) short-term growth rate is computed as the average of the growth in analysts' earnings forecasts over the first two years and analysts' five-year growth forecasts. The long-term growth rate is set equal to one-year ahead inflation for all firms.

d_{t+i} is the net dividends per share for fiscal year t+i (i>0) and is computed by multiplying the average payout ratio in years t-2 to t with the forecasted earnings per share for year t+i.

r_{CT}, r_{GLS}, r_{OJN} and r_{MPEG} are the implied costs of equity capital and are calculated as the internal rate of return from each of the above models. Since the models do not have a unique closed-form solution, an iterative procedure is used to estimate the values.

We obtain analyst earnings per share forecasts and long-term growth forecasts from IBES. All analyst estimates are mean consensus figures. Accounting data and three-month ahead stock price is from Compustat. For an observation to be included in the sample, we require data to be available on current stock price, analyst earnings per share forecast for next two years and either forecasted earnings per share for the next five-years or an estimate of long term earnings growth. Negative or missing earnings per share forecasts are replaced by extrapolating prior year earnings forecast with analyst's long-term growth forecasts. If long-term growth forecast is negative or missing, then it is replaced by growth in forecasted earnings per share over years t+2 to t+3.

TABLE 1: SAMPLE SELECTION

This table presents the sample construction criteria and the number of observations at each step. Analyst research reports are downloaded from Thomson One for the sample period of 1 Jan 2001-31 Dec 2015. We apply the following three criteria while searching for reports on Thomson One: (i) "Cost of Equity" appears in "Table of Contents" (ii) Geography is "United States" and (iii) Reports are not categorized as non-broker, industry or economy reports.

			Observations
(1)	Analyst research reports from Thomson One that contain mentions of "cost of equity"		31,632
(2)	Reports where COE was not extractable by textual analysis	(11,503)	
(3)	Observations where ticker from a report could not be matched to an I/B/E/S ticker	(2,000)	
(4)	Main sample of observations containing COE values		18,129
(5)	Retain only observations where CoE estimates for a firm are available from the same broker in the 45 days before and the 45 days after an earnings announcement.	(14,283)	
(6)	Sample with data for ΔCOE analysis around earnings announcements		2,466

TABLE 2: SUMMARY STATISTICS

The table presents summary statistics for the full sample of extracted analyst COE values from Thomson One analyst research reports and for all firms in IBES summary file. The sample period is from 2001-2015. The table also presents differences between the sample means. All variables are defined in Appendix I. § represents statistical significance at the 1% level from a t-test for differences in means and from a Wilcoxon rank-test for differences in the medians between the CoE Sample and IBES Sample.

	CoE sample						**IBES Sample**					
	N	Mean	Med	Std. Dev.	Min	Max	N	Mean	Med	Std. Dev.	Min	Max
COE	18,129	10.573	10.000	2.609	5.200	20.600						
RETURNS	18,129	15.45§	9.700§	59.1	-99.15	1607.27	62,469	8.748	5.15	51.21	-88.72	214.0
BETA	18,129	1.143§	1.070§	0.509	0.133	2.888	62,452	1.061	1.011	0.602	-0.193	2.877
BTM	17,954	0.443§	0.380§	0.396	-0.691	1.961	62,376	0.570	0.480	0.477	-0.323	2.782
MCAP	18,076	15.385§	15.570§	2.133	6.604	19.344	62,406	13.485	13.68	1.730	10.027	18.025
LEV	17,971	0.316§	0.280§	0.243	0.000	1.121	61,871	0.218	0.170	0.214	0.000	0.919
IDIO_VOL	18,124	0.314§	0.250§	1.149	-2.210	3.523	62,070	0.805	0.780	1.212	-1.724	4.122
MOMENTUM	17,983	0.155	0.110	0.719	-0.959	32.761	57,708	0.137	0.120	0.514	-1.255	1.960
LAG_RETURN	18,055	0.004§	0.000§	0.115	-0.660	1.827	59,857	0.025	0.011	0.128	-0.338	0.497
PROFITABILITY	18,023	0.060§	0.060§	0.210	-0.903	1.245	61,820	0.037	0.039	0.147	-0.703	0.689
INVESTMENTS	17,892	0.166§	0.060§	0.420	-0.315	2.770	61,224	0.239	0.210	0.675	-0.457	4.562

TABLE 3: ANALYST'S COST OF EQUITY ESTIMATE AND EXPECTED RETURNS

Panel A reports average returns for portfolios sorted on CoE. The returns (*RETURNS*) are estimated as the buy-and-hold stock returns from day 0 to day +360 relative to analyst report release date (day 0). Observations are sorted into terciles based on whether analysts' CoE estimates are in the top 30%, middle 40% or bottom 30%. Panel B presents the results of a regression of *RETURNS* on CoE and terciles of CoE values. CoE_rank is a ranked variable that takes the value 1 for the top 30%, 2 for the middle 40%, and 3 for the bottom 30% of CoE. CoE_MID takes a value of 1 if CoE observations are in the middle 40% and 0 otherwise. CoE_HIGH takes a value of 1 if CoE observations are in top 30% and 0 otherwise. ErnSurp(q+i) (i= 1 to 4) is the analyst forecast error in the first to fourth quarters following the release of an analyst report with a CoE estimate. Columns (1) - (3) and (5) present the results of a regression of *RETURNS* on individual analyst-level CoE estimates and firm characteristics. The regression specifications include time-, firm- and brokerage-fixed effects. Standard errors are clustered at the industry level. Column (4) presents the results for a portfolio-level analysis where analyst CoE estimates are classified into 25 portfolios each quarter. The average *RETURNS* for each portfolio are regressed on average CoE estimates and firm characteristics for the corresponding portfolio. The specification includes time-fixed effects and the standard errors are clustered at the portfolio level. The *t*-statistics are presented in parenthesis. *, ** and *** denote significance at 10%, 5% and 1% respectively.

Panel A: Univariate Portfolio Analysis

COE-sorted portfolio	**Average CoE**	**Average 1-year returns**
HIGH CoE portfolio	13.70%	21.5***
		(4.451)
MID CoE portfolio	10.25%	16.3***
		(4.230)
LOW CoE portfolio	8.23%	9.4***
		(8.029)
F-test that portfolio returns are equal (p-value)		*0.000*

Panel B: Regression Analysis

	PREDICTED	(1) *Analyst-Level RETURNS*	(2) *Analyst-Level RETURNS*	(3) *Analyst-Level RETURNS*	(4) *Portfolio-Level RETURNS*	(4) *Analyst-Level RETURNS*
CoE	+	3.326***			1.221***	3.912***
		(4.509)			(3.503)	(4.655)
CoE_rank	+		6.260***			
			(5.155)			
CoE_MID	+			7.394**		
				(2.613)		
CoE_HIGH	+			12.488***		
				(4.987)		
Ernsurp(q+1)	?					894.106**
						(2.336)
Ernsurp(q+2)	?					718.621
						(1.416)
Ernsurp(q+3)	?					318.194
						(0.948)
Ernsurp(q+4)	?					-393.329
						(-1.172)
Observations		18,129	18,129	18,129	1,408	12,633
R-squared		0.446	0.441	0.441	0.379	0.459

TABLE 4: ANALYST'S COST OF EQUITY ESTIMATE AND FIRM CHARACTERISTICS

This table reports results of pooled regression of analysts' CoE estimation on firm characteristics. All variables are defined in Appendix I. All specifications include time-, firm- and brokerage-fixed effects and the standard errors are clustered at the industry level. The *t*-statistics are presented in parenthesis. *, ** and *** denote significance at 10%, 5% and 1% respectively.

		(1)	(2)	(3)
	PREDICTED	*CoE*	*CoE*	*CoE*
BETA	+	0.517***	0.394***	0.389***
		(4.430)	(4.559)	(4.396)
BTM	+		1.216**	1.320**
			(2.236)	(2.429)
MCAP	-		-0.120***	-0.111***
			(-5.307)	(-4.908)
PROFITABILITY	+		-0.300	-0.271
			(-1.331)	(-1.290)
INVESTMENTS			-0.088	-0.092
			(-0.972)	(-0.955)
LEV				1.250***
				(2.728)
IDIO_VOL				0.022
				(1.489)
MOMENTUM	+			-0.010
				(-0.220)
LAG_RETURN	-			-0.412***
				(-3.200)
Observations		18,129	17,749	17,560
R-squared		0.694	0.705	0.706

TABLE 5: FUTURE RETURNS AND COE REGRESSIONS

This table reports results of pooled regression of buy-and-hold returns (*RETURNS*) in the 360 days following the analyst reports release date. All variables are defined in Appendix I. Columns (1) through (3) presents the results of a regression of *RETURNS* on analyst CoE estimates and firm characteristics. These specifications include time-, firm- and brokerage-fixed effects and the standard errors are clustered at the industry level. Column (4) presents the results for a portfolio-level analysis where analyst CoE estimates are classified into 25 portfolios each quarter. The average *RETURNS* for each portfolio are regressed on the average CoE estimates and firm characteristics for the corresponding portfolio. The specification includes time-fixed effects and the standard errors are clustered at the portfolio level. The *t*-statistics are presented in parenthesis. *, ** and *** denote significance at 10%, 5% and 1% respectively.

	PREDICTED	(1) *Analyst-Level RETURNS*	(2) *Analyst-Level RETURNS*	(3) *Analyst-Level RETURNS*	(4) *Portfolio-Level RETURNS*
CoE	+	3.280***	2.484***	2.293***	1.198***
		(4.727)	(3.377)	(2.985)	(4.553)
BETA	+	2.211	0.663	0.356	-0.292
		(0.678)	(0.202)	(0.099)	(-0.056)
BTM	+		30.593***	31.507**	-3.154
			(2.738)	(2.533)	(-0.218)
MCAP	-		-6.069***	-5.675***	-1.329
			(-3.429)	(-3.486)	(-0.946)
PROFITABILITY	+		14.958	15.394	28.694
			(1.163)	(1.167)	(0.656)
INVESTMENTS			-2.987	-3.213	-17.427***
			(-1.245)	(-1.152)	(-5.416)
LEV				26.479	12.907
				(1.415)	(1.537)
IDIO_VOL				-0.163	1.216
				(-0.316)	(0.392)
MOMENTUM	+			-5.980	-6.955
				(-1.372)	(-1.329)
LAG_RETURN	-			-59.257***	-30.685*
				(-6.432)	(-1.812)
Observations		18,129	17,749	17,560	1,363
R-squared		0.446	0.464	0.479	0.425

TABLE 6: CHANGES IN ANALYST COST OF EQUITY CAPITAL ESTIMATE AND EARNINGS NEWS

This table reports results of pooled regression of changes in CoE (*ΔCoE*) on Earnings Surprise (*Ernsurp*) and control variables. Panel A presents descriptive statistics for *Ernsurp* for each tercile of earnings surprise. Panel B presents the regression results of *ΔCoE* at analyst level regressed either on *Ernsurp* or *Ernsurp-terciles* (*Ernsurp_HIGH, Ernsurp_MID, Ernsurp_LOW*). Panel B (Panel C) presents regression results using analyst-firm-quarter level (firm-quarter level) observations. The dependent variable *ΔCoE* is the change in CoE values for a given firm by a specific broker around an earnings announcement for quarter q. The variables definitions are presented in Appendix I. All specifications include time- and brokerage-fixed effects and the standard errors are clustered at the industry-level. The t-statistics are presented in parenthesis. *, ** and *** denote significance at 10%, 5% and 1% respectively.

Panel A: Descriptive Statistics

	N	Mean	Median	Std. Dev.	Min	Max
ΔCoE	2,466	0.015	0.000	0.470	-2.000	2.600
Ernsurp (for high Ernsurp tercile)	740	0.005	0.002	0.007	0.001	0.106
Ernsurp (for mid Ernsurp tercile)	1000	0.000	0.000	0.000	0.000	0.001
Ernsurp (for low Ernsurp tercile)	726	-0.007	-0.001	0.023	-0.324	-0.000

Panel B: Analyst-quarter analysis

	(1) *ΔCoE*	(2) *ΔCoE*	(3) *ΔCoE*	(4) *ΔCoE*
Ernsurp	-2.377*	-2.207		
	(-1.697)	(-1.421)		
Ernsurp _HIGH Ernsurp*			3.062	2.820
			(0.702)	(0.737)
Ernsurp _MID Ernsurp*			3.571	9.771
			(0.136)	(0.359)
Ernsurp _LOW Ernsurp*			-5.164**	-4.793**
			(-2.577)	(-2.116)
MCAP		0.001		0.002
		(0.081)		(0.302)
BETA		0.021		0.018
		(0.968)		(0.833)
BTM		-0.001		-0.007
		(-0.033)		(-0.226)
PROFITABILITY		0.006		0.005
		(0.972)		(0.883)
INVESTMENTS		-0.044		-0.043
		(-1.112)		(-1.078)
LEV		0.109**		0.101**
		(2.134)		(2.003)
MOM		-0.007		-0.006
		(-0.810)		(-0.813)
RET		-0.149		-0.161
		(-1.199)		(-1.333)
IDIO_VOL		-0.014		-0.015
		(-1.205)		(-1.249)
Ernsurp _HIGH			0.030	0.655**
			(0.122)	(2.244)
Ernsurp _MID			0.038	0.671**
			(0.159)	(2.280)
Ernsurp _LOW			0.013	0.644**
			(0.055)	(2.190)
Observations	2,466	2,418	2,466	2,418
R-squared	0.082	0.092	0.085	0.095

Panel C: Firm-quarter analysis

	(1) ΔCoE	(2) ΔCoE	(3) ΔCoE	(4) ΔCoE
Ernsurp	-2.367	-1.966		
	(-1.479)	(-1.097)		
Ernsurp _HIGH Ernsurp*			4.678	4.794
			(1.345)	(1.553)
Ernsurp _MID Ernsurp*			4.192	10.116
			(0.147)	(0.342)
Ernsurp _LOW Ernsurp*			-2.869*	-2.883*
			(-1.976)	(-1.699)
MCAP		0.002		0.005
		(0.335)		(0.788)
BETA		0.024		0.014
		(1.140)		(0.641)
BTM		-0.001		-0.015
		(-0.037)		(-0.434)
PROFITABILITY		0.007		0.007
		(1.241)		(1.221)
INVESTMENTS		-0.041		-0.039
		(-1.043)		(-1.007)
LEV		0.117**		-0.016
		(2.299)		(-1.524)
MOM		-0.013		-0.011
		(-1.026)		(-1.034)
RET		-0.178		-0.216*
		(-1.495)		(-1.969)
IDIO_VOL		-0.015		-0.016
		(-1.424)		(-1.524)
Ernsurp _HIGH			0.402***	0.171
			(5.488)	(0.559)
Ernsurp _MID			0.415***	0.188
			(7.473)	(0.599)
Ernsurp _LOW			0.404***	0.173
			(5.800)	(0.562)
Observations	2,208	2,161	2,208	2,161
R-squared	0.090	0.103	0.099	0.112

TABLE 7: EVALUATING COE AS AN EXPECTED RETURN PROXY

This table reports results for measurement error variance of COE minus that of alternative expected returns proxies. Panel A presents results from the analysis of time-series error variances using a sample of 1963 firms over the sample period 2001-2015, while Panel B presents results from the analysis of cross-sectional error variance for 188 calendar months. Analyst Cost of Equity (COE) values are derived from Thomson One analyst research reports. The alternative expected return proxies are obtained from following models: Capital Asset Pricing Model, Fama-French 3-factor model, Fama-French 5- factor model and five implied costs of equity capital computed based on Claus and Thomas (2001), Gebhardt et al. (2001), Easton (2004) and Ohlson and Juettner-Nauroth (2005) and as the average of the earlier four ICC estimates (i.e., ICC_CT, ICC_GLS, ICC_MPEG, ICC_OJN and ICC_COMPOSITE). Factor loadings for CAPM, FF3 and FF5 models are estimated using the previous 360 days daily returns (i.e., days t-360 to t-1) relative to the CoE report release date (i.e., day t). The realized returns for computation of the error variances are measured either over a month (i.e., 30 days), a quarter (90 days) or a year (360 days) from the date of analyst report disclosing a CoE estimate. The *t*-statistics are presented in parenthesis. Panel B reports t-statistics based on Newey-West-adjusted standard errors.

Panel A: Time-Series Measurement-Error Variance (N = 1963)

Return-measurement period	*CAPM*	*FF3*	*FF5*	*ICC_CT*	*ICC_GLS*	*ICC_OJN*	*ICC_MPEG*	*ICC_COMPOSITE*
Monthly	5.014	5.748	6.294	-4.468	-8.013	-7.059	-9.628	-5.092
	(6.02)	(6.50)	(7.17)	(-3.68)	(-4.91)	(-4.57)	(-5.50)	(-4.30)
Quarterly	1.672	1.615	2.423	-3.963	-4.803	-6.039	-7.639	-3.862
	(1.21)	(1.08)	(1.58)	(-2.67)	(-2.94)	(-3.10)	(-3.64)	(-2.53)
Annual	-6.628	-5.567	-4.138	-12.514	-13.265	-13.596	-9.673	-10.895
	(-2.49)	(-2.20)	(-1.60)	(-4.38)	(-4.67)	(-4.14)	(-2.56)	(-3.72)

Panel B: Cross-Sectional Measurement-Error Variance (N = 188)

Return-measurement period	*CAPM*	*FF3*	*FF5*	*ICC_CT*	*ICC_GLS*	*ICC_OJN*	*ICC_MPEG*	*ICC_COMPOSITE*
Monthly	9.386	9.912	10.059	-48.293	-54.225	-61.575	-69.717	-50.523
	(4.29)	(4.07)	(4.12)	(-9.45)	(-9.35)	(-9.78)	(-10.62)	(-8.91)
Quarterly	9.183	10.251	9.361	-54.166	-55.687	-68.423	-77.775	-55.321
	(2.36)	(2.51)	(2.35)	(-7.90)	(-6.86)	(-8.61)	(-8.60)	(-8.17)
Annual	1.67	5.139	4.828	-97.807	-79.685	-117.700	-127.718	-99.686
	(0.12)	(0.35)	(0.34)	(-4.56)	(-3.56)	(-5.63)	(-5.15)	(-4.82)