Market inefficiency and implied cost of capital models

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ABSTRACT
In this paper I examine the impact of market inefficiency on the properties of implied cost of capital (ICC) models. I develop a simple model of measurement error in implied cost of capital models starting from the underlying primitives, investors’ and researcher’s earnings forecasts, and show that under reasonable assumptions, market inefficiency will bias the ICC estimate and the future returns in the same direction. This results in a positive relation between ICC estimates and future returns. Using a variety of approaches I show that, for the median ICC estimate, between 44% and 69% of the relation between ICC estimates and one-year-ahead stock returns stems from mispricing rather than expected returns. I also show the effect of mispricing is drastically reduced when using a value weighted analysis which suggests this may be a useful way to mitigate effect of mispricing on the ICC estimates. In subsequent analyses I find that, while intuitively appealing, controlling for earnings and discount rate news is unlikely to be effective in mitigating biases induced by mispricing within the set of measures I consider in my analyses.

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1. Introduction

Cost of capital is an important concept in finance and accounting research. The literature has long recognized that average realized returns offer a very noisy proxy of the cost of equity capital (e.g. Elton, 1999). Implied cost of capital (ICC) models potentially offer a promising alternative for estimating cost of capital, even if the estimates from these models contain some noise as well. Accounting researchers have used these models to assess the effects of disclosure quality (e.g. Botosan, 1997) and earnings quality (e.g. Francis, LaFond, Olsson, and Schipper, 2004) on the cost of equity capital. Many different ICC models have been developed in the literature and the question is how to evaluate the quality of the measures. Common approaches in the literature include test 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), the association future stock returns (e.g., Guay, Kothari, and Shu, 2005), and the association with future stock returns with controls for news (Easton and Monahan, 2005). A third approach developed in Easton and Monahan (2005) tries to explicitly model the measurement error in the ICC proxies rather than rely on any particular regression estimate.

Which of these approaches is best is the subject of an ongoing debate (e.g. Botosan, Plumlee, and Wen, 2010; Easton and Monahan, 2010). Given that the quality of ICC estimates is multi-dimensional, it is unlikely that one approach is sufficient.¹ Not only the variance of the measurement error, but also the extent to which is correlated with the true discount rate, potential mispricing and other firm characteristics, matters for research purposes. In this study, I focus on impact of potential market inefficiencies on the properties of ICC estimates, and in particular the

effect on the relation between ICC estimates and future returns. Given that many of the risk proxies are drawn from prior literature based on their ability to predict future returns, the findings in this paper have implications for those tests as well. To the extent ICC estimates vary in their ability to capture mispricing, it can have serious implications for the selection of ICC estimates for research and practical purposes.

In this paper I develop a model starting from the underlying primitives, investors’ and researcher’s earnings forecasts. This approach complements approaches in Easton and Monahan (2005) and Lee, So, and Wang (2010) which start from the assumption of a noisy cost of capital proxy. The advantage of starting from the underlying primitives is that it provides more insight into the sources and relative importance of measurement errors in the ICC estimates. As a result this approach can provide more guidance as to the direction and magnitude of the biases induced by these measurement errors. The model shows that under reasonable assumptions, market inefficiency will result in a positive relation between ICC estimates and future returns, and that this will result in an upward biased estimate on the ICC coefficient in a regression of future returns on ICC estimates.

In the empirical part of the paper I try to quantify the relative importance of expected returns and mispricing. I use the approach in Hou, Van Dijk, and Zhang (2010) as extended by Lee, So, and Wang (2010) in forecasting earnings and calculating ICC estimates. Consistent with these papers I find that ICC estimates predict future stock returns. I use two approaches to separate the competing hypotheses for these returns. First, I use earnings announcement returns to provide a lower bound on importance of mispricing. Based on the four models I examine, earnings announcement returns account for 16% to 51% of the returns to a hedge portfolio based on the extreme deciles of ICC estimates. My second approach tries to establish an upper bound
on the importance of mispricing by looking at the fraction of the average hedge portfolio return that is not explained by the Fama-French (1993) three factor model. Based on the four models I examine, the fraction of the predicted return unexplained by the three factors is between 59% and 83% of the expected return. Overall, these results suggest that for equal weighted returns a large fraction of the explanatory power is due to mispricing instead of expected returns.

Results for value weighted returns show a much smaller relative effect of mispricing for most but not all ICC models. This suggests that value weighting is a relatively effective method to mitigate the effect of mispricing. Using value weighting in tests designed to select the ‘best’ ICC estimates reduces the likelihood that ICC estimates are chosen because they are particularly affected by mispricing. It also suggests that in applications using ICC estimates one should use a value-weighted analysis when using ICC estimates to test whether a proposed risk factor is priced. Additionally, in these cases it is important to test returns around future earnings announcements to make sure that the proposed risk factor is not an anomaly in disguise. Since analyses of earnings announcements have much higher statistical power than annual buy and hold returns, this should not pose an undue burden.

The second part of the empirical work considers whether controlling for news proxies provides an effective control for the biases induced by mispricing. The model shows that theoretical case for controlling for news is ambiguous, and that the usefulness depends on the importance of measurement error in the researcher estimates of earnings and by extension the ICC estimates. My analyses suggest that the directional effects of the inclusion of news proxies on the ICC coefficient are most consistent with researcher induced measurement error rather than errors in realized returns. I conclude that on balance, my analyses suggest that the potential benefits of inclusion of the news proxies do not outweigh the risks.
The analysis in this paper contributes to the literature on implied cost of capital estimates and 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, the analyses in this paper 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, and the effect of including proxies for earnings news and discount rate news. 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, and I conclude in section 5.

2. **Modeling implied cost of capital under market inefficiency**

In valuing a stock investors use expectations of earnings and discount rates to arrive at a price. Implied cost of capital models invert this process by using the observed price of the stock and researchers’ estimates of earnings to derive a discount rate implied by the observed market price. It is well recognized in the literature that the resulting estimates will be noisy if the researcher cannot accurately estimated the investors’ expectations of earnings. A lot of the prior literature is focused on modeling the development of earnings after the first year and whether analysts’ forecasts can be used as a reliable estimate of investors’ expectation of earnings. In this section I focus instead on the properties of the implied cost of capital measure when in addition the investors’ expectations are noisy versions of the true expected earnings.

The model is structured as follows. For simplicity earnings are treated the same as cash flows, therefore instead of using a discounted cash flow model, the model participants will use a discounted earnings model. Both investors and the researcher forecast earnings one period ahead,
and both investors and the researcher assume that earnings \((E)\) are a random walk after that and that the discount rate \((r)\) is a time-series constant\(^2\). The firm is infinitely lived. Thus the price of the stock \((P)\) can be expressed as follows:

\[
P_t = \frac{E_i'[E_{t+1}]}{r}
\]  

(1)

The researcher observes this price and forms his own expectations of the one period ahead earnings to compute the implied cost of capital. Thus the implied cost of capital \((ICC)\) can be expressed as follows:

\[
ICC_t = \frac{E_r'[E_{t+1}]}{P_t}
\]  

(2)

The superscript on the expectation operators indicates a subjective expectation \((i = \text{investor} \text{ and } r = \text{researcher})\). Much of the prior literature on developing and evaluating implied cost of capital estimates focuses on the noise introduced by the researcher’s choice of the initial earnings estimates and the appropriate model for the development thereafter (e.g. random walk or mean reversion). In the model I will just focus on the quality of the earnings estimate and not on the choice of the earnings development thereafter. This simplification is without much loss of generality as the choice of earnings development model is also a forecast of earnings.

Next, I will discuss first separately discuss the properties of the ICC estimate and future returns under market inefficiency. Then I derive the relative impact of the mispricing on the ICC estimates versus future returns. This is followed by an analysis of the effect of mispricing on the

\(^2\) This precludes the biases introduced by a stochastic discount factor such as those discussed in Hughes, Liu, and Liu (2009).
relation between future returns and ICC estimates. Finally, I discuss the potential of alternative approaches to correct for the effect of mispricing.

2.1 Derivation of the implied cost of capital estimates

The key innovation in the model is an examination of the effect of potential market inefficiencies on the properties of implied cost of capital estimates. This is important because prior literature has documented a variety of anomalies, instances in which investors do not appear to correctly price (accounting) information, see Richardson, Tuna and Wysocki (2010) for a recent survey. This mispricing can affect the quality of implied cost of capital estimates since the stock price is used in the construction of these estimates. In the context of the model, market inefficiencies arise when investors forecast future earnings incorrectly given the available information at the time of the forecast ($\Omega_t$). Thus, the investors’ earnings expectation can be expressed as the true earnings expectation given the available information plus an error term ($\epsilon$):

$$E^i_t[\omega_{t+1}] = E^i_t[\omega_{t+1} | \Omega_t] + \epsilon_t$$  \hspace{1cm} (3)

Using this definition for the investors’ earnings expectation the stock price can be characterized as follows:

$$P_t = \frac{E^i_t[\omega_{t+1}]}{r} = \frac{E^i_t[\omega_{t+1} | \Omega_t] + \epsilon_t}{r}$$  \hspace{1cm} (4)

This expression has a very intuitive interpretation, if investors overestimate (underestimate) future earnings, the stock price will be higher (lower).

In deriving their own earnings forecast, ideally the researcher use the same (potentially biased) earnings forecast that the investors used. In that case the error in the earnings forecast would offset the error in the stock price and implied cost of capital estimate would equal the discount rate investors used. In practice, the investors’ earnings expectations are not readily observable, and researchers have to make their own forecasts of earnings. The natural proxy,
analysts’ forecasts of earnings, is subject to well-documented biases such as analysts’ optimism, which has been shown to adversely affect the quality of ICC estimates (Easton and Sommers, 2007). Recent advances using regression models to estimate future earnings manage to reduce the average biases in forecasts, but still contain substantial measurement error (Hou, Van Dijk, and Zhang 2010). Therefore, I model the researcher’s earnings forecast as the forecast based on all available information at the time of the forecast ($\Omega_t$) plus measurement error ($u_t$). The measurement error is assumed to have a zero mean. In that case:

$$E_r[E_{t+1}] = E_r[E_{t+1} | \Omega_t] + u_t \tag{5}$$

It is likely that the errors in the researcher’s and investors’ earnings forecasts are correlated, for example, if both are based in part on analysts’ forecasts. I therefore allow these errors to be correlated in the model. Using these two subjective earnings expectations, the current stock price and the ICC can be expressed as follows:

$$ICC_t = \frac{E_r[E_{t+1}]}{P_t} = \frac{E_r[E_{t+1}] \cdot r}{E_r[E_{t+1}]} = \frac{E_r[E_{t+1} | \Omega_t] + u_t \cdot r}{E_r[E_{t+1} | \Omega_t] + \varepsilon_t \cdot r} \tag{6}$$

From this expression it is clear that the two types of errors have opposite effects on the ICC estimate. If the researcher overestimates future earnings ($u > 0$), the ICC will be higher than the true discount rate, whereas if the investors overestimate future earnings ($\varepsilon > 0$), the ICC will lower than the true discount rate. As discussed earlier, if the two errors are identical then the ICC will equal the true discount rate.

It is also instructive to consider if the impact of the researcher’s and investors error on the ICC averages out in a broad cross-sectional sample. I derived the expected ICC allowing the two error terms to be correlated with each other, but not with the true discount rate. Using a second order Taylor expansion yields the following (details are provided in the Appendix):
\[
E[ICC_i] \approx \left( 1 - \frac{\text{cov}(\varepsilon_i, u_i)}{E_i[E_{t+1} | \Omega_i]^2} + \frac{\text{var}(\varepsilon_i)}{E_i[E_{t+1} | \Omega_i]^2} \right) \cdot E[r]
\] (7)

There are several noteworthy features in this expression. First, by itself, the noise in researcher’s earnings estimate averages out in the cross-section. The reason is that the researcher’s error is assumed to be mean zero and the ICC is linear in the researcher’s earnings estimate in the setting considered here, infinitely lived firms with earnings that follow a random walk.\(^3\) Second, the effect of mispricing on the ICC does not fully average out, even though the error has a zero mean. Using this estimation error variance as a measure of the inefficiency of the stock market, it follows that the ICC is upwardly biased for stocks that trade in less efficient markets, although the magnitude of this effect is expected to be relatively small as long as the mispricing is modest.\(^4\)

Finally, the upwards bias induced by market inefficiency is mitigated if the researcher’s error covaries positively with the investor’s estimation error. If the researcher exhibits all the same biases as the investors but to a larger degree, then the covariance term is larger than the variance term, and the predictions reverse. Ex-ante this seems unlikely, and in the model I only consider the case in which the covariance is weakly smaller than the variance.

2.2 Characterization of realized returns

The realized returns in the model are a function of the expected returns and news. There are two sources of news in the model. First, there is news about fundamentals as earnings for

\(^3\) 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.

\(^4\) For example, in the case where the standard deviation of the investors’ error is ten percent of the true earnings expectation the upward bias in the ICC is only one percent of the discount rate (r). For a discount rate of 10%, this would imply an upward bias of 10 basis points.
period \( t+1 \) are realized which also affects earnings forecast for all future periods. Second, the 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 earnings (cash flows) and the present value of expected future earnings which can again incorporate an estimation error term.

\[
P_{t+1} = E_t[E_{t+1} | \Omega_t] + n_{t+1} + \frac{E_t[E_{t+1} | \Omega_t] + n_{t+1} + \varepsilon_{t+1}}{r}
\]

(8)

To be true news, the earnings news \((n)\) has to have zero mean and be uncorrelated with the other random variables in the model. As with the regular earnings, the news in earnings is assumed to be a random walk. To capture the possibility that the current mispricing does not fully reverse itself in the next period, I allow the future mispricing to be correlated with the current mispricing. In particular, I decompose the future error into two components, the fraction of the old estimation error that persists \((\rho \varepsilon_t)\) and new error \((\delta_{t+1})\). The persistence parameter \((\rho)\) is expected to be greater than 0 and strictly less than 1. This yields the following expression for the future price:

\[
P_{t+1} = \frac{(1 + r)(E_t[E_{t+1} | \Omega_t] + n_{t+1}) + \rho \varepsilon_t + \delta_{t+1}}{r}
\]

(9)

Using this expression for the price at \( t+1 \) and the expression for the price at \( t \) (equation 4), the realized returns can be characterized as follows:

\[
R_{t+1} = \frac{P_{t+1} - P_t}{P_t} = \frac{rE_t[E_{t+1} | \Omega_t] + (1 + r)n_{t+1} - (1 - \rho)\varepsilon_t + \delta_{t+1}}{E_t[E_{t+1} | \Omega_t] + \varepsilon_t}
\]

(10)

Thus, future returns are increasing in the discount rate \((r)\), the earnings news \((n)\), the persistence of past overestimation \((\rho)\) and the amount of new overestimation \((\delta)\) of future earnings. If there were no mispricing this expression simplifies to realized returns equaling expected returns plus news. As with the ICC it is instructive to consider the impact of the market efficiency on the
realized returns in a broad cross-sectional sample. Using a second order Taylor expansion yields the following (details are provided in the Appendix):

\[ E[R_{t+1}] \approx E[r] + \frac{E[r] + (1 - \rho)}{E_t[E_{t+1} \mid \Omega_t]} \cdot \text{var}(e_r) \]  

(11)

In this case, even though the investors’ estimation error has a zero mean and the price is correct on average, the realized returns not equal the expected returns on average. This occurs because the mispricing affects both the numerator (future change in price) and the denominator (current period price) of the future returns. In particular, realized returns will on average be higher than the discount rate. The extent of the bias is increasing in the variance of estimation errors and fraction of mispricing that reverts within the period \((1 - \rho)\). The magnitude of the bias is expected to be relatively small as long as the mispricing is modest, though larger than the equivalent bias induced in the sample average ICC.\(^5\)

2.3 Relative impact of mispricing on implied cost of capital and realized returns

The prior sections demonstrate that both realized returns and implied cost of capital estimates are affected by mispricing. Consequently, one should be careful to in using ICC measures to separate risk from mispricing explanations of anomalies, as under both hypotheses we would expect a link between the potentially mispriced variable and the implied cost of capital. As a researcher we cannot directly observe the noise in the investors’ earnings estimates, but we may be able to measure some factor that is correlated with the noise. For example, according to Sloan (1996) investors overestimate future earnings for firms with high accruals and as a result these firms are overvalued. In that case, researchers using unbiased earnings estimates

\(^5\) For example, in the case where the standard deviation of the investors’ error is ten percent of the true earnings expectation the upward bias in the average realized returns is one percent of the sum of the discount rate \((r)\) and \((1 - \rho)\), whereas the effect on the ICC is only one percent of the discount rate (see also footnote 4). For a discount rate of 10\% and a mispricing persistence parameter of 0.4, this would imply an upward bias of 70 basis points versus 10 basis points for the ICC estimate. Also note that value weighted average returns do not suffer from this problem.
along with these overstated stock prices would then obtain downward biased ICC estimates. Similarly, firms with low accruals would have an undervalued stock price and hence upward biased ICC estimates.

This raises the question whether one of the two cost-of-capital estimation methods is more sensitive to mispricing than the other. The natural way to test this would be to regress both realized returns and ICC estimates on the mispricing proxy and compare the coefficients. In both cases we 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 (\( \varepsilon \)) as the mispricing proxy. To make sure the coefficient is not affected by the scale of the firm, I standardize the mispricing by the expected earnings level: \( E_t[E_{t+1} | \Omega_t] \). 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:

\[
\beta_{ICC,Mispricing} \approx \left( \frac{\text{cov}(\varepsilon_t, u_t)}{\text{var}(\varepsilon_t)} - 1 \right) E[r]
\]

(12)

If the two error terms 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 will be smaller but weakly negative. As before, if the researcher’s earnings estimate perfectly matches the investors’ earnings estimate, then the ICC is unaffected by mispricing, and the coefficient will be zero.

Similarly, we can regress the realized returns on the mispricing proxy. In that case, the coefficient can be expressed as follows:
From this it is clear that the coefficient is negative and larger than the coefficient in the regression using the ICC as the dependent variable. In particular, the gap between the two coefficients is larger if the portion of the mispricing that reverses within a year is larger (meaning the mispricing persistence, $\rho$, is smaller). For intermediate values of $\rho$ the coefficient in the realized returns regression will be several times larger than the coefficient in the ICC regression.

### 2.4 Implications for the relation between ICC and future returns

A common method of evaluating the level of noise in implied cost of capital estimates is by investigating their predictive ability with respect to future stock returns (e.g., Guay, Kothari, and Shu, 2005; and Easton and Monahan, 2005). The standard regression involves regressing future returns on the ICC estimate. In that case, the probability limit of the regression coefficient can be expressed as follows:

$$
\beta_{ICC} = \frac{\text{cov}(ICC, R_{t+1})}{\text{var}(ICC)}
$$

(14)

In the full model this expression is a function of four random variables ($\varepsilon$, $\delta$, $u$, and $n$) and once the model is estimated in a cross-section, the expected return ($r$) is a random variable as well. Two variables, the news variable ($n$) and the future innovation in mispricing ($\delta$), play no role in the probability limit of the coefficient estimate, since 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. It is therefore more instructive to consider a few special cases:
Random variables & Probability limit of the regression coefficient on the ICC estimate \\
$r, \delta, n$ & 1 \\
$\varepsilon, \delta, n$ & $(1 - \rho + r)/r$ \\
$u, \delta, n$ & 0 \\
$r, u, \delta, n$ & $\frac{\text{var}(r)}{\text{var}(E_r)} \left( \text{var}(r) + \frac{\text{var}(u)}{E_r^2 \Omega} \right)^2 \left( \text{var}(r) + E_r^2 \right)$ \n
The first result is the ideal case, the ICC measures true expected returns without error and the market is efficient, hence we get a coefficient of one. The second case is the case with market inefficiency but perfect researcher forecasts. The intuition is that if the mispricing fully reverses one period later, but the ICC spreads the mispricing effect over an infinite horizon, then the coefficient is the capitalization factor. If the mispricing partially persists then the coefficient will be smaller, but remain greater than 1 (for a derivation see the Appendix). In the third case the only random component in the ICC is the researcher induced noise; hence the correlation with realized returns is zero. The coefficient in the general model will be some weighted average of these three cases. The fourth case shows how that trade-off operates when the market is efficient, but the researcher’s earnings estimates have error and the discount rate varies cross-sectionally. The resulting equation is the multiplicative version of the standard attenuation bias caused by measurement error. As the variance of the measurement error becomes large (small) relative to the cross-sectional variance of the discount rate the coefficient moves to zero (one).

Combining these findings suggests the following. First, since news is uncorrelated with the other parameters, it does not bias the coefficients. However, it does introduce noise into the regressions. Thus, ex post, the realization of news may affect the relation between the ICC estimates and future returns. Second, mispricing results in a higher ICC coefficient in a
regression of future returns on ICC estimates. Third, in contrast, measurement error induced by the researcher’s earnings estimates drives down the ICC coefficient. Fourth, both these effects are mitigated when the measurement error in the investors’ and researcher’s earnings estimates is correlated.

2.5 Implications for the relation between ICC and future returns when controlling for news

Tests of the quality of the implied cost of capital estimates using future returns suffer from a lack of power. Most of the cross sectional variation in future returns comes from news about the firms’ cash flows and changes in their risk, rather than from variation in expected returns. To control for that the prior literature includes proxies for the cash flow and discount rate news in the regression (e.g. Easton and Monahan, 2005). Within the context of the model described above the natural way to construct a proxy for earnings news is to take the difference between the actual earnings and the researcher’s earnings estimates (scaled by price):

\[
EarnSurp_{t+1} = \frac{E_{t+1} - E'_{t+1}}{P_t} = \frac{r \cdot (n_{t+1} - u_t)}{E_t[E_{t+1} | \Omega_t] + \varepsilon_t}
\]

(15)

Recall that the ICC and the future returns can be expressed as follows:

\[
ICC_{t} = \frac{E_{t} [E_{t+1}]}{P_t} = \frac{E_t[E_{t+1} | \Omega_t] + u_t \cdot r}{E_t[E_{t+1} | \Omega_t] + \varepsilon_t}
\]

\[
R_{t+1} = \frac{P_{t+1} - P_t}{P_t} = \frac{rE_t[E_{t+1} | \Omega_t] + (1 + r)n_{t+1} - (1 - \rho)\varepsilon_t + \delta_{t+1}}{E_t[E_{t+1} | \Omega_t] + \varepsilon_t}
\]

If the market is efficient (\(\varepsilon=0\)), then the expected value of the future returns will equal the discount rate. However, while in that case future returns provide an unbiased estimate of the expected returns, the estimate is very noisy. If one could control for all the news (\(n\)), then the noise could be eliminated. In practice, one needs to estimate the news which introduces measurement error. As can be seen from the earnings surprise variable (\(EarnSurp\)), the
measurement error in the earnings news proxy is the same as the measurement error in the researcher’s earnings forecast \((u)\), and therefore the ICC and the earnings surprise variable will be negatively correlated. Given the positive relation between earnings surprise and future returns this implies that the coefficient on the ICC variable will be biased upwards after inclusion of the earnings surprise variable.

In the extreme case in which the expected return is a constant, the coefficient on the ICC will mirror the coefficient on the earnings surprise variable, in effect purging the measurement error from the earnings surprise variable. It can be shown that in that case:

\[
\beta_{\text{ICC}} = \beta_{\text{EarnSurp}} = 1 + \frac{1}{r}
\]

(16)

This despite the fact that under these assumptions, the ICC is pure noise and the true relation between ICC and future returns equals to zero. While admittedly, this is an extreme case that is unlikely to be descriptive, the general point is that controlling for earnings news induces an upward bias in the ICC coefficient.\(^6\) In practice, when the discount rate varies cross-sectionally, the magnitude of this bias will depend on the variances of the researcher’s measurement error relative to the variances of the true earnings news and the discount rates.

In the case of market inefficiency the use of news proxies may be more promising. In that case, using future returns as a proxy for expected returns yields both biased and noisy estimates. For the earnings surprise proxy to be effective in remedying the market inefficiency it needs to be reflective of the investors’ forecast errors. As can been seen from the earnings surprise proxy equation above, the investors’ forecast errors potentially enter in two way. Directly, because the

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\(^6\) 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 can be accomplished by 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.
investors’ forecast errors affect the stock price which is reflected in the denominator, and indirectly if the researcher’s forecast errors are positively correlated with the investors’ forecast errors, which seems plausible. The first effect, by itself, does not affect the correlation between the earnings surprise estimate and the ICC estimate. Therefore, in the case that the researcher’s earnings estimates are without error or if the error is uncorrelated with error in the investor’s estimates, controlling for news has no effect on the bias induced by mispricing but it may reduce the noise in the regression.

In the likely case that both the researcher’s and the investors’ earnings estimates contain measurement error the question is whether the inclusion of earnings news proxies is beneficial. The answer to this depends on the relative magnitude of the effect two errors. A simple test of whether the effect of the researcher’s or the investors’ measurement error dominates 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 inclusion of the earnings surprise variable in the regression.

2.6. The effect of market inefficiency on models of measurement error variances

The model so far focuses on the effect of market inefficiency on regressions of realized returns on the implied cost of capital proxies. Because the problems with realized returns the literature has attempted to directly model the structure of the measurement error in the ICC proxies. The most developed model is found in Easton and Monahan (2005). Using the approach in Vuolteenaho (2002), they decompose realized returns in 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, they “… 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 (p.534).” 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 2.5 arising from directly looking at the coefficients in the regression.

The question is how these assumptions compare to the structure of model developed in this paper, in particular whether these assumptions can accommodate market inefficiency. With respect to the measurement error in the ICC estimates due to the researcher’s earnings estimates, the assumption seems to track closely. As can be seen from section 2.1, under market efficiency, the measurement error in ICC is uncorrelated with (but not independent of) the true discount rate. As discussed in footnote 3, while this result does not generally hold, to the extent my model is a reasonable approximation, this assumption seems reasonable. However, as can be seen from sections 2.2 and 2.3, in case of market inefficiency the measurement error in the ICC proxy is correlated with the true discount rate. Moreover, the 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 based on objective expectations, however, in that case, the noise in the news variables will also be correlated with the underlying true value of the news. In addition, it is not clear that one would want to treat the two sources of measurement error in the ICC estimates the same. It seems therefore useful to complement these types of analyses with an explicit investigation of the impact of market inefficiency on the ICC estimates as is done in this paper.

7 Note however, that under the assumption that the ICC is equal to the true discount rate and uncorrelated noise, an easier way to evaluate the ICC estimates is available. In that case the variance of the ICC estimate is simply the sum of the variance of the true discount rate and the variance of the noise. Thus, within sample, the ICC estimates can simply be ranked by their relative variances, since the variance of the true discount rate will be the same across different proxies.
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 2007 with sufficient data on CRSP and Compustat to calculate the implied cost of capital estimates. In calculating the ICC measures, I follow the approach in Hou, Van Dijk, and Zhang (2010) 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 each year using the past 10 years of data (minimum of 6 years):

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

where $E_{j,t+\tau}$ ($\tau = 1, 2, 3, 4, \text{ or } 5$) denotes the earnings before extraordinary items (Compustat item IB) of firm $j$ in year $t+\tau$, 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 minus the change in current liabilities (Compustat item LCT). Each variable in the regression is winsorized at the 0.5 and 99.5 percentiles of that year to mitigate the effect of extreme observations.
The average annual coefficients and Fama-Macbeth t-statistics\(^8\) from these regressions are displayed in Table 1. Overall, the coefficient estimates are relatively similar to Hou, Van Dijk, and Zhang (2010) and Lee, So, and Wang (2010). On June 30\(^{th}\) of each year, each firm’s forecasted earnings are calculated using the most recent historical coefficient estimates applied to the most recent reported earnings and other explanatory variables. These are then used to predict book values using the beginning book values and the clean surplus assumption. The earnings and book values together with the market value of the equity (also measured on June 30\(^{th}\)) are then used to generate each of the ICC estimates. 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. In the current version of the paper I focus only on these four estimates, since 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. The four models are labeled GLS, EPR, GGM, and AGR. I discuss these 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 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.

\(^{8}\) 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.
\[ MVE_{i,t} = B_{i,t} + \sum_{\tau=1}^{11} \frac{E_{i}(ROE_{i,t+\tau} - r_i) \cdot B_{i,t+\tau-1}}{(1 + r_i)^\tau} + \frac{E_{i}[(ROE_{i,t+12} - r_i) \cdot B_{i,t+11}}{r_i \cdot (1 + r_i)^{11}} \]

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.

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

Similar to Lee, So, and Wang (2010), I consider two different forecast horizons, \( T=1 \) and \( T=5 \). The first simplifies to the earnings to price ratio using forecasted next period’s earnings (labeled EPR). The second model based on this uses the explicit earnings forecast for period 5 for the terminal value and use 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 is the case with 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):

\[
P_{i,t} = \frac{EPS_{i,t+1}}{r_i} + \frac{EPS_{i,t+2} + r_i \cdot DPS_{i,t+1} - (1 + r_i) \cdot EPS_{i,t+1}}{r_i \left( EPS_{i,t+3} + r_i \cdot DPS_{i,t+2} - (1 + r_i) \cdot EPS_{i,t+2} \right) + 1}
\]
As can be seen from this, the AGR model is essentially the EPR model plus a term correcting 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 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 is has the lowest average which is to be expected since 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 suggests that individual firms’ stock returns are mostly driven by news and thus a very noisy proxy of expected returns. As can be seen from Panel A, while the average individual firm return is about 13.6%, the returns are right-skewed with the median return (3.7%) less than the average risk free rate for the period (6.6%), and a standard deviation of about 75%. Since realized returns are the dependent variable in the regression this 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 relative limited, it is an empirical question as to whether there is sufficient data to achieve this. To provide initial evidence on this, 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 that the market risk premium is reliably positive.

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 37 annual returns periods starting from July 1, 1971 to June 30, 2008 as the main sample. While cross-sectional averaging reduces the standard deviation by about two-thirds (from a little over 75% to a little under 25%), still a significant fraction of years experiences a negative realized risk premium. Thus even though CRSP covers several thousand firms per year, the correlation among their returns is such that there is still significant variation left. Next I consider the effect of averaging over consecutive 5 year periods, within my sample period there are 33 overlapping 5 year periods. This results in an additional drop in the standard deviation of returns, although still more than 5% of the 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.

To get a sense of the stability of the estimates in this paper, which are based on a 37-year period, I next consider non-consecutive 36-year periods, dropping one year at a time. This shows how sensitive the results are to the exclusion of individual years. Unsurprisingly, this procedure results in the lowest standard deviation. In particular, the difference between the 5th and the 95th percentile is less than 2%. Panel D shows the same analysis with using the value weighted market return. Value weighted returns are less variable in general, but otherwise the inferences
are similar. Thus, while even with thousands of firms and 37 years the averaging is still not perfect, it is does seem to be reasonably effective.

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. In the next section, I discuss the analysis trying to quantify the relative importance of these two hypotheses. Then in section 4.2, I will discuss the effectiveness of controlling for news in remedying the effects of mispricing.

4.1 Estimating the relative importance of expected returns and mispricing

To help quantify the relative importance of mispricing and expected returns in explaining the relation between ICC estimates and future stock returns, I use two methods. First, to get a lower bound on the effect of mispricing, I examine the relation between ICC estimates and the returns around earnings announcements. This is a commonly used approach to separate risk and mispricing explanations for seemingly anomalous stock returns (e.g., Bernard and Thomas (1990), Bernard, Thomas, and Wahlen (1997)). If the mispricing is related to investors misestimating earnings, as it is in the model in section 2, 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.

The second approach tries to establish an upper bound for effect of mispricing by using the Fama-French three factor model (Fama and French, 1993). Under this approach returns that
are not explained by the three 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. 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). Combining these two approaches allows for an assessment for the magnitude of the mispricing effect.

Before trying to assess the magnitude of the potential mispricing I first examine the total explanatory power of the ICC estimates for future returns. On June 30th of each year firms are sorted into deciles based on the magnitude of their ICC estimates, with Decile 1 containing the firms with the lowest ICC. Then the returns for each firm are compounded from July 1st till June 30th of the next year. In case the 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 remaining firms of the respective ICC decile. Table III reports the average annual decile returns and hedge portfolio returns for each of the four ICC estimates. Panel A displays 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 and short in decile 1. The results confirm findings in Lee, So, and Wang (2010) that each of these four ICC estimates predict future stock returns. Panel B displays the value weighted returns (minus the value weighted market return). All four estimates continue to have positive hedge portfolio returns, which, with the exception of AGR, are also statistically significant.

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 announcement (three day windows around each of the four quarterly earnings
announcements). Each year these earnings announcement returns (minus the market return over the corresponding days) are averaged by decile. Table IV reports the average annual earnings announcement returns by decile. The hedge portfolio results indicate significant differences between decile 1 and decile 10, suggesting that mispricing explains part of the relation between ICC estimates and future stock returns. The hedge portfolio returns are positive and statistically significant for all four ICC estimates. The earnings announcement returns explain between 16% (EPR) and 51% (GGM) of the abnormal buy and hold returns from Table III (median 46%). 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 there are abnormal returns throughout the year, we would expect to see some abnormal returns around the earnings announcement as well. To correct for this, I subtract the following adjustment factor from the abnormal returns at the earnings announcements:

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

The results of this adjustment are virtually unchanged from the analysis above, the fraction of corrected earnings announcement returns to the full year buy and hold returns is now 0.43, 0.12, 0.48, and 0.44 for GLS, EPR, GGM, and AGR respectively.

A second, and related concern, is that one might expect to see higher than average risk premium on earnings announcement days given the greater information flows and risk on those
days. 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 the 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 nondiversifiable 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 to the results. To address this concern, I use the following approach. I assume that the proportion of expected returns in the earnings announcement day period is proportional to the fraction of the total return news occurring in the earnings announcement day period. Prior research finds that about 11% of the annual volatility occurs in the 12 day window around the earnings announcement, roughly double the fraction of days that fall in that window (Basu, Duong, Markov, Tan, 2010). I confirm this for my sample and the extreme deciles. When using this to compute the adjustment factor, the calculation is as follows:

\[
Adjustment = \left( \frac{1 + BHret}{1 + EAre} \right)^{0.11} - 1
\]

Using the correction factor, the fraction of corrected earnings announcement returns to the full year buy and hold returns is now 0.39, 0.06, 0.45, and 0.40 for GLS, EPR, GGM, and AGR respectively.
Panel B of Table IV documents the decile returns when the returns are value weighted. In general the hedge portfolio returns are lower than in Panel A, and only statistically significant for one of the four estimates (GLS). Comparing the value weighted earnings announcement returns to the value weighted buy and hold returns of Table III shows that the earnings announcement returns explain between 9% (AGR) and 16% (EPR) of the abnormal buy and hold returns from Table III (median 15%). These results suggest using value weighted analyses can help mitigate the effects of mispricing, at least for the set of estimates examined here.

The second analysis involves an examination of the effect of the Fama French risk factors on the returns to the ICC hedge portfolio. On June 30th of each year firms are sorted into deciles based on the magnitude of their ICC estimates. For the next twelve months the firm remains in the same decile. For each month the decile return is calculate as the average return of all firms in that decile for that month. This generates a timeseries of 444 monthly returns for each decile. I then subtract the risk free rate and regress the difference on the market risk premium (RMRF), the small firm premium (SMB) and the value premium (HML). Table V reports the coefficients from a timeseries regression of the monthly hedge portfolio returns on the three Fama-French factors. Panel A displays the case where individual stock returns are equal-weighted in creating the decile and hedge portfolio returns. The results indicate that the hedge portfolio returns for all four estimates load strongly on the HML factor, perhaps not surprising given that ICC estimates have a similar fundamentals to price flavor. They also exhibit a moderate to strong loading on the SMB factor. However, the loadings on the market factor are consistently negative. As a result, while the three factor model is reasonably successful in explain the timeseries variation in the hedge portfolio returns, it does a relatively poor job in explaining the average hedge portfolio return.
To assess the usefulness of the three factors in explaining the average hedge portfolio return, I compute the ratio of the monthly abnormal returns (the intercept) to the total monthly expected return. The latter is calculated as the intercept plus the factor loading times the average factor premium. Over this time period the average factor premiums were 0.46% per month for the market premium (RMRF), 0.16% per month for the small firm premium (SMB) and 0.45% per month for the value premium (HML). The fraction of the expected monthly return unexplained by the three factors, my estimate of the upper bound on the mispricing impact, ranges from 59% (GLS) to 83% (GGM) with a median of 69%. These results are consistent with the equal weighted earnings announcement returns and suggest that mispricing has a large effect on the relation between ICC estimates and future returns.

As with the other tests, I repeat the analysis using value weighted returns instead of equal weighted returns. The results are displayed in Panel B. With the exception of GLS, the abnormal returns are much lower than in the equal weighted case and not statistically significantly different from zero. Using the same method as above, the fraction of the expected monthly return unexplained by the three factors, ranges from -34% (AGR) to 51% (GLS) with a median of 10%. This suggests that use a value weighted analysis can effectively mitigate the effects of mispricing, again with the exception of the GLS measure. However, this is a bit of a double-edged sword. If the Fama-French three factors effectively explain the mean returns on the ICC hedge portfolio, then there is little room for other priced risk factors, unless these new factors displace the existing three factors.

4.2 Controlling for news in regression of future returns on ICC estimates

As discussed in section 2.5, the theoretical case for controlling for news depends on the importance of measurement error in the researcher estimates of earnings. In line with the model
developed there, 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 have a positive relation with future returns. While the model does not speak to changes in the discount rate, based on prior research I also include a measure for that. Following the prior 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.

Table VI reports the average coefficients of annual cross-sectional regression of future returns on the ICC estimates and proxies for earnings surprises and changes in discount rates (intercepts are included but not reported to conserve space). 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 8 sets of regressions, one set of equal weighted regressions for each of the four ICC estimates and one set of value-weighted regressions for each of the four ICC estimates. Within each set of regressions the sample is kept the same to enhance comparability. I will next discuss the results of the upper left set of regressions, the equal weighted regressions for the GLS estimate.

The first regression shows the simple regression of one-year-ahead stock returns on the GLS estimate of implied cost of capital. The coefficient is positive and significant confirming the results of the portfolio based approach in Table III. Note however that the coefficient is less than one, the prediction from the model in the case without measurement error in both the researcher’s and the investors’ earnings estimates. Also, the fact that the coefficient is less than one suggests that the effect of the researcher’s measurement errors dominates the effect of the
investors’ errors\textsuperscript{9}. 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 which is the earnings capitalization factor, again suggesting a fair amount of measurement error in the researcher’s earnings estimates. Consistent with the predictions in section 2.5, including both the ICC estimate and the earnings surprise proxy (changes in discount rate) results in a significantly larger (smaller) coefficient on the ICC estimate. Finally, putting all three variables in the regression results in an increase of the ICC coefficient relative to the simple regression, and both the earnings surprise and the change in discount rate proxy have the predicted sign.

The results for the other seven sets of regressions are generally consistent with the results discussed above. Including the earnings surprise proxy results in an increase in the coefficient on the ICC estimate, while including the change in discount rate proxy 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 in the coefficient on the ICC estimate and sometimes a decrease. The question is what to conclude from these results about the usefulness of controlling for news. The fact that the relations between the three variables can be explained by measurement error in the researcher’s estimates suggests that including the surprise proxies may do more harm than good. Certainly, including only one of the two proxies is harmful in understanding the quality of the ICC estimates.

The model developed in section 2 is not rich enough to establish whether including both news proxies helps neutralize or merely mitigate the bias induced by the measurement error. However, model does suggest some handle on such assessment. Since the mispricing should result in an upward bias of the ICC coefficients, it possible to see whether the ICC estimates with

\textsuperscript{9} Recall from section 2 that measurement error in the researcher’s earnings management leads to a downward bias in the coefficient, while measurement error in the investors’ earnings estimates leads to an upwards bias in the coefficients.
the most mispricing (according to the earnings announcement tests) have a more negative change in the ICC coefficient after inclusion of the news proxies. Based on Tables III and IV, the GLS, GGM, and AGR estimates have the highest fraction of returns due to mispricing (45%, 51%, and 46% resp.). Of these, GLS experiences a large increase in the coefficient, GGM a large decrease and AGR not much change following inclusion of the news proxies. The EPR estimate has relatively low mispricing (16%), but experiences a large increase the coefficient. Overall, these results do not suggest that the inclusion of the news proxies is very effective in reducing the bias induced by market inefficiency. Also, in this setting the incremental R-squared of the news proxies is relatively low suggesting that the other benefit of including them, reducing noise in returns, is not that important here.

One might wonder whether the fact that the measurement error in the news proxies and the measurement error in the ICC estimates are correlated is a good thing rather than a problem as discussed above. After all, earnings news proxy might ‘clean up’ the measurement error in the ICC estimate, thereby yielding a better coefficient. For example, in the case of the equal weighted GLS regressions discussed above, including just the earnings news proxy results in a jump of the coefficient on the ICC estimate from 0.39 to 1.02, very near the theoretical coefficient of 1. The counterpart of this approach in the earnings-response-coefficient literature would be Collins, Kothari, Shanken, and Sloan (1994). There are two issues with this. The first issue concerns the research objective. If the research objective is to examine the effect of the underlying construct, in this case expected returns, then having a control variable that ‘cleans up’ the noise in the proxy, in this the ICC estimate, is a good thing. However, if the objective is to examine the effect of the proxy itself, then cleaning out the measurement error through a control variable is not desirable. After all, we are not interested in whether expected
returns are related to future returns, but whether our particular proxy, the individual ICC estimate, is a reliable estimate of this. Then including proxies for the noise in this estimate, the effectiveness of which may vary across ICC estimates, will obscure the true relative ranking of the ICC estimates. The second issue is that, as discussed in section 2.5., including the earnings news proxy will lead to an increase in the coefficient on the ICC estimate even in the case in which expected returns do not vary and the ICC estimate is pure noise. Overall, these considerations suggest that the potential benefits of inclusion of the news proxies do not outweigh the risks.

5. 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 contain some noise as well. Many different ICC models have been developed and one approach to evaluate the level of noise in these models by investigating their predictive ability with respect to future stock returns (e.g., Guay, Kothari, and Shu, 2005; and Easton and Monahan, 2005). One concern with these tests is that these returns might be affected by market inefficiency in addition to expected returns. In this paper I develop a model starting from the underlying primitives, investors’ and researcher’s earnings forecasts, and show that under reasonable assumptions, market inefficiency will result in a positive relation between ICC estimates and future returns.

In the empirical part of the paper I try to quantify the relative importance of expected returns and mispricing. I use the approach in Hou, Van Dijk, and Zhang (2010) as extended by Lee, So, and Wang (2010) in forecasting earnings and calculating ICC estimates. Consistent with these papers I find that ICC estimates predict future stock returns. I use two approaches to
separate the competing hypotheses for these returns. First, I use earnings announcement returns to provide a lower bound on importance of mispricing. Based on the four models I examine, earnings announcement returns account for about 46% of the returns to a hedge portfolio based on the extreme deciles of ICC estimates. My second approach tries to establish an upper bound on the importance of mispricing by looking at the fraction of the average hedge portfolio return that is not explained by the Fama-French three factor model. Based on the four models I examine, the fraction unexplained by the three factors is about 69%. Overall, these results suggest that for equal weighted returns a large fraction of the explanatory power is due to mispricing instead of expected returns.

Results for value weighted returns show a much smaller relative effect of mispricing for most but not all ICC models. This suggests that value weighting is a relatively effective method to mitigate the effect of mispricing. Using value weighting in tests designed to select the ‘best’ ICC estimates reduces the likelihood that ICC estimates are chosen because they are particularly affected by mispricing. It also suggests that in applications using ICC estimates one should use a value-weighted analysis when using ICC estimates to test whether a proposed risk factor is priced. Additionally, in these cases it is important to test returns around future earnings announcements to make sure that the proposed risk factor is not an anomaly in disguise. Since analyses of earnings announcements have much higher statistical power than annual buy and hold returns, this should not pose an undue burden.

The second part of the empirical work considers whether controlling for news proxies provides an effective control for the biases induced by mispricing. The model shows that theoretical case for controlling for news is ambiguous, and the usefulness depends on the importance of measurement error in the researcher estimates of earnings and by extension the
ICC estimates. My analyses suggest that the directional effects of the inclusion of news proxies on the ICC coefficient are most consistent with researcher induced measurement error rather than errors in realized returns. I conclude that on balance, my analyses suggest that the potential benefits of inclusion of the news proxies do not outweigh the risks.

A caveat is that my conclusions are in part based on the model which is inevitably a simplification of reality. Introducing market inefficiency in particular suffers from an overabundance of degrees of freedom in the modeling choices. The model in this paper is based on relatively minimal assumptions that I believe offer a reasonable approximation of how market inefficiency would manifest itself in implied cost of capital estimates. Despite these limitations, the analyses in this paper should be useful to researchers interested in evaluating alternative cost of capital estimates or applying ICC estimates in tests of proposed risk factors.
References


Appendix

This appendix provides the derivations for the results provided in section 2. The starting point for the analyses is provided by the expressions for the implied cost of capital (ICC) estimate and the future returns:

\[
ICC = \frac{E_t[E_{t+1} | \Omega_t] + u_t}{E_t[E_{t+1} | \Omega_t] + \epsilon_t}, \quad r = \frac{A + u}{A + \epsilon}, \quad \text{A.1}
\]

\[
R_{t+1} = \frac{P_{t+1} - P_t}{P_t} = \frac{rA + (1 + r)n_{t+1} - (1 - \rho)\epsilon_t + \delta_{t+1}}{A + \epsilon_t} = \frac{Ar + (1 + r)n - (1 - \rho)\epsilon + \delta}{A + \epsilon}, \quad \text{A.2}
\]

Where \( A \) is the objective earnings expectation given all available information (= \( E_t[E_{t+1} | \Omega_t] \)), \( r \) is the discount rate used by investors, \( u \) is the error in the researcher’s earnings estimate, \( \epsilon \) is the error in the investor’s earnings estimate at time \( t \), \( \rho \) is the fraction of the mispricing that persists beyond \( t+1 \), and \( d \) is the innovation in the mispricing in period \( t+1 \). To simplify notation, all time subscripts are suppressed in the derivation. All random variables are uncorrelated with the other random variables, except for the two earnings estimation errors, \( \epsilon \) and \( u \), which can be correlated with each other.

To address having a random variable in the denominator, I use second order Taylor expansions around \( \epsilon = 0 \). Using this Taylor expansion and the fact that the expected value of \( u \) and \( \epsilon \) are zero give the following expression for the average ICC:

\[
E[ICC_t] = E\left[\frac{A + u}{A + \epsilon} \cdot r\right] \approx E\left[\frac{A + u}{A} - \frac{A + u}{A^2} \cdot \epsilon + \frac{A + u}{A^2} \cdot \epsilon^2\right] \cdot E[r]
\]

\[
E[ICC_t] \approx \left(1 - \frac{\text{cov}(\epsilon, u)}{A^2} + \frac{\text{var}(\epsilon)}{A^2}\right) \cdot E[r]
\]
Similarly, the expected value of future returns can be calculated as follows:

\[
E[R] = \mathbb{E} \left[ \frac{Ar + (1+r)n - (1-\rho)\varepsilon + \delta}{A + \varepsilon} \right]
\]

\[
E[R] \approx \mathbb{E} \left[ \frac{Ar + (1+r)n + \delta}{A} - \frac{(1-\rho)\varepsilon}{A} - \frac{(Ar + (1+r)n + \delta)\varepsilon}{A^2} + \frac{(Ar + (1+r)n + \delta)^2\varepsilon}{A^3} \right]
\]

\[
E[R] \approx E[r] + \frac{(1-\rho)\text{var}(\varepsilon)}{A^2} + r\frac{\text{var}(\varepsilon)}{A^2} = r + \frac{(1-\rho + E[r])\text{var}(\varepsilon)}{A^2}
\]

The next step is the analysis of the relative impact of mispricing on the ICC estimate and future returns. First, the probability limit of the regression coefficient in a regression of the ICC estimate on a mispricing proxy (\(\varepsilon/A\)):

\[
\text{cov}(\text{ICC}, \varepsilon / A) = \mathbb{E} \left[ \frac{A + u}{A + \varepsilon} \cdot r \cdot \frac{\varepsilon}{A} \right] - \mathbb{E} \left[ \frac{A + u}{A + \varepsilon} \right] \cdot \mathbb{E} \left[ \frac{\varepsilon}{A} \right] \approx \mathbb{E} \left[ \frac{\varepsilon - \varepsilon^2}{A^2} + \frac{e^2}{A^2} \right] \cdot \mathbb{E}[r] = \frac{\text{cov}(\varepsilon, u) - \text{var}(\varepsilon)}{A^2} \cdot \mathbb{E}[r]
\]

\[
\beta_{\text{ICC,Mispricing}} = \frac{\text{cov}(\text{ICC}, \varepsilon / A)}{\text{var}(\varepsilon / A)} \approx \frac{\text{cov}(\varepsilon, u) - \text{var}(\varepsilon)}{A^2} \cdot \mathbb{E}[r] \cdot \left( \frac{\text{var}(\varepsilon)}{A^2} \right)^{-1} = \left( \frac{\text{cov}(\varepsilon, u)}{\text{var}(\varepsilon)} - 1 \right) \cdot \mathbb{E}[r]
\]

Second, the probability limit of the regression coefficient in a regression of future returns on a mispricing proxy (\(\varepsilon/A\)):

\[
\text{cov}(R_{t+1}, \varepsilon / A) = \mathbb{E} \left[ \frac{Ar - (1-\rho)\varepsilon + (1+r)n + \delta}{A + \varepsilon} \cdot \frac{\varepsilon}{A} \right] - \mathbb{E} \left[ \frac{Ar - (1-\rho)\varepsilon + (1+r)n + \delta}{A + \varepsilon} \right] \cdot \mathbb{E} \left[ \frac{\varepsilon}{A} \right]
\]

\[
\text{cov}(R_{t+1}, \varepsilon / A) \approx \mathbb{E} \left[ \frac{\varepsilon - \varepsilon^2}{A^2} \right] \cdot \mathbb{E}[r] - \mathbb{E} \left[ \frac{(1-\rho)\varepsilon^2}{A^2} \right] = (-\mathbb{E}[r] - (1-\rho)) \cdot \frac{\text{var}(\varepsilon)}{A^2}
\]

\[
\beta_{\text{R_{t+1},Mispricing}} = \frac{\text{cov}(R_{t+1}, \varepsilon / A)}{\text{var}(\varepsilon / A)} \approx (-\mathbb{E}[r] - (1-\rho)) \cdot \frac{\text{var}(\varepsilon)}{A^2} \cdot \left( \frac{\text{var}(\varepsilon)}{A^2} \right)^{-1} = -\mathbb{E}[r] - (1-\rho)
\]

The last step in the analysis is the examination of the probability limit of the regression coefficient in a regression of future returns on the ICC estimate. Two variables, the new variable (\(n\)) and the future innovation in mispricing (\(\delta\), play no role in the probability limit of
the coefficient estimate since they are uncorrelated with the other variables and enter linearly in
the returns model. The cases in which only the discount rate or the error in the researcher’s
earnings estimates are random follow directly from a simplification of the formulas. In contrast,
the case in which the error in the investors’ earnings estimate is random is more involved. In that
case the probability limit of the coefficient can be approximated as follows:

\[ \text{cov}(\text{ICC}, R) = E[\text{ICC} \cdot R] - E[\text{ICC}] \cdot E[R] \]

\[ E[\text{ICC} \cdot R] = E\left[ \frac{Ar - (1 - \rho)\varepsilon + (1 + r)n + \delta}{A + \varepsilon} \right] \]

\[ E[\text{ICC} \cdot R] = E\left[ \frac{(Ar)^2 - Ar(1 - \rho)\varepsilon}{(A + \varepsilon)^2} \right] \]

\[ E[\text{ICC} \cdot R] \approx E\left[ \left( r^2 - \frac{2r^2\varepsilon}{A} + \frac{3r^2\varepsilon^2}{A^2} \right) - \left( \frac{r(1 - \rho)\varepsilon}{A} - \frac{2r(1 - \rho)\varepsilon^2}{A^2} \right) \right] \approx \left( r^2 + \frac{3r^2 \text{var}(\varepsilon)}{A^2} \right) - \left( \frac{2r(1 - \rho) \text{var}(\varepsilon)}{A^2} \right) \]

\[ E[\text{ICC}] \approx r + \frac{r \text{var}(\varepsilon)}{A^2} \]

\[ E[R] \approx r + \frac{(1 - \rho + r) \text{var}(\varepsilon)}{A^2} \]

\[ E[\text{ICC}] \cdot E[R] \approx r^2 + \frac{r^2 \text{var}(\varepsilon)}{A^2} + \frac{r(1 - \rho + r) \text{var}(\varepsilon)}{A^2} + \frac{r(1 - \rho + r) \text{var}(\varepsilon)^2}{A^3} \]

\[ E[\text{ICC}] \cdot E[R] \approx r^2 + \frac{r(1 - \rho) \text{var}(\varepsilon)}{A^2} + \frac{2r^2 \text{var}(\varepsilon)}{A^2} + \frac{r(1 - \rho + r) \text{var}(\varepsilon)^2}{A^4} \]

Putting the components of the covariance together yields the following approximation:

\[ \text{cov}(\text{ICC}, R) \approx \left( r^2 + \frac{3r^2 \text{var}(\varepsilon)}{A^2} + \frac{2r(1 - \rho) \text{var}(\varepsilon)}{A^2} \right) - \left( r^2 + \frac{r(1 - \rho) \text{var}(\varepsilon)}{A^2} + \frac{2r^2 \text{var}(\varepsilon)}{A^2} + \frac{r(1 - \rho + r) \text{var}(\varepsilon)^2}{A^4} \right) \]

\[ \text{cov}(\text{ICC}, R) \approx \frac{r^2 \text{var}(\varepsilon)}{A^2} + \frac{r(1 - \rho) \text{var}(\varepsilon)}{A^2} - \frac{r^2 \text{var}(\varepsilon)^2}{A^4} - \frac{r(1 - \rho) \text{var}(\varepsilon)^2}{A^4} \]
The variance of the ICC can be approximated as follows:

\[
E[ICC \cdot ICC] = E\left[ \left( \frac{Ar}{A + \varepsilon} \right)^2 \right] = E\left[ \frac{(Ar)^2}{(A + \varepsilon)^2} \right] \approx E\left[ r^2 - \frac{2r^2 \varepsilon}{A} + \frac{3r^2 \varepsilon^2}{A^2} \right]
\]

\[
E[ICC \cdot ICC] \approx r^2 + \frac{3r^2 \text{var}(\varepsilon)}{A^2}
\]

\[
E[ICC] \cdot E[ICC] \approx \left( r + \frac{r \text{var}(\varepsilon)}{A^2} \right)^2 = r^2 + \frac{2r^2 \text{var}(\varepsilon)}{A^2} + \frac{r^2 \text{var}(\varepsilon)^2}{A^4}
\]

\[
\text{var}(ICC) \approx r^2 + \frac{3r^2 \text{var}(\varepsilon)}{A^2} - \left( r^2 + \frac{2r^2 \text{var}(\varepsilon)}{A^2} + \frac{r^2 \text{var}(\varepsilon)^2}{A^4} \right) = \frac{r^2 \text{var}(\varepsilon)}{A^2} - \frac{r^2 \text{var}(\varepsilon)^2}{A^4}
\]

This gives the following probability limit for the coefficient estimate for the regression of future returns on the ICC measure:

\[
\beta_{ICC} = \text{cov}(ICC, R) / \text{var}(ICC)
\]

\[
\beta_{ICC} \approx \left( \frac{r^2 \text{var}(\varepsilon)}{A^2} + \frac{r(1 - \rho) \text{var}(\varepsilon)}{A^2} - \frac{r^2 \text{var}(\varepsilon)^2}{A^4} - \frac{r(1 - \rho) \text{var}(\varepsilon)^2}{A^4} \right) \cdot \left( \frac{r^2 \text{var}(\varepsilon)}{A^2} - \frac{r^2 \text{var}(\varepsilon)^2}{A^4} \right)^{-1}
\]

\[
\beta_{ICC} \approx \left( \frac{r^2 \text{var}(\varepsilon)}{A^2} - \frac{r^2 \text{var}(\varepsilon)^2}{A^4} \right) + \left( \frac{r(1 - \rho) \text{var}(\varepsilon)}{A^2} - \frac{r(1 - \rho) \text{var}(\varepsilon)^2}{A^4} \right) \cdot \left( \frac{r^2 \text{var}(\varepsilon)}{A^2} - \frac{r^2 \text{var}(\varepsilon)^2}{A^4} \right)^{-1}
\]

\[
\beta_{ICC} \approx 1 + \frac{1 - \rho}{r} = \frac{1 - \rho + r}{r}
\]
Table I: Cross-sectional earnings forecast models

This Table reports the timeseries 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:

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

where \( E_{j,t+\tau} (\tau = 1, 2, 3, 4, \text{ or } 5) \) denotes the earnings before extraordinary items (Compustat item IB) of firm \( j \) in year \( t+\tau \), 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 for 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 minus the change in current liabilities (Compustat item LCT). Each variable in the regression is winsorized at the 0.5 and 99.5 percentiles of that year to mitigate the effect of extreme observations.

<table>
<thead>
<tr>
<th>Years ahead</th>
<th>Intercept</th>
<th>EV</th>
<th>TA</th>
<th>DIV</th>
<th>DD</th>
<th>E</th>
<th>NEGE</th>
<th>ACC</th>
<th>R-squared</th>
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<td>-0.007</td>
<td>0.277</td>
<td>-2.304</td>
<td>0.649</td>
<td>0.110</td>
<td>-0.077</td>
<td>0.855</td>
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<td>9.27</td>
<td>-6.00</td>
<td>32.50</td>
<td>0.31</td>
<td>-8.97</td>
<td></td>
</tr>
<tr>
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<td>0.021</td>
<td>-0.005</td>
<td>0.438</td>
<td>-1.919</td>
<td>0.526</td>
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<td>25.81</td>
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<td></td>
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<td>-0.006</td>
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<td>0.486</td>
<td>3.061</td>
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<td>0.764</td>
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<td>2.941</td>
<td>-0.101</td>
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<td>10.62</td>
<td>-2.28</td>
<td>17.51</td>
<td>-3.11</td>
<td>15.83</td>
<td>3.35</td>
<td>-6.48</td>
<td></td>
</tr>
<tr>
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<td>0.043</td>
<td>-0.014</td>
<td>0.351</td>
<td>-2.097</td>
<td>0.521</td>
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<td>8.96</td>
<td>4.56</td>
<td>-9.34</td>
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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 following the approach in Beaver, McNichols and Price, 2007). Panel C and Panel D show the distribution of the equal weighted and value weighted market risk premium respectively. The returns and estimates are given in %. Significance levels are indicated by stars: *** significant at 1%, ** significant at 5%, * significant at 10%, all based on two-tailed tests.

Panel A: Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Std Dev</th>
<th>P5</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
<th>P95</th>
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<tbody>
<tr>
<td>Realized return</td>
<td>138,617</td>
<td>13.8</td>
<td>75.6</td>
<td>-67.0</td>
<td>-24.7</td>
<td>3.7</td>
<td>34.8</td>
<td>121.9</td>
</tr>
<tr>
<td>ICC_GLS</td>
<td>114,775</td>
<td>10.6</td>
<td>6.7</td>
<td>2.8</td>
<td>6.9</td>
<td>9.6</td>
<td>13.0</td>
<td>20.4</td>
</tr>
<tr>
<td>ICC_EPR</td>
<td>95,296</td>
<td>9.0</td>
<td>8.8</td>
<td>1.1</td>
<td>3.7</td>
<td>6.6</td>
<td>11.5</td>
<td>23.9</td>
</tr>
<tr>
<td>ICC_GGM</td>
<td>121,286</td>
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<td>9.2</td>
<td>2.0</td>
<td>5.1</td>
<td>8.2</td>
<td>13.9</td>
<td>27.8</td>
</tr>
<tr>
<td>ICC_AGR</td>
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<td>12.9</td>
<td>1.2</td>
<td>4.0</td>
<td>7.6</td>
<td>14.0</td>
<td>34.7</td>
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Panel B: Correlation Table

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<tr>
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<th>Realized return</th>
<th>ICC_GLS</th>
<th>ICC_EPR</th>
<th>ICC_GGM</th>
<th>ICC_AGR</th>
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</thead>
<tbody>
<tr>
<td>Realized return</td>
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<td>0.053***</td>
<td>0.100***</td>
<td>0.052***</td>
<td>0.050***</td>
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<tr>
<td>ICC_GLS</td>
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<td>1</td>
<td>0.716***</td>
<td>0.683***</td>
<td>0.563***</td>
</tr>
<tr>
<td>ICC_EPR</td>
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<td>0.728***</td>
<td>0.721***</td>
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<td></td>
<td></td>
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<td>0.664***</td>
</tr>
<tr>
<td>ICC_AGR</td>
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Panel C: Equal weighted market risk premium

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<th>Std Dev</th>
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<th>P25</th>
<th>Median</th>
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<th>P95</th>
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<td>Annual realized risk premium</td>
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<td>8.6</td>
<td>23.8</td>
<td>-29.7</td>
<td>-2.0</td>
<td>10.7</td>
<td>19.0</td>
<td>40.3</td>
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<tr>
<td>5 year average risk premium</td>
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<td>10.5</td>
<td>8.0</td>
<td>-2.5</td>
<td>4.8</td>
<td>11.3</td>
<td>15.1</td>
<td>23.1</td>
</tr>
<tr>
<td>10 year average risk premium</td>
<td>28</td>
<td>10.2</td>
<td>4.6</td>
<td>4.1</td>
<td>7.5</td>
<td>9.4</td>
<td>11.5</td>
<td>18.9</td>
</tr>
<tr>
<td>20 year average risk premium</td>
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<td>9.2</td>
<td>1.9</td>
<td>7.0</td>
<td>8.2</td>
<td>8.7</td>
<td>10.9</td>
<td>12.1</td>
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<td>0.7</td>
<td>7.8</td>
<td>8.4</td>
<td>8.6</td>
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**Panel D: Value weighted market risk premium**

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<th>Std Dev</th>
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<th>Median</th>
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<tbody>
<tr>
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<td>15.4</td>
<td>23.6</td>
</tr>
<tr>
<td>5 year average risk premium</td>
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<td>6.2</td>
<td>6.7</td>
<td>-3.6</td>
<td>1.9</td>
<td>6.0</td>
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<tr>
<td>10 year average risk premium</td>
<td>28</td>
<td>7.0</td>
<td>3.2</td>
<td>1.3</td>
<td>5.9</td>
<td>7.4</td>
<td>8.4</td>
<td>11.8</td>
</tr>
<tr>
<td>20 year average risk premium</td>
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<td>7.3</td>
<td>1.9</td>
<td>4.1</td>
<td>6.4</td>
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<td>10.1</td>
</tr>
<tr>
<td>37 year average risk premium</td>
<td>36</td>
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<td>0.5</td>
<td>4.7</td>
<td>5.0</td>
<td>5.2</td>
<td>5.4</td>
<td>6.0</td>
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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 raw stock returns in 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 respective ICC decile. Fama-MacBeth t-statistics are listed to the right of the estimates. Significance levels are indicated by stars: ***, significant at 1%, ** significant at 5%, * significant at 10%, all based on two-tailed tests.

**Panel A: Equal weighted returns**

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<th>Decile</th>
<th>GLS</th>
<th>t-stat</th>
<th>EPR</th>
<th>t-stat</th>
<th>GGM</th>
<th>t-stat</th>
<th>AGR</th>
<th>t-stat</th>
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<td>-2.77</td>
<td>-1.15</td>
<td>-4.03</td>
<td>-2.00</td>
</tr>
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<td>-2.90</td>
<td>-1.64</td>
<td>-3.04</td>
<td>-1.97</td>
<td>-2.27</td>
<td>-1.49</td>
</tr>
<tr>
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<td>-1.82</td>
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10-1 5.63*** 1.69  8.09**  2.52  6.99**  2.16  6.45**  2.44

**Panel B: Value weighted returns**

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10-1 11.30*** 3.52  8.60***  2.55  6.47**  2.10  4.27  1.37
Table IV: Relation between ICC estimates and returns around earnings announcements

This Table reports the average annual earnings announcement returns for each ICC decile. Earnings announcement returns are compounded for the twelve days around earnings announcement (three day windows for each of the four quarterly earnings announcements). Fama-MacBeth t-statistics are listed to the right of the estimates. Hedge portfolio significance levels are indicated by stars: *** significant at 1%, ** significant at 5%, * significant at 10%, all based on two-tailed tests.

Panel A: Equal weighted returns

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Panel B: Value weighted returns

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

This Table reports the coefficients from a timeseries regression of monthly hedge portfolio returns on the three Fama-French factors. For each of the ICC estimates portfolio assignment is based on the most recent ICC estimates. Each of the regression uses the full 444 months of available returns. Panel A (Panel B) displays the case where individual stock returns are equal-weighted (value-weighted) in creating the decile and hedge portfolio returns. Significance levels of the abnormal returns are indicated by stars: *** significant at 1%, ** significant at 5%, * significant at 10%, all based on two-tailed tests.

**Panel A: Equal weighted returns**

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Table VI: Predictive ability of ICC for future returns when controlling for news

This Table reports the average coefficients of annual cross-sectional regression of future returns on the ICC estimates and proxies for earnings surprises (ES) and changes in discount rates (DRS) (intercepts are included but not reported to conserve space). 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). Significance levels based on Fama-MacBeth standard errors are indicated by stars: *** significant at 1%, ** significant at 5%, * significant at 10%, all based on two-tailed tests.

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