Market inefficiency and implied cost of capital models

Tjomme O. Rusticus
Kellogg School of Management
Northwestern University
2001 Sheridan Road, suite 6229
Evanston, IL 60208
t-rusticus@northwestern.edu

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ABSTRACT

In this paper, I examine the impact of market inefficiency on the properties of implied cost of capital (ICC) estimates. I show that market inefficiency will bias the relation between the ICC estimate and the future returns upwards. Using recently developed ICC estimates based on regression generated earnings forecasts, I show that, on average, between 35% and 61% of the relation between ICC estimates and one-year-ahead stock returns stems from mispricing rather than expected returns. The biases induced by mispricing are most severe for firms with significant limits to arbitrage, and less severe for firms that are larger, more liquid, and have lower transaction costs, and for ICC estimates based on adjusted analyst forecasts. In addition I find that controlling for earnings and discount rate news is not an effective control for mispricing, but that controlling for earnings announcement news is.

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1. Introduction

Cost of capital is an important concept in finance and accounting research. The literature has long recognized that realized returns offer a noisy proxy of the cost of equity capital (e.g. Elton, 1999). An alternative approach is provided by implied cost of capital (ICC) models, which derive the cost of capital as the internal rate of return that equates the market value of equity and forecasts of future earnings. These models potentially offer a promising alternative for estimating cost of capital, even if the estimates also contain measurement error. They have been widely used in accounting research to examine the impact of the quality of a firm's accounting and voluntary disclosures on its cost of capital, and are increasingly appearing in the finance literature.

Given their reliance on market prices, ICC estimates are potentially affected by mispricing. The purpose of my study is to examine the effect of mispricing on the properties of ICC estimates and the relation between ICC estimates and future returns. As discussed in Lewellen (2010), departing from market efficiency creates some ambiguity about what the implied cost of capital is supposed to measure. It could either be the discount rate, *r*, that investors use to price the stock, or the true expected return embedded in the market price as would be observed by a rational outsider. Throughout the paper, I assume that the researcher's objective is to recover the investors' discount rate. This is motivated by how the implied cost estimates are used in the literature, namely tests of proposed risk factors.[1]

[1] Examples from the accounting literature include the cost of capital effects of annual report disclosures (Botosan, 1997), AIMR rankings of firm disclosures (Botosan and Plumlee, 2002), various dimensions of earnings quality (Francis, LaFond, Olsson, and Schipper, 2004), accounting restatements (Hribar and Jenkins, 2004), voluntary disclosure and earnings quality (Francis, Nanda, and Olsson, 2008), cross-listing (Hail and Leuz, 2009), and voluntary disclosures of corporate social responsibility reporting (Dhaliwal, Li, Tsang, and Yang, 2011). Examples from the finance literature include tests of the market risk premium (Claus and Thomas, 2001), tests of the Intertemporal CAPM (Pastor, Sinha, and Swaminathan, 2008), tests of international asset pricing models (Lee, Ng, and Swaminathan, 2009), and the pricing of default risk (Chava and Purnanadam, 2010).

The effect of market inefficiency on the relation between ICC and future returns is important because this relation serves as one of the main ways of testing the quality of ICC models (e.g., Guay, Kothari, and Shu, 2011; Easton and Monahan, 2005). Other approaches in the literature include tests of the association between ICC estimates and a series of proposed risk factors based on prior research (e.g. Gebhardt, Lee, and Swaminathan, 2001; Botosan and Plumlee, 2005) and explicit modeling of the measurement error in the ICC proxies (Easton and Monahan, 2005). Which of these approaches is best is the subject of ongoing debate (e.g., Botosan, Plumlee, and Wen, 2010; Easton and Monahan, 2010). Many recent papers combine tests on the relation with future returns with other approaches for evaluating the quality of ICC estimates (e.g., Gode and Mohanram, 2003; Botosan, Plumlee, and Wen, 2010; Hou, Van Dijk, and Zhang, 2012; and Lee, So, and Wang, 2010).

In evaluating the quality of ICC estimates, the prior literature focuses on measurement error in the estimates induced by the researcher's need to choose a valuation approach and earnings forecasts that may not closely correspond to how investors price the stock. The resulting ICC estimate is often characterized as the true discount rate plus an uncorrelated measurement error, similar to the "classic measurement error" in econometrics. When combined with the notion that realized returns are equal to expected returns plus the effect of news, a natural way to evaluate ICC estimates is to regress future returns on the implied cost of capital estimates. While realized returns should, on average, move one-for-one with the true expected returns, measurement error in the ICC estimates will lead to attenuation bias, biasing the coefficient away from one towards zero. The quality of the ICC estimates is then captured by the coefficient on the ICC estimate; higher quality estimates have higher coefficients.

When adding market inefficiencies to this framework, I show that under reasonable assumptions, market inefficiencies affect ICC estimates in the same direction as realized returns. For example, overvalued firms will have both a lower ICC and, once the mispricing reverses, lower future returns. This outcome results in a positive relation between ICC estimates and future returns and an upward-biased ICC coefficient in a regression of future returns on ICC estimates. This is problematic because it reverses the quality ordering of regression coefficients; stocks more affected by mispricing will have higher coefficients, but now this will be indicative of lower rather than higher quality.

The magnitude of the mispricing bias in ICC estimates depends not only on the amount on mispricing in the stock, but also on the extent to which the researcher's earning forecasts and valuation models are able to correct for these errors. In particular, if the researcher's forecasts suffer from similar errors as the investors, the effect of mispricing on the ICC estimates is mitigated. This leads to the following conundrum: as researchers continue to improve the quality of their earnings forecasts and valuation models to reduce the measurement error problem, they will likely exacerbate the problems introduced by market inefficiencies. Given that ICC estimates vary in their ability to capture mispricing, this has serious implications for the selection of ICC estimates for research and practical purposes.[2]

In the empirical part of the paper, I examine the relative importance of mispricing for the relation between ICC estimates and future returns. A difficulty in quantifying this effect is that a positive relation between ICC estimates and future returns is expected under both market efficiency and market inefficiency. To separate mispricing from expected returns as an

[2] In my analysis, I focus on the impact of potential market inefficiencies on the relation between ICC estimates and future returns. However, my analysis also has implications for tests on the relation between ICC and "known risk factors", given that many of the risk proxies are drawn from prior literature based on their ability to predict future returns.

explanation for the relation between ICC estimates and future returns I examine the relation between ICC estimates and the returns around earnings announcements. This is a commonly used method to separate risk and mispricing explanations for seemingly anomalous stock returns (e.g., Bernard and Thomas (1990), Bernard, Thomas, and Wahlen (1997)). If the relation between ICC estimates and future returns is due to mispricing, then one would expect part of this mispricing to be corrected once the earnings are released. In my empirical tests, I use the regression based approach in Hou, Van Dijk, and Zhang (2012) and Lee, So, and Wang (2010) to forecast earnings and calculate ICC estimates. Consistent with these papers, I find that ICC estimates are related to stock returns in the year following the determination of the ICC estimates. Based on the four ICC models I examine, earnings announcement returns account for 18% to 57% of the total annual returns on a hedge portfolio based on the extreme deciles of ICC estimates. This suggests that the impact of mispricing is economically important.

Another approach is to partition the sample into subsamples according to whether market inefficiency is more or less likely ex-ante, and then to compare the strength of the relation between ICC estimates and future returns. The relation should be stronger in subsamples with greater market inefficiency. Using several of the measures suggested by the limits-to-arbitrage literature (firm size, share liquidity, and transaction costs), I examine whether hedge portfolio returns are higher in subsamples with greater mispricing. For annual returns, 10 out of 12 tests go in the predicted direction, while 12 out of 12 tests go in the predicted direction for earnings announcement returns. However, the results are only statistically significant for the earnings announcement tests.

My final approach is based on asset pricing tests using the Fama-French three factor model (Fama and French, 1993) and the Carhart four factor model (Carhart, 1997). Unlike prior studies that investigate whether there is a predictable relation between ICC estimates and risk factors, I examine the fraction of hedge portfolio returns that can be explained by the factor model. Under this approach returns that are not explained by the risk factors are assumed to be the result of mispricing. This provides an upper bound to the magnitude of the mispricing, because unmodeled risk factors could also provide an explanation. Based on the four models I examine, the fraction of the predicted return left unexplained by the three factors is between 24% and 81% of the average monthly hedge portfolio returns.

In subsequent analyses I find that the earnings announcement returns are much reduced when using ICC estimates based on adjusted analyst forecasts consistent with these estimates being less affected by mispricing. In addition I examine whether controlling for earnings and discount rate news is an effective control for mispricing. I find that it does not, and that in addition, controlling for noisy proxies can introduce biases rather than correct for them. I propose a new way of controlling for earnings surprises that uses earnings announcement news and find that it does provide an effective (partial) control against mispricing.

My analysis in this paper contributes to the literature on implied cost of capital estimates by demonstrating the directional effects and the importance of biases introduced by mispricing. My findings should be of use to researchers interested in evaluating alternative cost of capital estimates or applying ICC estimates in tests of proposed risk factors. From a portfolio selection perspective, my analyses should be helpful in determining the extent to which ICC estimates can be used to earn abnormal returns.

The remainder of this paper is organized as follows. In the next section, I discuss the model and the predictions regarding the relation between ICC estimates and future returns. Then in section 3, I discuss the data and the calculation of the four implied cost of capital models. In section 4, I discuss the research design and the results. Section 5 contains several additional analyses, and I conclude in section 6.

2. Background and motivation

Implied cost of capital (ICC) models use observed stock prices to estimate the cost of capital. This stock price can be defined as the sum of its fundamental value and any mispricing. Standard valuation theory suggests that the fundamental value is equal to the present value of expected future dividends. Thus the (ex-dividend) price of a stock can be expressed as follows:

$$P_t = FV_t + MP_t = \sum_{t=1}^{\infty} \frac{E_t[D_{t+\tau} \mid \Omega_t]}{(1+r)^{\tau}} + MP_t,$$

where FV is the fundamental value, MP is the mispricing, D_t is the dividend at time t, E_t is the time t rational expectation given the information set, Ω, and r is the discount rate. In line with the implied cost of capital literature (e.g. Easton and Monahan, 2005) I assume a constant discount rate.[3]

Researchers use observable market prices, P_t, and try to infer the discount rate, r. The ICC is estimated as the internal rate of return that equates the market prices to the present value of the researcher specified dividend forecasts, that is:

$$ICC_t = IRR[P_t; E_t[D_{t+1} \mid \Omega_t] + u_{t+1}; E_t[D_{t+2} \mid \Omega_t] + u_{t+2};....],$$

where ICC is the implied cost of capital estimate, IRR is the internal rate of return operator, and u_t is the researcher's estimation bias for dividends at time t, i.e., the difference between the researcher's estimate of future dividends and the rational expectation of future dividends given the information set, Ω. Note that researcher's typically forecast (abnormal) earnings, not

[3] See Hughes, Liu, and Liu (2009) for a discussion of the biases introduced in the ICC estimates when the actual discount rate is stochastic.

dividends. However, these are used in a residual income based valuation model. Since the residual income is a reformulation of the dividend discount model, my representation is without loss of generality (e.g. Lundholm and O'Keefe, 2001).

Given that the ICC estimate uses the market price, it is potentially affected by any mispricing. For a given set of researcher based forecasts, the more the stock is overvalued (undervalued), the lower (higher) the ICC estimate. A complicating factor is that the errors in the researcher's earnings forecasts are potentially correlated with the mispricing. There are two sources of error in the researcher's implied dividend estimates: i) the initial explicit analyst or regression based earnings forecasts may contain predictable biases, or, ii) the model used to forecast beyond the initial period may be incorrect. Thus, potential sources of correlation include if researchers and investors both rely on the same flawed analyst forecasts or use the same valuation heuristics. This mitigates the effect of mispricing on the ICC estimate.[4]

Eventually the mispricing reverses and affects future stock returns, leading to lower (higher) returns for overvalued (undervalued) stock. This induces a positive relation between ICC estimates and future stock returns, since mispricing affects the ICC estimates in the same direction. In particular, in a regression of future returns on ICC estimates, the presence of mispricing will bias the coefficient upwards. Ironically this occurs because the impact of mispricing on the ICC estimate is smaller than the impact on realized returns. The reason is that, because of the constant discount rate assumption, the ICC models average the effect of mispricing over the entire horizon of the firm, whereas the mispricing generally reverses in a much shorter period. This upward bias of pricing errors contrasts with the downward bias that is induced by estimation error in the researcher's forecasts and models. In the Appendix I formalize

[4] In extreme cases it is even possible that the researcher's estimates incorporate the mispricing to such a degree that the relation between mispricing and ICC estimates reverses. This is less likely with more sophisticated forecasting models. The model in the Appendix formulizes the exact conditions under which this occurs.

these intuitions and show the exact bias in a simplified model. Again these biases will be mitigated by any correlation between the errors in the researcher's earnings forecasts and the mispricing.

A difficulty in empirically quantifying the overall effect of is that a positive relation between ICC estimates and future returns is expected under both market efficiency and market inefficiency. While the model clearly indicates that market inefficiency will bias the coefficient upwards, the magnitude of this bias depends on unobservable parameters. I use several empirical approaches to separate mispricing from expected returns as an explanation for the relation between ICC estimates and future returns.

My first approach involves an examination of returns around earnings announcements. This is a commonly used method to separate risk and mispricing explanations for seemingly anomalous stock returns (e.g., Bernard and Thomas (1990), Bernard, Thomas, and Wahlen (1997)). If the relation between ICC estimates and future returns is due to mispricing, then one would expect part of this mispricing to be corrected once the earnings are released. As a result, the returns on the ICC hedge portfolio should be concentrated around the earnings announcement. For example, assume investors overvalue a particular stock because they overestimate its future earnings. The higher market value will result in a lower ICC estimate, and once the earnings are announced the stock price will drop. As a result, the direction of the earnings announcement returns is predictable ex-ante based on the ICC estimate. In contrast, if the relation between ICC estimates and future returns is the result of differences in expected returns, no difference between earnings announcement periods and other trading days would be expected. My empirical approach is then to compare the earnings announcement returns of an ICC-based hedge portfolio to the returns over the full year. Since earnings announcements are only one potential trigger for mispricing reversals, this approach provides a lower bound to the impact of mispricing.

My second approach is to partition the sample into subsamples based on whether market inefficiency is more or less likely ex-ante, and then to compare the strength of the relation between ICC estimates and future returns. The relation should be stronger in subsamples with greater market inefficiency. Using several measures suggested by the limits–to-arbitrage literature (firm size, share liquidity, and transaction costs), I examine whether hedge portfolio returns are higher in subsamples with greater mispricing. A potential complication is that the firms with the greatest limits to arbitrage may also have the largest errors in the forecasts, which would work against the effect of mispricing. Therefore I also examine the earnings announcement returns in these subsamples. Even if the subsamples differ in the degree of researcher estimation error, the ratio of earnings announcement returns to annual returns should be higher for firms with greater limits-to-arbitrage.

My final approach is based on asset pricing tests using the Fama-French three factor model (Fama and French, 1993) and the Carhart four factor model (Carhart, 1997). Unlike prior studies, which investigate whether a predictable relation between ICC estimates and risk factors exists, I examine the fraction of hedge portfolio returns that cannot be explained by the factor model. Under this approach, returns that are not explained by the risk factors are assumed to be the result of mispricing. This provides an upper bound on the magnitude of the mispricing, because unmodeled risk factors could also provide an explanation. In fact, the search for such new risk factors is one of the motivations for the development of implied cost of capital models (e.g., Botosan, 1997). The next section describes the data and measurement of the different ICC models.

3. Data and measurement

The sample consists of firms listed on the NYSE, Amex and Nasdaq with sharecodes 10 or 11 for the period from 1971 to 2009 with sufficient data on CRSP and Compustat to calculate the implied cost of capital estimates. In calculating the ICC measures, I follow the earnings estimation approach in Hou, Van Dijk, and Zhang (2012) and Lee, So, and Wang (2010). Rather than using analysts' forecasts of earnings, this approach is based on a pooled cross-sectional earnings forecasting model for years t+1 through t+5. The following model is estimated for each year, using the past 10 years of data (minimum of 6 years):

$$E_{j,t+\tau} = \beta_0 + \beta_1 EV_{j,t} + \beta_2 TA_{j,t} + \beta_3 DIV_{j,t} + \beta_4 DD_{j,t} + \beta_5 E_{j,t} + \beta_6 NEGE_{j,t} + \beta_7 ACCT_{j,t} + \varepsilon_{j,t+\tau},$$

where $E_{j,t+\tau}$ (τ = 1, 2, 3, 4, or 5) denotes the earnings before extraordinary items (Compustat Item IB) of firm j in year t+ τ, and all explanatory variables are measured at the end of year t: $EV_{j,t}$ is the enterprise value of the firm (defined as total assets (Compustat Item AT) plus the market value of common equity (Compustat Item PRCC_F times Compustat Item CSHO) minus the book value of common equity (Compustat Item CEQ)), $TA_{j,t}$ is the total assets (Compustat Item AT), $DIV_{j,t}$ is the dividend to common shareholders (Compustat Item DVC), $DD_{j,t}$ is a dummy variable that equals 0 if $\text{DIV}_{j,t}$ is positive and 1 otherwise, $NEGE_{j,t}$ is a dummy variable that equals 1 for firms with negative earnings before extraordinary items (Compustat Item IB) and 0 otherwise, and $ACC_{j,t}$ is total accruals. Total accruals are calculated as the change in current assets (Compustat Item ACT) plus the change in debt in current liabilities (Compustat Item DLC) minus the change in cash and short term investments (Compustat Item CHE) and in current liabilities (Compustat Item LCT). Each variable in the regression is winsorized at the 0.5 and 99.5 percentiles for that year to mitigate the effect of extreme observations.

The average annual coefficients and Fama-Macbeth t-statistics[5] from these regressions are displayed in Table I. Overall, the coefficient estimates are relatively similar to Hou, Van Dijk, and Zhang (2012) and Lee, So, and Wang (2010). Each year, the firm's next year's earnings are estimated using the most recent historical coefficient estimates applied to the most recent reported earnings and to other explanatory variables. These are then used to predict future book values by means of the beginning book values and the clean surplus assumption. The earnings and book values, combined with the market value of the equity, are then used to generate each of the ICC estimates. To allow for sufficient time for financial statements to be reported to the market, I measure the market value of equity four months after the fiscal year end.[6] I exclude the Fama-French (1997) banking industry due to a lack of available data for the accrual measures.

Lee, So, and Wang (2010) evaluate seven models of implied cost of capital, four of which reliably predict future stock returns in the year following the portfolio formation (labeled GLS, EPR, GGM, and AGR). In this paper, I focus on these four models. Given that the purpose of my analysis is to quantify the relative importance of market inefficiency and expected returns in the relation between ICC and future returns, it seems sensible to concentrate on measures that have a proven ability to predict future stock returns. I discuss each of these four models in more detail below.

The first model (GLS) is based on Gebhardt, Lee and Swaminathan (2001). This model is based on the residual income framework and uses explicit forecasts of earnings for the first three

[5] Note that these t-statistics are likely overstated due to the use of overlapping windows and a serially correlated dependent variable. This does not pose any problems since only the coefficients are used in computing the ICC estimates; this presentation facilitates comparison with prior research, which also uses Fama-MacBeth t-statistics.
[6] Lee, So, and Wang (2010) use the June 30th market values regardless of when the fiscal year end occurs. The approach I use is more standard in the market efficiency literature as it more closely matches the timing of earnings releases and the measurement of the market values. My results are very similar when using this alternative approach.

years followed by a nine year period in which the return on equity (ROE) linearly reverts to the industry median ROE (based on the 49 Fama-French (1997) industries). The industry median ROE is calculated using the past ten years of data (minimum of five years). The terminal value is computed as the present value of the capitalized period 12 residual income.

$$MVE_{i,t} = B_{i,t} + \sum_{\tau=1}^{11} \frac{E_t[ROE_{i,t+\tau} - r_i) \cdot B_{i,t+\tau-1}}{(1+r_i)^{\tau}} + \frac{E_t[(ROE_{i,t+12} - r_i) \cdot B_{i,t+11}}{r_i \cdot (1+r_i)^{11}},$$

where $MVE_{i,t}$ is the market value of equity of firm i at time t, B is the book value of equity, ROE is the return on equity, and r_i is the internal rate of return that solves the equation.

The next two models (EPR and GGM) are based on the Gordon Growth Model. The models are based on the dividend discount models with explicit dividend forecasts for the first few years, followed by discounted earnings in perpetuity thereafter (implicitly assuming a 100% pay-out ratio in those later years). Growth in earnings and dividends is only assumed in the explicit forecasting period.

$$MVE_{i,t} = \sum_{\tau=1}^{T-1} \frac{D_{i,t+\tau}}{(1+r_i)^{\tau}} + \frac{E_{i,t+T}}{r_i \cdot (1+r_i)^{T-1}}$$

Similar to Lee, So, and Wang (2010), I consider two different forecast horizons, T=1 and T=5. The first simplifies to the forward earnings to price ratio using the forecasted earnings for the next period (labeled EPR). The second version of the model uses the explicit earnings forecast for Period 5 for the computation of the terminal value and the forecasted earnings times the historical dividend pay-out ratio to get the dividend forecasts (labeled GGM).

The final ICC model (labeled AGR) is based on an abnormal earnings capitalization model proposed by Easton (2004). The specific version considered here contains explicit forecasts of earnings for the first two years and a perpetual growth rate in abnormal earnings thereafter derived from the forecasted implicit growth rate in Year 3. The exact formula is as follows (expressed in per share amounts):

$$P_{i,t} = \frac{EPS_{i,t+1}}{r_i} + \frac{EPS_{i,t+2} + r_i \cdot DPS_{i,t+1} - (1+r_i) \cdot EPS_{i,t+1}}{r_i \cdot \left(r_i - \dfrac{EPS_{i,t+3} + r_i \cdot DPS_{i,t+2} - (1+r_i) \cdot EPS_{i,t+2}}{EPS_{i,t+2} + r_i \cdot DPS_{i,t+1} - (1+r_i) \cdot EPS_{i,t+1}} + 1 \right)}.$$

As can be seen above, the AGR model is essentially the EPR model plus a term that corrects for growth in abnormal earnings. Consistent with Lee, So, and Wang (2010), I truncate each ICC estimate at 0% and 100% to mitigate the effect of extreme observations.

The descriptive statistics for the four ICC measures and the one-year-ahead realized stock returns are displayed in Table II, Panel A. The realized returns are the compounded monthly raw stock returns in the 12 months following the portfolio formation date (including delisting returns, in following the approach in Beaver, McNichols, and Price, 2007). Comparing the ICC estimates to the realized returns, it is clear that while the mean estimates are reasonably similar, the variance of realized returns is much higher. Amongst the ICC estimates, EPR has the lowest average, which is to be expected, as this method ignores any growth in earnings after the first year. The correlation table in Panel B shows that all four ICC estimates are positively correlated with future returns and strongly positively correlated with each other.

The high standard deviation of realized returns relative to reasonable estimates of the variation in expected returns suggests that individual firms' stock returns are mostly driven by news and are thus a very noisy proxy of expected returns. As can be seen from Panel A, while the average individual firm return is about 14.6%, the returns are right-skewed with the median return (3.8%) less than the average risk free rate for the period (6.3%), and a standard deviation of about 80%. When realized returns are the dependent variable in a regression on ICC estimates, the cash flow news and discount rate news should average out. However, given that returns are correlated in the cross-section due to common economic shocks and that the time-series of data is relatively limited, it becomes an empirical question as to whether there is sufficient data to achieve this outcome. To provide initial evidence on the speed of convergence, I examine the effect of averaging across firms and time on the distribution of returns. To provide a benchmark, I consider the distribution of the market risk premium rather than the market return. A minimum test of the efficacy of averaging should be whether it results in a reliably positive market risk premium.

The effect of cross-sectional averaging can be seen from the first row in Panel C, which contains the realized risk premium for the equal-weighted market portfolio. This is calculated as the difference between the realized return on the market (CRSP EWRETD) and the one-year treasury rate over the same 38 annual returns periods, starting from July 1, 1972 through June 30, 2010; the same time period as the analysis in later tables. While cross-sectional averaging reduces the standard deviation by about two-thirds (from slightly over 80% to slightly over 24%), a significant fraction of years nevertheless experiences a negative realized risk premium. Thus even though CRSP covers several thousand firms per year, the correlation among their returns is such that the news does not average out.

I next consider the effect of averaging over consecutive 5 year periods; my sample period contains 34 overlapping 5 year periods. This results in an additional drop in the standard deviation of returns, although still more than 5% of the 5 year periods experience a negative realized risk premium. Extending the averaging period to 10 or 20 years further reduces the standard deviation and results in a less than 5% chance of experiencing a negative realized risk premium. Thus, while not perfect, these results suggest that over a sufficiently long period, the averaging of returns is reasonably effective in diversifying the impact of cash flow and discount rate news.

4. Research design and results

The model in section 2 suggests that mispricing will lead to a positive correlation between ICC estimates and future stock returns. This is also the expected relation in the absence of mispricing when the ICC estimates correctly predict the expected return component of future stock returns. Therefore, a regression of future returns on the ICC estimates does not provide a clear separation between these two hypotheses. My first approach, discussed in section 4.1, is to examine the relation between ICC estimates and the returns around earnings announcements. My second approach, discussed in section 4.2, relies on asset pricing tests using the Fama-French three factor model (Fama and French, 1993) and the Carhart four factor model (Carhart, 1997).

4.1 Examination of earnings announcement returns

First, I examine the explanatory power of the ICC estimates for future returns at the annual level. As discussed in Section 3, each year I calculate each firm's ICC using forecasts of future earnings and the market price four months after the fiscal year end data. I then assign firms to decile portfolios based on the distribution of the ICC estimates in the prior year, with Decile 1 containing the firms with the lowest ICC. The use of the prior year's ICC distribution avoids a look-ahead bias when determining the relative magnitude of the ICC estimates (Foster, Olsen, and Shevlin, 1984). In case a firm delists during the year, the returns include delisting returns following the procedure in Beaver, McNichols, and Price (2007). Any delisting proceeds are then invested in the market portfolio. Table III reports the average annual decile returns and hedge portfolio returns for each of the four ICC estimates. The table reports the equal weighted returns (minus the equal weighted market returns) for each decile and the returns of a hedge portfolio that is long in Decile 10 (highest ICC) and short in Decile 1 (lowest ICC). The results confirm findings in Lee, So, and Wang (2010), that each of these four ICC estimates predicts future stock returns.

To determine the impact of mispricing on the returns in Table III, I next examine the returns around the earnings announcement in the year following the portfolio formation. Annual earnings announcement returns are created by compounding the returns for the twelve days around earnings announcements (three-day windows around each of the four quarterly earnings announcements) and subtracting the market return over the corresponding days. Panel A of Table IV reports the average annual earnings announcement returns by decile. The hedge portfolio results indicate statistically significant and economically important differences between Decile 1 and Decile 10, suggesting that mispricing explains part of the relation between ICC estimates and future stock returns.

In Panel B, I compare the earnings announcement returns to the annual returns. The earnings announcement returns explain between 18% (EPR) and 57% (GGM) of the market adjusted buy-and-hold returns from Table III (median 38%). This suggests that mispricing has a large impact on the overall relation between ICC estimates and future stock returns. These findings are also consistent with prior literature that has found that various fundamentals-to-price trading strategies, which are related to ICC trading strategies, yield a disproportionate share of the returns around earnings announcements (e.g., La Porta, Lakonishok, Shleifer, and Vishny, 1997; Ali, Hwang, and Trombley, 2003).

There are two potential concerns with this test. First, given that the hedge portfolio returns occur throughout the year, one would expect some of them to appear around earnings announcements even if they are risk premiums instead of mispricing. To correct for this, I subtract the following adjustment factor from the abnormal returns at the earnings announcements:

$$Adjustment = \left(\frac{1+BHret}{1+EAret}\right)^{\frac{12}{252-12}} - 1.$$

The results following this adjustment are largely unchanged from those of the analysis above, the fraction of corrected earnings announcement returns to the full year buy-and-hold returns now ranges from 14% (EPR) to 55% (GGM) of the market adjusted buy-and-hold returns.

A second and related concern is that one might expect to see a higher than average risk premium on earnings announcement days given the greater information flows and risk on those days. Thus, merely controlling for the number of days in this period may be insufficient. One indication for this is that the earnings announcement returns are positive on average, even though they have been market adjusted. These positive abnormal returns are consistent with prior literature that documents positive abnormal returns around earnings announcements (e.g., Ball and Kothari, 1991; Chambers, Jennings and Thompson, 2004; Cohen, Dey, Lys, and Sunder, 2007). This prior literature argues that positive returns occur because of non-diversifiable risk associated with earnings announcements, for which investors require a premium. Cohen et al. (2007) find a three-day average excess return of 0.15% for a large sample of earnings announcements from 1978 to 2001.

While, a priori, it is not clear that the risk introduced by earnings announcements is non-diversifiable, I try to rule this out as an alternative explanation of the results. I assume that the proportion of expected returns in the earnings announcement day period is proportional to the volatility in the earnings announcement period. This is a conservative approach, given that news is mostly firm-specific and thus more likely to be diversifiable than news on an "average" trading day. Prior research finds that about 11% of the annual volatility occurs in the 12 day window around the four quarterly earnings announcements, more than double the expected volatility given the number of days that fall in that window (Basu, Duong, Markov, and Tan, 2010). I confirm that this fraction is similar for my sample, and in particular, holds for the extreme deciles. When using this share of the annual volatility to compute the adjustment factor, the calculation is as follows:

$$Adjustment = \left(\frac{1+BHret}{1+EAret}\right)^{\frac{0.11}{1-0.11}} - 1.$$

Using this adjustment factor, the fraction of corrected earnings announcement returns to the full year buy-and-hold returns ranges from 8% (EPR) to 52% (GGM) of the market adjusted buy-and-hold returns.

Another way to examine the effect of mispricing is to partition the sample into subsamples based on whether market inefficiency is more or less likely ex-ante, and then to compare the strength of the relation between ICC estimates and future returns. The relation should be stronger in subsamples with greater market inefficiency. Using several measures suggested by the limits–to-arbitrage literature (firm size, share liquidity, and transaction costs), I examine whether hedge portfolio returns are higher in subsamples with greater mispricing. The first limits-to-arbitrage measure is the market value of equity; smaller firms are expected to be more subject to mispricing. The second measure is the Amihud (2002) illiquidity measure (calculated as the ratio of absolute daily returns to dollar trading volume), a measure of the price impact of trades. The final measure is the LDV transaction cost measure, obtained from a structural model of trading frictions developed by Lesmond, Ogden, and Trzcinka (1999). Prior research in accounting has found each of these measures to be related to variation in mispricing due to post-earnings-announcement drift (Bernard and Thomas, 1990; Chordia, Goyal, Sadka, Sadka, and Shivakumar, 2009; and Ng, Rusticus, and Verdi, 2008, respectively).

Each year the sample is divided at the median of each variable and firms are assigned to ICC deciles within each subsample. As before, each year returns and earnings announcement returns are averaged within decile. The time series average hedge portfolio returns and the Fama-MacBeth t-statistics are shown in Table V. I test whether the hedge portfolio returns are larger in the samples where mispricing is more likely. For each measure, the subsample most susceptible to mispricing is listed first. I then subtract the hedge portfolio return of the second subsample from the first, so that positive differences are consistent with the prediction. For annual returns, 10 out of the 12 tests go in the predicted direction; for earnings announcement returns, 12 out of 12 tests go in the predicted direction. However, these results are statistically significant only for the earnings announcement tests.

4.2 Examination of asset pricing tests using factor models

My final approach is based on asset pricing tests using the Fama-French three factor model (Fama and French, 1993) and the Carhart four factor model (Carhart, 1997). Unlike prior studies that investigate whether a predictable relation between ICC estimates and risk factors exists, I examine the fraction of hedge portfolio returns that cannot be explained by the factor model. Under this approach, returns that are not explained by the risk factors are assumed to be the result of mispricing. This provides an upper bound on the magnitude of the mispricing, because unmodeled risk factors could also provide an explanation.

Each month, firms are sorted into deciles based on the magnitude of their most recent ICC estimates. For each month, the decile return is calculated as the average return of all firms in that decile for that month. This generates a time series of 468 monthly returns for each decile (444 month for GGM due to the need for five year forward looking forecasts). I then subtract the risk free rate and regress the difference on the market risk premium (MKTRF), the small firm premium (SMB), and the value premium (HML). Table VI reports the coefficients from a time series regression of the monthly hedge portfolio returns on the three Fama-French factors. Panel A displays the classic Fama-French three factor model. The results indicate that the hedge portfolio returns for all four estimates load strongly on the HML factor, which is perhaps not surprising given that ICC estimates are related to fundamentals-to-price measures. Loadings on the SMB factor are more mixed, and those on the market factor are mostly negative.

To assess the usefulness of the three factors in explaining the average hedge portfolio return, I compute the ratio of the average monthly abnormal returns (the intercept) to the average monthly total hedge portfolio return.[7] The fraction of the average monthly return that remains unexplained by the three factors is 24% for GLS, 65% for EPR, 81% for GGM, and 73% for AGR. Thus, on average, 61% of monthly returns are unexplained by the three factor model. These results are consistent with earnings announcement returns and suggest that mispricing has a large effect on the relation between ICC estimates and future returns.

In Panel B, I repeat the analysis using the Carhart four factor model, which adds a momentum factor to the Fama-French three factor model. Compared to the three Fama-French factors, there is less consensus in the literature as to whether momentum is truly a risk factor, I therefore show these results mainly for illustrative purposes. As shown in Panel B, all four ICC models load negatively on the momentum factor. As can be inferred from the model intercepts,

[7] The average monthly return is also equal to the intercept plus the factor loading times the average factor premium. Over this time period, the average factor premiums were 0.45% per month for the market premium (MKTRF), 0.20% per month for the small firm premium (SMB), 0.42% per month for the value premium (HML), and 0.73% per month for the momentum premium (HML).

abnormal returns are larger under the four factor model. The fraction of the average monthly return that remains unexplained by the three factors is 60% for GLS, 78% for EPR, 111% for GGM, and 122% for AGR. Fractions greater than 100% indicate that the abnormal returns are larger than the total returns. Thus, on average, 93% of monthly returns are unexplained by the four factor model.

5. Additional analyses

In this section I discuss several additional analyses. First in section 5.1, I examine the effects of market inefficiency when using ICC estimates based on bias-adjusted analyst forecasts. Then in section 5.2, I discuss the efficacy of controlling for earnings news and discount rate news when examining the relation between ICC estimates and future returns. Finally, in section 5.3, I discuss the implications of market inefficiency for models of measurement error in ICC estimates.

5.1 Using analyst forecasts to construct the ICC estimates

Recent work in improving the quality of ICC estimates has taken one of two approaches. The first approach is the development of regression-based earnings forecast models which I use in the empirical analyses above. The second approach involves applying corrections for predictable errors to analyst forecasts prior to using them in calculating ICC estimates (e.g. Gode and Mohanram, 2010; Larocque, 2011). The disadvantage of approaches using analyst forecasts is that the sample is limited to firms and years with analyst following. This limits the applications of the ICC estimates. However, from the perspective developed in this paper, biases introduced by market inefficiency, this may actually be an advantage given that mispricing may be less severe among firms covered by analysts.

In this section, I repeat the analyses of Section 4 using the approach in Gode and Mohanram (2010). Their approach consists of two steps. First, using historical data they regress analyst forecast errors on a wide variety of variables related to predictable biases in the forecasts.[8] Second, for each firm-year they use the current realizations of these variables and the historical coefficients to derive a predicted bias which is then subtracted from the analyst forecast before computing the ICC estimates. The ICC estimates are calculated using these corrected forecasts and market values measured 6 months after the prior fiscal year end. Using analyst forecasts from I/B/E/S, I apply their approach to calculate ICC estimates for each of the four models I examine (GLS, EPR, GGM, and AGR) for the period 1984-2009.

The results of the earnings announcement tests are displayed in Panel A of Table VII. The annual buy-and-hold returns to a hedge portfolio that is long in the highest ICC decile and short in the lowest ICC decile are positive and statistically significant for all four models, extending findings in Gode and Mohanram (2010) to different ICC models. The hedge portfolio earnings announcement returns are also positive, but only statistically significant for two of the four models. When considering the ratio of earnings announcement returns to annual returns, they are much lower than the corresponding ratios in Table IV. These results suggest that biases introduced by market inefficiency are likely to be less severe for analyst forecast based ICC estimates.[9]

Panel B displays the results of the Fama-French three factor model. All four hedge portfolio abnormal returns are positive, but only two are statistically significant. The fraction of

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[8] The variables used are accruals, sales growth and change in gross PPE, all measured at the end of the prior fiscal year; book-to-market, earnings to price, both using market values measured at six months after the fiscal year end; buy-and-hold return for the 12 months ending at six months after prior fiscal year; and the analysts' revision in one year ahead EPS from three months after prior fiscal year end to six months after prior fiscal year.

[9] In untabulated tests I confirm results in prior research that ICC estimates based on unadjusted have no explanatory power whatsoever.

the average monthly return that remains unexplained by the three factors is 40% for GLS, 82% for EPR, 75% for GGM, and 55% for AGR. Thus, on average, 63% of monthly returns are unexplained by the three factor model. Results based on the Carhart (1997) four factor model are very similar (untabulated). The fraction of the average returns unexplained is similar to those in Table V. Overall, when considering both tests the results suggest that analyst forecast based ICC estimates are less subject to biases introduced by market inefficiency although a significant impact cannot be ruled out.

5.2 Examination of the relation between ICC and future returns when controlling for news

Prior research suggests that most of the cross sectional variation in returns comes from news about the firms' cash flows and discount rates, rather than from variation in expected returns. To control for these sources of variation, some of the prior literature includes proxies for the cash flow and discount rate news in the regression (e.g., Easton and Monahan, 2005). The return effects of cash flow news and discount rate news should average out given a sufficiently large sample and time period. However, by controlling for unwanted sources of variation in returns, including earnings news and discount rate new proxies should increase the power of the tests. It is an open question whether controlling for news helps to mitigate the biases induced by market inefficiency.

Earnings surprise proxies can potentially help mitigate the biases induced by mispricing if they can capture the earnings surprise from the perspective of the investors. Within the context of the model described in section 2, if the investors' earnings forecast were observable, the earnings surprise proxy can be calculated as the difference between the earnings realization and the investors' earnings forecast:

$$Investor\_Earnings\_Surprise_{t+1} = \frac{X_{t+1} - (E_t[X_{t+1}] + \varepsilon_{t+1})}{P_t} = \frac{n_{t+1} - \varepsilon_{t+1}}{P_t},$$

where X_t is the earnings in time t, ε_{t+1} is the ex-ante error in the investors' earnings forecast of next period's earnings and n_{t+1} is the cash flow shock in period $t+1$. Thus the earnings surprise from the investors' perspective contains both the true earnings news and a reversal of their prior error. As discussed in section 2 and the model in the Appendix, the ICC estimate is also negatively correlated with the error in the investors' earnings forecast. Therefore, this earnings surprise proxy will be positively correlated with the ICC estimate and controlling for it in the regression should help reduce the impact of mispricing.

Unfortunately, the investors' earnings forecasts are not directly unobservable. However, the researcher's earnings forecasts are observable. Therefore, the earnings surprise proxy will be based on the difference between the earnings realization and the researcher's earnings forecast:

$$Measured\_Earnings\_Surprise_{t+1} = \frac{X_{t+1} - (E_t[X_{t+1}] + u_{t+1})}{P_t} = \frac{n_{t+1} - u_{t+1}}{P_t},$$

where ut+1 is the ex-ante error in the researcher's earnings forecast of next period's earnings. As can be seen from the earnings surprise variable, the measurement error in the earnings news proxy is the same as the measurement error in the researcher's earnings forecast (u_{t+1}). Thus, unless the researcher's errors are correlated with the investors' errors, using this proxy does not address the bias due to mispricing. As the covariance between u_t and ε_t increases, this proxy becomes more useful. Ironically, at the same time, the bias in the ICC estimates caused by mispricing becomes smaller, and thus the need to control for it becomes less.

A potential concern with controlling for earnings news is that the measurement error in the earnings surprise proxy is related to the measurement error in the ICC estimate. This induces a negative correlation between the ICC estimate and the earnings surprise proxy. Given the positive relation between earnings surprises and future returns, this implies that the coefficient on the ICC variable will be biased upwards after the inclusion of the earnings surprise variable when regressing future returns on ICC estimates.[10] Since the opposite holds if the earnings surprise proxy accurately captures the investors' forecast error a simple test to determine which effect dominates—the researcher's or the investors' measurement error—is to examine the correlation between the ICC and the earnings surprise measure. If the correlation is negative, the researcher's measurement error dominates, and the coefficient on ICC will be biased upwards after including the earnings surprise variable in the regression.

An alternative approach would be to try to find a proxy for the earnings surprise that is not mechanically related to the measurement error in the ICC estimates due to reliance on the same earnings forecasts. One such proxy would the earnings announcement returns. While this does not measure the full earnings surprise over the year, the advantages are that it is not dependent on any forecasts of earnings, and in addition it is known be related reversal of mispricing. Thus it is a good (partial) control for mispricing. A related method would be to simply subtract the earnings announcement return from the annual return. However, the advantage of the control variable approach is that the coefficient is not constrained to be one. For example, if returns on other days are correlated with the earnings announcement return (e.g. because of post-earnings-announcement-drift) then the control variable approach will capture this, but the subtraction method will not.

Next, I empirically examine the impact of controlling for news on the relation between ICC estimates and future returns. In line with the model developed above, I calculate the earnings surprise (ES) as the realized one-year-ahead earnings minus the forecasted earnings scaled by the market value at the portfolio formation date. In the regression, this is expected to

[10] Note that the opposite holds for proxies for changes in the discount rate if those proxies are also based on the same researcher earnings estimates. For example, this holds when using the change in the ICC as a proxy for the change in the discount rate as in Easton and Monahan (2005). This suggests that including both news proxies may mitigate any bias on the ICC coefficient. Since the model is based on a constant discount rate, I cannot quantify this effect.

have a positive relation with future returns. While the model in the Appendix does not speak to changes in the discount rate, I draw on prior research to include a measure for that as well. Following the previous literature, the proxy for changes in the discount rate is the difference between the one-year-ahead ICC estimate and the current ICC estimate (DRS). In the regression, this is expected to have a negative relation with future returns. Finally, following my alternative approach, I include the earnings announcement returns as a proxy for the earnings surprise.

Table VIII reports the average coefficients of annual cross-sectional regressions of future returns on the ICC estimates and proxies for earnings surprises and changes in the discount rates. The realized returns are the compounded monthly raw stock returns in the 12 months following the portfolio formation date (including delisting returns, following the approach in Beaver, McNichols and Price, 2007). There are four sets of regressions, one for each of the four ICC estimates. Within each set of regressions the same sample is maintained, to enhance comparability. I next discuss the results of the first set of regressions, those for the GLS estimate.

The first regression shows the simple regression of one-year-ahead stock returns on the GLS estimate of the implied cost of capital. The coefficient is positive and significant, confirming the results of the portfolio-based approach in Table III. The coefficient is less than one, which suggests that the downward bias effect of the researcher's measurement errors is larger than the upward bias effect of the investors' errors. The second regression shows a strong relation between earnings news and future returns. However, this coefficient (the ERC) is much less than the theoretical coefficient, the earnings capitalization factor; this again suggests a large amount of measurement error in the researcher's earnings estimates. Consistent with the predictions above, after including the earnings surprise proxy the ICC coefficient is higher than in the first regression. The third regression shows that after including the discount rate proxy the

ICC coefficient is lower than in the first model. The fourth regression combines all three variables in the regression resulting in an increase of the ICC coefficient relative to the simple regression, and both the earnings surprise and the change in the discount rate proxy have the predicted sign. This suggests that controlling for both surprise proxies does not help mitigate the bias due to market inefficiency. Finally, the fifth regression uses the alternative approach with earnings announcement returns as the earnings surprise proxy. This regression model has the best explanatory power of all models. In addition, the earnings announcement variable is strongly positive with a coefficient that is slightly greater than one. The coefficient on the ICC variable drops relative to the first regression which is supposed to happen when a valid proxy for mispricing is included.

The results for the other three ICC models are generally consistent with the results discussed above. In all cases the ICC estimates are negatively correlated with the earnings surprise proxy, and including both in the regression results in an increase in the coefficient on the ICC estimate. Including the change in the discount rate proxy consistently results in a decrease in the coefficient on the ICC estimate. Including both surprise proxies leads to more ambiguous results, sometimes resulting in an increase, sometimes a decrease, in the coefficient on the ICC estimate. These results are consistent with correlated measurement error in the ICC estimates and the news proxies, and inconsistent with the news proxies being effective in controlling for mispricing. Given that the potential benefit of controlling for news, increased power, is relatively small given the low R-squareds, these results suggest that researchers may be better off not controlling for news despite its intuitive appeal. In contrast, controlling for earnings announcement returns has the greatest explanatory power and consistently moves the coefficient on the ICC estimate in the predicted direction.

5.3 The effect of market inefficiency on models of measurement error variances

In addition to applying regression based tests, researchers have attempted to directly model the structure of the measurement error in the ICC proxies. In this section, I briefly discuss the implication of market inefficiency for this approach. The measurement error variance approach originates with Easton and Monahan (2005). Using the variance decomposition approach in Vuolteenaho (2002), they decompose realized returns into expected returns, cash flow news and expected return news. They then consider the case in which the empirical proxy for each of these constructs consists of the true construct plus measurement error. To identify the measurement error in the expected return proxy, Easton and Monahan (2005; p.534) "*assume that the measurement error in a particular proxy is uncorrelated with the true underlying construct, but may be correlated with the true value of the other constructs and the measurement errors in the remaining proxies*." By allowing the measurement error in the ICC proxy to be correlated with the measurement error in the news proxies, they can avoid some of the problems discussed in section 5.2 that arise from directly looking at the coefficients in the regression.

The assumptions closely match the model in the Appendix in the case in which the market is efficient. In the model, under market efficiency, the measurement error in ICC is uncorrelated with (but not independent of) the true discount rate. However, because the market inefficiency has a non-linear effect on the ICC estimate, the measurement error portion of the ICC proxy is correlated with the true discount rate. Moreover, the variance decomposition does not include a specific term for the (reversal of the) mispricing. One can change the interpretation of the news variables, to measure news from the investors' perspective rather than from objective expectations, however, the noise in the news variables will then also be correlated with the underlying true value of the news.

While the model can potentially be adapted to incorporate market inefficiency, it is not clear this is desirable. Given the very different effects of the biases induced by market inefficiency and errors in researcher's earnings estimates, it is not clear that trying to combine the two into one overall measurement error measure is helpful. It seems therefore more useful to complement analyses of measurement error variances with an explicit investigation of the impact of market inefficiency on the ICC estimates, as is done in this paper.

6. Conclusion

The literature has long recognized that realized returns offer a very noisy proxy of expected returns (e.g. Elton, 1999). Implied cost of capital (ICC) models offer a promising alternative method for estimating cost of capital, even if the estimates from these models also contain measurement error. Because ICC estimates rely on market prices, they are potentially affected by mispricing. In this paper, I examine the effects of potential market inefficiencies on the properties of ICC estimates and the relation between ICC estimates and future returns. Building on a model starting from the underlying primitives, investors' and researcher's earnings forecasts, I show that under reasonable assumptions, market inefficiencies will bias ICC estimates in the same direction as realized returns, though to a lesser degree. As a result, errors in ICC estimates due to mispricing lead to an upward biased coefficient in a regression of future returns on ICC estimates. This is important, because errors in ICC estimates due to errors in researcher's earnings estimates lead to downward biased coefficients, and the prior literature uses larger coefficients as evidence of higher quality.

Using recently developed ICC estimates based on regression generated earnings forecasts, I empirically examine the importance of these theoretical effects. I find that a significant fraction, 38% on average, of annual hedge portfolio returns are concentrated around earnings announcements. The bias caused by market inefficiencies is particularly severe in sample firms with significant limits-to-arbitrage that make them more prone to mispricing. For smaller firms, less liquid firms, and firms with higher transactions costs, on average, 52% of annual hedge portfolio returns are concentrated around earnings announcements. I complement these results using a factor pricing approach. I find that, on average, the three Fama-French factors only explain 39% of the difference in returns between high and low ICC deciles, leaving 61% of the returns unexplained.

In robustness tests, I examine the performance of ICC estimates based on bias-adjusted analyst forecasts. Because this can only be computed for firms with analyst coverage, mispricing may be less of a concern. I find that the fraction of annual hedge portfolio returns that are concentrated around earnings announcements is much lower for these estimates, about 10% on average. These results are suggestive of lower bias due to mispricing for these ICC estimates. However, the three Fama-French factors only explain 37% of the difference in returns between high and low ICC deciles, leaving 63% of the returns unexplained. Thus, I cannot rule out that mispricing potentially has significant effects on these ICC estimates as well.

My model and empirical results show that the bias introduced by mispricing is a function of both the amount of mispricing in the stock and how well the researcher's earnings forecasts and ICC model capture this mispricing. This has two important implications. First, it implies that different ICC estimates will be differently affected thus mispricing biases affect the relative ranking of different ICC estimates. Second, it suggests that biases induced by market inefficiency will become more severe as researchers continue to improve the quality of their earnings forecasts and valuation models. This suggests that an explicit consideration of the effects of market inefficiency will become increasingly important. The analyses in this paper should be useful to researchers interested addressing these issues when evaluating alternative cost of capital estimates or applying ICC estimates in tests of proposed risk factors.

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Appendix

The market value of a stock can be defined as the sum of its fundamental value and any mispricing. Standard valuation theory suggests that the fundamental value is equal to the present value of expected future dividends. In line with the implied cost of capital literature (e.g. Easton and Monahan, 2005) I assume a constant discount rate. Thus the (ex-dividend) price of a stock can be expressed as follows:

$$P_t = FV_t + MP_t = \sum_{t=1}^{\infty} \frac{E_t[D_{t+\tau} \mid \Omega_t]}{(1+r)^{\tau}} + MP_t, \tag{1}$$

where *FV* is the fundamental value, *MP* is the mispricing, D_t is the dividend at time *t*, E_t is the time *t* rational expectation given the information set, Ω, and *r* is the discount rate. One way of specifying any mispricing is as a sequence of estimation errors regarding future dividends, i.e., a stock is overvalued (undervalued) if investors overestimate (underestimate) future dividends. In that specification, the price can be expressed as follows:

$$P_t = FV_t + MP_t = \sum_{t=1}^{\infty} \frac{E_t[D_{t+\tau} \mid \Omega_t] + \varepsilon_{t+\tau}}{(1+r)^{\tau}}, \tag{2}$$

where ε_t is the estimation bias for dividends at time *t*, i.e., the difference between the investors' expectation of future dividends and the rational expectation of future dividends given the information set, Ω.

Researchers use observable market prices, P_t, to infer the cost of capital as the internal rate of return that equates the market prices to the present value of the researcher specified dividend forecasts, that is:

$$ICC_t = IRR[P_t; E_t[D_{t+1} \mid \Omega_t] + u_{t+1}; E_t[D_{t+2} \mid \Omega_t] + u_{t+2};....], \tag{3}$$

Where *ICC* is the implied cost of capital estimate, *IRR* is the internal rate of return operator, and u_t is the researcher's estimation bias for dividends at time *t*, i.e., the difference between the researcher's estimate of future dividends and the rational expectation of future dividends given the information set, Ω. Note that researcher's typically do not directly forecast dividends, but instead use a residual income model with varying assumptions about future (abnormal) earnings growth. Since the residual income is a reformulation of the dividend discount model, my representation is without loss of generality (e.g. Lundholm and O'Keefe, 2001)

To simplify this model so that the implied cost of capital (ICC) can be derived analytically, I will assume a random walk structure in which earnings are fully distributed and there is no growth on average. This implies that $E_t[D_{t+1}|\Omega_t] = E_t[D_{t+\tau}|\Omega_t]$ and $\varepsilon_{t+1} = \varepsilon_{t+\tau}$ for all τ, and the stock can be priced as a perpetuity:

$$P_t = FV_t + MP_t = \frac{E_t[D_{t+1}] + \varepsilon_{t+1}}{r}, \tag{4}$$

The researcher's dividend estimates are similarly a random walk, so that $u_{t+1} = u_{t+\tau}$ for all τ, so that the ICC can be estimated by replacing the investors' dividend forecast with the researcher's dividend forecast and solving for the discount rate:[11]

$$ICC_t = \frac{E_t[D_{t+1} \mid \Omega_t] + u_{t+1}}{P_t} = \frac{E_t[D_{t+1} \mid \Omega_t] + u_{t+1}}{E_t[D_{t+1} \mid \Omega_t] + \varepsilon_{t+1}} \cdot r. \tag{5}$$

From this expression it is clear that the two types of errors have opposite effects on the ICC estimate. Holding all else equal, if the researcher overestimates future dividends ($u_{t+1} > 0$), the ICC will be higher than the true discount rate, whereas if the investors overestimate future dividends ($\varepsilon_{t+1} > 0$), the ICC will be lower than the true discount rate.

[11] This set up has the benefit that the ICC estimate in linear in the researcher's earnings estimate. This linearity does not generally hold. If one considers a finitely lived firm under otherwise similar assumptions, the ICC is no longer linear in the researcher's earnings estimates and therefore the ICC will be biased in the presence of these errors. For example, Lambert (2009) considers a two-period firm and shows that the ICC is downwardly biased in the presence of errors in the researcher's earnings estimate. To the extent that the combined assumption of a random walk and an infinitely lived firm is a reasonable approximation, the bias is likely to be small.

Given that the two error terms are potentially correlated, "all else equal" results can be misleading. If the two errors are identical ($\varepsilon_{t+1} = u_{t+1}$) then the ICC will equal the true discount rate. This is a special case of the setting in which the researcher's earnings estimate suffers from the exactly same errors as the investors' estimate plus some additional, uncorrelated errors. Stated formally, this is the case if $u_{t+1} = \varepsilon_{t+1} + \lambda_{t+1}$ and $\text{cov}(\varepsilon_{t+1}, \lambda_{t+1}) = 0$, which implies that $\text{cov}(\varepsilon_{t+1}, u_{t+1}) = \text{var}(\varepsilon_{t+1})$. Thus, for market mispricing to affect the ICC estimate, the researcher's dividend estimate needs to be (somewhat) informative about the error in the investors' dividend expectations. Prior research has provided evidence that this is a plausible assumption for both analyst and regression-based earnings forecasts. For example, Gleason and Lee (2003) provide evidence that investors under-react to analyst forecasts, and Bernard and Thomas (1990) and Sloan (1996) provide evidence that simple time-series patterns in earnings and decompositions of earnings components can be used to earn excess returns. Therefore, in discussing the model I only consider cases where the researcher's earnings expectations are weakly informative of the error in investors' earnings expectations (i.e., $\text{cov}(\varepsilon_{t+1},u_{t+1}) \leq \text{var}(\varepsilon_{t+1})$).[12]

Realized returns in the model are a function of expected returns and news. There are two sources of news in the model. First, earnings and dividends for period $t+1$ are realized (which also affects dividend forecasts for all future periods). Second, earnings news may trigger a change in the amount of mispricing. The price at the end of $t+1$ is thus the sum of the realized dividend and the present value of expected future dividends, which can again incorporate a mispricing term:

$$P_{t+1} = E_t[D_{t+1} \mid \Omega_t] + n_{t+1} + \frac{E_t[D_{t+1} \mid \Omega_t] + n_{t+1} + \varepsilon_{t+2}}{r} \tag{6}$$

[12] It is theoretically possible that the $\text{cov}(\varepsilon_t,u_t) > \text{var}(\varepsilon_t)$. However, this would lead to the counterintuitive result that higher ICC estimates are associated with lower future returns. This is possible with very stale forecasts, but unlikely to happen with more sophisticated approaches.

To be true news, the earnings news (n) has to have zero mean and be uncorrelated with the other random variables in the model (r, ε, and u). As before, I assume the news in earnings follows a random walk process. To capture the possibility that the current mispricing does not fully reverse itself in the next period, I allow future mispricing to be correlated with current mispricing. In particular, I decompose the future error into two components, the portion of the old estimation error that persists ($\rho\varepsilon_{t+1}$) and an orthogonal new mispricing component (δ_{t+2}). The persistence parameter (ρ) is expected to be greater than 0 and strictly less than 1. This yields the following expression for the price at $t+1$:

$$P_{t+1} = \frac{(1+r)(E_t[D_{t+1} \mid \Omega_t] + n_{t+1}) + \rho\varepsilon_{t+1} + \delta_{t+2}}{r}. \tag{7}$$

Using equations (7) and (4), the realized return from t to $t+1$ is:

$$R_{t+1} = \frac{P_{t+1} - P_t}{P_t} = \frac{rE_t[D_{t+1} \mid \Omega_t] + (1+r)n_{t+1} - (1-\rho)\varepsilon_{t+1} + \delta_{t+2}}{E_t[D_{t+1} \mid \Omega_t] + \varepsilon_{t+1}}. \tag{8}$$

Thus, future returns are increasing in the discount rate (r), cash flow news (n_{t+1}), and the amount of the new overestimation (δ_{t+2}) of future dividends. Future returns are increasing (decreasing) in the persistence of past overestimation (ρ) if the prior mispricing (ε_{t+1}) is positive (negative). If there is no mispricing, equation (10) can be simplified to the realized returns being equal to the expected return plus news.

Using these specifications, I can now identify two important results regarding the impact of mispricing on implied cost of capital estimates.

Result 1: ICC estimates are less affected by mispricing than realized returns

This can be seen by deriving the regression coefficient for both realized returns and ICC estimates on a mispricing proxy and compare the coefficients. In both cases, one would expect a negative coefficient: the more investors overestimate future earnings, the higher the current prices and the lower the ICC and future returns. Since I am interested in the relative effects, I can, without loss of generality, use the actual estimation error (ε) as the mispricing proxy. To prevent the coefficient from being affected by the scale of the firm, I standardize the mispricing by the rational expected dividend: $E_t[D_{t+1} \mid \Omega_t]$. In that case, the probability limit of the coefficient in a regression of the ICC estimate on the mispricing proxy can be expressed as follows[13]:

$$p\lim \beta_{ICC,Mispricing} \approx \left(\frac{\operatorname{cov}(\varepsilon_{t+1}, u_{t+1})}{\operatorname{var}(\varepsilon_{t+1})} - 1 \right) \cdot E[r]. \tag{9}$$

If the two error terms (ε_{t+1} and u_{t+1}) are uncorrelated, then the coefficient will be equal to minus one times the average discount rate. If the researcher's earnings estimate suffers from some of the same problems as the investors' earnings estimate, then the covariance term will be positive and the coefficient smaller but weakly negative. As before, if the researcher's earnings estimate is not informative about the error in the investors' expectations ($\operatorname{cov}(\varepsilon_{t+1},u_{t+1}) = \operatorname{var}(\varepsilon_{t+1})$), then the ICC is unaffected by mispricing, and the coefficient will be zero.

Similarly, one can derive the regression coefficient for a regression of realized returns on the mispricing proxy. In that case, the probability limit of the coefficient is:

$$p\lim \beta_{R_{t+1},Mispricing} \approx -E[r] - (1-\rho). \tag{10}$$

From this it is clear that the expected coefficient is negative and larger than the coefficient in the regression using the ICC as the dependent variable. In particular, the difference between the two coefficients is larger if the portion of the mispricing that reverses within a year is larger (meaning the mispricing persistence, ρ, is smaller). For intermediate values of ρ, the coefficient in the

[13] This result and subsequent results are derived using a second order Taylor expansion. Derivations are available on request.

realized returns regression will still be several times larger than the coefficient in the ICC regression. Thus, in expectation ICC estimates are less affected by mispricing than realized returns.

Result 2: Mispricing induces an upward bias in the relation between realized returns and ICC estimates

This can be seen by deriving the regression coefficient for a regression of realized returns on the ICC estimate. In the model discussed above this expression is a function of four random variables (ε_t, δ_{t+2}, u_t, and n_{t+1}) and, once the model is estimated in a cross-section, the expected return (r) is a random variable as well. Two variables, the earnings news variable in period $t+1$ (n_{t+1}) and the innovation in mispricing in period $t+1$ (δ_{t+2}), play no role in the probability limit of the coefficient estimate, as they are uncorrelated with the other variables and enter linearly in the returns model (they do, however, affect the variance of the estimator). However, the other variables are either correlated or enter in a multiplicative manner. As a consequence, the resulting equation is hard to interpret; therefore, I analytically derive three limiting conditions and use simulations to show the intermediate results.

In particular, in addition to the 'free' variables (n_{t+1} and δ_{t+2}) I vary each of the three main random variables in the model (r, ε_{t+1}, and u_{t+1}) one at a time, holding the other two at their respective means. These three cases are summarized in the table below.

Random variables	Probability limit of the regression coefficient on the ICC estimate
r, δ_{t+2}, n_{t+1}	1
u_{t+1}, δ_{t+2}, n_{t+1}	0
ε_{t+1}, δ_{t+2}, n_{t+1}	$(1-\rho+r)/r$

The first two cases are consistent with prior literature. If the discount rate (r) varies cross-sectionally and both error variances are zero, the coefficient on the ICC estimate is one. If only u varies cross-sectionally then the ICC estimate is pure noise; hence the correlation with realized returns is zero. Thus prior research has considered coefficients closer to one as evidence of higher quality ICC estimates.

The third case is the case with market inefficiency but perfect researcher forecasts. Since the persistence of mispricing (ρ) is between zero and one, this coefficient is always weakly greater than one. The intuition behind this result is as follows. Consider the case in which the mispricing fully reverses one period later ($\rho = 0$). In that case the returns occur in one year, but the ICC spreads the mispricing effect over an infinite horizon, thus the coefficient is the capitalization factor ($(1+r)/r$). The coefficient in the general model will be a weighted average of these three cases, with researcher measurement error (u) driving the coefficient down, market inefficiency (ε) driving the coefficient up, and the covariance between ε and u, and the persistence moderating these effects.

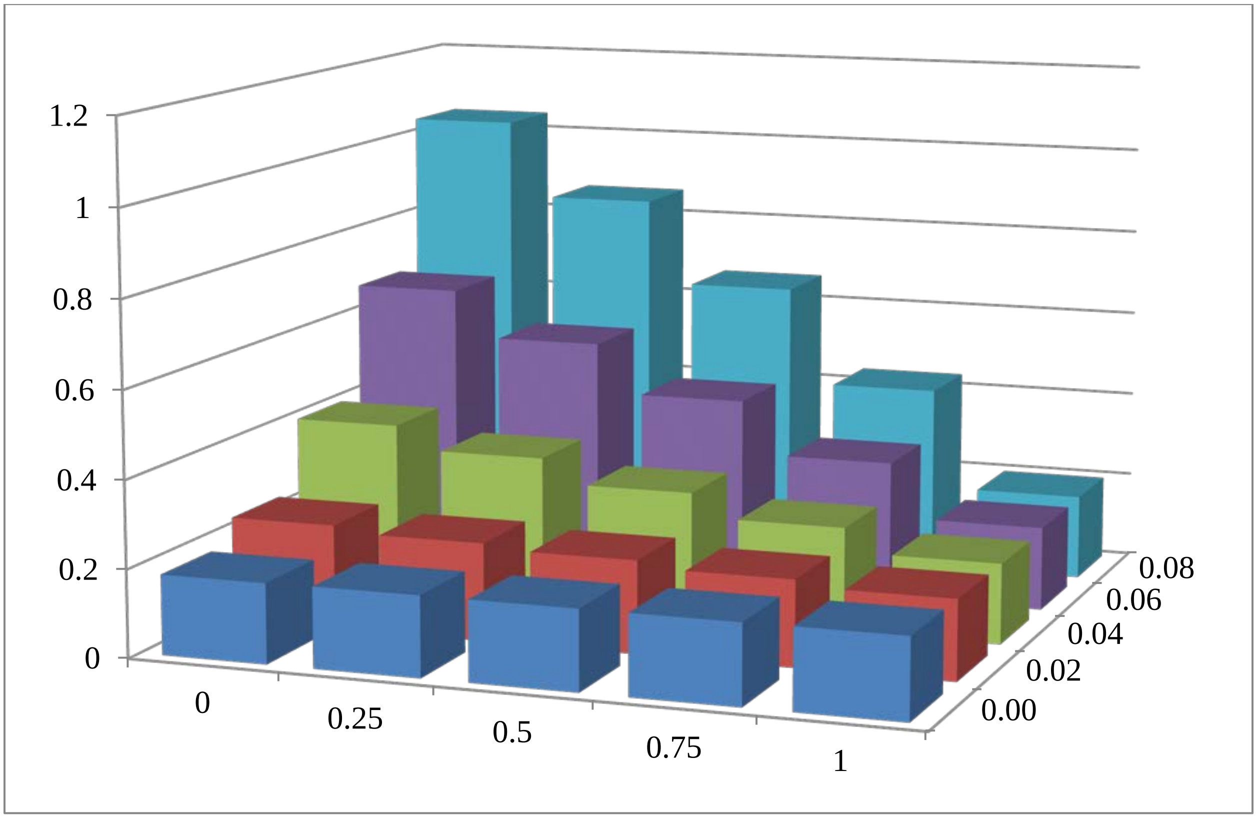
To see how the coefficient behaves in intermediate cases I simulate two sets of regression estimates in which I vary the amount of mispricing, the amount of researcher estimation error and the covariance between the two. To aid in the interpretation I reparameterize these variables as follows. I measure the extent of mispricing by the average absolute value of the mispricing using the formula for the expected value of the half normal distribution:

$$Average\_absolute\_mispricing = \frac{\sigma(\varepsilon)}{E_t[D_{t+1} \mid \Omega_t]}\sqrt{\frac{2}{\pi}},$$

Where $\sigma(\varepsilon)$ is the standard deviation of the investors' estimation errors. Another way to think about this variable is that a hedge portfolio that is long (short) in the half of the sample that is undervalued (overvalued) will earn returns approximately equal to twice the average absolute mispricing once the mispricing reverses. I similarly reparameterize the researcher's estimation error. I measure the degree of overlap between the researcher's and the investors' estimation error as the cov(ε_{t+1},u_{t+1})/ var(ε_{t+1}). If the fraction is 0 then the investors' and the researcher's estimation error are uncorrelated, if the fraction is 1, then the researcher's estimates share the same error as the investors' estimates, and the ICC is unaffected by the mispricing.

The results are displayed in Figures A.1 and A.2. Figure A.1 shows that as the degree of mispricing increases from front to back the regression coefficient on the ICC estimate is increasing and can reach above 1. This effect is mitigated from left to right by the degree of overlap between the researcher's and the investors' estimation error, with no effect of mispricing once the overlap reaches 1. Figure A.2 shows that for a given level of mispricing in the sample, reducing the error in the researcher's estimates reduces attenuation bias, but at the same time exacerbates the effect of mispricing, both of which increase the coefficient. There are two main implications of these results. First, ICC models that use samples with greater mispricing are likely to have more biased coefficients. Second, this effect is mitigated for ICC models whose implicit dividend forecasts have a greater degree of overlap with investors' estimation errors.

Figure A.1 Impact of mispricing on the ICC regression coefficient

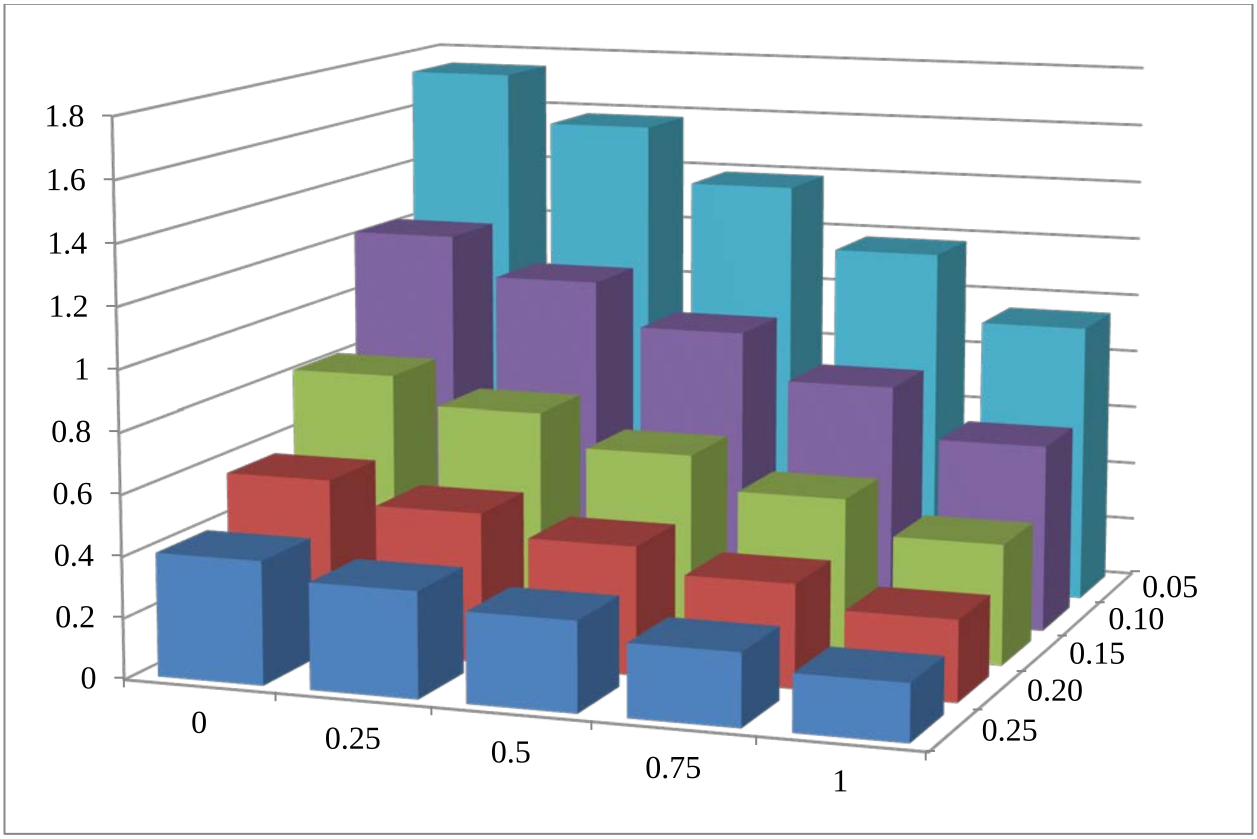


This figure shows the average regression coefficients of the following regression:

$$R_{t+1} = \alpha + \beta \cdot ICC_t + \varphi.$$

The vertical axis shows the average b-coefficient from the regression. From the front to the back I vary the amount of mispricing in the sample. The front row has no mispricing; the second row is parameterized so that the average absolute mispricing is 2% of the stock's fundamental value, and so on. From left to right I vary the fraction of the investors' estimation error that is shared by the researcher. If the fraction is 0 then the investors' and the researcher's estimation error are uncorrelated, if the fraction is 1, then the researcher's estimates share the same error as the investors' estimates, and the ICC is unaffected by the mispricing. Each column shows the average regression coefficient of 1000 simulations with the indicated inputs, the number of observations is 1000 per simulation; the average discount rate is set to 10% with a standard deviation of 1.5%; the researcher's estimation error is parameterized such that the average absolute estimation error is 25%.

Figure A.2 Impact of researcher error on the ICC coefficient in the presence of mispricing



This figure shows the average regression coefficients of the following regression:

$$R_{t+1} = \alpha + \beta \cdot ICC_t + \varphi.$$

The vertical axis shows the average b-coefficient from the regression. From the front to the back I vary the amount of researcher estimation error in the sample. The front row is parameterized so that the average absolute estimation error is 25% of the stock's fundamental value, and so on. From left to right I vary the fraction of the investors' estimation error that is shared by the researcher. If the fraction is 0 then the investors' and the researcher's estimation error are uncorrelated, if the fraction is 1, then the researcher's estimates share the same error as the investors' estimates, and the ICC is unaffected by the mispricing. Each column shows the average regression coefficient of 1000 simulations with the indicated inputs, the number of observations is 1000 per simulation; the average discount rate is set to 10% with a standard deviation of 1.5%; the researcher's estimation error is parameterized such that the average absolute mispricing is 4% of the stock's fundamental value.

Table I: Cross-sectional earnings forecast models

This table reports the time series average regression coefficients of annual pooled cross-sectional earnings forecasting regressions estimated using the past 10 years of available data (minimum of 6 years). The model estimated is as follows:

$$E_{j,t+\tau} = \beta_0 + \beta_1 EV_{j,t} + \beta_2 TA_{j,t} + \beta_3 DIV_{j,t} + \beta_4 DD_{j,t} + \beta_5 E_{j,t} + \beta_6 NEGE_{j,t} + \beta_7 ACCT_{j,t} + \varepsilon_{j,t+\tau}$$

where $E_{j,t+\tau}$ (τ = 1, 2, 3, 4, or 5) denotes the earnings before extraordinary items (Compustat Item IB) of firm j in year t+ τ, and all explanatory variables are measured at the end of year t: $EV_{j,t}$ is the enterprise value of the firm (defined as total assets (Compustat Item AT) plus the market value of common equity (Compustat Item PRCC_F times Compustat Item CSHO) minus the book value of common equity (Compustat Item CEQ)), $TA_{j,t}$ is the total assets (Compustat Item AT), $DIV_{j,t}$ is the dividend to common shareholders (Compustat Item DVC), $DD_{j,t}$ is a dummy variable that equals 0 if $DIV_{j,t}$ is positive and 1 otherwise, $NEGE_{j,t}$ is a dummy variable that equals 1 for firms with negative earnings before extraordinary items (Compustat Item IB) and 0 otherwise, and $ACC_{j,t}$ is total accruals. Total accruals are calculated as the change in current assets (Compustat Item ACT) plus the change in debt in current liabilities (Compustat Item DLC) minus the change in cash and short term investments (Compustat Item CHE) and in current liabilities (Compustat Item LCT). Each variable in the regression is winsorized at the 0.5 and 99.5 percentiles for that year to mitigate the effect of extreme observations.

Years ahead	Intercept	EV	TA	DIV	DD	E	NEGE	ACC	R-squared
1	1.512	0.018	-0.007	0.296	-2.284	0.624	-0.287	-0.071	0.859
	3.49	*12.45*	*-5.35*	*9.95*	*-4.73*	*37.24*	*-0.89*	*-8.49*	
2	1.075	0.022	-0.006	0.427	-1.442	0.537	1.334	-0.084	0.811
	2.10	*10.49*	*-2.95*	*11.11*	*-3.13*	*24.27*	*3.52*	*-5.93*	
3	0.701	0.030	-0.007	0.393	-1.190	0.507	1.938	-0.130	0.785
	1.07	*10.51*	*-2.34*	*12.36*	*-2.68*	*17.51*	*3.91*	*-8.07*	
4	0.414	0.039	-0.011	0.446	-0.799	0.432	1.256	-0.086	0.762
	0.62	*10.90*	*-2.76*	*15.70*	*-1.48*	*15.27*	*1.86*	*-7.31*	
5	0.694	0.046	-0.015	0.287	-0.921	0.522	1.811	-0.106	0.742
	1.06	*11.74*	*-3.28*	*4.80*	*-1.33*	*9.33*	*2.74*	*-8.91*	

Table II: Descriptive statistics

This table reports the descriptive statistics for the four ICC estimates and the one-year ahead realized stock returns. The realized returns are the compounded monthly raw stock returns in the 12 months following the portfolio formation date (including delisting returns in accordance with the approach in Beaver, McNichols and Price, 2007). Panel C shows the distribution of the equal weighted realized market risk premium. The returns and implied cost of capital estimates are given in percents. *, **, and *** indicate statistical significance at 10, 5, and 1 percent levels based on two-tailed tests.

Panel A: Descriptive statistics

	N	Mean	Std Dev	P5	P25	Median	P75	P95
Realized return	157,148	14.6	80.5	-67.8	-25.3	3.8	36.2	125.4
ICC_GLS	136,512	10.7	6.5	2.5	7.2	9.8	13.0	20.3
ICC_EPR	104,165	9.0	8.5	1.2	3.8	6.8	11.5	23.2
ICC_GGM	126,310	10.4	8.5	2.2	5.1	8.0	13.0	25.9
ICC_AGR	117,214	11.0	12.8	1.2	3.9	7.2	12.9	34.3

Panel B: Correlation Table

	Realized return	ICC_GLS	ICC_EPR	ICC_GGM	ICC_AGR
Realized return	1				
ICC_GLS	0.043***	1			
ICC_EPR	0.091***	0.681***	1		
ICC_GGM	0.041***	0.645***	0.730***	1	
ICC_AGR	0.042***	0.540***	0.610***	0.577***	1

Panel C: Equal weighted market risk premium

	N	Mean	Std Dev	P5	P25	Median	P75	P95
Annual realized risk premium	38	8.6	24.1	-29.4	-5.0	11.2	19.1	40.3
5 year average risk premium	34	10.3	8.0	-2.0	3.8	11.2	15.0	23.0
10 year average risk premium	29	9.9	4.6	4.2	6.6	8.9	11.5	18.9
20 year average risk premium	19	9.2	1.9	7.0	8.2	8.8	10.7	12.1

Table III: Relation between ICC estimates and future returns

This table reports the average annual decile returns and hedge portfolio returns for each of the four ICC estimates. The realized returns are the compounded monthly market adjusted stock returns for the 12 months following the portfolio formation date (including delisting returns following the approach in Beaver, McNichols and Price, 2007). Delisting proceeds are reinvested in the market index. Fama-MacBeth t-statistics are listed to the right of the estimates. *, **, and *** indicate statistical significance at 10, 5, and 1 percent levels based on two-tailed tests.

Decile	GLS	*t-stat*	EPR	*t-stat*	GGM	*t-stat*	AGR	*t-stat*
1	-2.66	*-1.14*	-4.83	*-2.61*	-3.69	*-1.87*	-4.08	*-2.49*
2	-2.48	*-1.71*	-3.46	*-2.07*	-3.80	*-2.87*	-3.44	*-2.55*
3	-1.92	*-1.74*	-1.79	*-1.41*	-2.73	*-2.49*	-3.32	*-3.16*
4	0.61	*0.57*	-0.58	*-0.53*	-1.62	*-1.59*	-1.42	*-1.22*
5	-0.65	*-0.53*	-1.00	*-0.88*	-2.09	*-1.93*	-1.19	*-1.00*
6	-0.12	*-0.12*	0.60	*0.41*	-1.64	*-1.40*	-0.24	*-0.19*
7	0.40	*0.44*	0.07	*0.04*	-0.67	*-0.59*	-0.28	*-0.23*
8	0.96	*0.83*	0.22	*0.14*	-1.02	*-0.89*	-0.91	*-0.74*
9	0.38	*0.30*	2.20	*1.41*	-1.02	*-0.70*	0.62	*0.40*
10	3.94	*1.92*	2.96	*2.00*	1.63	*0.91*	2.16	*0.93*
10-1	6.61**	*1.97*	7.79***	*2.73*	5.31**	*2.10*	6.24**	*2.02*

Table IV: Relation between ICC estimates and returns around earnings announcements

This table reports the average annual earnings announcement returns for each ICC decile. Market adjusted earnings announcement returns are compounded for the twelve days around earnings announcements (three day windows for each of the four quarterly earnings announcements). Fama-MacBeth t-statistics are listed to the right of the estimates. *, **, and *** indicate statistical significance at 10, 5, and 1 percent levels based on two-tailed tests.

Panel A: Earnings announcement returns by ICC decile

Decile	GLS	*t-stat*	EPR	*t-stat*	GGM	*t-stat*	AGR	*t-stat*
1	-0.30	*-1.22*	0.17	*0.59*	-0.27	*-1.17*	0.42	*1.73*
2	-0.38	*-2.32*	0.17	*0.82*	0.20	*1.25*	0.12	*0.74*
3	0.24	*1.59*	0.36	*1.68*	0.37	*1.84*	0.31	*1.71*
4	0.42	*2.14*	0.80	*4.31*	0.39	*2.02*	0.34	*2.08*
5	0.78	*3.95*	0.61	*2.82*	0.28	*1.30*	0.39	*1.93*
6	0.94	*4.23*	0.64	*2.75*	-0.04	*-0.21*	0.56	*2.67*
7	0.76	*4.37*	0.61	*3.28*	0.02	*0.13*	0.36	*2.20*
8	0.69	*3.24*	0.67	*3.06*	0.48	*1.90*	0.01	*0.03*
9	0.92	*3.61*	0.49	*2.59*	0.90	*3.11*	1.29	*2.99*
10	2.42	*6.00*	1.57	*5.39*	2.77	*5.53*	2.57	*4.87*
10-1	2.72***	*5.53*	1.40***	*4.10*	3.04***	*5.27*	2.15***	*3.91*

Panel B: Comparison of earnings announcement and annual hedge portfolio returns

	GLS	EPR	GGM	AGR
Earnings announcement (EA) returns	2.72	1.40	3.04	2.15
Annual buy-and-hold (BH) returns	6.61	7.79	5.31	6.24
Ratio of EA returns to annual BH returns	41%	18%	57%	34%
Ratio after correcting for number of EA days	38%	14%	55%	31%
Ratio after correcting for volatility on EA days	34%	8%	52%	27%

Table V: Cross-sectional variation in the relation between ICC and future returns

This table reports the cross-sectional variation in hedge portfolio returns formed using the four ICC estimates. Each year firms are sorted into two groups based on each of the following variables: market value of equity (MVE), the Amihud illiquidity measure, and the LDV transaction cost measure. The results are reported for each subsample, as is the difference between the two subsamples. The column on the left displays the annual hedge portfolio returns for each subsample, and the column on the right displays the earnings announcement hedge portfolio returns. All returns are reported in percents. Fama-MacBeth t-statistics are listed below the hedge portfolio returns. *, **, and *** indicate statistical significance at 10, 5, and 1 percent levels based on two-tailed tests.

	Annual buy–and-hold returns				Earnings announcement returns			
MVE	GLS	EPR	GGM	AGR	GLS	EPR	GGM	AGR
Small	5.68	6.16**	4.51	5.89	3.24***	1.95***	4.00***	2.75***
	1.48	*2.36*	*1.45*	*1.64*	*4.62*	*3.95*	*4.32*	*3.71*
Large	5.32*	6.22*	4.69	1.29	0.90***	0.13	0.79*	-0.34
	1.82	*1.76*	*1.27*	*0.49*	*2.89*	*0.38*	*1.84*	*-0.95*
Difference	0.36	-0.07	-0.18	4.73	2.34***	1.83***	3.21***	2.99***
	0.11	*-0.03*	*-0.04*	*1.31*	*3.00*	*2.99*	*2.90*	*4.03*
Amihud	GLS	EPR	GGM	AGR	GLS	EPR	GGM	AGR
Illiquid	7.44**	7.44***	4.42	4.81	3.58***	1.85***	4.04***	2.51***
	2.23	*2.92*	*1.50*	*1.48*	*5.43*	*3.64*	*4.74*	*3.72*
Liquid	4.52	5.50	3.60	2.17	0.67*	0.29	0.55	-0.28
	1.41	*1.51*	*0.89*	*0.82*	*1.84*	*0.77*	*1.24*	*-0.75*
Difference	2.92	1.93	0.82	2.83	2.91***	1.56**	3.49***	2.71***
	0.98	*0.79*	*0.17*	*0.85*	*3.71*	*2.42*	*3.36*	*4.00*
LDV	GLS	EPR	GGM	AGR	GLS	EPR	GGM	AGR
High cost	6.92*	7.71***	6.48**	5.58	3.16***	2.11***	4.27***	2.41***
	1.90	*2.94*	*2.28*	*1.51*	*3.94*	*3.39*	*4.44*	*2.98*
Low cost	4.48	4.49	1.47	1.55	0.73**	0.22	0.24	0.01
	1.52	*1.26*	*0.41*	*0.62*	*2.45*	*0.66*	*0.69*	*0.04*
Difference	2.44	3.22	5.01	3.99	2.43***	1.88**	4.03***	2.28***
	0.75	*1.31*	*1.21*	*1.10*	*2.76*	*2.55*	*3.97*	*2.69*

Table VI: Explanatory power of Fama-French three factor model

This table reports the coefficients from time series regressions of monthly hedge portfolio returns on the risk factors identified in Fama and French (1993) and Carhart (1997). For each of the ICC estimates, portfolio assignment is based on the distribution of the trailing twelve months of ICC estimates. Panel A displays the regression results of the Fama-French three factor model containing the realized market risk premium (MKTRF), the small firm premium (SMB), and the value premium (HML). Panel B displays the regression results of the Carhart four factor model, which augments the three factor model with a momentum factor (UMD). *, **, and *** indicate statistical significance at 10, 5, and 1 percent levels based on two-tailed tests.

Panel A: Fama-French three factor model

	Intercept	MKTRF	SMB	HML	# months	R-Squared
GLS	0.108	0.026	0.003	0.770	468	0.25
	0.56	*0.61*	*0.04*	*11.83*		
EPR	0.408***	-0.186	-0.149	0.784	468	0.52
	2.99	*-6.02*	*-3.39*	*16.88*		
GGM	0.759***	-0.204	0.166	0.558	444	0.21
	3.72	*-4.50*	*2.53*	*8.12*		
AGR	0.436**	-0.083	0.334	0.319	468	0.11
	2.40	*-2.02*	*5.73*	*5.17*		

Panel B: Carhart four factor model

	Intercept	MKTRF	SMB	HML	UMD	# months	R-Squared
GLS	0.266	-0.008	0.002	0.715	-0.163	468	0.27
	1.38	*-0.18*	*0.03*	*10.87*	*-3.89*		
EPR	0.489***	-0.204	-0.149	0.755	-0.084	468	0.53
	3.53	*-6.50*	*-3.43*	*15.99*	*-2.78*		
GGM	1.041***	-0.264	0.177	0.455	-0.302	444	0.29
	5.28	*-6.01*	*2.85*	*6.82*	*-7.11*		
AGR	0.732***	-0.147	0.332	0.215	-0.305	468	0.22
	4.21	*-3.73*	*6.09*	*3.62*	*-8.09*		

Table VII: Relation between future returns and ICC estimates based on analyst forecasts

This table reports the results of sensitivity tests using ICC estimates based on corrected analyst forecasts following the approach in Gode and Mohanram (2010). Panel A displays the earnings announcement returns and the annual buy–and-hold returns for the hedge portfolio that is long in the highest ICC decile and short in the lowest ICC decile. Returns are expressed in percents and Fama-MacBeth t-statistics are listed below the returns. The bottom part of Panel A expresses the earnings announcement returns as a percentage of the annual returns. Panel B displays the regression results of the Fama-French three factor model. *, **, and *** indicate statistical significance at 10, 5, and 1 percent levels based on two-tailed tests.

Panel A: Comparison of earnings announcement and annual hedge portfolio returns

	GLS	EPR	GGM	AGR
Earnings announcement (EA) returns	1.14**	0.17	0.24	0.67*
	2.30	*0.34*	*0.56*	*1.65*
Annual buy-and-hold (BH) returns	5.68*	6.79**	4.54*	5.21**
	1.92	*2.09*	*1.67*	*2.29*
Ratio of EA returns to annual BH returns	20%	2%	5%	13%
Ratio after correcting for number of EA days	16%	-2%	1%	9%
Ratio after correcting for volatility on EA days	10%	-9%	-6%	2%

Panel B: Fama-French three factor model

	Intercept	MKTRF	SMB	HML	# months	R-Squared
GLS	0.136	0.078	0.157	0.551	312	0.20
	0.75	*1.91*	*2.70*	*8.87*		
EPR	0.357**	-0.078	-0.261	0.598	312	0.42
	2.14	*-2.08*	*-4.88*	*10.44*		
GGM	0.248*	0.077	-0.067	0.175	312	0.06
	1.66	*2.27*	*-1.40*	*3.39*		
AGR	0.140	0.048	-0.055	0.357	312	0.16
	0.93	*1.43*	*-1.14*	*6.96*		

Table VIII: Relation between ICC and future returns when controlling for news

This table reports the average coefficients of the annual cross-sectional regression of future returns on the ICC estimates and proxies for earnings surprises (ES) and changes in discount rates (DRS). The realized returns are the compounded monthly raw stock returns in the 12 months following the portfolio formation date (including delisting returns following the approach in Beaver, McNichols and Price, 2007), the earnings surprise (ES) is the difference between the realization of earnings and the model forecast scaled by market value, and the change in discount rate (DRS) is the change in the ICC estimate during the year. *, **, and *** indicate statistical significance at 10, 5, and 1 percent levels based on two-tailed tests.

ICC estimate = GLS

Model	Intercept	ICC	ES	DRS	EAR	R-Squared
1	0.110***	0.363*				0.009
	2.71	*1.82*				
2	0.033	1.086***	0.889***			0.072
	0.86	*5.35*	*23.80*			
3	0.183***	-0.282		-1.426***		0.046
	3.87	*-1.09*		*-6.05*		
4	0.108**	0.415	0.897***	-1.475***		0.108
	2.42	*1.62*	*20.67*	*-6.48*		
5	0.111**	0.119			1.135***	0.116
	2.52	*0.67*			*18.57*	

ICC estimate = EPR

Model	Intercept	ICC	ES	DRS	EAR	R-Squared
1	0.102***	0.329***				0.008
	3.12	*3.20*				
2	0.062*	1.095***	1.023***			0.087
	1.92	*10.17*	*19.94*			
3	0.106***	0.416***		0.098		0.027
	3.26	*3.47*		*1.50*		
4	0.068**	1.031***	1.275***	-0.456***		0.115
	2.09	*8.97*	*14.35*	*-3.89*		
5	0.108***	0.168			1.156***	0.130
	2.97	*1.43*			*18.48*	

ICC estimate = GGM

Model	Intercept	ICC	ES	DRS	EAR	R-Squared
1	0.135***	0.389***				0.009
	4.00	*2.88*				
2	0.094***	0.755***	0.831***			0.066
	2.90	*6.03*	*13.60*			
3	0.166***	-0.009		-1.331***		0.042
	4.67	*-0.06*		*-4.63*		
4	0.127***	0.340**	0.878***	-1.442***		0.103
	3.59	*2.25*	*12.35*	*-4.87*		
5	0.116***	0.168			1.120***	0.116
	3.06	*1.43*			*18.02*	

ICC estimate = AGR

Model	Intercept	ICC	ES	DRS	EAR	R-Squared
1	0.119***	0.364***				0.011
	3.81	*3.55*				
2	0.109***	0.468***	0.785***			0.064
	3.55	*4.57*	*20.54*			
3	0.139***	0.135		-0.320***		0.019
	4.14	*1.19*		*-3.55*		
4	0.127***	0.257**	0.780***	-0.296***		0.071
	3.88	*2.47*	*20.98*	*-3.54*		
5	0.108***	0.127*			1.145***	0.115
	3.25	*1.81*			*19.42*	