Analysts' Estimates of the Cost of Equity Capital*

Karthik Balakrishnan
Jesse H. Jones Graduate School of Business
Rice University
karthik.balakrishnan@rice.edu

Lakshmanan Shivakumar
London Business School
Regent's Park
London NW1 4SA, UK
lshivakumar@london.edu

Peeyush Taori
Peeyush Taori
Hong Kong University Business School
Hong Kong
peeyusht@hku.hk

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Abstract

We explore a large sample of analysts' estimates of the cost of equity capital (CoE) to evaluate their usefulness as expected return proxies (ERP). We find that the CoE estimates are significantly related to a firm's beta, size, book-to-market ratio, leverage, and idiosyncratic volatility but not other risk proxies. Even after controlling for the popular return predictors, the CoE estimates incrementally predict future stock returns. This predictive ability is better explained as the CoE estimates containing ERP information rather than reflecting stock mispricing. When evaluated against traditional ERPs, including the implied costs of capital, the CoE estimates are found to be the least noisy. Finally, we document CoE responses around earnings announcements, demonstrating their usefulness to study discount-rate reactions of market participants. We conclude that analysts' CoE estimates are meaningful ERPs that can be fruitfully employed in a variety of asset pricing contexts.

Keywords: Analysts, cost of equity, expected stock returns, implied cost of equity capital

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1. Introduction

Researchers spanning economics, finance, and accounting have spent decades to better understand the fundamental determinants of the costs of capital, yet little is known about the actual costs of equity (CoE) capital, as market participants' expected returns are generally unobservable. Thus, researchers have typically relied on realized returns or implied costs of capital (ICC) metrics as proxies for expected stock returns, leading to calls for the identification of alternative benchmarks to test asset pricing theories.[1] In response, in this paper we evaluate the CoE capital disclosed by sell-side analysts as a proxy for expected stock returns and their usefulness in asset pricing tests.

Analysts' CoE estimates offer several advantages over the currently popular proxies for expected stock returns, such as realized returns, CAPM, Fama-French models, and ICC. First, analysts' CoE estimates are directly observable and do not require researchers' assumptions. Also, these estimates could reflect investors' expected returns irrespective of their underlying asset pricing models, making them attractive to appraise asset pricing theories. Moreover, analysts' CoE estimates can be useful to study discount rate reactions at specific events, such as earnings announcements. In contrast, existing metrics cannot cleanly disentangle discount rate effects from other effects (i.e., cash flow effects and mispricing effects) on stock prices.

There are at least two reasons to expect analysts' CoE estimates to be reliable proxies of expected stock returns. First, a vast body of literature has shown that analysts' outputs, such as earnings forecasts, target prices, stock recommendations, etc., are good expectation measures, implying that even analysts' CoE estimates could be a good measure of expected stock returns. Secondly, as part of their job, analysts interact with a wide variety of market participants (investors, portfolio managers, traders, and equity sales people), who share their information about expected stock returns to enable the analysts to tailor their stock selections and recommendations.[2] This direct information collection from investors could give analysts an

[1] In his presidential address to the American Finance Association, Elton (1999) asserts that "developing better measures of expected returns and alternative ways of testing asset pricing theories that do not require realized returns have a much higher payoff than any additional development of statistical tests that continue to rely on realized returns as a proxy for expected returns."

[2] For instance, while discussing their research with investor-clients, analysts gather indications of investment interest based on potential returns offered by the firms, giving them a sense of the returns demanded for stocks with specific characteristics. Investor-clients might also privately reveal to analysts their threshold returns for investing in a particular stock or, more generally, the stock characteristics and risk factors that influence their threshold levels. Because investors eventually price stocks by trading in them, the input they provide is likely to result in analysts' CoE estimates indirectly reflecting the returns demanded by investors, regardless of the underlying asset pricing models they use. Also, as investors ultimately determine the stock market prices, the CoE

advantage when estimating expected returns.

However, there are also good reasons why analysts' CoE estimates may not be reliable proxies of expected returns. While analysts' earnings forecasts, target prices, and recommendations are informative, it does not necessarily follow that analysts' CoE estimates are also a useful or an informative metric. This is because, unlike other metrics, it is not possible to evaluate the accuracy of CoE estimates by ex post comparing the CoE values to corresponding actuals. Consequently, it is not possible to scrutinize, compensate or otherwise incentivize analysts to expend time or effort on these estimates. Consistent with the notion that analysts expend little effort on discount rate estimates, studies examining a small sample of analyst reports and survey responses have shown that analysts' discount rate estimates suffer from significant execution errors and questionable choices (Green, Hand and Zhang, 2016; Mukhlynina and Nyborg, 2016). Supporting the view that analysts' CoE estimates are not very systematic or meaningful, Mukhlynina and Nyborg (2016) provide this 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."

Informal discussions with analysts and anecdotes also suggest that analysts might strategically generate their CoE estimates to justify pre-determined target prices or stock recommendations. For instance, an analyst with a strong "buy" instinct based on narrative analysis might opt for a lower CoE estimate in the valuation model to better persuade clients about particular stock recommendation.[3] Thus, the issue of whether analysts' CoE estimates are reliable proxies of expected stock returns is ultimately an empirical one.

We address this issue by evaluating a sample of 31,049 CoE estimates for US stocks parsed out of analyst reports covering the period from 2001 to 2017. We begin our empirical analysis by asking what type of analysts reveal their CoE estimates and for what type of firms. As not all analysts reveal their CoE estimates in every report, this test serves to reveal the supply- and

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estimates could be incrementally informative about expected returns impounded in stock prices over theoretically-motivated or otherwise known risk or characteristic-based factors.

[3] A recent episode involving Morgan Stanley illustrates this possibility. On March 27, 2017, nearly a month after helping Snap Inc. raise $3.4 billion in an IPO, Morgan Stanley published its first equity research report on the firm and gave it a target price of $28.00. A day later, the bank issued a revised report correcting tax calculation errors, which reduced the projected cash flows by nearly $5 billion. In spite of this correction, the bank did not change its target price, preferring instead to reduce its CoE estimate from 9.9% to 8.1%. While the change in CoE could have been innocuous, there were clear incentives for Morgan Stanley to change its discount rate, as otherwise, the bank would not have been able to justify a buy recommendation or issue a target price comparable to peers. Although interesting, this anecdote need not be representative of the approaches employed by a broader set of analysts to estimate CoE.

demand-side determinants of the analysts' decisions to provide CoE estimate and the generalizability of our results. Consistent with the notion that inexperienced analysts aim to signal diligence to investors and with investors demanding more information from such analysts, we find that the CoE estimates are more likely to be supplied by analysts with less overall experience, those who have followed a covered firm for a shorter period, and those that cover fewer firms. Additionally, we find that analysts are more likely to provide CoE estimates for firms that are harder to value and have greater investor interest.

Next, using a univariate analysis and a multivariate regression of future stock returns on CoE estimates, we document that analysts' CoE estimates are positively related to future realized returns. Further, we find that CoE estimates are systematically related to a firm's beta, book-to-market ratio, size, leverage, and idiosyncratic volatility but unrelated to profitability, investments, price momentum, short-term return reversals, and liquidity. Our evidence that analysts give weight to market beta, firm size, and book-to-market ratio is partly consistent with the recent survey results of Mukhlynina and Nyborg (2016). They find that approximately three-quarters of respondents claim to regularly use the capital asset pricing model (CAPM) to estimate discount rates. However, less than 5% of the respondents claim to use the Fama-French three-factor model, and the authors report that less than half regularly adjust CoE for a firm's leverage.[4] One possible explanation to reconcile our findings with the survey evidence is that analysts may not formally use the Fama-French model to compute CoE estimates but may still heuristically adjust for the firm characteristics (namely size and book-to-market ratio) reflected in that model.

We next show that the predictive ability of CoE estimates for future returns holds even after controlling for firm characteristics that are commonly interpreted as risk proxies. This suggests that analysts' CoE estimates have incremental predictive power for future returns over commonly used risk proxies. Although not the focus of this study, this finding potentially reflects the ability of analysts to gather information on expected returns from investors or their better ability to measure risk factor loadings compared to researchers.

Next, we evaluate the performance of CoE estimates as a proxy for expected stock returns relative to other popular proxies for expected returns, such as ICC based on analyst forecasts, as well as cross-sectional earnings forecasts and proxies obtained from an empirical

[4] Pinto, Robinson and Stowe (2015) find that about half of the surveyed analysts and portfolio managers use a judgmentally determined hurdle rate in their valuation models.

implementation of the CAPM and Fama-French three- and five-factor models. Several studies examine the ICC computed using earnings forecasts as inputs to an accounting-based valuation model (Ohlson and Juettner-Nauroth, 2005) and then inverting the valuation model. While some studies claim that these ICC measures are a good proxy for time-varying expected returns (e.g., Pastor, Sinha and Swaminathan, 2008; Frank and Shen, 2016), significant concerns remain about their reliability 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. Therefore, we empirically benchmark analysts' CoE estimates against ICC measures, along with the discount rates obtained from the CAPM and Fama-French models. Using the pair-wise-comparison approach of Lee, So and Wang (2017), we find that analysts' CoE estimates tend to have the lowest measurement errors for longer-term expected returns. These are in line with our findings that CoE estimates contain incrementally useful information for future stock returns and suggest that where available, analysts' CoE estimates are a useful alternative to commonly used proxies.

Since analysts could obtain their CoE values by reverse engineering them from their earnings forecasts and pre-determined target prices, the CoE estimates may reflect stock mispricing. To test this possibility, we conduct three additional analyses. First, we investigate the ability of CoE to predict future non-earnings announcement period returns on the notion that price-corrections often occur at future earnings announcement periods. Second, since analysts' target prices are likely to reflect their views on pricing errors, we check the predictive power of CoE for returns after controlling for the information in their target prices. Third, we use mutual fund outflows as exogenous shocks to the level of stock mispricing and examine changes in CoE estimates. None of the findings from these tests support the view that analysts' CoE estimates reflect mispricing. However, we cannot rule out the possibility that there are other types of stock mispricings reflected in analysts' CoE estimates.

We next consider the issue of the usefulness of analysts' CoE estimates in asset pricing tests by re-examining the relation between the ICC metrics and future realized returns in the spirit of Easton and Monahan (2005) and Guay et al. (2011). Corroborating the concerns raised with using realized returns to test the reliability of ICC metrics (Botosan et al., 2011), we show that the relation between the ICC metrics and future realized returns is highly sensitive to the choice of regression specification (viz., conducting the analysis at the firm or portfolio level, inclusion of time fixed effects or firm fixed effects, etc.). In contrast, when we replace realized returns with CoE metrics in the regressions, we obtain a more consistent set of results. These latter regression results also show that the coefficients on the CoE metrics are significantly lower than the theoretically predicted value of 1, suggesting that the ICC metrics potentially suffer from severe measurement errors, even though they are positively correlated with the observable CoE metrics provided by analysts.

Lastly, to demonstrate the usefulness of analysts' CoE estimates for examining discount rate reactions, we investigate the conjecture of Hecht and Vuolteenaho (2006) that earnings news contains both cash flow news and discount rate news. Analyzing changes in analysts' CoE estimates around earnings releases reveals that their CoE estimates increase when firms announce large earnings surprises, irrespective of their sign. This suggests that analysts view firms with volatile earnings as riskier and that extreme earnings news conveys information about both cash flows and discount rates. These results are in line with prior evidence documenting investors' preference for smoother earnings and potentially provide a new explanation for managers' preferences to report smoothed earnings (Graham, Harvey and Rajgopal, 2005; Francis, LaFond, Olsson and Schipper, 2004).

We make several contributions to the literature. First, to the best of our knowledge, this is the first study to provide a systematic, large-scale evaluation of analysts' CoE estimates. Prior studies evaluating analysts' discount rates do so at best in an indirect manner by examining ICC measures (i.e., the discount rates estimated by researchers based on market prices and analysts' earnings forecasts).[5] However, ICC estimates depend on researchers' assumptions and choice of models and have been controversial as proxies for expected stock returns due to the mixed evidence on their reliability (Easton and Monahan, 2016).

Also, while analysts play a key role in financial markets by processing information and providing several data outputs to aid market participants' decisions, prior research has predominantly focused on earnings forecasts, leading Kothari, So and Verdi (2016) to encourage researchers to examine other aspects of analysts' reports and paint a more complete view of the information contained in such reports. By evaluating an important input to

[5] Prior studies have also assessed investment and valuation risk ratings provided by analysts (e.g., Liu et al., 2007, 2012; Joos et al., 2016). These studies document that analysts' risk ratings are informative about a firm's stock price volatility, beta, idiosyncratic risk, financial distress risk or operating risks. While potentially related, analysts' risk-ratings and CoE estimates are distinct constructs with no clear mapping between them. Unlike CoE estimates, risk-rating measures can incorporate both priced and unpriced risks. In addition, each analyst uses his/her own risk-rating scale, making them difficult to compare across brokerages.

valuation, our study extends our understanding of the information in analysts' reports.

Our study also complements survey-based evidence showing that many analysts regularly ignore financial theories, preferring instead to rely on their judgement or heuristics to estimate discount rates (e.g., Bancel and Mittoo, 2014; Pinto et al., 2015).[6] These surveys, however, cannot answer whether analysts' estimates of discount rates, even if subjectively determined, are useful proxies of expected stock returns. Our empirical evidence provides insight on the usefulness of these proxies.

Our study also contributes to the understanding of empirical asset pricing tests, where the lack of observable discount rates has been a perennial concern. Our evidence shows that analysts' CoE estimates are useful and less noisy alternatives to realized returns. Further, our results point out that ICC metrics, particularly those based on time series earnings forecasts, are positively correlated with proxies for expected stock returns, but that more work is needed to improve these measures and eliminate measurement errors. We also show that analysts view large unexpected earnings, whether positive or negative, as increasing a firm's risk.

Some caveats are in order. We focus exclusively on analysts' revealed CoE estimates. Analysts who use unreasonable or instinct-driven discount rates may choose not to disclose their discount rates to avoid public scrutiny of their estimates. Thus, our conclusions may not be applicable to cases where analysts do not reveal their CoE estimates or to firms without analyst coverage. As is the case with the literature on analysts' earnings forecasts and stock recommendations, our analyses should also be viewed as conditional on analysts deciding to disclose their estimates. Also, it is important to note that we are not claiming that analysts' CoE estimates are unambiguously superior to ICC metrics and other expected return proxies. Each of these metrics has its advantages and disadvantages. While we document several advantages to using analysts' CoE estimates as an expected return proxy, the main disadvantage is their relatively limited data coverage.

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

[6] Pinto et al. (2015) find that about half of the surveyed analysts and portfolio managers use a judgmentally determined hurdle rate in their valuation models. Bancel and Mittoo (2014) find that while most respondents rely on the CAPM, they make subjective adjustments to their discount rates to incorporate additional factors.

2. Research Methodology

We first examine the type of firms for which analysts' CoE estimates are available by investigating the determinants of their decisions to disclose these estimates. This analysis focusses on the supply- and demand-side factors that affect the provision of CoE estimates.[7] On the supply side, we consider the role of analysts' incentives to use CoE estimates as a signaling mechanism to establish credibility, as suggested by Jung, Shane and Yang (2012). Inexperienced analysts who have little reputation or rapport with investors and portfolio managers stand to gain more by signaling diligence and opening themselves to greater scrutiny for their valuation judgements. These analysts are more likely to be transparent in their reports about their valuations (including their CoE estimates) and modeling. Also, investors typically need more valuation details from inexperienced analysts to fully grasp the rationale behind their recommendations and target prices.[8] However, it is possible that well-established analysts have greater confidence in their CoE estimates (either because of their better estimation abilities or because of their access to a wider-network of clients to garner the data) and so, disclose these more often than their less-experienced peers. For each firm-quarter, we use two measures to capture an analyst's experience: the number of years the analyst has been following that specific firm (*FIRMEXP*) and the number of years the analyst has covered stocks in general (*CAREEREXP*).

Analysts are also more likely to disclose their CoE estimates when they have the time to estimate CoE carefully. Accordingly, for each analyst quarter, we include two alternative proxies for busyness: the number of firms covered by the analyst in that quarter (*FIRMSCOVERED*) and the market capitalization of the covered firm (*MCAP*) based on the belief that larger firms are likely to require greater analyst effort. However, *MCAP* could also capture demand-side effects arising from greater investment interest from investors and portfolio managers, implying that analysts are more likely to reveal their CoE estimates for larger firms.

We also include the accuracy of an analyst's earnings forecasts for a given firm-quarter

[7] As CoE estimates are almost always disclosed in the context of valuations done using either the discounted cash flow (DCF) or the residual income valuation (RIV) models, the decision to disclose CoE is more appropriately viewed as analysts' decision to be more comprehensive and transparent about their valuation inputs and their choices of valuation models.
[8] Informal discussions with analysts confirm these conjectures, where they point out that buy-side clients typically ask junior analysts more questions on the inputs used in their valuation models than they ask their senior and more experienced peers.

(*AFERROR*) as a proxy for either the analyst's busyness or their incentive to be transparent. Analysts with a poor forecasting record are either too busy to conduct careful research or have poorer inherent abilities, in which case they would be warier of revealing the details of their valuation models. Also, motivated by Lee and So's (2017) finding that analysts' decisions to follow a firm reflect the analysts' private information on the firm, we include analyst coverage, measured by the number of analyst estimates (*NUMANALYSTS*), as an additional determinant.

On the demand side, we expect firms that are more visible, harder to value, and more risky to be the ones where investors stand to benefit the most from detailed disclosures of valuation model inputs, as such disclosures allow the investors to delve deeper into the reasons behind an analyst's recommendations. In terms of harder to value firms, we expect high-growth, volatile, and illiquid firms to be the ones for which detailed disclosures of valuation models, including CoE estimates, would be the most valuable. To proxy for these firm characteristics, we include book-to-market ratio (*BTM*), investments (*INVESTMENTS*), idiosyncratic volatility (*IDIO_VOL*), liquidity (*LIQUIDITY*), and share turnover (*TURNOVER*). We also include institutional ownership (*INSTOWN*) on the belief that institutional investors might scrutinize analysts' recommendations more closely, and therefore demand more detailed disclosures from analysts. Further, to capture visibility, in addition to firm size and analyst coverage, we include past firm performance, measured as momentum (*MOMENTUM*), past one-month return (*LAG_RETURN*), and profitability (*PROFITABILITY*). Lastly, to capture the demand for transparency from investors in more risky firms, we include leverage (*LEV*) and stock beta (*BETA*).

Thus, we estimate the following regression after merging our sample of analysts' CoE estimates with the IBES sample of earnings forecasts:

$$CoE\ DUMMY_{it} = \propto + \beta_1 * \ Determinants_{it} + \ \varepsilon_{it}, \qquad (1)$$

where the $CoE\ DUMMY_{it}$ variable takes a value of 1 when a firm has a CoE estimate in the Thomson Reuters report and is 0 otherwise. *Determinants* is the vector of determinant variables discussed above. For this analysis, we do not include any fixed effects, as this could effectively "throw the baby out with the bath water" if analysts' disclosure decisions are sticky over time or across firms.[9,10]

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:

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

where *Firm Characteristic*$_z$ represents a vector of variables that prior studies have shown to explain the cross-section of equity returns. To avoid multicollinearity problems from including a vast number of return predictors, we restrict our attention to the more commonly used return predictor variables (Fama and French, 2015; Hou et al., 2015). Based on the five-factor Fama and French (2015) model, we include the 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), idiosyncratic volatility (Ang et al., 2006, 2009; Hou and Loh, 2011), and liquidity (Amihud, 2002). The empirical computations of these variables are presented in Appendix I. The regression also includes firm fixed effects, calendar quarter fixed effects (based on the analyst report date), and brokerage fixed effects.

Next, we examine the relation between analysts' CoE estimates and future stock returns following traditional empirical asset pricing research, such as Fama and French (1992). If analyst CoE estimates are meaningful, we expect the cross-sectional differences in future realized returns to be associated with CoE. To test this, we use the following panel regression:

$$Future\ Returns_{it} = \propto + \beta_1 * CoE_{ibt} + \gamma_i + \mu_t + \vartheta_b + \varepsilon_{it,} \quad (3)$$

where CoE_{ibt} is the CoE extracted from an analyst report for firm *i* in quarter *t* by brokerage

[9] The determinants analysis of CoE disclosures is intended to provide preliminary evidence only, as it is based on the assumption that the IBES observations that do not match with our CoE sample are cases where analysts do not disclose CoE. This assumption may not be an accurate description of reality as the various channels employed by analysts to distribute their outputs, such as IBES and Thomson One, are not identical (Amiram et al., 2019). Ideally, to ensure that the reports are correctly categorized for the CoE disclosure in the determinants analysis, one would need access to all reports on the Thomson One database (which exceeds 3 million over our sample period), and to be able to manually check every report for CoE disclosure. This is not feasible given the limited resources and the data vendor's restrictions on large-scale downloads.

[10] In untabulated analyses, we investigate whether a specific set of analysts or brokerage firms consistently disclose their CoE estimates in every report, but do not find such patterns.

house b. $Future\ Returns_{it}$ is the 360-day buy-and-hold returns following the date of the analyst's report.[11] We include firm fixed effects, calendar quarter fixed effects based on the analyst's report date, and brokerage fixed effects to subsume time-invariant firm and brokerage characteristics and market-wide effects and cluster standard errors at the industry level.

Including firm fixed effects in the regression forces identification to be based on within-firm variations in stock returns and analysts' CoE. While this process mitigates concerns of omitted correlated variables, it could also lower the power of the tests if expected returns are largely time-invariant. Hence, we also examine the specification after excluding the fixed effects to test the robustness of our results. We do not control for analyst-specific characteristics in our main analyses to avoid losing observations when we merge our CoE estimate sample with IBES sample.

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, 2017. Rather than download all analyst reports (3.05 million), we search (using the Thomson One search feature) the reports for the phrase "cost of equity" and restrict the geography to the "United States."[12] As measurement errors can result from backing out CoE estimates for analysts who reveal only the weighted average cost of capital estimates, we restrict our analysis to those who directly state their CoE estimates. All non-broker, industry, and economy reports are removed from the search criteria. This search produces 57,211 equity reports that are downloadable, which we subject to textual analysis to extract the CoE.[13] Using the parsing approach detailed in the Online Appendix and after merging the extracted CoE estimates with daily CRSP data, we end up with 31,049 observations with CoE estimates. The sample spans 14,794 firm-quarter

[11] If a firm delists within the 360-day period, then the buy-and-hold returns include the CRSP delisting returns.

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

[13] As most reports in the Thomson Reuters-Thomson One database are primarily short strategy updates (less than 10 pages long) from analysts, only 2% of these reports meet our CoE sample requirements. The size of our CoE sample is, however, more comparable to those reported in recent analysts' studies, especially those relying on target prices, long-term growth or recommendations data. For instance, Iselin et al. (2020) identify 83,683 contemporaneous revisions of target prices and stock recommendations by analysts on IBES database over the period 2004-2018. Jung et al. (2012) analyze a sample of 9,307 long-term growth forecasts from IBES covering the period 1994 to 2006.

observations, 2,370 firms, and 214 brokerages.[14, 15] The sample firms on average account for 38% of the firms in the CRSP database by market capitalization. For the tests that examine changes in CoE estimates around earnings announcement, the number of observations used is 4,783. Our sample selection procedure is summarized in Panel A of Table 1.

Panel B of Table 1 presents the distribution of the sample by brokerages, as well as the fraction of total reports from the brokerage in Thomson One that contains a CoE estimate. To calculate the fraction of total reports, we scale the number of reports with a CoE estimate by the number of search results as a proxy for total reports from that brokerage firm.[16] While our sample covers 214 brokerages, Morningstar accounts for 44% of the sample firms. Figure 1, which illustrates the number of Morningstar and non-Morningstar reports over time, shows that most of the Morningstar reports are from the last three years of our sample. Hence, to ensure that our results are not exclusively driven by Morningstar reports, we check the robustness of our results to excluding Morningstar observations. Moreover, the last column of Panel B in Table 1 shows that except for Morningstar and Singular Research, only a small percentage of analysts' reports contain CoE estimates. This mirrors the fact that most analyst reports are short updates about a firm's strategy, operating performance or earnings reports and do not contain analysts' valuations. This is also in line with the observation in Bradshaw, Eritmur and O'Brien (2016) that much of analysts' compensation depends on qualitative rather than quantitative output. Finally, no brokerage firm in our sample provides CoE estimates in 100% of their reports.

To understand how analysts compute their CoE values, we randomly selected 100 reports from our sample and read through the discussions of the CoE metrics. Although these estimates are almost always presented in the context of valuation, there are significant variations in the way analysts discuss their measurement of CoE. While some of the reports only mention a CoE value, others specify the model used (e.g., CAPM). Specifically, in 37% of the 100 reports, analysts explicitly state the use of the CAPM, or we can infer the use of a CAPM-based asset pricing model. For 57% of the sample, the reports simply specify the CoE values but do not mention the model used for computing the CoE estimate. For the remaining 6%, we cannot

[14] While some of the analyst reports are provided by research firms that do not provide brokerage services, for simplicity we follow IBES and refer to all firms providing analyst reports as "brokerages".
[15] For comparison, IBES has 10,394 unique firms with data available on target prices and 8,438 unique firms with data on long-term growth forecasts over the same sample period.
[16] Unfortunately, we are not able to provide an accurate estimate for Smith Barney because this brokerage has been removed from the brokerage name search in Thomson One after its mergers and name changes.

infer the asset pricing model, although beta values are mentioned alongside CoE values.[17]

To provide a meaningful description of our sample, we compare the summary statistics for our sample containing the extracted CoE estimates ("CoE sample") to the IBES unadjusted details file for the same period (2001-2017). We restrict the IBES sample to observations that have earnings-per-share (EPS) forecasts for either the year ahead or at least one of the next four quarters ahead. We then match the two databases at the firm-brokerage-quarter level,[18] which produces 22,295 CoE estimates for the merged sample.[19]

Table 2 provides the descriptive statistics for the non-missing data for the merged sample. All variables except returns are winsorized at 1% and 99%.[20] The extracted CoE estimates have a mean (median) of 10.11% (9.4%) and range from 5.00% to 19.85%.[21]

A comparison of firm and analyst characteristics across the CoE sample and the IBES sample reveals significant differences in the means and medians of all variables. The mean annual stock returns for the CoE (IBES) sample is 16.47% (11.27%). The CoE sample firms are larger, more leveraged, and more liquid but that have smaller beta values, lower book-to-market ratios, and lower idiosyncratic volatility the IBES sample firms. These firms also have better performance in terms of accounting profitability, make lower investments on average, and have greater institutional ownership compared to the full IBES sample. Lastly, we find that analysts disclosing CoE estimates tend to have less experience but provide more accurate forecasts, on average, than experienced analysts. These systematic differences in the characteristics of firms and analysts in both samples suggest that analysts do not randomly select firms for which to reveal CoE estimates and highlights the need for caution in extrapolating results from firms that reveal CoE estimates.

4. Results and Discussion

4.1. Analysts' decision to provide CoE estimates

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[17] As a comparison, Pinto et al. (2015) find that about half of the surveyed analysts and portfolio managers use a judgmentally determined hurdle rate in their valuation models. It is also worth pointing out that although many analysts could claim to rely on the CAPM in their reports, practical implementation of the model still allows them subjectivity in the measurement of risk-free rates, factor loadings, risk premiums, etc.
[18] Full details of the matching process are provided in the online appendix.
[19] The merged sample represents 20.5% of the overall IBES observations with data available on target prices, long-term growth forecasts and stock recommendations.
[20] All of our inferences continue to hold when we alternatively winsorize the variables at 1.5% or 2% on either side.
[21] CoE estimates in Morningstar reports tend to cluster around 7.5%, 9% and 11%. We do not observe such clustering among other reports.

Table 3 presents the results from estimating equation (1) using either ordinary least squares (OLS) or logit regressions. The results are broadly consistent across the two estimation procedures and reveal that the issuance of an estimate (*CoE DUMMY*) is negatively associated with an analyst's firm-level experience, career experience, and coverage of firms. These results suggest that analysts with less experience tend to disclose CoE estimates more often, consistent with their having greater incentives to be transparent. By disclosing their valuations, inexperienced analysts appear more willing to incur greater scrutiny for their valuation determinations. The significant coefficients on firm size and on the number of firms covered by analysts indicate that analysts are more likely to disclose their CoE estimates when there is greater demand for information and when they have greater confidence in their valuations.

We also find that CoE disclosure is more likely by firms that have higher leverage, lower investments, and lower profitability, consistent with the heightened risks facing investors in these stocks seeking more information. In addition, we find that recent stock performance affects the CoE disclosure decision, which provides support for Lee and So (2017), who suggest that analysts change their actions based on stock price performance. Finally, there is some evidence that CoE estimates are more likely to be disclosed when firms are less liquid, thus information asymmetry is likely to be higher. But there is little evidence to suggest that analysts' disclosure decisions are related to their earnings forecast accuracy or to a firm's growth potential, idiosyncratic volatility or institutional ownership. Finally, the R-squared value of the OLS regression is small, indicating that a vast part of the variance in CoE disclosure remains unexplained.

Overall, the results in Table 3 are consistent with analysts disclosing their CoE estimates more often to signal their quality, in line with the arguments of Jung et al. (2012) for long-term growth forecasts, and when the CoE disclosures are likely to be more beneficial to investors. The findings also indicate the need for caution when extrapolating the findings to a wider population of firms that do not have analysts' CoE estimates.[22]

[22] To examine whether the results above are unique to analysts' decisions to reveal CoE estimates or reflect their incentives to disclose all valuations, we re-estimate equation (1) after replacing the CoE disclosure variable with alternative indicator variables for disclosure of cash flow forecasts, target price forecasts, and stock recommendations (obtained from IBES). In untabulated results, we find that the disclosure determinants for each of the outputs is different with the exception of *FIRMEXP*, which is negatively correlated with all outputs. These differences and their underlying reasons are not the focus of this study and could be potentially affected by IBES's coverage choices for these analysts' outputs.

4.2. *Cost of equity capital and firm characteristics*

In this subsection, we examine the variation of CoE with firm characteristics by estimating equation (2). The results in Table 4 show that CoE estimates are greater for firms with higher beta, which is consistent with the predictions of the CAPM. The coefficient on beta is 0.35 (*t*-statistic = 4.58) in column (1), and declines to about 0.30 in columns (2) and (3) when other firm characteristics are controlled for.[23] The positive coefficient on beta is largely in line with the evidence in Mukhlynina and Nyborg (2016), who report that 76% of surveyed analysts almost always or always use the CAPM.

As seen in column (3) in Table 4, other than beta, analysts' CoE estimates also reflect the effects of book-to-market ratio, size, leverage, and idiosyncratic volatility. The significant coefficients on book-to-market ratio and size are interesting, as Mukhlynina and Nyborg (2016) find that less than 5% of survey respondents report using the Fama-French three-factor model. In line with prior empirical evidence, analysts' estimates of expected returns are positively correlated with book-to-market ratio and negatively correlated with firm size. The coefficient on book-to-market ratio is 0.008, and that on size is -0.10. The coefficients on leverage and idiosyncratic volatility are significantly positive, with values of 0.010 and 0.031, respectively. These coefficients suggest that analysts view more leveraged and more volatile firms as being riskier. The signs of the coefficients on these factors are all consistent with those predicted by theory or prior empirical evidence. Additional results, reported in the Online Appendix, confirm that these conclusions are robust to replacing brokerage fixed effects with analyst fixed effects, as well as to excluding Morningstar's CoE estimates.

4.3. *Analysts' CoE estimates and future realized returns*

We next investigate whether analysts' CoE estimates capture investors' expected returns by correlating their CoE estimates to ex post realized returns. If analysts' CoE estimates do a good job of capturing expected returns, we expect them to be positively related to future realized returns. In this analysis, for each CoE estimate, we track the stock returns in the 360 calendar days following the corresponding report's release date.

To evaluate both the time series and cross-sectional implications of expected return proxies,

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[23] We do not attempt to interpret the magnitude of the coefficient on beta for a variety of reasons. First, as the regressions include firm fixed effects, 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 the number of analysts using the CAPM and Fama-French models and the amount of analysts updating their discount rate computations to reflect concurrent changes in betas and market risk premiums.

we first sort all of the observations based on analysts' CoE estimates into three portfolios (top 30%, mid 40%, and bottom 30%) and analyze their average returns. Panel A of Table 5 shows a monotonic relation between analyst CoE estimates and average realized returns across the portfolios, irrespective of whether we equally-weight or value-weight the portfolio returns. The average equally-weighted return for the bottom 30% of CoE estimates is 12.8%, which increases to 15.7% for the mid-CoE portfolio and to 19.7% for the portfolio with the highest CoE. Meanwhile, the average CoE varies from 7.55% for the lowest CoE portfolio to 12.65% for the highest CoE portfolio. The greater spread of average realized returns across portfolios is possibly because they contain greater measurement errors than analysts' CoE estimates, an issue discussed below. F-test results strongly reject the null hypothesis that the average realized returns are equal across the portfolios. We arrive at a similar conclusion using value-weighted returns.

As an alternative approach to uncovering the relation between CoE estimates and future stock returns, we regress the one-year returns following each analyst report release date on the analysts' CoE estimates. The results reported in Panel B in Table 5 reveal a strong positive correlation. The coefficient on analysts' CoE estimates is 2.178 (column (1)), suggesting that the ex post realized returns are, on average, double 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 5.077, which suggests that expected portfolio returns increase by 5.07% as one moves from the lowest to the highest CoE portfolio. 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 individual analyst-level CoE estimates and conduct the analyses using firm-level observations.

Returning to our finding in column (1), the coefficient of 2.178 implies that for every 1% increase in the CoE estimate, the realized returns increase by 2.2%. This is surprising, as the coefficient should be 1 if realized returns and CoE estimates are unbiased estimates of expected returns. The large coefficient, which is significantly different from 1, is due to either analysts' consistently underestimating CoE values or extreme measurement noise in individual stock returns. The measurement noise explanation is particularly plausible, 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, in each quarter, we sort all observations into 25 portfolios based on the CoE values released in that quarter. For each portfolio-quarter, we then compute the averages of the dependent and independent variables used in the regressions for column (1) and then re-estimate the column (1) regression after replacing the analyst-level variables with these portfolio averages.[24] As shown in column (3) in Panel B of Table 5, the coefficient on CoE is 1.179 and is not statistically different from 1, which confirms that analysts' CoE estimates are unbiased predictors of stocks' future returns.

Our main specification includes firm fixed effects. A drawback of this approach is that the fixed effect accounts for variations in future CoE not known as of the analyst report date. To mitigate any concern of look-ahead bias arising from the fixed effects, we re-estimate the regression without any fixed effects. Results presented in column (4) in Table 5 confirm that our findings are robust to this modification. Finally, we examine the robustness of the findings to excluding Morningstar estimates given that their reports constitute a large fraction of the sample. The results presented in columns (5) and (6) suggest that our conclusions are not driven by these reports. Also, comparing the CoE coefficients across columns (1) and (5) or across columns (4) and (6) indicates that including or excluding Morningstar reports has little impact.

We check the robustness of our conclusions to employing a calendar year approach for ranking CoE estimates and computing stock returns. Specifically, we rank CoE estimates at the end of each calendar year and measure the returns for all CoE estimates issued in a calendar year to the 360-day stock returns computed from January 1 of the next calendar year. To avoid stale estimates, in this analysis we only use CoE values in analyst reports from July 1 through December 31 of each calendar year.[25]

The results presented in columns (1) - (4) of Panel C confirm that our earlier inferences continue to hold. The coefficient on CoE is 2.03 and is comparable to that observed in column (1) of Panel B. Also, from columns (2) to (4), we find that the results are robust to excluding Morningstar reports, as well as to excluding fixed effects. These conclusions are also robust to replacing the continuous values of CoE in this analysis with CoE ranks created for each year, as the results show in columns (5) - 8. Overall, these results show that analysts' CoE estimates are robustly related to future realized returns.

4.4. Incremental information in analysts' CoE estimates for future stock returns

[24] Portfolio-level regressions include time fixed effects and cluster the standard errors at the portfolio level. On average, each portfolio-quarter has 21 observations. Our results are robust to forming 15 or 20 portfolios in each quarter, instead of 25.

[25] Our findings are also robust to restricting the CoE estimates to those issued from October 1 to December 31.

We next examine whether analysts' CoE estimates are related to future returns because they reflect firm characteristics that are known to be related to future returns or whether these estimates contain incremental information to predict stock returns. We address this issue by repeating the regression of future returns on analysts' CoE as in equation (2), while additionally controlling for known return predictors.

Interestingly, the results in Panel A of Table 6 show that analysts' CoE estimates are significantly positively related to one-year-ahead stock returns even after controlling for known return predictors. The coefficient on CoE estimates is 2.066 when only beta is controlled for in the regressions. This is comparable to the coefficient in column (1) of Panel B in Table 5 and indicates that the inclusion of beta has little effect on the magnitude of the coefficient. The coefficient on CoE estimates decreases to 1.293 when additional return predictors are included in the regression, but the statistical significance remains intact, as shown in columns (2) and (3). Column (4) presents the results from an analysis at the portfolio level, similar to the previous approach shown in the results in column (3) of Table 5, Panel B.[26] We find that the coefficient on CoE estimates is 0.844, which is insignificantly different than the theoretically predicted value of 1.[27] The coefficients on the control variables in column (3) are generally consistent with the literature.[28]

To check the robustness of our results, we conduct a variety of tests. First, when we exclude fixed effects, the coefficient on CoE in column (1) in Panel B of Table 6 continues to be significantly positive and has a value close to the theoretically predicted value of 1. Second, we replace brokerage fixed effects with analyst fixed effects in the regression. This reduces the sample size due to IBES data requirements (column (2)), but the coefficient on CoE remains significantly positive. Third, estimating the regressions separately for the Morningstar sub-sample and a sub-sample with Morningstar excluded (columns (3) - (6)), reveals that the CoE coefficients are significantly positive for both sub-samples and are comparable (1.86 vs 1.43), Fourth, we repeat the regression after splitting our sample into roughly two sub-periods, each

[26] The average number of observations per portfolio for this analysis is 21.

[27] To check whether potential serial correlations in returns across years affect our conclusions, we repeated the analyses after deleting data for alternate years. This modification makes very little difference to our inferences. For instance, in the regression corresponding to the results in column (3), the coefficient on CoE is 1.69 and the *t*-statistic is 3.60 when alternate-year data are removed.

[28] Although the beta coefficient in Panel A of Table 6 is significantly positive, this is not a robust result. The coefficient becomes insignificant when we compute the beta using the Dimson (1979) approach, irrespective of whether it is estimated using monthly returns over a five-year rolling window, as done in Fama and French (1992) or using daily returns over a yearly window, as done in Hong and Sraer (2016). These modifications do not materially affect the CoE coefficients or its significance.

with an equal number of observations. As Morningstar estimates are primarily available only in the last three years of the sample, we exclude these observations from this analysis to have relatively comparable samples across the sub-periods. The CoE estimates are statistically significant in both sub-periods (columns (5) and (6)). Lastly, column (7) reveals that our inferences are unaffected by switching to a calendar year approach (as done in Column 2 of Table 5, Panel C).

As an alternative test, we use the portfolio-based calendar returns approach that is commonly employed in the asset pricing literature. This analysis extends the calendar year approach employed at the individual stock level in Table 5 to a broader portfolio-level analysis and tests whether portfolios sorted on CoE yield greater cross-portfolio return dispersion than that achieved by sorting portfolios on other firm-specific characteristics. Specifically, we examine whether returns associated with seven popular characteristics-based factors (viz., five Fama-French factors, the momentum factor, and Pastor and Stambaugh's liquidity factor) fully explain the returns of CoE-sorted portfolios.[29] If the incremental predictive power of analysts' CoE estimates exists only at a more granular stock level, then we expect this incremental predictive ability to weaken in this analysis of broad-based portfolios.

For each calendar month starting October 2002, we form terciles of portfolios based on analyst CoE estimates issued in the previous three months. We require that a minimum of 50 CoE observations are available in a month for portfolio formation.[30] If a firm has multiple CoE estimates released during the past three months, then we use the average of these estimates to sort the firms into portfolios. We hold each portfolio for 12 months and then compute the average monthly returns for each of the next 12 months. To ascertain returns for this strategy for each calendar month, we take the average returns across all portfolios that are held in that month. This results in 183 calendar month observations for our sample period.

Columns (1) – (3) in Table 7 present results of regressing monthly CoE-tercile returns on the seven factor returns. Column (4) presents results for the CoE-hedge portfolio (High minus Low) returns. The results reveal a monotonically increasing alpha across the CoE terciles and

[29] We obtain monthly liquidity factor returns from Robert Stambaugh's website (http://finance.wharton.upenn.edu/~stambaug/) and all other factor returns from Kenneth French's website (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

[30] October 2002 is the first month in our sample with the required minimum number of observations. Our conclusions are robust to reasonable changes in the number of portfolios formed or the minimum observations required for portfolio formation. Also, we focus on monthly returns and form portfolios for each month to mitigate concerns relating to lack of power.

that the alpha on the hedge portfolio is significantly positive. These results confirm that the incremental predictive ability of analysts' CoE estimates for future stock returns exist even at a broader portfolio level.

As an alternative test for the incremental return-predictive ability of CoE estimates, we conduct a horserace of analysts' CoE estimates with 23 alternative expected return proxies (ERPs). The alternative ERPs are those obtained from: the CAPM, the Fama and French (1993) three-factor model, the Fama and French (2015) five-factor model, and five ICC estimates (where each ICC estimate uses four different choices of inputs for earnings forecasts). The models of ICC are those from Gebhardt et al. (2001), Claus and Thomas (2001), Easton (2004), Ohlson and Juettner-Nauroth (2005), and a composite estimate computed as the simple average of the above four ICC estimates.[31] Following much of the literature, we obtain the earnings forecast inputs for these models from analyst earnings forecasts. In addition, we examine ICC measures computed using earnings forecasts from the cross-sectional forecasting model of Hou et al. (2012), as well as from the earnings persistence (EP) and residual income (RI) model of Li and Mohanram (2014).

For each CoE estimate, 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 returns.[32] The calculations of the ICC estimates replicate the approach used in previous studies (Claus and Thomas, 2001; Gebhardt et al., 2001; Easton, 2004; Ohlson and Juettner-Nauroth, 2005) and are discussed in Appendix II. We set all negative ERP estimates to missing and winsorize estimated factor loadings and ICC estimates at the 1% and 99% levels.

The results are reported in Table 8. To conserve space, we report results only for the composite measures of ICC that are based on the four alternative approaches to forecasting earnings: analysts' forecasts (*ICC_COMPOSITE_ANALYST*), Hou et al.'s (2012) model (*ICC_COMPOSITE_HOU*), and Li and Mohanram's (2014) EP model and RIV model (*ICC_COMPOSITE_EP* and *ICC_COMPOSITE_RIV*). Our main conclusions are identical

[31] To avoid losing observations for want of ICC estimates, we exclude missing ICC metrics in the computation of the *ICC_COMPOSITE* measure.
[32] Analyst forecasts used in computation of ICC proxies are obtained from IBES.

across the individual ICC metrics.

It is worth noting that a significant fraction of our sample has negative values for the traditional ERPs and ICC metrics, which reduces the sample size. The largest decline is for ERPs obtained from the Fama-French models, with nearly half the observations having negative ERPs.[33] Importantly, irrespective of how the ERPs are measured, we find CoE estimates to be statistically significant in all the regressions. While the ERPs obtained from the CAPM (*CAPM*), and the Fama-French 3-factor (*FF3*) and five-factor models (*FF5*) are statistically related to future returns, they do not subsume the predictive ability of the CoE estimates. The coefficient on the CoE estimate is around 2.20 with a *t*-statistic greater than 4.0 in the regression that includes the *FF5* expected returns. These results suggest that both CoE estimates and the alternative ERPs have incremental information over each other about future expected returns. As for the coefficients on traditional ERPs, most of the ERPs are significantly positively related to future realized returns. The one exception is the insignificant coefficient on *ICC_COMPOSITE_ANALYST,* which is consistent with the evidence in prior studies (e.g., Easton and Monahan, 2005).[34]

Overall, the results in Table 8 consistently demonstrate that analysts' CoE estimates are incrementally informative about future expected stock returns. Thus, while there may be anecdotal evidence suggesting otherwise, we find little systematic evidence to support the notion that analysts' CoE estimates are noisy or merely represent figures that are reverse engineered to support pre-determined stock recommendations. Analysts' use of judgmental values and subjectivity seem to yield CoE values that have incremental predictive power for future returns in the sample we examine.

Although identifying the source of some analysts' superior ability is beyond the scope of our study, we speculate on two mutually inclusive explanations for this finding. First, analysts benefit from frequent interactions with a wide range of investors, traders, and equity sales people, who may share information on their required returns with the analysts. For instance, an investor could request that an analyst present research ideas that would potentially earn a return of at least 8% for large technology stocks or 10% for small, unprofitable stocks in the

[33] Our conclusions for CoE are unaffected if we include the negative ERPs in the regressions, instead of setting them to missing.
[34] In addition to the ICC composite measures we report, we also considered ICC metrics that are computed based on the bias-adjusted earnings forecasts of analysts, as done in Mohanram and Gode (2013). We find the coefficient on this ICC metric to be insignificant in our regressions and analysts' CoE estimates continue to be statistically significant.

automotive sector and so on. Traders and investors, in turn, affect stock prices by investing in those that are expected to deliver their threshold returns or by avoiding or shorting those that are expected to yield below the required returns. Thus, if analysts reflect the inputs received from investors and other market participants in their CoE estimates, then these estimates could effectively reflect the expected returns that investors employ in pricing stocks and so may be incrementally informative about future stock returns.

An alternative possibility is 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 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 and soft information while evaluating risk.

4.5.Relative performance of alternative expected return proxies

We next investigate which of the two — analysts' CoE estimates or the earlier discussed ERPs — are less noisy proxies of expected stock returns. We employ the approach of Lee et al. (2017), who provide a framework for comparing the performance of alternative ERPs based on the 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 canceled 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 the variance of measurement errors across alternative ERPs is estimable and can be used to conduct a pair-wise evaluation of alternative ERPs. Although Lee et al. (2017) also show that the evaluations of ERPs could be conducted either cross-sectionally (i.e., cross-sectional variation in ERPs should reflect the cross-sectional variation in firms' expected returns) or over time (i.e., the time series variation in a firm's ERP should reflect variations in its expected returns over time), we conduct only cross-sectional evaluations as only a limited number of firms in our sample have a sufficiently long time series of CoE estimates.

Lee et al. (2017) provide an estimate of the average cross-sectional error variance (*AvgCSVar*) for a given expected return proxy (*erp*) as follows:

$$AvgCSVar^{erp} = \frac{1}{T}\sum_t CSVar_t^{erp}$$

$$CSVar_t^{erp} = Var_t(\widehat{er}_{i,t}) - 2Cov_t(r_{i,t+1}, \widehat{er}_{i,t}), \tag{5}$$

where $Var_t(\widehat{er}_{i,t})$ is the cross-sectional variance of a given ERP, $Cov_t(r_{i,t+1}, \widehat{er}_{i,t})$ is the cross-sectional covariance between the ERP and realized stock returns in period t+1, and T is the total number of periods in the sample. To compare any two expected return proxies, we can use a pair-wise comparison of the average cross-sectional error variances.

Therefore, for each of the 202 months in our sample for which we have sufficient data to compute $CSVar_t^{CoE}$, we compute a pair-wise difference between $CSVar_t^{CoE}$ and the corresponding $CSVar_t^{erp}$ for each of the 23 benchmark ERPs that we employed in the horserace above (Table 8). We then evaluate whether the time series average of the pair-wise differences is significantly different from zero.[35]

The results from the analysis of pair-wise differences are presented in Table 9. Each entry is the average of the monthly difference in measurement error variance for the CoE estimate and the variance error for a benchmark ERP. A significantly negative value indicates that the CoE estimate has a lower measurement error variance and is therefore of higher quality relative to the benchmark ERP, and vice versa.

We report results from tests that measure realized returns over three alternative windows (monthly, quarterly, and annually) beginning the day the analyst report includes a CoE estimate. 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 these CoE estimates are likely to reflect analysts' longer-term view of a firm's expected returns.[36]

When using monthly realized returns, we find that the CoE estimates of expected returns perform worse than the factor-based asset pricing models but better than all of the ICC estimates.[37] However, when the measurement horizon for realized returns is lengthened, the

[35] We average all relevant variables (such as CoE and $r_{i,t+1}$) in firm-months with multiple CoE estimates. The 23 benchmark ERPs are estimated annually and the most recent annual estimate is used for a given month. Consistent with our earlier analysis, we winsorize all measurement error variances at 1% and 99%.
[36] 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 for analyses based on quarterly or annual returns.
[37] Our results are not directly comparable to Lee et al. (2017) due to sample composition differences.

superiority of factor-based asset pricing models diminishes. 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 ICC estimates. Collectively, these findings indicate that analysts' CoE estimates are better proxies for expected returns, particularly over long horizons.

4.6. Analysts' CoE estimates and stock mispricing

The predictive ability of analysts' CoE estimates for future realized returns could either reflect their ability to identify the returns demanded by investors for bearing risk or their ability to identify stock mispricing. To distinguish between these, we perform three additional analyses. First, motivated by the evidence in prior empirical asset pricing studies that stock mispricings are often corrected in subsequent earnings announcements (e.g., Bernard and Thomas, 1989; Sloan, 1996), we repeat our baseline analyses that correlate CoE estimates with ex post realized returns after additionally controlling for earnings announcement returns (measured as the three-day stock returns around earnings announcements) in the four quarters subsequent to the analysts' report date. If the relation between the CoE estimate and realized future returns is driven by stock mispricing, then the coefficient on CoE estimates should be attenuated in these regressions.[38] Inconsistent with the mispricing explanation, the results in column (1) of Panel A in Table 10, when compared to those in column (1) of Panel B in Table 5, shows that the coefficient on CoE are materially unchanged by the additional controls.

Second, motivated by the fact that target prices are analysts' most direct and actionable outputs to investors and should reflect the totality of their views on stock mispricing, we check whether the predictive ability of CoE estimates is subsumed by the information contained in analysts' target prices. We implement this investigation by extending our baseline regression specification (Table 6, Panel A, column (3)) to include an analyst's expected returns implied in their target prices (*TP_EXP_RETURNS*) as an additional control.[39] The results in column (2) of Panel A in Table 10 suggest that our conclusions remain unchanged and that the expected returns embedded in target prices do not subsume the coefficient on the CoE estimate. This evidence also fails to support the mispricing explanation.

[38] In untabulated analyses, we estimate the regression after replacing the dependent variable (i.e., future 360-day returns) with returns measured only over non-earnings announcement periods. Our conclusions remain unaltered.

[39] The target prices are obtained from IBES. *TP_EXP_RETURNS* is computed as follows: [(Analyst's target Price/Report date share price – 1) *100 – CoE], where report date share price is the share price on the analysts' report release date. Whether or not CoE is subtracted in the above definition is immaterial for our conclusions.

Lastly, we examine whether analysts systematically change their CoE estimates when a stock gets mispriced for exogenous non-fundamental reasons. Coval and Stafford (2007) and Edmans, Goldstein and Jiang (2012) find that stocks owned by a mutual fund experiencing large capital outflows face substantial selling pressure, which causes stock mispricing. Lee and So (2017) show that analysts are aware of such pricing errors. These suggest that, if CoE estimates reflect mispricing, then analysts' CoE revision in these periods should be systematically related to fund outflow-induced price pressure. But no such relation is expected if the CoE estimates reflect firm risk.[40]

For each calendar quarter, we identify mispriced firms as those that are owned by at least one fund experiencing an outflow >=5% in that quarter and restrict our analyses to these firms. We construct a measure of fund outflow-induced price pressure (*MF_Flows*) for each firm-quarter by following the approach in Edmans et al. (2012). The details are in Appendix I. Firms that are not owned by any fund experiencing an outflow >= 5% in a given quarter are dropped from the analysis. For each CoE estimate in a calendar quarter, we compute the change in the CoE estimate (*CoE_DELTA*) as the difference between the most recent CoE estimate in the prior twelve months (i.e., pre-period) and the first CoE estimate in the 12 subsequent months (i.e., post-period). To maintain comparability, we require the CoE estimates to be issued by the same brokerage firm in the pre- and post-periods. If analysts revise their CoE estimates in response to stock mispricing, then we expect a significant relation between *CoE_DELTA* and *MF_Flows*.

We test the above prediction by regressing *CoE_DELTA* on *MF_Flows* and control variables. The results Panel B in Table 10 reveal no significant relation between *MF_Flows* and *CoE_DELTA*. This finding suggests that analysts do not changes their CoE estimates in response to fund outflow-induced mispricing.

Overall, our results do not support the view that CoE estimates reflect stock mispricing. While this is indicative of analysts' CoE estimates reflecting fundamental risk, we cannot rule out the possibility that the CoE estimates reflect other types of stock mispricing that we do not examine

[40] Although we could also have examined upward price pressures induced by mutual fund inflows, Khan et al. (2012) document that managers make seasoned equity offerings (SEOs) when their stocks are overpriced on account of fund inflows. As such equity issuance affects a firm's cost of capital, it is difficult to separate the mispricing effects on CoE estimates in these situations from those driven by changes in underlying fundamentals. In addition, Coval and Stafford (2007) do not find any mispricing-related reversals in the two quarters following large fund inflows, casting doubt on whether analyses based on CoE changes in the quarter subsequent to large fund inflows would have sufficient power to uncover the mispricing effects on CoE estimates.

here. It is also possible that mispricing is a priced risk (e.g., Brennan and Wang, 2010), but we are unable to uncover this source of risk.

5. Asset Pricing Tests using Analysts' CoE Estimates

We next examine whether CoE estimates can be fruitfully employed in empirical asset pricing tests. Prior asset pricing tests have relied almost exclusively on realized stock returns as the proxy for expected stock returns. However, at his 1999 presidential address to the American Accounting Association, Elton (1999) points out that realized returns, even when measured over long periods are likely to be "a very poor measure of expected returns." Motivated by this, we examine in Subsection 5.1 whether CoE estimates are a useful alternative to realized returns in evaluating alternative ICC measures. We then demonstrate, in Subsection 5.2, the usefulness of analysts' CoE estimates to study discount rate reactions to corporate news. Specifically, we investigate whether earnings news conveys information about discount rate changes to market participants.

As our analyses here require data on CoE estimates, one needs to be careful about extrapolating our results in this section to a wider population. As observed earlier, analysts provide CoE estimates only for a limited sub-set of firm-quarters and that too for non-randomly chosen samples. These could potentially affect the generalizability of our results to the larger and wider sample of observations typically employed in the ICC and earnings-announcement literatures.

5.1.Benchmarking ICC estimates

Prior research evaluating the reliability of ICC metrics as measures of expected stock returns provides mixed evidence (Easton and Monahan, 2005; Guay et al., 2011; Botosan and Plumlee, 2005; Easton and Monahan, 2016). One source of these ambiguous results could be the reliance on noisy realized returns as benchmarks in the tests (Elton, 1999; Botosan et al., 2011). Therefore, we re-evaluate the ICC proxies using CoE estimates and compare these results to tests based on realized returns with a specific focus on the sensitivity of the results to methodological choices.

Our focus on the sensitivity of the results is predicated on the notion that vastly different results across equally acceptable research choices make it difficult to draw robust conclusions. As pointed out by Bronfenbrenner (1972), "A useful econometric study …. should either justify its own answers to a few key questions involving sensitivity or show that its results would hold almost equally well with alternative answers. If the study fails on both counts, it can be indicted for excessive sensitivity or for deficient robustness.” Therefore, we suggest that less-sensitive results might be preferred when no clear predictions or reasons exist for the sensitivity.

Our test of ICC metrics is similar in spirit to Hou et al. (2012) and Li and Mohanram (2014) wherein future realized returns are regressed on different ICC metrics. To conserve space, we report results only for composite ICC measures: *ICC_COMPOSITE_ANALYST, ICC_COMPOSITE, HOU, ICC_COMPOSITE_EP*, and *ICC_COMPOSITE_RIV*. We regress the 12-month realized buy-and-hold returns measured starting from July 1 of each year on ICC metrics measured in the previous 12 months. The results reported in column (1) of Panel A in Table 11 document a significant relation between ICC metrics and future realized returns when the metric is measured as in Li and Mohanram (2014), but not when measured using the Hou et al. (2012) approach or using the analysts’ earnings forecasts. Interestingly, when we include a time fixed effect in the regression, which effectively converts the dependent variable to an excess return measure as our time fixed effects absorb the risk-free returns and market risk premium over every 12-month period (i.e., July 1 to June 30), we find *ICC_COMPOSITE_ANALYST* is significantly negatively related to future returns. In contrast, none of the other ICC metrics are significantly related to future returns. However, when we include firm fixed effects in regression, the results in column (3) show that all ICC metrics become significantly positive.

When we replace calendar year returns with a rolling 12-month return measurement period where the returns measurements begin three months after the ICC metric computation date, as in Li and Mohanram (2014), we find in column (4) that all ICC metrics are positively and significantly related to future realized returns.[41] Also, consistent with Li and Mohanram (2014), the coefficients on *ICC_COMPOSITE_EP* and *ICC_COMPOSITE_RIV* have the largest magnitudes. When we conduct the analysis at the portfolio-level, we find in column (5) that *ICC_COMPOSITE_HOU* has the largest magnitude and *ICC_COMPOSITE_ANALYST* is statistically insignificant.

We next repeat the earlier analysis after replacing future realized returns with the average CoE

[41] We obtain qualitatively similar results to those reported in column (4) when we restrict the analysis to include only firms with a December fiscal year-end and measure the realized returns to start from April 1 of each year. Also, due to the small number of years in our sample, we do not use the Fama-MacBeth approach as done by Li and Mohanram (2014). Petersen (2009) documents that the panel data approach with fixed effects and clustering of standard errors is more likely to yield unbiased inferences than the Fama-MacBeth approach.

estimates of analysts measured over the same period as the realized returns.[42] In contrast to the earlier findings, in Panel B of Table 11, the results are consistent across all regression specifications. The results show that the ICC metrics are positively related to analysts' CoE estimates in almost all regressions. Also, when we compare the coefficient magnitude across the metrics, we find that the Li and Mohanram (2014) metrics always have the highest magnitude. The coefficient magnitudes are, however, far below their theoretically predicted value of 1.

Overall, the results in Table 11 show that the analyses based on analysts' CoE estimates yield a consistent set of results, while those based on realized returns are highly sensitive to choices of regression specification. While the sensitivity of results to regression specifications may be reasonable, the lack of a clear prediction and explanation for the sensitivity makes it difficult to draw strong inferences. In contrast, the consistency of the results using analysts CoE estimates makes it easier to conclude that the ICC metrics reflect information about expected stock returns; however, the low coefficient values on these metrics, relative to the theoretical prediction, indicate they suffer from significant measurement issues.

The main point of this analysis is to show that using analysts' CoE estimates as a benchmark, not the realized returns, yields a consistent set of conclusions. Whether such consistency is appropriate (i.e., justified by asset pricing theories or econometric predictions) and a valuable attribute of asset pricing tests is beyond the scope of this paper.[43]

5.2.Discount rate reactions to news events

Traditionally studies have interpreted earnings news as exclusively reflecting cash flow information to investors. These studies typically ignore any discount rate information in the earnings news, mainly due to their inability to differentiate between the cash flow reactions and the discount rate reactions. More recently, attempts have been made to separate stock price changes into a cash flow component and a discount rate component, but inferences using these approaches have, at best, been tentative (Chen and Zhao, 2009; Rusticus, 2014). In this context, analysts' CoE estimates offer a new approach to directly evaluating the discount rate reactions of some of the market's most sophisticated participants around major corporate events. In this

[42] Our conclusions are similar if, instead of averages, we use the first CoE estimate from the measurement window.
[43] For example, Lee et al. (2017) argue that the beta coefficient is not a good indicator and instead recommend focusing on error variances.

subsection, we demonstrate this advantage by evaluating analysts' discount rate reactions to earnings news.

Specifically, we reevaluate the conclusions in Hecht and Vuolteenaho (2006), who show, using the Campbell (1991) return decomposition approach, that higher realizations of earnings are associated with increases in expected returns. We reexamine this issue by relating changes in CoE estimates around an earnings announcement to the earnings news released in that announcement. Our analysis uses the following regression:

$$\Delta CoE_{ibt} = \propto + \beta_1 Ernsurp_{it} + \sum_{j=2}^{n} \beta_j * Z_j + \mu_t + \vartheta_b + \varepsilon_{it}, \quad (4)$$

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). We require the same brokerage firm to have provided CoE estimates both in the pre- and post-earnings announcement periods. Although this restriction substantially reduces the sample size, it enables a cleaner assessment of the analysts' CoE responses. *Ernsurp* is the analysts' EPS forecast error revealed at the earnings announcement and is defined as the IBES actuals minus the median consensus EPS estimate, scaled by stock price at the end of the earnings reporting quarter.[44]

We control for risk and other firm characteristics in the regressions by including the variables (Z_j) considered in equation (3) as additional controls. Untabulated analyses reveal that our qualitative results are unaffected by including either changes in these variables or their levels. The regressions also include time and brokerage fixed effects and cluster standard errors at the industry level. As the CoE variable is already included in the changes and *Ernsurp* captures news, we do not additionally consider firm fixed effects. All accounting variables, including *Ernsurp*, are winsorized at the 1% and 99% levels.

To allow for potential non-linearity in the relation between *ΔCoE* and *Ernsurp*, as implied by the negative correlation between earnings smoothness and ICC measures shown in Francis et

[44] In this analysis, we merge the IBES sample with the CoE estimate sample by firm ticker and quarter. To avoid losing observations from requiring EPS forecasts of a specific analyst, we estimate *Ernsurp* using the median consensus forecasts. The consensus forecasts are computed for each earnings announcement using the analysts' latest estimates in the 90 days prior to the earnings announcement date. Our qualitative results are, however, unaffected if we replace the consensus forecasts with the forecasts of the brokerage firm whose CoE changes are analyzed.

al. (2004), we include the squared term of *Ernsurp* in the regression.[45] As an alternative, we sort all observations into deciles based on *Ernsurp* and include interactive indicator variables for each decile group (namely, *Ernsurp_Decile1* to *Ernsurp_Decile10*). Panel A of Table 12 presents univariate statistics for the variables in equation (4). The average *ΔCOE* is 0.014 percentage points, with the changes ranging from -1.8 to +2.5 percentage points. The average *Ernsurp* is 0.008 for the highest Ernsurp decile and -0.010 for the lowest decile. The average earnings surprise for all other deciles is close to zero. These results indicate that, apart from the extreme deciles, none of the others contain any material news at earnings announcements.

The results from estimating equation (4) are presented in Panel B of Table 12. When *Ernsurp* is included in the regression, its coefficient in column (1) is insignificant. However, when we include a squared term for *Ernsurp*, we find the coefficient on this squared term to be positive and significant (column (2)), indicating that analysts are more likely to change their CoE estimates when earnings news are larger in magnitude. When we allow the coefficient on *Ernsurp* to vary across the *Ernsurp* deciles, we find the coefficient to be insignificant for deciles 2 to 9, which is not surprising given the lack of significant news for these portfolios. However, the coefficients for the two extreme deciles are statistically significant, with the coefficient being negative for the lowest decile and positive for the highest decile.

The coefficient on *Ernsurp*Ernsurp_Decile1* is -7.008 (*t*-statistic = -2.63) when no control variables are included in the regression, implying that a one standard deviation greater negative earnings surprise (0.010) for this group increases their CoE estimates by seven bps. The corresponding coefficient on *Ernsurp*Ernsurp_Decile10* is 12.26 (*t*-statistic = 2.27), implying that a one standard deviation greater positive earnings surprise (0.005) for this group increases analysts' CoE estimates by six bps. For comparison, the average CoE estimate for both extreme deciles is 11%. These indicate that analysts increase their CoE estimates when a firm reports extreme earnings surprises and that they consider volatile earnings to represent risk, a finding that is consistent with those of Francis et al. (2004) and Rountree et al. (2008). This result also provides a potential explanation for why managers prefer to report smooth earnings (Graham et al., 2005) and confirms that analysts take their computations of CoE seriously, incorporating fundamental news in their estimates.

6. Conclusions

[45] Rountree, Weston and Allayannis (2008) also show that cashflow volatility is negatively valued by investors and that a 1% increase in cash flow volatility results in an approximately 0.15% decrease in firm value.

We explore a large sample of cost of equity (CoE) capital disclosed by sell-side analysts as a proxy for expected stock returns and for their usefulness in asset pricing tests. We first show that analysts' CoE estimates are related to firm characteristics that are typically associated with risk factors, such as a firm's beta, book-to-market ratio, and firm size, and that they strongly predict future stock returns. In addition, analysts appear to adjust their CoE estimates for leverage and idiosyncratic volatility but do not give weight to a firm's profitability or investments. We also find little evidence that other return predictors, such as momentum, matter for CoE estimates, suggesting that analysts do not consider every return predictor as relevant for the CoE estimates.

We next document that analysts' CoE estimates have incremental predictive power for future returns over other known predictors, which suggests that analysts tend to be privy to investors' views on required returns and can incorporate this information in their CoE estimates. We speculate that, since these investors are also the ones determining the stock market prices, the CoE estimates can be a potential model-free proxy of expected stock returns. We conduct additional tests to investigate whether the incremental predictive power of CoE estimates for returns arises from estimates reflecting stock mispricing, but find no empirical support for this. Also, when we compare the measurement noise in analysts' CoE estimates relative to other popular expected return proxies (including ICC metrics), we find analysts' CoE estimates are the least noisy proxies for expected stock returns based on the Lee et al. (2017) metric.

Our findings suggest that the CoE estimates are not only good proxies for expected stock returns, but should be good benchmarks for use in asset pricing tests. We test this implication by employing the CoE estimates in tests of reliability of ICC metrics. The results show that using CoE estimates as a benchmark, instead of the traditional realized returns, provide more consistent results and that the ICC metrics are relatively noisy proxies of expected stock returns.

Lastly, we demonstrate that analysts' CoE estimates can be employed to evaluate the market's discount rate reactions around corporate events. We find that CoE estimates increase following extreme earnings news, which supports the conjecture that earnings news contain both cash flow and discount rate news and that analysts view uncertain earnings as implying higher stock risk. These findings potentially explain the preference of managers to report smoothed earnings, as documented in Graham et al. (2005).

In conclusion, several empirical asset pricing tests are hampered by the lack of observability of discount rates and typically rely on realized stock returns to capture expected stock returns. We suggest that analysts' discount rates can be a useful alternative proxy for expected stock returns. However, like research that relies on analysts' earnings forecasts and ICC, 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 analyst CoE estimates are unavailable.

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Appendix I

Variable Definitions

This appendix provides the variable definitions. Measurements of firm characteristics immediately 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 the CRSP's daily files.

Variable	**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	1-year-ahead buy-and-hold returns (in percentage), measured from day 0 to day +360, where day 0 is the release date of analyst report disclosing a CoE estimate.
$BETA_t$	Firm-specific beta, obtained from a 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 the natural log of the number of shares outstanding multiplied by the stock price at the end of the fiscal quarter preceding the analyst's report release date.
BTM_t	Book-To-Market Ratio, defined as the ratio of the book value of equity to the market value of equity at the end of the fiscal quarter preceding the analyst's report release date. BTM is expressed in percentage.
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 the analyst's report release date. Leverage is expressed in percentage.
$IDIO\_VOL_t$	Idiosyncratic volatility is computed as $(1-R^2)/R^2$, where R^2 is estimated from a regression of excess daily stock returns, expressed as a percentage, 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. Momentum is expressed in percentage.
LAG_RETURN_t	Percentage stock returns in the calendar month immediately preceding the analyst report release month.
PROFITABILITY	Operating profitability, measured as operating profit divided by book value of equity and expressed in percentage. Operating profit is computed as revenues minus cost of goods sold minus selling, general and administrative expenses minus interest expense. All variables are taken from the fiscal quarter just preceding the analyst's report release date.
INVESTMENTS	Investments made by a firm, expressed as a percentage. It is measured as the percentage growth in total assets over the four quarters ending in the most recent fiscal quarter prior to the analyst's report release date.
LIQUIDITY	Percentage measure of liquidity computed using the Amihud (2002) approach. For each month, we compute the ratio of the daily absolute stock return to the daily dollar trading volume and scaled by -10^6. *LIQUIDITY* is then defined as

	the average of the monthly ratios over the 12-months before the month in which an analyst report with CoE estimate is released.
FIRMEXP	The number of years of experience an analyst has in covering a specific firm. For each firm-quarter, it is measured as the difference between the latest date an analyst issues a report in IBES and the first time the analyst's name appears on IBES as covering that particular firm.
CAREEREXP	The total number of years of experience for an analyst. For each quarter, it is measured as the difference between the latest date an analyst issues a report in IBES and the first time that analyst's name appears on IBES.
NUMANALYSTS	The number of analysts covering a firm in a quarter obtained from IBES Unadjusted Detail file.
AFERROR	Analyst forecast error. For each quarter, it is measured as the absolute value of the difference between year-ahead actual EPS value and corresponding analyst forecast scaled by absolute of actual EPS value. If year-ahead actuals or forecast values are unavailable, these are replaced by quarter-ahead actuals and the corresponding forecast value.
FIRMSCOVERED	The number of firms covered by an analyst in a quarter. Measured using IBES Unadjusted Detail file.
INSTOWN	The fraction of institutional ownership for a firm in a quarter. It is computed as the total shares held by institutions divided by total shares outstanding at the end of the quarter for the firm. Institutional Ownership data is obtained from Thomson Reuter's 13F filings database.
MF_Flows	Mutual fund price pressure variable, computed as outflows for a stock in a quarter resulting from price pressures experienced by mutual fund outflows in that quarter. Computed similar to Edmans et al., 2012. The *MF_Flows* variable is constructed using quarterly data on Mutual Fund holdings from Thomson, and monthly mutual fund flows data from CRSP MF database. *MF_Flows* for a firm i in quarter t is computed using the following formula: $MF\_Flows_{i,t} = \sum_{j-1}^{m} \frac{F_{j,t} * SHARES_{i,j,t-1} * PRC_{i,t-1}}{TA_{j,t-1} * VOL_{i,t}}$, where summation is done only for those funds which experience an outflow of >=5%. If a firm is not owned by any funds experiencing an outflow >=5% in a given quarter, then that firm-quarter is dropped from this analysis. $F_{j,t}$ is a flow variable that is computed for a fund j as $(TNA_{j,t} - TNA_{j,t-t} * (1 + R_{j,t})/TNA_{j,t-1}$. *TNA* is the total net assets for a fund, and R is returns experienced by a fund. SHARES is the number of shares held by a fund, *VOL* is dollar trading volume for a stock, and *PRC* is the end of the quarter price of the stock.[46]
CoE_DELTA	Change in the CoE estimate around a following a stock-price pressure event, computed as the difference between the most recent CoE in the twelve months prior to the event and the first CoE estimate in the subsequent twelve months.
TURNOVER	*TURNOVER* for firm i in month m is defined as trading volume in month m scaled by shares outstanding (expressed in thousands) for the firm.

[46] We closely follow Edmans et al. (2012) in the construction of *MF_Flows*. For every firm i and quarter t, we use the previous quarter's fund-holdings as an instrument. This approach assumes that, when faced with fund outflows, mutual funds sell each stock in their portfolio roughly in proportion to the percentage outflows suffered that month. Also, we consider only mutual funds that have experienced outflows of at least 5% of total assets, because only extreme outflows are likely to have an impact on stock pricing. Lastly, because the impact of a given outflow on prices depends on the stock's liquidity, the dollar outflows are scaled by the stock's dollar trading volume.

Appendix II

Implied cost of equity capital models

We estimate the 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 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 earnings per share forecasts. • For subsequent nine years, residual income is computed assuming the firm's 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 the 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 $t + i$ ($i > 0$).
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 the OJN model. The short-term growth rate is computed as the growth in earnings forecasts over the first two years. The long-term growth rate is set to be equal to the one-year ahead inflation rate for all firms.
d_{t+i} is the net dividend 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. As the models do not have a unique closed-form solution, an iterative procedure is used to estimate the values.

Inputs based on Analyst Earnings Forecasts: We obtain analyst earnings per share forecasts and long-term growth forecasts from IBES. All of the analyst estimates are mean consensus figures. Accounting data and three-month-ahead stock price are 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 the 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 forecasts with an analyst's long-term growth forecasts. If a long-term growth forecast is negative or missing, it is replaced by growth in forecasted earnings per share over the years t+2 to t+3.

Inputs based on Hou et al. (2012)/Li and Mohanram (2014) EP-Model and *RIV-Model:* For the cross-sectional earnings forecast models, we run the models as specified in these papers and estimate one-, two-, three-, four-, and five-year ahead earnings forecasts. Accounting data for estimating these models are from Compustat. We compute long-term and short-term growth forecasts for OJN model based on growth in earnings from year 4 to year 5, and year 1 to year 2 respectively.

Figure 1: NUMBER OF MORNINGSTAR AND NON-MORNINGSTAR REPORTS OVER TIME

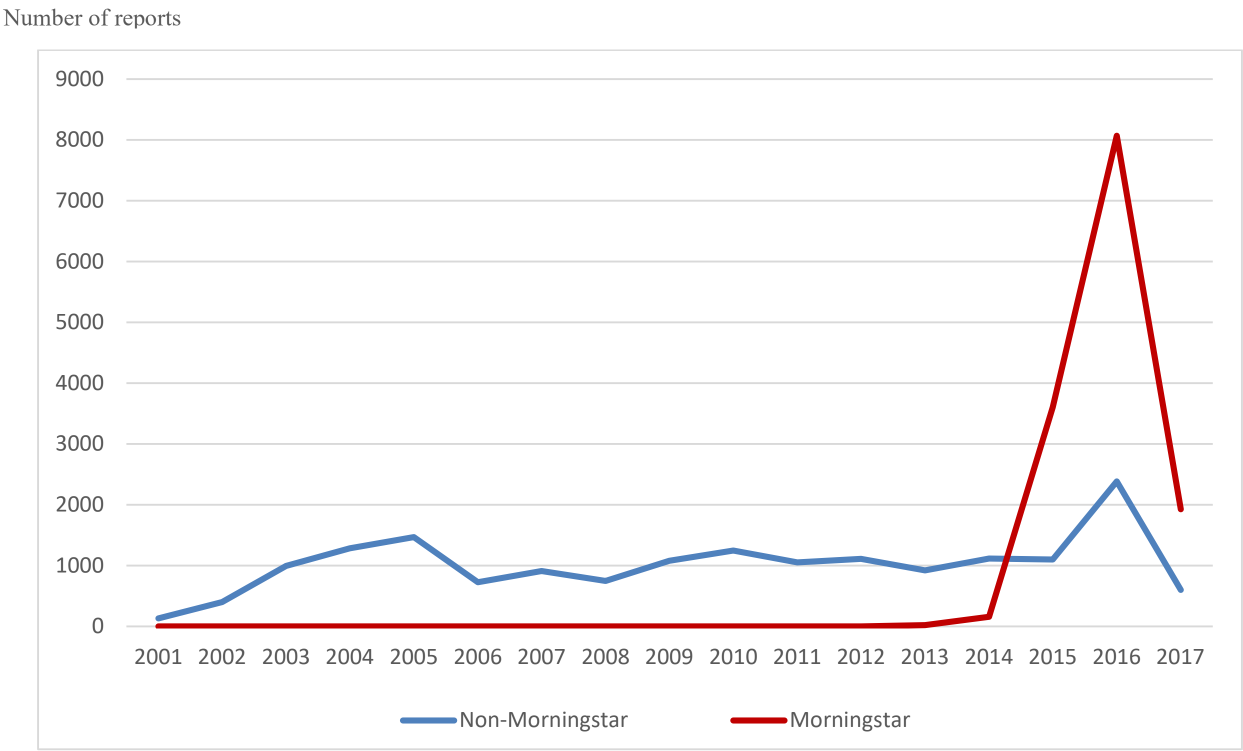

TABLE 1: SAMPLE SELECTION AND DESCRIPTION

Panel A of 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 January 1, 2001 to December 31, 2017. We apply the following three criteria while searching for reports on Thomson One: (i) "Cost of Equity" appears in "Text" and (ii) Geography is "United States" and (iii) reports are not categorized as non-broker, industry or economy reports. Panel B presents the distribution of the final sample for the top 20 brokerage firms providing CoE estimates.

Panel A: Sample selection

			Observations
(1)	Analyst research reports from Thomson One that contain mentions of "cost of equity"		57,211
(2)	Reports where COE was not extractable by textual analysis	(22,567)	
(3)	Observations where ticker from a report could not be matched to an IBES ticker	(3,595)	
(4)	Final sample of observations containing COE values		31,049
(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.	(26,266)	
(6)	Sample with data for ΔCOE analysis around earnings announcements		4,783

Panel B: Sample distribution by brokerage firm (top 20 brokerages)

Brokerage Firm	**# of reports**	**% of sample**	**% of Thomson One Reports**
Morningstar	13755	44.3	53.9
Morgan Stanley	2534	8.2	2.2
Barclays	1036	3.3	1.0
Deutsche Bank Research	871	2.8	0.7
UBS Research	987	3.2	0.8
Citigroup	792	2.6	1.6
Singular Research	741	2.4	44.0
Credit Suisse - North America	600	1.9	0.3
Smith Barney†	566	1.8	N/A
Jefferies	544	1.8	0.6
CIBC World Markets Corp.	495	1.6	1.6
RBC Capital Markets	476	1.5	0.4
Macquarie Research	445	1.4	1.7
Wunderlich Securities	379	1.2	2.8
Canaccord Genuity	375	1.2	1.3
Wells Fargo Securities, LLC	366	1.2	0.3
A.G. Edwards & Sons, Inc.	335	1.1	2.1
J P Morgan	295	1.0	0.2
Piper Jaffray	270	0.9	0.3
Maxim Group LLC	269	0.9	2.8

† We are not able to provide an accurate estimate for Smith Barney because this brokerage has been removed from the brokerage name search in Thomson One subsequent to its mergers and name changes.

TABLE 2: SUMMARY STATISTICS

The table presents the summary statistics for firm characteristics for stocks that have analysts' CoE estimates available. For comparison purposes, the table also reports the corresponding statistics for all stocks with earnings per share (EPS) estimates available in the IBES unadjusted details file. The EPS estimate needs to be available for at least one of the following IBES's forecast period indicators: 1, 6, 7, 8, or 9. The sample period is from 2001-2017. All variables are defined in Appendix I.[§] represents statistical significance at the 1% level from a *t*-test for differences in means across the CoE sample and the IBES sample and from a Wilcoxon rank-test for differences in the medians across the samples.

	CoE sample						**IBES sample**					
	N	Mean	Med	Std. Dev.	Min	Max	*N*	Mean	Med	Std. Dev.	Min	Max
CoE	31,049	10.11	9.40	2.35	5.00	19.85						
RETURNS	31,049	16.47[§]	13.21[§]	44.15	-99.15	1700.00	3,328,671	11.27	8.19	53.40	-99.99	4012.56
BETA	31,045	1.18[§]	1.10[§]	0.55	0.07	3.07	3,327,941	1.18	1.12	0.56	0.02	2.98
BTM	30,834	43.50[§]	35.57[§]	39.10	-55.64	202.18	3,250,075	51.43	41.92	41.86	-24.31	241.64
MCAP	30,996	15.67[§]	15.85[§]	2.00	7.38	19.44	3,260,258	8.01	7.97	1.77	3.99	12.16
LEV	30,813	31.60[§]	29.14[§]	22.46	0.00	101.15	3,250,489	23.75	20.91	20.29	0.00	89.42
IDIO_VOL	31,038	0.38[§]	0.31[§]	1.13	-2.08	3.58	3,325,244	0.48	0.41	1.15	-2.02	3.68
MOMENTUM	30,893	10.07[§]	6.67[§]	59.32	-97.72	3276.19	3,304,132	12.03	7.48	55.75	-99.82	4337.5
LAG_RETURN	30,973	0.62	0.60	11.23	-68.26	182.73	3,312,564	0.55	0.65	13.25	-98.39	1349.51
PROFITABILITY	30,908	6.27[§]	5.93	19.80	-88.28	111.18	3,062,600	5.97	5.98	14.81	-67.54	75.37
INVESTMENTS	30,775	13.09[§]	4.88[§]	36.12	-37.97	239.67	3,174,826	14.79	6.92	34.46	-41.17	208.60
LIQUIDITY	31,045	-0.30[§]	-0.02[§]	1.15	-8.89	0.00	3,322,262	-2.13	-0.07	10.20	-86.18	-0.00
FIRMEXP	22,295	4.14[§]	3.00[§]	3.82	1.00	23.00	3,433,875	5.02	3.00	4.56	1.00	23.00
CAREEREXP	22,295	10.81[§]	8.00[§]	8.33	1.00	34.00	3,433,875	13.38	12.00	8.92	1.00	34.00
NUMANALYSTS	22,295	16.89[§]	16.00[§]	9.11	1.00	40.00	3,433,875	14.86	13.00	9.17	1.00	40.00
AFERROR	21,281	1.12[§]	0.99[§]	0.88	0.08	7.47	3,186,889	1.14	0.99	0.90	0.08	7.47
FIRMSCOVERED	22,295	14.91[§]	14.00[§]	8.34	1.00	43.00	3,433,875	15.14	14.00	7.61	1.00	43.00
INSTOWN	19,006	0.73[§]	0.78[§]	0.23	0.00	1.00	2,764,585	0.71	0.78	0.25	0.00	1.00
TURNOVER	31,028	2.22[§]	1.67[§]	1.84	0.31	11.40	3,326,175	2.65	1.90	2.42	0.14	14.19

TABLE 3: DETERMINANTS OF ANALYST PROVISION OF COST OF EQUITY ESTIMATES

The table presents the results of a multivariate analysis of the determinants of analyst provision of CoE estimates. *CoE DUMMY* is an indicator variable that takes a value of 1 when an analyst discloses the CoE estimate and zero otherwise. All other variables are defined in Appendix I. Column (1) provides estimates from an OLS regression of *CoE DUMMY* on the determinant variables, while column (2) reports estimates from a logit analysis. Standard errors are clustered at the industry level. The *t*-statistics are presented in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	OLS	*Logit*
FIRMEXP	-0.0002***	-0.0338*
	(-3.71)	(-1.93)
CAREEREXP	-0.0002***	-0.0318***
	(-5.23)	(-4.98)
FIRMSCOVERED	-0.0002***	-0.0277***
	(-3.61)	(-3.27)
MCAP	0.0022***	0.2904***
	(6.06)	(5.49)
AFERROR	-0.0000	-0.0037
	(-0.11)	(-0.13)
BTM	-0.0000	-0.0007
	(-1.24)	(-0.62)
NUMANALYSTS	-0.0000	-0.0042
	(-0.46)	(-0.33)
IDIO_VOL	-0.0001	-0.0142
	(-0.54)	(-0.73)
LIQUIDITY	-0.0000**	-0.0038
	(-2.08)	(-0.96)
INSTOWN	-0.0002	0.0861
	(-0.15)	(0.46)
BETA	0.0001	0.0416
	(0.23)	(0.47)
LEV	0.0001***	0.0157***
	(2.95)	(4.16)
MOMENTUM	-0.0000	-0.0001
	(-0.43)	(-0.22)
LAG_RETURN	0.0000**	0.0021***
	(2.38)	(2.81)
PROFITABILITY	-0.0000*	-0.0035*
	(-1.68)	(-1.91)
INVESTMENTS	-0.0000***	-0.0023**
	(-3.19)	(-2.47)
TURNOVER	-0.0001	-0.0116
	(-0.76)	(-0.64)
Observations	2,259,534	2,259,534
R-squared	0.004	N/A

TABLE 4: ANALYSTS' COST OF EQUITY ESTIMATES AND FIRM CHARACTERISTICS

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

		(1)	(2)	(3)
		Full	*Full*	*Full*
		sample	*sample*	*sample*
	PREDICTED	*CoE*	*CoE*	*CoE*
BETA	+	0.350***	0.293***	0.305***
		(4.58)	(4.60)	(4.84)
BTM	+		0.007**	0.008**
			(2.08)	(2.20)
MCAP	-		-0.111***	-0.102***
			(-5.07)	(-5.42)
PROFITABILITY	+		-0.001	-0.001
			(-0.78)	(-0.66)
INVESTMENTS	-		-0.001	-0.001
			(-1.56)	(-1.41)
LEV	+			0.010**
				(2.42)
IDIO_VOL	+			0.031***
				(3.09)
MOMENTUM	+			-0.000
				(-0.84)
LAG_RETURN	-			-0.000
				(-0.07)
LIQUIDITY	-			-0.049
				(-0.89)
Observations		31,045	30,592	30,323
R-squared		0.678	0.687	0.688

TABLE 5: ANALYSTS' COST OF EQUITY ESTIMATES AND EXPECTED RETURNS

This table presents results from analysis of CoE estimates and subsequent stock returns. Panel A reports the equally weighted and value-weighted 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 the 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 analyst-level CoE estimates or on the CoE rank, which takes the value 2 for the top 30%, 1 for the middle 40%, and 0 for the bottom 30% of CoE estimates. Portfolio-level analyses are conducted by forming 25 portfolios each quarter based on the CoE estimates released within that quarter. The average *RETURNS* for each portfolio are regressed on average CoE estimates for the corresponding portfolio. The portfolio specification includes time fixed effects and the standard errors are clustered at the portfolio level. Panel C presents the results from regressions of calendar year returns (*CALENDAR_RETURNS*) on *CoE* and *CoE_Yearly_Rank*. The *CALENDAR RETURNS* are computed for each analyst report as the 360-day buy-and-hold stock returns from the January 1 to December 31 of the following year. *CoE_Yearly_Rank* is computed by forming terciles (top 30%, middle 40% or bottom 30%) at end of each calendar year using only analysts' CoE estimates that were disclosed between July 1st and December 31st of that year. In analysts-level regressions, the fixed effects specifications include time, firm, and brokerage fixed effects and standard errors are clustered at the industry level. The portfolio-level regressions include time fixed effects and cluster the standard errors at the portfolio level. The t-statistics are presented in parentheses. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Panel A: Univariate Portfolio Analysis

COE-sorted portfolio	**Average CoE**	**Average 1-year Equally-weighted returns**	**Average 1-year Value-weighted returns**
HIGH CoE portfolio	12.65%	19.7***	19.51***
		(8.11)	(8.57)
MID CoE portfolio	9.41%	15.7***	15.67***
		(12.39)	(12.09)
LOW CoE portfolio	7.55%	12.8***	12.63***
		(15.06)	(14.93)
F-test that portfolio returns are equal (p-value)		0.000	0.000

Panel B: Regression Analysis

	PREDICTED	(1) *Analyst-Level RETURNS*	(2) *Analyst-Level RETURNS*	(3) *Portfolio-Level RETURNS*	(4) *Analyst-Level RETURNS*	(5) *Analyst-Level RETURNS*	(6) *Analyst-Level RETURNS*
CoE	+	2.178***		1.179***	1.431***	2.274***	1.516***
		(4.20)		(3.19)	(3.30)	(3.97)	(3.55)
CoE_rank	+		5.077***				
			(4.07)				
Morningstar reports		Included	Included	Included	Included	Excluded	Excluded
Fixed Effects		Yes	Yes	Yes	No	Yes	No
Observations		31,049	31,049	1,465	31,049	17,270	17,270
R-squared		0.494	0.492	0.465	0.006	0.536	0.008

Panel C: Calendar Time Returns

	PREDICTED	(1) Analyst-Level RETURNS	(2) Analyst-Level RETURNS	(3) Analyst-Level RETURNS	(4) Analyst-Level RETURNS	(5) Analyst-Level RETURNS	(6) Analyst-Level RETURNS	(7) Analyst-Level RETURNS	(8) Analyst-Level RETURNS
CoE	+	2.030***	1.484**	2.566***	1.671***				
		(2.47)	(2.28)	(3.07)	(2.97)				
CoE_Yearly _rank	+					5.527***	4.336**	6.287***	3.137**
						(3.90)	(2.64)	(4.24)	(2.03)
Morningstar reports		Included	Included	Excluded	Excluded	Included	Included	Excluded	Excluded
Fixed Effects		Yes	No	Yes	No	Yes	No	Yes	No
Observations		16,062	16,062	8,485	8,485	16,062	16,062	8,485	8,485
R-squared		0.516	0.006	0.590	0.010	0.515	0.005	0.587	0.003

TABLE 6: FUTURE RETURNS AND COE REGRESSIONS

This table reports the results of pooled regression of *RETURNS* on analysts' CoE estimates and common return predictors. All variables are defined in Appendix I. The regression in columns (1) - (3) include time-, firm- and brokerage-fixed effects and cluster standard errors at the industry level. Column (4) presents the results for a portfolio-level analysis where, in each quarter, analyst CoE estimates disclosed in that quarter are classified into 25 portfolios. The average *RETURNS* for each portfolio are regressed on the average CoE estimates and average firm characteristics for that portfolio. The specification includes time-fixed effects and clusters standard errors at the portfolio level.

Panel B reports results for robustness tests of the full specification model (reported in column (3) of Panel A), and results from subsample analyses of the full specification model. Column (1) presents results without any fixed effects. In column (2), we replace brokerage fixed effects with analyst fixed effects, where analyst data are from IBES. Column (3) presents results for the sample of Morningstar estimates. Column (4) present results for sample of non-Morningstar estimates. Columns (5) and (6) estimate the regressions for sub-groups formed by dividing the non-Morningstar estimates into two sub-periods with equal number of observations. Column (7) presents results using calendar time approach, as done in column (2) of Table 5, Panel C.

Panel A: Main Regressions

	(1)	(2)	(3)	(4)
	Full sample	*Full sample*	*Full sample*	*Full sample*
	Analyst-Level RETURNS	*Analyst-Level RETURNS*	*Analyst-Level RETURNS*	*Portfolio-Level RETURNS*
CoE	2.066***	1.429***	1.293***	0.844***
	(4.27)	(4.02)	(3.51)	(4.28)
BETA	6.052***	4.322***	4.327**	-1.839
	(2.97)	(2.70)	(2.38)	(-0.62)
BTM		0.287***	0.272***	0.154
		(4.29)	(3.87)	(1.08)
MCAP		-5.115***	-4.165***	-1.030
		(-6.31)	(-6.06)	(-1.05)
PROFITABILITY		0.006	0.012	-0.007
		(0.12)	(0.24)	(-0.22)
INVESTMENTS		-0.034*	-0.031	-0.131***
		(-1.77)	(-1.52)	(-7.33)
LEV			0.322***	0.100*
			(2.71)	(1.72)
IDIO_VOL			-0.472	4.509
			(-1.58)	(0.96)
MOMENTUM			-0.093**	-0.015
			(-2.19)	(-0.62)
LAG_RETURN			--0.457***	-0.307**
			(-8.46)	(-2.47)
LIQUIDITY			-6.999***	-0.154
			(-4.41)	(-1.40)
Observations	31,045	30,592	30,323	1,455
R-squared	0.496	0.520	0.544	0.499

Panel B: Robustness checks and Subsample analyses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	No fixed effects	*Analyst fixed effects*	*Only Morningstar*	*Excluding Morningstar*	*Early Sub-period excluding Morningstar*	*Later Sub-period excluding Morningstar*	*Calendar Returns and No fixed effects*
CoE	1.142***	1.966***	1.858*	1.430***	1.992**	0.877**	1.214**
	(3.052)	(5.56)	(1.761)	(3.41)	(2.34)	(2.28)	(2.480)
Control Variables	Included	Included	Included	Included	Included	Included	Included
Observations	30,323	21,272	13,647	16,676	8,338	8,338	15,640
R-squared	0.021	0.676	0.635	0.583	0.647	0.677	0.031

TABLE 7: CALENDAR TIME PORTFOLIO ANALYSES

This table reports the results of calendar time portfolio regressions of *RETURNS* (defined in Appendix I) on the Fama-French five-factors, momentum factor, and Pastor and Stambaugh's liquidity factor. For every month, portfolios are formed on terciles of CoE values released in the prior three months. We require that there is a minimum of 50 CoE observations in a month for portfolio formation. Portfolio returns are equally weighted, except in column (5), where they are value weighted. Excess return (*Rm-Rf*) is computed as return minus risk-free rate, *SMB* is Small-Minus-Big size factor, *HML* is High-Minus-Low growth factor, *RMW* is operating profitability factor, *CMA* is investments factor, *MOM* is momentum factor and *LIQ* refers to Pastor and Stambaugh's liquidity factor. Columns (1) to (3) present the results for the lowest tercile, middle tercile and the top tercile portfolio returns, respectively. Columns (4) and (5) present the results for the equally-weighted and value-weighted hedge returns (top tercile returns minus bottom tercile returns), respectively. The t-statistics are presented in parentheses. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

	(1) *Tercile 1 Portfolio*	(2) *Tercile 2 Portfolio*	(3) *Tercile 3 Portfolio*	(4) *Hedge Portfolio*	(5) *Hedge Portfolio VW-returns*
Rm-Rf	0.988***	1.041***	1.039***	0.051	0.066
	(28.54)	(33.68)	(16.71)	(0.79)	(1.057)
SMB	0.238***	0.427***	0.616***	0.378***	0.371***
	(4.48)	(9.02)	(6.64)	(3.81)	(3.898)
HML	-0.218***	-0.126***	-0.290***	-0.072	-0.070
	(-4.13)	(-2.68)	(-3.06)	(-0.73)	(-0.735)
RMW	0.030	-0.183***	-0.967***	-0.997***	-0.963***
	(0.43)	(-2.90)	(-7.60)	(-7.52)	(-7.580)
CMA	0.146*	-0.067	0.446***	0.300*	0.292*
	(1.70)	(-0.87)	(2.90)	(1.87)	(1.902)
MOM	-0.163***	-0.178***	-0.400***	-0.237***	-0.237***
	(-6.04)	(-7.38)	(-8.24)	(-4.68)	(-4.888)
LIQ	-1.650	-1.769	1.884	3.533	1.996
	(-0.96)	(-1.15)	(0.61)	(1.10)	(0.648)
ALPHA	0.144	0.368***	0.595***	0.451**	0.509**
	(1.19)	(3.39)	(2.72)	(1.98)	(2.340)
Observations	183	183	183	183	183
R-squared	0.904	0.941	0.882	0.590	0.604

TABLE 8: FUTURE RETURNS REGRESSIONS CONTROLLING FOR ALTERNATIVE EXPECTED RETURN PROXIES

This table reports the results of pooled regression of *RETURNS* (defined in Appendix I) on alternative measures of expected return proxies (ERPs). The alternative ERPs are obtained from the following models: *CAPM*, Fama-French three-factor model (*FF3*), Fama-French five-factor model (*FF5*), and the averages of four ICC metrics computed using alternative earnings forecasts: *ICC_COMPOSITE_ANALYST, ICC_COMPOSITE_HOU, ICC_COMPOSITE_EP,* and *ICC_COMPOSITE_RIV*. For each CoE estimate, the corresponding benchmark ERPs is computed using data available as of the corresponding analyst report date *t*. For the CAPM, FF3 and FF5 models, factor loadings are estimated using daily returns over the period *t*-1 to *t*-360 and the ERPs for each specific model are then computed based on the estimated factor loadings and the factor returns for day *t*. The calculations of the ERPs from ICC models are described in Appendix II. We winsorize estimated factor loadings and ICC estimates at the 1% and 99% levels. All negative ERP estimates are set to missing. These specifications include time, firm, and brokerage fixed effects and the standard errors are clustered at the industry level. The t-statistics are presented in parentheses. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

	(1) *Analyst-Level RETURNS*	(2) *Analyst-Level RETURNS*	(3) *Analyst-Level RETURNS*	(4) *Analyst-Level RETURNS*	(5) *Analyst-Level RETURNS*	(6) *Analyst-Level RETURNS*	(7) *Analyst-Level RETURNS*
CoE	2.086***	2.054***	2.202***	1.285***	1.905***	1.931***	1.870***
	(2.84)	(3.66)	(4.02)	(3.70)	(3.52)	(3.69)	(3.56)
CAPM	3.725***						
	(5.36)						
FF3		3.778***					
		(5.51)					
FF5			3.457***				
			(3.47)				
ICC_ COMPOSITE _ANALYST				0.352			
				(1.62)			
ICC_ COMPOSITE _HOU					0.653***		
					(4.68)		
ICC_ COMPOSITE _ EP						0.926***	
						(4.62)	
ICC_ COMPOSITE _RIV							0.916***
							(4.07)
Observations	16,040	15,712	15,701	24,496	24,542	24,561	24,513
R-squared	0.480	0.466	0.476	0.503	0.460	0.463	0.461

TABLE 9: EVALUATING COE AS AN EXPECTED RETURN PROXY

This table presents the results from the analysis of cross-sectional error variances computed using the Lee et al. (2017) approach. The variances are computed for 202 calendar months over the sample period 2001-2017. Analyst CoE values are derived from Thomson One analyst research reports. The alternative expected return proxies (ERPs) are obtained as described in Table 8. The realized returns for computation of the error variances are measured over a month (i.e., 30 days), a quarter (90 days) or a year (360 days) from the date of the analyst report disclosing a CoE estimate. Panel A presents the average measurement error variance for the CoE estimates. Panel B reports the results for measurement error variance of CoE minus that of alternative ERPs. The t-statistics are presented in parentheses. The *t*-statistics are based on Newey-West-adjusted standard errors when return-measurement periods are either a quarter or a year.

Panel A: Average Measurement-error Variance

Return Measurement Period	*Average CoE Measurement Error Variance*
Monthly	5.516
Quarter	4.758
Annual	-3.407

Panel B: Measurement-error variance of CoE minus that of alternative expected returns proxies

Return measurement period	*CAPM*	*FF3*	*FF5*	*ICC_ COMPOSITE _ANALYST*	*ICC_ COMPOSITE _HOU*	*ICC_ COMPOSITE _EP*	*ICC_ COMPOSITE _RIV*
Monthly	7.187	7.749	7.837	-43.752	-23.580	-26.493	-22.447
	(4.91)	(5.65)	(5.48)	(-10.13)	(-8.86)	(-7.62)	(-7.87)
Quarterly	6.408	6.936	6.905	-48.260	-24.364	-28.429	-22.596
	(2.38)	(2.57)	(2.62)	(-8.10)	(-5.11)	(-5.44)	(-4.79)
Annual	-3.744	-1.581	-1.777	-83.209	-38.132	-35.207	-27.454
	(-0.35)	(-0.16)	(-0.19)	(-4.78)	(-3.82)	(-4.04)	(-2.48)

TABLE 10: CoE AND STOCK MISPRICING

This table presents results of tests between CoE and stock mispricing. Panel A presents results from pooled regression of RETURNS (defined in Appendix I) on *CoE* and contemporaneous earnings announcement returns (*ErnAnnRet(q+i)* (*i*=1 to 4)). *ErnAnnRet(q+i)* is the buy-and-hold returns in the three-days around the earnings announcement made in quarter *q+i*. For each CoE estimate, quarter q refers to the quarter in which the analyst report disclosing the CoE estimate was released. Column 2 presents regression results when the relevant analyst's predicted returns, as implied by their target prices (*TP_EXP_RETURNS*), are included as an additional control variable. *TP_EXP_RETURNS* is computed as follows: [(Analyst's target Price/Report date share price – 1) *100 – CoE], where report date share price is the share price on the analysts' report release date. Panel B presents results for changes in CoE estimates (*CoE_DELTA*) following a stock-price pressure event induced by mutual funds experiencing high outflows (*MF_Flows*). For each firm-quarter, we compute *MF_Flows* following Edmans et al. (2012) approach. *CoE_DELTA* is computed around each stock-price-pressure event as the difference between the most recent CoE in the prior twelve months (i.e., pre-period) and the first CoE estimate in the subsequent twelve months (i.e., post-period). All variables are defined in Appendix I. These specifications include time-, firm- and brokerage-fixed effects and cluster the standard errors at the industry level. The t-statistics are presented in parentheses. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

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Panel A: Including future earnings announcement returns and target price-implied expected returns

	(1)	(2)
	Analyst-Level RETURNS	*Analyst-Level RETURNS*
CoE	2.205***	1.483***
	(4.09)	(3.37)
ErnAnnRet(q+1)	1.072***	
	(10.87)	
ErnAnnRet (q+2)	1.053***	
	(11.38)	
ErnAnnRet (q+3)	0.965***	
	(21.84)	
ErnAnnRet (q+4)	0.194**	
	(2.19)	
TP_EXP_RETURNS		2.322
		(0.48)
BETA		3.780
		(1.39)
BTM		0.219**
		(2.09)
MCAP		-3.658***
		(-2.81)
PROFITABILITY		0.048
		(0.79)
INVESTMENTS		-0.040
		(-1.40)
LEV		0.279*
		(1.99)
IDIO_VOL		-0.088**
		(-2.43)
MOMENTUM		-0.037
		(-1.22)
LAG_RETURN		-0.417***
		(-6.19)
LIQUIDITY		-7.279***
		(-3.47)
Observations	28,997	7,967
R-squared	0.530	0.586

Panel B: Using Mutual Fund Outflows

	(1)	(2)
	CoE_DELTA	*CoE_DELTA*
MF_Flows	0.473	0.136
	(1.54)	(0.49)
BETA		0.042
		(1.16)
BTM		0.002**
		(2.47)
MCAP		-0.026*
		(-1.96)
PROFITABILITY		0.002**
		(2.45)
INVESTMENTS		0.001
		(1.59)
LEV		0.000
		(0.07)
IDIO_VOL		0.027
		(1.05)
MOMENTUM		-0.002**
		(-2.19)
LAG_RETURN		-0.009***
		(-3.17)
LIQUIDITY		0.009
		(0.59)
Observations	10,563	10,422
R-squared	0.055	0.070

TABLE 11: FUTURE RETURNS AND COE REGRESSED ON ALTERNATIVE EXPECTED RETURN PROXIES

This table reports the results of pooled regressions of buy-and-hold future realized returns (*RETURNS*) (Panel A) or Cost of Equity (*CoE*) (Panel B) on different ICC metrics. Each coefficient reported below is obtained from a separate regression of *RETURNS* (or *CoE*) on the ICC metric mentioned in the row header. We match each ICC estimate, which are computed annually at a firm's fiscal year-end, with the realized returns (*RETURNS*) and with the average values of CoE estimates, both measured over a 12-month period starting from subsequent July (i.e., July 1st to June 30th of following year). Columns (1) - (3) present results based on different fixed effect structures. Column (4) measures the dependent variables to start three months after the ICC metric measurement date (rather than subsequent July) and measures all variables (*RETURNS,* CoE and the ICC metrics) as their raw values minus the risk-free rate. Column (5) replicates column (1) analyses using portfolio-level data for each ICC metric, using the following procedure. On June 30th of each year, we sort stocks into 25 portfolios based on its most recent ICC metric in the last twelve months. We then regress portfolio-averages of future *RETURNS* and average *CoE* (both measured over a 12-month period starting July 1st) on the portfolio averages of the relevant ICC metric. Standard errors are clustered at the industry level except for portfolio level analysis where standard errors are clustered at the portfolio level. All variables are defined in Appendix I. The ICC metrics are defined in Appendix II. The t-statistics are presented in parentheses and the number of observations in square brackets. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Panel A. Regressions of RETURNS on ICC measures

	(1)	(2)	(3)	(4)	(5)
Level of analysis:	*Firm*	*Firm*	*Firm*	*Firm*	*Portfolio*
Return measurement period:	*Fixed*	*Fixed*	*Fixed*	*Rolling*	*Fixed*
Return measure:	*Raw*	*Raw*	*Raw*	*Excess*	*Raw*
*ICC_*	-0.057	-0.198**	0.366**	0.693***	-0.093
COMPOSITE_ANALYST	(-0.62)	(-2.65)	(2.45)	(2.35)	(-0.71)
	[5,674]	[5,674]	[5,674]	[5,666]	[451]
*ICC_*	0.362	0.203	0.936***	0.873***	0.906***
COMPOSITE_HOU	(1.21)	(0.67)	(2.69)	(2.98)	(8.13)
	[5,544]	[5,544]	[5,544]	[5,546]	[451]
*ICC_*	0.605**	0.430	1.282***	1.203***	0.813**
COMPOSITE_EP	(2.16)	(1.34)	(3.16)	(4.46)	(4.29)
	[5,547]	[5,547]	[5,547]	[5,546]	[451]
*ICC_*	0.639**	0.432	1.328***	1.314***	0.827***
COMPOSITE_RIV	(2.01)	(1.20)	(3.15)	(4.09)	(4.42)
	[5,531]	[5,531]	[5,531]	[5,529]	[451]
Time Fixed Effects	No	Yes	Yes	No	No
Firm Fixed Effects	No	No	Yes	No	No

Panel B. Regressions of CoE on ICC measures

	(1)	(2)	(3)	(4)	(5)
Level of analysis:	*Firm*	*Firm*	*Firm*	*Firm*	*Portfolio*
Return measurement period:	*Fixed*	*Fixed*	*Fixed*	*Rolling*	*Fixed*
Return measure:	*CoE*	*CoE*	*CoE*	*CoE*	*CoE*
ICC_ COMPOSITE_ANALYST	0.040***	0.033***	0.014	0.076***	0.019**
	(5.05)	(3.65)	(1.16)	(7.19)	(2.22)
	[5,674]	[5,674]	[5,674]	[5,666]	[451]
ICC_ COMPOSITE_HOU	0.055***	0.054***	0.036***	0.106***	0.052***
	(4.69)	(4.78)	(4.36)	(10.21)	(5.10)
	[5,544]	[5,544]	[5,544]	[5,546]	[451]
ICC_ COMPOSITE_EP	0.093***	0.076***	0.044***	0.127***	0.098***
	(7.71)	(7.10)	(4.30)	(10.46)	(5.78)
	[5,547]	[5,547]	[5,547]	[5,546]	[451]
ICC_ COMPOSITE_RIV	0.092***	0.077***	0.043***	0.134***	0.091***
	(7.67)	(6.98)	(3.39)	(11.18)	(7.43)
	[5,531]	[5,531]	[5,531]	[5,529]	[451]
Time Fixed Effects	No	Yes	Yes	No	No
Firm Fixed Effects	No	No	Yes	No	No

TABLE 12: CHANGES IN ANALYSTS' COST OF EQUITY CAPITAL ESTIMATES AND EARNINGS NEWS

This table reports the results of pooled regression of changes in CoE (*ΔCoE*) around an earnings announcement on earnings surprises (*Ernsurp*) at the announcement. Panel A presents descriptive statistics for *Ernsurp* for each decile of earnings surprises. Panel B presents the regression results of *ΔCoE* on *Ernsurp* and control variables. The dependent variable Δ*CoE* is the difference in CoE estimate disclosed by a brokerage firm after an earnings announcement (specifically in days 0 to +45 relative to an earnings announcement date, day 0) and the CoE estimate disclosed by the same brokerage firm in the 45 days before the earnings announcement (i.e., days -1 to -45). Columns (3) and (4) allow the coefficients on *Ernsurp* to vary across earnings-surprise deciles by interacting it with indicator variables (*Ernsurp_Decile1*- *Ernsurp_Decile10*). These regressions also include the indicator variables by themselves, but their coefficients are not reported. The variable definitions are presented in Appendix I. The regressions use analyst-firm-quarter level observations and include time- and brokerage-fixed effects. Standard errors for all regressions are based on clustering at the industry-level. The t-statistics are presented in parentheses. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Panel A: Descriptive Statistics

	N	Mean	Median	Std. Dev.	Min	Max
ΔCoE	4,783	0.014	0.000	0.406	-1.800	2.500
Ernsurp (Decile1)	478	-0.010	-0.006	0.010	-0.032	-0.002
Ernsurp (Decile2)	478	-0.001	-0.001	0.000	-0.002	-0.001
Ernsurp (Decile3)	357	-0.000	-0.000	0.000	-0.000	-0.000
Ernsurp (Decile4)	600	0.000	0.000	0.000	0.000	0.000
Ernsurp (Decile5)	478	0.000	0.000	0.000	0.000	0.000
Ernsurp (Decile6)	479	0.000	0.000	0.000	0.000	0.000
Ernsurp (Decile7)	478	0.000	0.000	0.000	0.000	0.001
Ernsurp (Decile8)	479	0.001	0.001	0.000	0.001	0.002
Ernsurp (Decile9)	478	0.002	0.002	0.000	0.002	0.004
Ernsurp (Decile10)	478	0.008	0.006	0.005	0.003	0.019

Panel B: Multivariate analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔCoE	*ΔCoE*	*ΔCoE*	*ΔCoE*	*ΔCoE*	*ΔCoE*
Ernsurp	-0.847	1.037		-0.848	0.828	
	(-0.53)	(0.70)		(-0.49)	(0.52)	
Ernsurp_Squared		137.590***			133.523***	
		(3.18)			(2.84)	
*Ernsurp_Decile1*Ernsurp*			-7.008**			-6.478**
			(-2.63)			(-2.38)
*Ernsurp_Decile2*Ernsurp*			9.577			8.894
			(0.20)			(0.19)
*Ernsurp_Decile3*Ernsurp*			18.620			2.151
			(0.13)			(0.02)
*Ernsurp_Decile4*Ernsurp*			12.726			42.395
			(0.05)			(0.18)
*Ernsurp_Decile5*Ernsurp*			-488.868*			-499.239*
			(-1.74)			(-1.83)
*Ernsurp_Decile6*Ernsurp*			190.160			210.129
			(0.91)			(1.15)
*Ernsurp_Decile7*Ernsurp*			134.465			142.147
			(1.16)			(1.15)
*Ernsurp_Decile8*Ernsurp*			10.614			-2.587
			(0.16)			(-0.04)
*Ernsurp_Decile9*Ernsurp*			13.575			13.460
			(0.41)			(0.40)
*Ernsurp_Decile10*Ernsurp*			12.260**			11.891**
			(2.27)			(2.20)
BETA				0.024**	0.019*	0.022**
				(2.51)	(1.97)	(2.08)
BTM				-0.000	-0.000	-0.000
				(-0.04)	(-0.36)	(-0.08)
MCAP				0.004	0.006	0.004
				(0.75)	(1.24)	(0.78)
PROFITABILITY				0.000***	0.000***	0.000***
				(2.90)	(3.10)	(3.04)
INVESTMENTS				-0.000	-0.000	-0.000
				(-1.23)	(-1.08)	(-1.11)
LEV				0.001	0.000	0.000
				(1.49)	(0.98)	(1.47)
IDIO_VOL				-0.008	-0.010	-0.009
				(-1.27)	(-1.48)	(-1.31)
MOMENTUM				-0.000	-0.000	-0.000
				(-1.04)	(-1.01)	(-1.04)
LAG_RETURN				-0.001	-0.001*	-0.001*
				(-1.66)	(-1.82)	(-1.87)
LIQUIDITY				-0.008	-0.003	-0.004
				(-0.68)	(-0.27)	(-0.34)
Observations	4,783	4,783	4,783	4,708	4,708	4,708
R-squared	0.081	0.085	0.089	0.086	0.090	0.093

ONLINE APPENDIX

for "Analysts' Estimates of the Cost of Equity Capital"

1. DATA AND SAMPLE

1.1 CoE Data Extraction

Extracting the CoE measure from unstructured analyst reports is challenging. First, these reports are in PDF format and do not have a uniform structure. The CoE measure is not provided in the same location in every report. In fact, a report may not even contain a CoE measure despite being identified in our initial search, as an analyst may mention "cost of equity" as 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. Across a variety of reports, we examine the patterns that analysts 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 CoE 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. We also remove CoE values that are below 1% and above 60%. Through this process, we extract CoE figures from 34,644 analyst reports. The missed reports either do not provide CoE in one of the identified patterns or do not provide a numerical estimate of CoE.

We merge the extracted analyst CoE estimates with daily *CRSP* data using the ticker information provided in the analyst reports. Although this task is more straightforward than the extraction of CoE estimates because tickers appear at the top of every report, there is still variation across reports as to where and how the ticker information is presented. For example, analysts may provide either the exchange ticker or the Bloomberg ticker. We thus lose 3,595 firm-year observations in this matching process.

1.2 Matching CoE estimates with IBES data

We match our sample of CoE estimates with the IBES unadjusted details file as follows. The IBES sample is restricted to observations that have an available EPS forecast for either the year ahead or at least one of the next four quarters ahead.[47] The matching process is not straightforward, as the two databases use entirely different methods to gather analyst outputs. We choose to match the databases at the firm-brokerage-quarter level, as imposing additional requirements, such as matching analyst names or report dates, causes a substantial loss of observations.[48] Our matching approach effectively assumes that in each brokerage firm, the same analyst covers a given firm throughout a given quarter. Although we believe this is a reasonable assumption based on our own understanding of how brokerages assign analysts to cover firms, we also empirically verify this assumption in the IBES database. We find that this assumption holds in nearly 90% of the IBES firm-quarters. After this matching procedure, we end up with 22,295 observations (out of our original sample of 31,049 observations).

[47] We require forecasts to have forecast period indicator (FPI) to be equal to 1, 6,7, 8,or 9.

[48] IBES and Thomson Reuters gather different outputs (PDF reports versus numeric values entered into the IBES system) and these appear to occur at different points in time, causing differences across the databases in EPS values, reporting dates, etc. Even matching the two databases by brokerage firms is not straightforward, as the PDF reports from Thomson Reuters disclose the name of the brokerage firm issuing the report, while IBES only provides a proprietary broker ID in a numerical format. Therefore, to merge by brokerage firm, we first create a broker name-broker ID mapping file using a triangulation approach. Specifically, from one randomly selected PDF report for each brokerage firm, we manually take the ticker, date and EPS value as the three triangulation points and require at least two of these to match with a data point in IBES. This provides us with an initial list of potential broker name-broker ID mappings. We then confirm these mappings by validating them in at least 10 other randomly selected PDF reports. That is, for the selected ten reports from Thomson Reuters, we confirm that at least two of the three triangulation points match with the data in IBES.

2. ROBUSTNESS CHECKS

Table 4: Relation between CoE and firm-characteristics

In this section, we ascertain the robustness of the relations documented in Table 4 of the paper between CoE estimates and firm-characteristics to two changes. First, we consider the robustness of our findings to the inclusion of analyst fixed effects. Our findings (reported in the main text) are based on brokerage fixed effects because of the high accuracy with which we can match databases based on brokerage identifier as against analyst identifier. Still, to alleviate any concerns that our results are driven by unobserved heterogeneity among analysts, we also consider analyst fixed effects. The match between Thomson Reuters and IBES based on analyst names is not feasible because IBES does not disclose analysts' full names. Therefore, to identify in IBES the analysts providing the report, we assume that a unique one-to-one mapping exists between analysts and brokerage firms in any given quarter and then obtain the analyst identifier from IBES that is associated with the brokerage firm providing the report.[49] Findings presented in Column (1) of Table A4 indicate that our findings from Table 4 of the manuscript continue to hold. The only difference is that the coefficient on idiosyncratic volatility is no longer significant.

Secondly, given that reports from Morningstar constitute a large fraction of the sample, we also check for the robustness of the findings documented in Table 4 to the exclusion of this sample. Results presented in Column (2) of Table A4 confirms the earlier findings.

[49] We validate this assumption by generating descriptive statistics on number of analysts who issue reports for a brokerage in a quarter.

TABLE A4: ANALYST'S COST OF EQUITY ESTIMATE AND FIRM CHARACTERISTICS

This table reports results for robustness tests of the full specification model (reported in Column (3) of Table 4 of the paper) and results from subsample analyses of the full specification model. In Column (1), we replace brokerage fixed effects with analyst fixed effects, where analyst data are from IBES. Column (2) present results for the sample of non-Morningstar estimates separately.

		(1) *Analyst fixed effects*	(2) *Sample excluding Morningstar*
	PREDICTED	*CoE*	*CoE*
BETA	+	0.293***	0.404***
		(3.43)	(3.69)
BTM	+	0.008**	0.011**
		(2.68)	(2.14)
MCAP	-	-0.085**	-0.102***
		(-2.54)	(-4.47)
PROFITABILITY	+	-0.001	-0.001
		(-0.29)	(-0.71)
INVESTMENTS	-	-0.001	-0.001
		(-0.71)	(-0.66)
LEV	+	0.013**	0.015**
		(2.42)	(2.38)
IDIO_VOL	+	-0.010	0.012
		(-0.65)	(0.66)
MOMENTUM	+	-0.001	-0.000
		(-1.52)	(-0.63)
LAG_RETURN	-	-0.002	-0.003*
		(-0.91)	(-1.84)
LIQUIDITY	-	-0.053	-0.031
		(-0.77)	(-0.50)
Observations		21,272	16,676
R-squared		0.776	0.689