Is Beta Still Useful Over A Longer-Horizon? –An Implied Cost of Capital Approach*

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Abstract

Despite the crucial role of the market factor in Fama and French's three-factor model, the market beta has failed to explain the cross-sectional differences in expected returns proxied by the future realized returns of individual stocks. However, current evidence does not necessarily reject the explanatory power of the market beta in expected returns over longer-horizons. We use the future implied costs of capital as the proxy instead of future realized returns in order to link beta to longer-horizon expected returns. In contrast to the current results we find that the future implied cost of capital is both positively and significantly related to the conventional beta estimate, implying that beta could still explain future cross-sectional expected return differences. Moreover, uncertainty risk could be important when focusing on longer-horizons. We propose using analyst dispersion as a proxy for the uncertainty risk, and find that it strongly predicts future implied cost of capital as well. Furthermore, some prior studies have shown that the failure of beta in explaining cross-sectional return differences over a shorter-horizon is due to the lack of forward-looking information. Since changes in the implied cost of capital contain such unique information, we propose a simple adjustment to the conventional beta measure. The explanatory power of the adjusted beta for future return difference is accordingly proved to be strong.

Key Words: analyst forecast dispersion, cross-sectional stock returns, expected return, implied cost of capital, longer horizon, market beta.

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Abstract

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1 Introduction

Perhaps the most important advance in modern finance is the Sharpe-Lintner-Black Capital Asset Pricing Model (CAPM), yet we are far from finding strong empirical support especially from a cross-sectional perspective. Despite that fact that individual security returns indeed covary with the market factor strongly over time (see Fama and French, 1996), their market risk measure beta does not seem to explain their cross-sectional return differences, contradicting to what theory predicts. In most current studies, in order to increase testing power, researchers focus on relatively short horizon by using the next month's realized return as a proxy for the expected return in cross-sectional regressions. Motivated by the work of Kothari, Shanken, and Sloan (1995) who find much higher cross-sectional explanatory power of beta over a longer horizon, we propose to use the future implied cost of capital (ICC) in this paper as an alternative measure of the longer-horizon expected return. Our results suggest that the conventional beta estimates indeed strongly explain the future ICC estimates, implying that the CAPM beta is still useful in assisting managers to determine their cost of capital over longer-run. In addition, we find that investors also care about the uncertainty risk over longer-horizon as approxied by analyst forecast dispersion.

The empirical failure of the CAPM beta documented by Fama and French (1992) seems to be robust and confirmed in many subsequent studies. Several factors might have led to this empirical failure, such as inefficiency in beta estimate. As a result, most current studies focuses on either "fixing" the beta estimate, such as using portfolio beta (see, Fama and French, 1992), conditional beta, cash flow beta, and so on, or proposing additional factors other than the market factor. Another possibility, as argued by Jagannathan and Wang (1996), is that a conditional version of the CAPM might actually hold, which implies a very different version of the static model that is been tested. However, Lewellen and Nagel (2006) claim that the additional effect of the conditional model from time-varying beta and risk premium are too small to account for the failure of the market beta. Recently Xu and Zhao (2012) find that the failure of beta largely concentrates among stocks with both large systematic and idiosyncratic risks due to beta reversal. Similarly, Buss and Vilkov (2012) suggest that investors' expectations might change quite often in short-run, which is difficult to be captured by historical beta estimate. Instead, they show that the beta estimated from options data contains investors' forward-looking information, which is better suited to explain future return differences among individual stocks despite the issue of limited sample.

One important issue that has been overlooked is the horizon that the CAPM is likely to hold. Theoretically, the CAPM builds with respect to investors' investment horizon. If most investors holds investment assets over a longer-horizon, we should focus on testing the explanatory power of beta over such a time-horizon. As long as the horizon is not too long such that new investment opportunities might arrive causing the risk structure change as suggested by Merton (1987) and the expected returns are mean-reverting, the CAPM should hold over a longer-horizon. However, it seems to be odd to use a pretty long series of historical data to estimate beta, while using one period of future return as a proxy for expected return to examine the risk and return relation in most empirical studies. In fact, even when future expected returns are rising, consistent with a high current beta estimate, the next period price will drop consequently, resulting a low realized return next period. In contrast, we focus on the explanatory power of historical beta estimate over longer-horizons. This idea is preliminary supported by evidence in Kothari, Shanken, and Sloan (1995) over quarterly horizons although their primary concern is that monthly returns would be subject to short-term trading friction, non-synchronic trading, or seasonality.

However, it is difficult to implement the test over longer horizon without sacrificing the effective sample size as in Kothari, Shanken, and Sloan (1995). Since it is notoriously difficult to estimate the expected returns, researchers usually employ conditioning variables in time-series studies and future realized returns in cross-sectional studies as in the Fama-MacBeth testing procedures. Because of our different focus, we choose not to follow the suit. In searching for a reliable estimate for expected return over longer horizon, and to ensure a reasonable sample size, We employ future implied cost of capital instead to proxy for longer-run expected returns. Despite the common criticism of ICC estimates, it is promising in the following aspects. First, from a theoretical perspective, it is defined as the unique discount rate that equates future expected cash flows to current stock price. Since it is in the same spirit as the internal rate of return, it is the perceived average return over time even when the actual future expected returns might be time-varying. In other words, it focuses more on longer-horizon. Second, different from realized returns, we are able to incorporate additional information, such as analyst earning forecast, in estimation. Potentially, it might be a better measure for future expected return. Third, different from low frequency measures, such as quarterly returns, ICC can be updated each month, which can increase the test power from large sample. Finally, similar to the practice of using $t + 1$ return, we estimate ICC using $t+1$ information. In this case, we not only avoid possible mechanical effect when time t information is used to estimate ICC, but also truely focus on longer horizon in future. In implementation, we utilize the Pastor, Sinha and Swaminathan's (2008) approach to estimate ICCs as a proxy for expected returns and find strong evidence for the explanatory power of the conventional beta estimate. This evidence not only provides support for the CAPM at a longer horizon, but also rationalizes managers' use of the conventional beta measure when making capital budgeting decisions.

The implied cost of capital is extensively studied in the accounting literature. Generally speaking, there are three approaches to estimate ICC depending on the valuation models, assumptions about terminal values, and the growth rate. For example, Botosan (1997) and Brav, Lehavy and Michael (2005) use the dividend discount model with the target price as the terminal value. In contrast, O'Hanlon and Steele (2000) and Gebhardt, Lee and Swaminathan (2001) apply the residual income model of Ohlson (1995). Some researchers such as Gode and Mohanram (2003) and Easton (2004) also use the Ohlson and Juettner-Nauroth (OJ) model that assumes the earnings growth rate converges to long-term economic growth rate. It is true that these measures of ICC have low correlation with realized returns as show by Easton and Monahan (2005). This evidence bears no substance in our analysis if we focus on longer-horizon expected return. Next period realized return could be very poor proxy for expected return to begin with as discussed earlier. In fact, Easton and Monahan (2005) also show that these commonly used proxies has no meaningful correlation with short-run realized returns after controlling for shocks to expected cash flows and discount rates. In other words, the next period realized return does seems to reflect short-term shocks to cash flow or discount rate, which might be treated as noises in longer-term estimate of expected return. Because of the issues raised by these studies when focusing on short horizon, we examine the longer horizon in this paper instead.

In fact, other studies that focus on risk-return relation do find supporting evidence for the use of ICC. Although the risk-return relation is at the heart of modern finance, French, Schwert and Stambaugh (1987) only find weak evidence when investigating the contemporaneous relations between the average market return and market volatility. One reason behind the discrepancy might be the inefficiency in estimating expected returns using average returns. For example, Lee, Ng and Swaminathan (2009) document that ICC estimates have less than one-tenth the volatility of realized return based expected return estimates, indicating smaller estimation errors. In fact, Pastor, Sinha and Swaminathan (2008) accordingly use the ICC instead of the average realized return as an estimate for expected return, and find strong support for the risk-return relation on the market level. On the international front, Lee, Ng and Swaminathan (2009) test the international asset pricing model using the ICCs estimated in the current period to proxy for firms' expected returns. They do find encouraging evidence especially for the currency beta to explain the cross-sectional variations.

Because of the strong risk-return relation established in Pastor, Sinha and Swaminathan's (2008), we construct our future ICC measures based on their approach with some modifications. First, differing from Pastor, Sinha and Swaminathan (2008), we examine the risk-return relation at individual stock levels. As a result, we use industry growth rate as a firm's long-term growth rate when estimating its ICC. Second, since we focus on longer-horizon, we use ICC estimated at time $(t + 1)$ as a proxy for future expected return. This procedure also allows us to avoid possible mechanical effect when both return and ICC are estimated at time t as in most current study (see, for example, Lee, Ng and Swaminathan, 2009). As a result, we find strong evidence that the conventional beta estimates can significantly explain cross-sectional differences in expected return estimates, which rationalize the use of the market factor in Fama and French's (1993) three-factor model. Hence, the conventional practice of computing capital costs using historical beta estimates may indeed be acceptable, although we should interpret the estimate a little differently.

When focusing on longer horizon, investors might also care about the uncertainty risk. In recent literature many researchers have discovered the importance of uncertainty risk in determining security returns. For instance, Zhang (2006) claims that greater information uncertainty should produce relatively higher expected returns following good news. If analyst forecast dispersion not only reflects possible asymmetric information (or differences in opinion) but also contains information for uncertainty in their estimation, then it can serve as a proxy for the uncertainty risk, in which case it deserves a positive premium as well. Barron and Stuerke (1998) use the forecast dispersion as an uncertainty measure in their study. Considering the uncertainty risk can also be more important in our context if investors have applied various approaches to determine the cost of capital and analysts have different ways to forecast future earnings. We thus include forecast dispersion in our cross-sectional regression and find a strong positive relation between future expected returns approxied by ICC and the current analyst forecast dispersion. This is in contrast to Diether, Malloy and Scherbina's (2002) finding of a puzzling negative effect between analyst forecast dispersions and future returns. The difference exactly highlights the importance of our focus on longer-term relation. In short-term, forecast dispersion could proxy for differences in investor opinions. If security prices are determined by investors' with optimistic view due to short sale constraints, stocks with higher dispersions is more likely to be overpriced and lead to lower future returns than otherwise.[1] This overpricing effect might dominate in the short-run and become a significant component in the realized return, but the uncertainty risk factor should overpower this overpricing effect in the long-run.[2]

Despite the shortcomings in applying the future realized return to proxy for the expected return, it is model-free and widely used in empirical studies. Perhaps, it is equally important to have a more accurate estimate of beta that explains future realized returns for shorter-term risk management purpose. Xu and Zhao (2012) have shown that the beta and return relation holds well for most of the stocks, implying that the conventional beta measure should not be completely abandoned. Instead, we might be able to adjust the conventional beta estimates to achieve better predictability

[1]Gebhardt, Lee and Swaminathan (2001) also find that forecast dispersion and ICC are negatively correlated. But their results are based on a contemporaneous regression.

[2]Forecast dispersion may also serve as a control in our setting. Both Easton and Monahan (2005) and Gode and Mohanram (2013) claim that the ICC itself might not be a good proxy for expected returns. As large predication errors would result in the weak association between analyst-based ICC and future realized earnings, including forecasting dispersion in cross-sectional regression can therefore indirectly control for these forecast errors and improve the reliability of analyst-based ICC measures.

in short-run. One of the potential issues for the conventional beta estimate to explain future returns is the lack of forward-looking perspective, as discovered by Buss and Vilkov (2012). There might be certain forward-looking information that is not completely captured by the market but is reflected in analysts' forecasts in short-run, partly due to the imbalance between optimistic and pessimistic investors. The differential information effect on the systematic risk measure beta is unlikely to be linear, and may be reflected more accurately through the ICC estimate. Hence, we adjust the conventional beta estimates using the corresponding firms' changes in the relative historical ICC estimates. A direct change adjustment is not compatible since beta is a relative measure. Although both beta and ICC estimates use time t information, ICC contains additional analyst forward-looking information which should reflect investors' perceived views regarding future returns.

We rerun the cross-sectional regression employing the adjusted beta. In a sharp contrast to the original Fama and French (1992) results we find that the adjusted beta becomes marginally significant and positive when used alone. However, when the adjusted beta and the analyst dispersion measure are used together, both variables are strongly significant. Since both variables are related to analyst forecast they may share a similar noise component. When used together, their common noise component might have offset with each other, and each therefore becomes very significant (see Run, Sun and Xu, 2012). Moreover, our results from applying the adjusted beta are robust over time and under different controls. In order to assess the quality of the estimated expected returns relative to the actual realized returns, when plotting the average predicted returns based on the adjusted beta against the average realized returns for the 100 size and book-to-market sorted portfolio. As predicted, all portfolios lie around the 45 degree line pretty closely. Again, our evidence not only supports the importance of the market factor in asset pricing, but also suggests the need to improve the conventional beta estimate using additional information.

This study contributes to the literature in three important ways. First, prior evidence is very weak regarding the explanatory power of beta for the expected return proxied by the future realized return. Instead, we focus on the predictive power of conventional beta estimates over a longer horizon using ICC as a proxy for future expected returns. As a result, we are able to establish a strong link between the beta risk and return. This is in contrast to both the existing studies in finance and the accounting literature which investigates the "contemporaneous" beta and ICC relation but often finds mixed results. Second, we introduce analyst dispersion as a proxy for the uncertainty risk and estimate its impact on ICC. Our evidence shows that forecast dispersion is positively related to ICC as expected. This is in sharp contrast to the puzzling effect when realized returns are used. Finally, we propose an adjusted beta measure that is not only solely based on historical information but also incorporates the forward-looking information embedded in the ICC measure. This new beta measure tends to be better in explaining the cross-sectional return differences, which can be easily adopted in other risk-return studies.

The rest of this paper is organized as follows. Section 2 describes the research methodology. Section 3 discusses all main variables used in this study and the data sample employed. Section 4 contains our empirical analysis. Section 5 provides concluding comments.

2 Methodology

Different from existing studies, we focus on longer-horizon relation between beta and future expected return. Since we use future implied cost of capital to proxy for future expected return, we first derive a relation between future ICC and current beta under certain assumptions. We then provide the theoretical foundation for our adjusted beta measure

2.1 Future Implied Cost of Capital and Expected Return

Similar to the idea of internal rate of return in capital budgeting and the yield to mature in bond pricing, the ICC is the same rate to discount the expected future expected dividends so that we can equate their present value to the current stock price. Denote $r_{e,t+1}$ as the ICC estimated at time $t+1$. For notation convenience, we ignore the subscript i for individual stock for now.

$$P_{t+1} = \sum_{j=1}^{\infty} \frac{E_{t+1}(D_{t+1+j})}{(1+r_{e,t+1})^j}, \tag{1}$$

where P_{t+1} and D_{t+1} are the stock price and the dividends at time $t+1$, respectively. This nonlinear equation can be linearized using the log-linearization methodology developed by Campbell and Shiller (1988). In particular, the dividend-price ratio commonly used in asset pricing literature can be expressed as,

$$d_{t+1} - p_{t+1} = -\frac{k}{1-\rho} - E_{t+1}\left[\sum_{j=0}^{\infty} \rho^j \Delta d_{t+2+j}\right] + \frac{1}{1-\rho} r_{e,t+1} \tag{2}$$

where $d_{t+1} \equiv \ln(D_{t+1})$, $p_{t+1} \equiv \ln(P_{t+1})$, $\rho = 1/(1+D/P)$, $k = -\ln(\rho) - (1-\rho)\ln(1/\rho - 1)$, $\Delta d_{t+1} \equiv d_{t+1} - d_t$ is the dividend growth rate, and D/P is the steady-state dividend-price ratio.

Similarly, if we apply the log-linearization to the return identify,

$$r_{t+1} = \ln(R_{t+1}) = \ln\left[\frac{P_{t+1}}{P_t}\left(1 + \frac{D_{t+1}}{P_{t+1}}\right)\right] = p_{t+1} - p_t + \ln(1 + \exp(d_{t+1} - p_{t+1}),$$

and using recursive substitution, we can also obtain an expression for the dividend-price ratio as,

$$d_t - p_t = -\frac{k}{1-\rho} - E_t\left[\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}\right] + E_t\left[\sum_{j=0}^{\infty} \rho^j r_{t+1+j}\right] \tag{3}$$

Equations (2) and (3) are derived without any theory. In fact, from comparing the two equations, we see that the ICC is defined as the following,

$$r_{e,t+1} = E_{t+1}\left[\sum_{j=0}^{\infty} (1-\rho)\rho^j E_{t+1+j}(r_{t+2+j})\right]. \tag{4}$$

In other words, ICC is indeed the weighted average of future expected returns ans discussed in the introduction.

In order to establish the line between future ICC and current expected return, we need more structural assumption. Since the dividend-price ratio is very persistent in practice, we can assume the following $AR(1)$ model,

$$d_{t+1} - p_{t+1} = \phi + \theta(d_t - p_t) + \eta_{t+1}. \tag{5}$$

Denote $n_{d,t+1} = E_{t+1}\left[\sum_{j=0}^{\infty} \rho^j \Delta d_{t+2+j}\right] - \theta E_t\left[\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}\right]$ as the cash-flow news. We can substitute equations (2) and (3) into equation (5) to derive the following relation,

$$r_{e,t+1} = [(1-\rho)\phi + (1-\theta)k] + \theta E_t\left[\sum_{j=0}^{\infty} (1-\rho)\rho^j r_{t+1+j}\right] + (1-\rho)[\eta_{t+1} + n_{d,t+1}]. \tag{6}$$

If we further assume that the conditional expected return, $\mu_r \equiv E_t(r_{t+1})$ also follow an

$AR(1)$ process,

$$\mu_{t+1} = \omega + \delta\mu_t + u_{t+1}, \tag{7}$$

equation (7) can be simplify to,

$$r_{e,t+1} = [(1-\rho)\phi + (1-\theta)k + \frac{\rho\theta}{1-\delta\rho}\omega] + \frac{1-\rho}{1-\delta\rho}\theta\mu_t + (1-\rho)[\eta_{t+1} + n_{d,t+1}]. \tag{8}$$

When the conditional CAPM holds with $\mu_{i,t} = \beta_{i,t}\lambda_{m,t}$, we can establish the following relation between future ICC and current beta,

$$r_{e,i,t+1} = \kappa + \gamma_t\beta_{i,t} + \epsilon_{i,t+1}, \tag{9}$$

where $\kappa = (1-\rho)\phi+(1-\theta)k+\frac{\rho\theta}{1-\delta\rho}\omega$, $\gamma_t = \frac{1-\rho}{1-\delta\rho}\theta\lambda_{m,t}$, and $\epsilon_{i,t+1} = (1-\rho)[\eta_{i,t+1}+n_{d,i,t+1}]$. Therefore, equation (9) is the foundation for our cross-sectional study.

2.2 The Adjusted Beta Measure

Over a short-horizon, beta does not seem to predict future return difference without incorporate other information. In our framework, however, since ICC measures tend to contain analysts' forward-looking information, we may able to adjust the conventional beta estimates to achieve better predictive power. The following analysis provides the theoretical base for our proposed adjustment.

We start from the main result in Campbell (1991) as represented by the following equation,

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j\Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j r_{t+1+j}. \tag{10}$$

This equation basically says that surprise in future returns are either a result of future cash flow news (the first term) or the discount rate news (the second term). If we denote

$n_{d,t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}$, and use the definition for ICC from equation (4), we can rewrite equation (10) as the following for individual stock i,

$$r_{i,t+1} = E_t r_{i,t+1} - \rho(r_{e,i,t+1} - E_{e,i,t}) + n_{d,i,t+1}. \tag{11}$$

Since the ICC measure is persistent, we can further assume the following $AR(1)$ structure from an empirical perspective,

$$r_{e,i,t+1} = a_i + c_i r_{e,i,t} + e_{i,t+1}, \tag{12}$$

Again, when the conditional CAPM holds with $\mu_{i,t} = \beta_{i,t}\lambda_{m,t}$, we can plug in equation equation (12) into equation (11) to arrive the following equation,

$$r_{i,t+1} = \left(\beta_{i,t} + \rho(1 - c_i)\frac{r_{e,i,t}}{r_{m,t}}\right) r_{mi,t+1} + (n_{d,i,t+1} - \rho e_{i,t+1}). \tag{13}$$

Not to lose generality, we assume that the expected market risk premium at t, $r_{m,t}$, is close to time t aggregate ICC, $r_{e,t}$. We can thus define $b_{i,t} = \frac{r_{e,i,t}}{r_{e,t}}$ as the relative ICC. In implementation, we suppose to estimate c_i. When the whole sample is used to estimate c_i, it might introduce forward looking bias. To avoid the bias, we can use a difference measure $(b_{i,t} - b_{i,t-1})$ to approximate for $(1 - c_i)b_{i,t}$. In other words, our adjusted beta is defined as, $\beta_{i,t} + (b_{i,t} - b_{i,t-1})$. In general, the variation in the historical beta estimates seem to be low. From the regression theory, low variation in the explanatory variable will reduce the power when testing the significance of parameter estimate. As a practical matter, we further adjust the historical beta by a factor that is proportional to the square of the historical ICC ratio, that is the adjusted beta $\hat{\beta}_{i,t}$ is defined as,

$$\hat{\beta}_{i,t} = \left(\frac{b_{i,t}}{b_{i,t-1}}\right)^2 \times [\beta_{i,t} + (b_{i,t} - b_{i,t-1}]. \tag{14}$$

3 Data and Variable Construction

3.1 Estimating ICC

To use the ICC is as a proxy for expected returns over a longer-horizon, we follow Pastor, Sinha and Swaminathan (2008) to estimate the ICC. In particular, we use the annualized analyst earnings forecasts to proxy for each firm's future cash flows. Although future cash flows are unknown and analysts do make prediction mistakes, it is reasonable to consider the consensus (mean) one- and two-year ahead EPS forecasts as proper proxies for the expected cash flows at that time. When the forecasting horizon is short there would be fewer unexpected uncertainties, making the forecast more reliable. This is consistent with both Gebhardt, Lee and Swaminathan (2001) and Pastor, Sinha and Swaminathan (2008). We follow their methodology to construct the ICC estimate, but we also find it important to consider the quarterly estimate. When the testing period is relatively short analysts should be more precise in forecasting. We accordingly employ quarterly estimates instead of one-year EPS estimates when they are available. If quarterly estimates are missing then we use one-year EPS estimate as previous literature.

We need further assumptions regarding the long-run growth patterns in order to estimate cash flows beginning from $t + 3$ since only one- and two-year advance EPS forecasts are directly employed. Pastor, Sinha and Swaminathan (2008) claim that the final steady-state rate should resemble the long-run average GDP growth rate; however, we focus on individual risk-return relations instead of the market-level used in Pastor, Sinha and Swaminathan (2008). We therefore employ Gebhardt, Lee and Swaminathan's (2001) long-run industry growth as the ultimate growth rate in order to introduce more distinctive characteristics in our ICC estimates. We assume that cash flows beyond $t+2$ would follow a mean-reverting process, resulting in long-run industry growth rate at the end. In particular we compute forecasts from year $t+4$ to year $t+T+1$ by mean-reverting the year $t+3$ earnings growth rate to the long-run industry growth rate. Following Pastor, Sinha and Swaminathan (2008), the exponential process is chosen because it would allow the growth rate, which might appear extreme in earlier stages, to mean-revert rapidly. Given this rapid mean reversion, any potential biases in analysts' short-term earnings forecasts should not have large effects on the long-run growth rates, and therefore also on the estimated ICC. This paper chooses 15-year horizon (T=15) consistent with prior studies.

Note that part of the EPS would be distributed to shareholders in terms of dividends. The earnings forecasts should therefore not be directly applied as future inflows because they would overstate the firm's real cash income and introduce bias into the ICC estimates. Consistent with prior literature we employ the plowback rate as the fraction of earnings reinvested by the firm, which also equals one minus the payout ratio, to combine with the EPS forecast and determine the exact amount of future cash flows to be discounted. Pastor, Sinha and Swaminathan (2008) claim that the plowback rate should also follow a mean-reverting process where the product of the steady-state return and plowback rate is equal to the steady-state growth rate in earnings. This measure differs from Gebhardt, Lee and Swaminathan's (2001) use of the historical dividend payout ratio, but such a dynamic conversion should be more compatible with the ultimate steady assumption; hence we employ it in this study as well. The formula for calculating the ICC estimate is expressed in the following:

$$P_t = \sum_{k=1}^{T} \frac{FE_{t+k} \times (1 - b_{t+k})}{(1 + r_e)^k} + \frac{FE_{t+T+1}}{r_e \times (1 + r_e)^T} \tag{15}$$

where r_e is the ICC estimate, P_t is the current market price, FE is the forecast earning, and b is the plowback rate.

The ICC estimates for all firms could be easily solved using the above non-linear equation; however, many solutions prove to be far from realistic. Similar to prior studies we drop all estimates less than zero, but the estimate sample still contains many potential outliers that could not be reasonably trimmed using a single benchmark. As a result, if a firm's annual earnings either increase or decrease by 500%, we will drop all related observations because the analysts will not be able to forecast such a large change. Their forecasts would either be far from the realized earnings or problematic, and that is typically where the outliers are generated. We did compare our ICC estimation with both Gebhardt, Lee and Swaminathan (2001) and Pastor, Sinha and Swaminathan (2008), finding that the summary statistics are very similar except that our sample is less volatile. The conventional beta is also significantly positive under all settings. Consequently, all of our following empirical results are expressed under our filtered sample only.

3.2 Analyst Forecast Dispersion

In recent literature, researcher start to pay attention to the uncertainty risk. This types of risk might be more important in our context since we are focusing on longer horizon. Unfortunately, there is no clear guidance as to what proxies are accurate in measuring such a risk. Therfore, we choose analyst forecast dispersion as a proxy for two reasons. First, it seems to be a natural choice, since a large uncertainty risk will result in large a variation among analysts' forecasts. It is also possible that a large dispersion among analysts is a result of asymmetric information. However, this is less likely over a longer horizon. One may also argue that the dispersion measure is a poor proxy for uncertainty risk since analysts may make the same type of mistake. As long as there is no systematic bias over longer horizon, such a potential issue will be minimum. Second, since we have already used the first moment of analyst forecasts in our ICC estimate, dispersion measure might serve as a control for the estimation error in ICC.

Diether, Malloy and Scherbina (2002) define analyst dispersion as the standard deviation of earnings forecasts scaled by its absolute mean each month. Following construction the authors also compare the standard deviation computed using individual analyst forecasts from the Detail History file and the direct standard deviation from the Summary file, finding that the two measures are very similar. We therefore only employ the Summary History file's standard deviations throughout this study. Consistent with prior studies, we turn to the unadjusted file because the adjustment of stock splits would result in a smoother time series, making the standard deviations would appear smaller than the actual value. However, some forecast dispersions are still extremely large or small even after scaling and winsorizing, so we employ log forecast dispersion for all empirical tests as well. The regression results from the two are very similar, and we only report the results using log forecast dispersion.

3.3 The Beta Estimate

We follow Fama and French (1992) to estimate the historical beta measure. In particular, each individual firm's beta is estimated by regressing its 24 to 60 monthly returns preceding July of year t (as available) on the current and lagged market portfolio returns. We use this pre-ranking beta as the main testing variable since it can capture additional time-varying variance. Beta might also be estimated using high frequency returns, such as daily returns. In fact, Merton (1987) has suggested that volatility can be estimated more accurately from high frequency data. Therefore, we estimate the monthly beta by fitting the market model to daily returns each month for each stock as a robustness check.

Other control variables in the test include size, Book-to-Market (BTM), average turnover, residual coverage debt-to-market, industry ICC premia, Long-Term-Growth rate (LTG) and lagged returns. Size and BTM are the traditional risk proxies in related tests. Fama and French (1992) match the accounting data for fiscal yearends in calendar year $t-1$ with returns from July of year t to June of year $t+1$ in order to ensure that accounting information is known before explaining returns. In particular, a firm's market capitalization in December of year $t-1$ is used to compute its BTM, and the market capitalization in June of year t is used as a measure of its size. We employ the same matching strategies, applying log size and log BTM for better distribution.

Apart from including size and BTM, we follow Gebhardt, Lee and Swaminathan (2001) by controlling for other common factors such as debt-to-market ratio, average industry ICC premia and LTG. Similar to size and BTM, we employ the log debt-to-market and use the firm's market capitalization in December of year $t-1$ to compute the denominator. The average industry ICC premia are computed as the mean of all ICCs available within each industry on a monthly basis. Consistent with Gebhardt, Lee and Swaminathan (2001), we use the yield of 10-year government bond as the risk-free rate in computing the ICC premia. LTG, the mean of all individual analysts' long-term growth rate forecasts, is directly obtained from I/B/E/S. Both the average industry ICC premia and LTG are lagged one month.

Diether, Malloy and Scherbina (2002) consider return momentum using returns from $t-12$ to $t-2$ and $t-36$ to $t-13$ respectively in order to disentangle the effect of forecast dispersion from stock fundamentals and additional risk measures. They also estimate the residual coverage using analyst coverage regressed on firm size and BTM, as well as the average turnover estimated during the previous 250 days, both of which are lagged one month. We consider these controls in our tests as well, expecting to better understand the role of beta and forecast dispersion under the ICC settings.

3.4 Data

We use three main data sets in this study. Balance sheet items such as earnings long-term debt, etc. are from the COMPUSTAT industrial database. Trading information including both daily and monthly stock returns is from the Center for Research in Security Prices database (CRSP). Analyst forecasts for EPS and LTG are from the Institutional Brokers' Estimate System (I/B/E/S). All U.S. companies at the intersection of NYSE, AMEX and NASDAQ stock exchanges and listed on these three main databases over the period from 1976 to 2011 are included. The starting point for our sample is consistent with Pastor, Sinha and Swaminathan (2008), because that is when I/B/E/S began to provide analyst forecasts. We also obtain the 100 portfolio returns formed on size and book-to-market ratio from the data library of Kenneth French's website in order to test the performance of the adjusted beta. The risk-free rate, 10-year government bond yield, comes from the St. Louise Fed for computing ICC premia. As a common practice we drop financial institutions such as banks and insurance companies (firms with SIC codes from 6000 to 6999) due to their abnormally high leverages.

Table 1 contains the summary statistics for all main testing variables. All variables included have been winsorized at the 0.5% level in order to avoid the outliers. The ICC, although estimated as the annual cost of capital, is converted in the monthly term to order to be compatible with the monthly returns.

Insert Table 1 Approximately Here

Consisting of 710,840 observations, our sample has a slightly smaller size compared to other related studies under similar testing periods. The main reason is that we exclude observations whose annual earnings either increase or decrease by 500% from the last fiscal yearend. Such drastic changes could barely be forecasted by analysts, which would introduce large prediction errors and should not be employed for ICC estimation.

4 Main Findings

We begin with the sortings of returns and ICCs from 1976 to 2011 based on beta and forecast dispersion. These 100 portfolios are formed at the end of June each year and the equal-weighted returns are calculated for the next 12 months. We use the NYSE breakpoints for both beta and forecast dispersion, then allocate our observations into 10 beta or forecast dispersion portfolios respectively. Since our sample is limited by the I/B/E/S data, using an I/B/E/S-based benchmark might be misleading. However, the I/B/E/S breakpoints are still employed for the same two-dimensional sorting as a robustness check. The outcomes are comparatively similar, and we only report the average statistics using the NYSE breakpoints in Table 2.

Insert Table 2 Approximately Here

Consistent with Fama and French (1992), when portfolios are formed on beta alone we observe an unclear relation between the beta and return in Panel A. The spreads between the average returns across beta portfolios are not following any consistent patterns regardless of the magnitude of forecast dispersion. Moreover, none of the return differences between the largest and smallest beta groups are significantly different from zero, and the T-values of which are extremely small as well. Our preliminary evidence of the unclear association between beta and return is therefore in line with prior studies. Besides, Diether, Malloy and Scherbina (2002) claim that the return should decrease when forecast dispersion is high because investors tend to be optimistic regarding controversial stocks. Although not very significant, the return spreads between the high and low analyst dispersion groups are always negative, consistent with Diether, Malloy and Scherbina's (2002) argument.

Panel B of Table 2 provides the same two-dimensional sorting using the ICCs. In contrast to the returns, the average portfolio ICCs are clearly increasing with the beta and forecast dispersion. Despite some minor fluctuations, the ICC clearly increases when the beta becomes larger, echoed with the strongly positive T-values for the ICC differences between the largest and smallest beta groups. Likewise, the ICC spreads across the forecast dispersion groups indicate a strongly positive correlation between the ICC and forecast dispersion as well. It is clear that the risk components involved with the ICCs are very different from those with actual returns when compared to Panel A.

To better understand how return and ICC relate to beta and other risk proxies, we now conduct monthly Fama-Macbeth regressions following Fama and French (1992) using return and ICC as the dependent variable respectively. Note that for better distribution we also consider the log return and log ICC since certain values could still be extreme after winsorizing. The log results are very similar in terms of significance to those under raw forms, so we conduct the following tests using the raw return and ICC. Forecast dispersion is also added in the regression for two reasons. First, Gode and Mohanram (2013) argue that large predication errors might bias the association between analyst-based ICC and future earnings, thus analyst dispersion should be used as a proper control for forecast quality. Second, Barron and Stuerke (1998) employ forecast dispersion as an uncertainty measure. Uncertainty risk is also important in our context since we are using the future ICC to proxy for the expected return over a longer horizon where the uncertainty risk could not be ignored. The average slopes and Newey-West adjusted T-statistics are summarized in Table 3.

Insert Table 3 Approximately Here

The overall beta effect is weakly negative as shown in Panel A of Table 3, implying that the role of beta in explaining cross-sectional returns is indeterminant, hence is in line with the prior weak evidence of beta's cross-sectional explanatory power. Our forecast dispersion evidence is consistent with Diether, Malloy and Scherbina's (2002) that return and forecast dispersion are negatively correlated, implying that investors tend to be optimistic regarding controversial stocks and would suffer from losses later. Note that we also apply the raw forecast dispersion without the log and scaling of the stock's absolute price, both of which suggest the same evidence.

In contrast, beta in Panel B is significantly positive in explaining the cross-sectional ICCs, which are also robust across different time periods. Moreover, size is negative and BTM is positive, both of which are rather consistent and strong under the ICC settings as in Fama and French (1992). Alternatively speaking, all risk proxies could effectively explain the future expected return proxied by the ICC. One possible explanation is that the ICC settings contain fewer abnormal and noisy components as in the realized returns. This allows the real risk-return relation to become clearer since it might have been obscured among the realized returns. However, forecast dispersion is significantly positive, indicating that the optimism of investors fades away under this ICC setting. It is true that Gebhardt, Lee and Swaminathan (2001) find this relation to be negative, but our test settings differ from theirs. We construct the ICC every month following Pastor, Sinha and Swaminathan (2008) instead of using the annual estimation. We also consider quarterly information in order to introduce more short-run accuracy and exclude observations experiencing extreme changes in realized earnings. Furthermore, we find a negative mean-variance pattern in forecast earnings, suggesting that Gebhardt, Lee and Swaminathan's (2001) negative correlation of forecast dispersion and ICC might be a simple reflection of how forecast dispersion relates to forecast earnings. Our evidence would be further tested in the robustness checks. If the positive association of forecast dispersion and the ICC does hold, it means that future returns as proxied by the ICC do compensate for the uncertainty and controversy related to a particular stock, which might have overweighed the optimistic overpricing effect found in earlier studies.

Overall, Table 3 shows that the unclear cross-sectional relation between beta and returns does exist, but beta is rather powerful in explaining the future ICCs. Forecast dispersion is negatively related to return, while this correlation is reversed under the ICC settings. To test the effectiveness of these results, we also conduct the same regression using the log return and ICC, applying the post-ranking beta instead of the pre-ranking beta, and replicating Pastor, Sinha and Swaminathan's (2008) construction of the ICC without quarterly information and other filters. All of these results are in support of the positive association between beta or forecast dispersion and the ICC. We therefore introduce the lagged ICC as a further control of the ICC estimate, focusing on how beta or forecast dispersion explains the innovative ICC components. This regression is also performed at two sub-sample periods for better investigation. The average slopes and Newey-West adjusted T-statistics are summarized in Table 4.

Insert Table 4 Approximately Here

As shown in Table 4, both beta and forecast dispersion are consistently positive across time but the coefficients and T-statistics are greatly reduced after controlling for the lagged ICC. This is in line with our expectations because the ICC tends to be consistent across time for each firm. The coefficient of the lagged ICC is approximately 0.86, which seems much larger than all other independent variables. Nevertheless, beta and forecast dispersion are still rather strong across different time periods, indicating that they do explain certain future expected returns under the ICC settings.

We have already employed various mathematic forms and data filters in order to make sure that our results are not random, and we now directly test the exact explanatory power of beta. This is measured by computing the root mean square error (RMSE) of the realized and predicted ICCs respectively. In particular, we employ the average cross-sectional regression coefficients for the past 36 months and the current beta variable in order to compute the predicted ICC for each stock on a monthly basis. Note that only the conventional beta is employed as the independent variable because we want to measure the exact extent of the future ICC that could be explained by beta. We then compute the average return using the next three years' records and subtract this ex-post average from the predicted ICC. Finally, we square all residual ICCs and take the average value on a monthly basis. Likewise, we also compute the differences between the actual ICC at $t + 1$ and the ex-post average return for comparison. If the RMSE of the ICC predicted by beta has a smaller RMSE then it implies that the ICC predicted by beta does capture greater stock variations than its actual counterpart. Alternatively speaking, beta does effectively predict future stock variations under the ICC settings. The RMSE for both ICCs are summarized in Table 5.

Insert Table 5 Approximately Here

As shown in Table 5, the RMSE of the predicted ICC is significantly lower than that of the realized ICC, implying that beta does predict certain stock performances under the ICC settings. We also plot the two groups' RMSEs across all firms involved in the sample for better understanding for better understanding, as shown in Figure 1.

Insert Figure 1 Approximately Here

Figure 1 clearly indicates that the RMSEs for the predicted ICC are relatively smaller, and clustered in a small gap close to zero. In contrast, the realized ICC's RMSEs are largely scattered in the graph and most are far above the clustering of the predicted ICCs. These results are consistent with Table 5, suggesting that more future stock performances are captured by the predicted ICC and the beta effect does hold under the ICC settings. Therefore, we find it intuitive to improve the conventional beta by incorporating certain ICC information. This should also be a robustness check of our prior findings for the risk-return relation under the ICC settings. We begin with constructing a relative ICC estimate. The nominator is computed by subtracting the 10-year government bond yield from the ICC estimates, and for the denominator we use the equal- and value-weighted ICC premia respectively. Both sets of relative ICC estimates are tested to see whether or not they could help improve the conventional beta. We then incorporate the changes in these relative ICC estimates into the conventional beta. Note that the changes in relative ICC estimates would be the most important aspects of the forward-looking predictions, which directly reflect analysts' most recent firm perceptions. We therefore incorporate the mean and ratio changes of the ICC betas with the historical beta. We also take the square of the ratio change because we want to introduce greater variations across different firms. Since some adjusted beta estimations turn out to be extremely large or small we limit all adjusted betas between -1 and 5: adjusted betas less than -1 are set to be -1, and those greater than 5 are set to 5. We can therefore avoid the potential impact of certain outliers as well as obtaining a predictor with a reasonable amount of variations. The regression results for the adjusted beta are provided in Table 6.

Insert Table 6 Approximately Here

Consistent with our expectation, the adjusted beta is positively related to the returns, implying that our adjustment does help improve the explanatory power of the conventional beta. When the beta contains more forward-looking information and becomes more variant, it could still be a good predictor for individual stock returns even without the ICC settings. This result is rather strong under different controls and for both the equal- and value-weighted relative ICC estimates. Apart from the traditional historical rolling beta estimated each year, we also consider beta estimated using daily information each month as a robustness check. The monthly beta estimates contain greater time-varying explanatory power, and might therefore help further improve the conventional approach. This stream of beta estimates is generously provided by Yihua Zhao. The regression results are summarized in Table 7.

Insert Table 7 Approximately Here

Similar to Table 6, both the equal- and value-weighted adjusted daily betas are consistently positive in the regression. Yet, the coefficients and T-values have not experienced significant changes, implying that the prior results are not random and the monthly beta variations do not introduce much additional explanatory power into the relative ICC estimate changes. Alternatively speaking, the forward-looking ICC information is an essential component for improving the explanatory power of beta, and beta could successfully predict future returns in a robust way following this adjustment. We also use the adjusted beta to predict each stock's next-month return and reconstruct the 100 portfolios based on size and book-to-market following Fama and French. We plot these predicted portfolio returns against the standard portfolio realized returns obtained from Kenneth French's website in order to examine the prediction power of our adjusted beta. We do not conduct this comparison using individual observations because there would be many abnormal returns or predictions involved, but such components would offset each other at the portfolio basis. In particular, we employ equal-weighted portfolio returns since value-weighted portfolio returns would be dominated by large firms' patterns. The plottings of the two adjusted betas are shown in Figure 2 below.

Insert Figure 2 Approximately Here

As seen from the figure, the newly-constructed returns estimated by the equal- and value-weighted adjusted betas both exhibit a very similar pattern to the standard Fama and French 100 portfolio returns. Most of the plots fall around the 45 degree line and the outliers are minor. The adjusted beta could therefore be considered a good predictor of future returns even when there are no ICC settings. This adjusted beta measure might be employed by other studies regarding the risk-return relation as well.

5 Conclusions

Most empirical studies on the cross-sectional explanatory power of the CAPM beta focus on short-term (e.g. monthly). There are two potential issues that might cause the failure in current empirical studies. First, the use of next period realized return as a proxy for expected return might be extreme noisy since it might be affected by investors' short-term behavior. Second, most investors may invest in the underlying securities over a longer-term. If this is the case, despite weak explanatory power of beta in short-run, it might still be useful to explain longer-horizon expected returns.

In order to effectively estimate the expected return over longer-horizon and maintain the same number of monthly observation, we propose to use the future ICC estimates as proxies. After controlling for other potential effectives, we find that the historical beta estimate can strongly predict the cross-sectional expected return differences over longer-horizon. Our focus on longer-term also allows us to study the uncertainty risk proposed in the recent literature. Using analyst forecast dispersion, we find that stocks with large dispersion tend to have high long-term expected return approxied by future ICC.

Over short-horizon, we also improve the explanatory power of the conventional beta estimate by incorporating the ICC information. In particular, we propose to adjust the historical beta by changes in the relative ICC estimate since it might reflect investors' forward-looking information. Our empirical evidence demonstrate that the adjusted beta is promising in explain the cross-sectional return difference.

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Table 1: Descriptive statistics

This table reports the summary statistics for stocks that are listed in the NYSE, AMEX, or NASDAQ during July 1976 and December 2011. Return is the monthly stock return. ICC is estimated following Pastor, Sinha and Swaminathan (2008). Beta is estimated by regressing 24 to 60 monthly returns preceding July of year t (as available) on the market portfolio returns. Size is the nature logrithm of market capitalization at June year t. BTM is the nature logrithm of book equity value of the fiscal year ended in year $t-1$ divided by market capitalization at December year $t-1$. FD is the nature logrithm of the standard deviation of earnings forecasts scaled by the absolute value of the forecast mean. DTM is the nature logritm of long-term debt of the fiscal year ended in year $t-1$ divided by market capitalization at December of year $t-1$. LTG is the mean of analysts' expected annual growth rate in operating earnings over the firm's next full business cycle. Industry premia is the monthly industry average ICC premia. Turnover is the average of the firm's turnover divided by the mean turnover of its stock exchange in the past 250 days. Residual coverage is the residual from yearly regressions of ln(1+coverage) on Size and BTM. Ret(-12:-2) is the compounding return using preceding 2 to 12 monthly returns. Ret(-36:-13) is the compounding return using preceding 13 to 36 monthly returns. EW and VW Adjusted Betas are constructed through incorporating the changes in ICCs into the conventional beta. All variables, except EW and VW Adjusted Betas, are winsorized at 0.5% to avoid the outliers. EW and VW Adjusted Betas are limited between -1 and 5.

Variable	Obs	Mean	Std. Dev.	10%	50%	90%
Return	710834	1.22	13.34	-12.78	0.69	15.40
ICC	710834	1.09	0.84	0.28	0.85	2.35
Beta	710834	1.31	0.79	0.36	1.21	2.38
FD	570245	-2.97	1.19	-4.42	-3.10	-1.33
Size	710750	12.82	1.73	10.59	12.71	15.21
BTM	710834	-0.60	0.73	-1.61	-0.54	0.31
DTM	612243	-1.71	1.77	-4.24	-1.35	0.20
LTG	513711	15.88	7.48	7.27	15	25.89
Industry premia	690634	0.53	0.34	0.03	0.58	0.93
Turnover	690384	1.11	0.83	0.32	0.87	2.27
Residual coverage	536701	0.01	0.47	-0.64	0.02	0.63
Ret(-12:-2)	696535	15.87	42.71	-32.59	9.91	70.28
Ret(-36:-13)	651907	40.91	74.03	-35.01	25	135.35
EW Adjusted Beta	691113	1.55	1.34	0.23	1.20	3.66
VW Adjusted Beta	691113	1.55	1.35	0.23	1.20	3.67

Table 2: Average returns and ICCs for portfolios formed on Beta and Size

Portfolios are formed each year at the end of June, using 10 NYSE Beta and Size benchmark. Return is the monthly stock return. ICC is estimated following Pastor, Sinha and Swaminathan (2008). Beta is estimated by regressing 24 to 60 monthly returns preceding July of year t (as available) on the market portfolio returns. Size is the nature logrithm of market capitalization at June year t.

Panel A: Average return

		Beta											
		Low	2	3	4	5	6	7	8	9	High	High-Low	T-stat
	Low	1.41	1.29	1.32	1.21	1.29	1.13	1.23	1.35	1.49	1.44	0.03	0.08
	2	1.22	1.13	1.12	1.16	0.93	1.26	1.25	1.05	1.02	0.70	-0.52	-1.39
	3	1.13	1.25	1.01	1.10	1.01	1.33	1.14	1.12	1.16	0.98	-0.16	-0.30
	4	1.25	1.21	1.09	1.18	1.29	1.00	1.17	0.97	1.06	0.96	-0.29	-0.66
Analyst	5	0.98	1.03	1.02	0.99	1.13	1.23	0.94	1.33	1.12	0.86	-0.11	-0.23
Dispersion	6	1.09	1.13	0.89	1.24	0.96	1.18	1.21	1.24	1.20	1.25	0.16	0.56
	7	1.06	0.96	1.41	1.29	1.11	1.20	1.22	0.99	1.21	1.05	-0.01	-0.14
	8	1.13	1.47	1.38	1.25	1.41	0.80	0.98	0.99	0.94	1.32	0.19	0.58
	9	1.48	1.33	0.99	1.27	1.01	1.00	0.82	1.18	1.15	1.30	-0.19	-0.21
	High	1.12	1.04	1.15	1.16	1.12	1.06	0.97	1.10	0.98	1.19	0.07	-0.01
	High-Low	-0.29	-0.25	-0.17	-0.05	-0.18	-0.07	-0.27	-0.25	-0.51	-0.25	0.04	
	T-stat	-0.47	-0.62	-0.45	-0.11	-0.54	-0.12	-0.90	-0.93	-1.61	-0.80		

Panel B: Average ICC

		Beta											
		low	2	3	4	5	6	7	8	9	High	High-Low	T-stat
	Low	0.70	0.64	0.67	0.68	0.72	0.76	0.77	0.86	0.85	1.07	0.37	19.69
	2	0.65	0.67	0.67	0.68	0.76	0.69	0.76	0.79	0.82	0.94	0.30	20.06
	3	0.63	0.69	0.69	0.72	0.74	0.79	0.81	0.80	0.90	0.94	0.31	28.53
	4	0.71	0.69	0.76	0.75	0.85	0.81	0.78	0.86	0.92	0.99	0.28	23.62
Analyst	5	0.71	0.76	0.82	0.85	0.88	0.84	0.89	0.89	0.90	1.02	0.32	22.12
Dispersion	6	0.79	0.81	0.85	0.85	0.89	0.91	0.94	0.91	1.02	1.09	0.30	22.77
	7	0.84	0.84	0.93	0.96	0.98	1.00	0.99	1.08	1.08	1.18	0.34	22.91
	8	0.92	0.93	1.03	1.10	1.08	1.13	1.13	1.19	1.22	1.25	0.32	20.20
	9	1.08	1.13	1.23	1.26	1.39	1.33	1.38	1.35	1.37	1.44	0.36	12.40
	High	1.35	1.50	1.43	1.47	1.51	1.52	1.46	1.54	1.47	1.49	0.14	4.29
	High-Low	0.65	0.86	0.76	0.79	0.79	0.76	0.69	0.68	0.62	0.42	-0.23	
	T-stat	19.95	25.61	29.52	31.48	28.85	33.42	36.00	30.16	33.96	22.74		

Table 3: Sub-period means of slopes from monthly FM cross-sectional regressions

This table reports the average coefficients in the monthly Fama-MacBeth cross-sectional regressions for stocks listed in the NYSE, AMEX, or NASDAQ during July 1976 and December 2011. Return is the monthly stock return. ICC is estimated following Pastor, Sinha and Swaminathan (2008). Beta is estimated by regressing 24 to 60 monthly returns preceding July of year t (as available) on the market portfolio returns. Size is the nature logrithm of market capitalization at June year t. BTM is the nature logrithm of book equity value of the fiscal year ended in year $t-1$ divided by market capitalization at December year $t-1$. FD is the nature logrithm of the standard deviation of earnings forecasts scaled by the absolute value of the forecast mean. DTM is the nature logritm of long-term debt of the fiscal year ended in year $t-1$ divided by market capitalization at December of year $t-1$. LTG is the mean of analysts' expected annual growth rate in operating earnings over the firm's next full business cycle. Industry premia is the monthly industry average ICC premia. Turnover is the average of the firm's turnover divided by the mean turnover of its stock exchange in the past 250 days. Residual coverage is the residual from yearly regressions of ln(1+coverage) on Size and BTM. Ret(-12:-2) is the compounding return using preceding 2 to 12 monthly returns. Ret(-36:-13) is the compounding return using preceding 13 to 36 monthly returns. Panel A provides the regression results using return as the dependent variable. Panel B provides the regression results using ICC as the dependent variable. The T-statistics are calculated based on the Newey-West standard errors. All variables are winsorized at 0.5% to avoid the outliers.

Panel A: Regression estimates using return as the dependent variable

Intercept	Beta	FD	Size	BTM	DTM	LTG	Industry premia	Turnover	Residual coverage	Ret (-12:-2)	Ret (-36:-13)
1.200	-0.050										
(6.25)	(-0.42)										
1.467	-0.059		-0.015	0.189							
(2.58)	(-0.59)		(-0.38)	(2.47)							
1.142	-0.034		0.011	0.173	-0.051	0.004	-0.451	-0.142	0.135	0.005	0.00002
(1.92)	(-0.42)		(0.28)	(2.81)	(-2.83)	(0.49)	(-2.37)	(-2.35)	(2.5)	(2.3)	(0.04)
0.642	-0.010	-0.158									
(2.73)	(-0.09)	(-3.49)									
0.980	-0.021	-0.112	-0.006	0.202	-0.044	0.006	-0.416	-0.098	0.137	0.004	-0.0003
(1.61)	(-0.26)	(-2.8)	(-0.15)	(3.04)	(-2.54)	(0.76)	(-2.17)	(-1.71)	(2.43)	(1.84)	(-0.53)

Panel B: Regression estimates using ICC as the dependent variable

Intercept	Beta	FD	Size	BTM	DTM	LTG	Industry premia	Turnover	Residual coverage	Ret (-12:-2)	Ret (-36:-13)
0.843	0.177										
(43.44)	(12.32)										
2.363	0.128		-0.111	0.102							
(19.19)	(8.82)		(-12.53)	(7.25)							
1.327	0.082		-0.062	0.085	0.048	0.016	0.506	0.076	-0.034	-0.003	-0.001
(19.71)	(13.15)		(-15.88)	(7.05)	(19.87)	(20.55)	(19.29)	(8.96)	(-3.91)	(-16.23)	(-15.02)
1.526	0.112	0.228									
(61.81)	(9.84)	(25.52)									
1.631	0.055	0.171	-0.040	0.033	0.037	0.012	0.436	0.034	-0.057	-0.002	-0.0006
(21.23)	(9.86)	(28.02)	(-8.81)	(3.17)	(21.84)	(16.15)	(20.74)	(5.32)	(-6.46)	(-14.75)	(-11.07)

Table 4: Sub-period means of slopes from monthly FM cross-sectional regressions (lagged ICC controlled)

This table reports the average coefficients in the monthly Fama-MacBeth cross-sectional regressions for stocks listed in the NYSE, AMEX, or NASDAQ during July 1976 and December 2011. ICC is used as the dependent variable, and the one-month lagged ICC is added in addition to other controls as a robustness check. Return is the monthly stock return. ICC is estimated following Pastor, Sinha and Swaminathan (2008). Beta is estimated by regressing 24 to 60 monthly returns preceding July of year t (as available) on the market portfolio returns. Size is the nature logrithm of market capitalization at June year t. BTM is the nature logrithm of book equity value of the fiscal year ended in year $t-1$ divided by market capitalization at December year $t-1$. FD is the nature logrithm of the standard deviation of earnings forecasts scaled by the absolute value of the forecast mean. DTM is the nature logritm of long-term debt of the fiscal year ended in year $t-1$ divided by market capitalization at December of year $t-1$. LTG is the mean of analysts' expected annual growth rate in operating earnings over the firm's next full business cycle. Industry premia is the monthly industry average ICC premia. Turnover is the average of the firm's turnover divided by the mean turnover of its stock exchange in the past 250 days. Residual coverage is the residual from yearly regressions of ln(1+coverage) on Size and BTM. Ret(-12:-2) is the compounding return using preceding 2 to 12 monthly returns. Ret(-36:-13) is the compounding return using preceding 13 to 36 monthly returns. Panel A provides the regression results during July 1976 to June 1992. Panel B provides the regression results during July 1992 to December 1992. The T-statistics are calculated based on the Newey-West standard errors. All variables are winsorized at 0.5% to avoid the outliers.

Panel A: Regression estimates using return as the dependent variable

Intercept	Beta	FD	Size	BTM	DTM	LTG	Industry premia	Turnover	Residual coverage	Ret (-12:-2)	Ret (-36:-13)	Lagged ICC
0.763	0.222											
(49.58)	(9.48)											
1.522	0.148	0.266										
(35.85)	(8.13)	(25.72)										
2.393	0.112	0.229	-0.072	0.075								
(27.29)	(6.37)	(20.68)	(-10.11)	(3.63)								
1.892	0.056	0.202	-0.051	0.047	0.041	0.013	0.351	0.049	-0.025	-0.003	-0.001	
(33.47)	(6.32)	(32.74)	(-12.15)	(1.93)	(14.75)	(9.35)	(11.1)	(6.66)	(-2.19)	(-10.1)	(-6.86)	
0.182	0.025	0.029										0.867
(17.8)	(7)	(13.39)										(132.52)
0.276	0.015	0.020	-0.010	0.005	0.006	0.002	0.019	0.011	-0.004	-0.0004	-0.0001	0.857
(18.04)	(5.42)	(14.52)	(-9.94)	(1.24)	(8.59)	(5.51)	(3.99)	(7.61)	(-1.77)	(-7.64)	(-3.65)	(226.47)

Panel B: Regression estimates using ICC as the dependent variable

Intercept	Beta	FD	Size	BTM	DTM	LTG	Industry premia	Turnover	Residual coverage	Ret (-12:-2)	Ret (-36:-13)	Lagged ICC
0.923	0.134											
(39.01)	(18.02)											
1.531	0.077	0.191										
(60.18)	(11.2)	(25.45)										
2.179	0.063	0.169	-0.051	0.023								
(18.85)	(8.44)	(28.66)	(-6.24)	(2.76)								
1.464	0.055	0.151	-0.033	0.024	0.034	0.011	0.490	0.025	-0.078	-0.002	-0.001	
(14.26)	(7.53)	(27.64)	(-5.17)	(4.1)	(18.58)	(14.35)	(25.63)	(2.84)	(-7.97)	(-12.24)	(-9.19)	
0.183	0.014	0.017										0.857
(29.95)	(8.7)	(10.13)										(185.43)
0.223	0.010	0.011	-0.007	0.005	0.004	0.001	0.036	0.006	-0.011	-0.0002	-0.0001	0.864
(14.82)	(4.81)	(7.96)	(-6.32)	(2.7)	(10.93)	(7.94)	(6.89)	(3.54)	(-4.63)	(-4.48)	(-3.33)	(175.35)

Table 5: Root mean square error of ICC prediction

This table compares the root mean square errors of realized ICC and the ICC predicted using beta only. The predicted ICC is estimated based on the average cross-sectional regression coefficients of the past 36 months and the current beta variable at a monthly basis. For both realized ICC and predicted ICC, we subtract the average annualized ex-post stock return, which is estimated using up to the next 36 months' stock return from now. Both differences are squared and averaged for each month.

Variable	Mean	Std. Dev.	Min	10%	50%	90%	Max
RMSE of predicted ICC	0.99	0.17	0.54	0.66	1.04	1.13	1.23
RMSE of realized ICC	1.28	0.18	0.73	1.00	1.31	1.47	1.60

Table 6: Improved Beta effect

This table reports the average coefficients in the monthly Fama-MacBeth cross-sectional regressions for stocks listed in the NYSE, AMEX, or NASDAQ during July 1976 and December 2011. Return is the monthly stock return. ICC is estimated following Pastor, Sinha and Swaminathan (2008). Beta is estimated by regressing 24 to 60 monthly returns preceding July of year t (as available) on the market portfolio returns. Size is the nature logrithm of market capitalization at June year t. BTM is the nature logrithm of book equity value of the fiscal year ended in year $t-1$ divided by market capitalization at December year $t-1$. FD is the nature logrithm of the standard deviation of earnings forecasts scaled by the absolute value of the forecast mean. DTM is the nature logritm of long-term debt of the fiscal year ended in year $t-1$ divided by market capitalization at December of year $t-1$. LTG is the mean of analysts' expected annual growth rate in operating earnings over the firm's next full business cycle. Industry premia is the monthly industry average ICC premia. Turnover is the average of the firm's turnover divided by the mean turnover of its stock exchange in the past 250 days. Residual coverage is the residual from yearly regressions of ln(1+coverage) on Size and BTM. Ret(-12:-2) is the compounding return using preceding 2 to 12 monthly returns. Ret(-36:-13) is the compounding return using preceding 13 to 36 monthly returns. EW and VW Adjusted Betas are constructed through incorporating the changes in ICCs into the conventional beta. All variables, except EW and VW Adjusted Betas, are winsorized at 0.5% to avoid the outliers. EW and VW Adjusted Betas are limited between -1 and 5. The T-statistics are calculated based on the Newey-West standard errors.

Panel A: Regression estimates using EW Adjusted Beta

Intercept	EW Adjusted Beta	FD	Size	BTM	DTM	LTG	Industry premia	Turnover	Residual coverage	Ret (-12:-2)	Ret (-36:-13)
0.988	0.073										
(5.08)	(1.63)										
0.756	0.089		0.023	0.215							
(1.21)	(2.52)		(0.55)	(2.61)							
0.894	0.123		0.025	0.173	-0.047	-0.001	-0.537	-0.170	0.131	0.005	0.00003
(1.49)	(3.89)		(0.63)	(2.79)	(-2.53)	(-0.09)	(-2.62)	(-2.62)	(2.54)	(2.27)	(0.05)
0.387	0.103	-0.193									
(1.46)	(2.45)	(-3.99)									
0.668	0.139	-0.133	0.008	0.207	-0.038	0.001	-0.500	-0.121	0.139	0.004	-0.0004
(1.08)	(4.68)	(-3.24)	(0.19)	(3.06)	(-2.14)	(0.16)	(-2.42)	(-1.98)	(2.52)	(1.73)	(-0.6)

Panel B: Regression estimates using VW Adjusted Beta

Intercept	VW Adjusted Beta	FD	Size	BTM	DTM	LTG	Industry premia	Turnover	Residual coverage	Ret (-12:-2)	Ret (-36:-13)
0.987	0.074										
(5.07)	(1.64)										
0.754	0.090		0.023	0.216							
(1.21)	(2.53)		(0.55)	(2.61)							
0.893	0.123		0.025	0.173	-0.047	-0.001	-0.537	-0.170	0.131	0.005	0.00003
(1.49)	(3.91)		(0.63)	(2.79)	(-2.53)	(-0.09)	(-2.62)	(-2.62)	(2.54)	(2.27)	(0.05)
0.386	0.103	-0.193									
(1.46)	(2.46)	(-3.99)									
0.667	0.139	-0.133	0.008	0.207	-0.038	0.001	-0.500	-0.121	0.139	0.004	-0.0004
(1.08)	(4.7)	(-3.24)	(0.19)	(3.06)	(-2.14)	(0.17)	(-2.42)	(-1.98)	(2.52)	(1.73)	(-0.6)

Table 7: Improved Beta effect using Beta estimated from daily returns

This table reports the average coefficients in the monthly Fama-MacBeth cross-sectional regressions for stocks listed in the NYSE, AMEX, or NASDAQ during July 1976 and December 2011. Return is the monthly stock return. ICC is estimated following Pastor, Sinha and Swaminathan (2008). Beta is estimated by regressing 24 to 60 monthly returns preceding July of year t (as available) on the market portfolio returns. Size is the nature logrithm of market capitalization at June year t. BTM is the nature logrithm of book equity value of the fiscal year ended in year $t-1$ divided by market capitalization at December year $t-1$. FD is the nature logrithm of the standard deviation of earnings forecasts scaled by the absolute value of the forecast mean. DTM is the nature logritm of long-term debt of the fiscal year ended in year $t-1$ divided by market capitalization at December of year $t-1$. LTG is the mean of analysts' expected annual growth rate in operating earnings over the firm's next full business cycle. Industry premia is the monthly industry average ICC premia. Turnover is the average of the firm's turnover divided by the mean turnover of its stock exchange in the past 250 days. Residual coverage is the residual from yearly regressions of ln(1+coverage) on Size and BTM. Ret(-12:-2) is the compounding return using preceding 2 to 12 monthly returns. Ret(-36:-13) is the compounding return using preceding 13 to 36 monthly returns. EW and VW Adjusted Betas are constructed through incorporating the changes in ICCs into the monthly beta constructed on the daily returns. All variables, except EW and VW Adjusted Betas, are winsorized at 0.5% to avoid the outliers. EW and VW Adjusted Betas are limited between -1 and 5. The T-statistics are calculated based on the Newey-West standard errors.

Panel A: Regression estimates using EW Adjusted Beta

Intercept	EW Adjusted Daily Beta	FD	Size	BTM	DTM	LTG	Industry premia	Turnover	Residual coverage	Ret (-12:-2)	Ret (-36:-13)
1.031	0.057										
(4.96)	(1.67)										
1.000	0.070		0.008	0.203							
(1.49)	(2.38)		(0.17)	(2.37)							
1.116	0.086		0.010	0.174	-0.048	0.001	-0.514	-0.166	0.129	0.005	0.00004
(1.8)	(3.28)		(0.24)	(2.81)	(-2.59)	(0.19)	(-2.45)	(-2.5)	(2.52)	(2.26)	(0.06)
0.471	0.079	-0.185									
(1.63)	(2.21)	(-3.62)									
0.961	0.099	-0.124	-0.010	0.205	-0.040	0.003	-0.472	-0.119	0.131	0.004	-0.0003
(1.52)	(3.89)	(-3)	(-0.25)	(3.04)	(-2.25)	(0.41)	(-2.23)	(-1.89)	(2.38)	(1.7)	(-0.56)

Panel B: Regression estimates using VW Adjusted Daily Beta

Intercept	VW Adjusted Daily Beta	FD	Size	BTM	DTM	LTG	Industry premia	Turnover	Residual coverage	Ret (-12:-2)	Ret (-36:-13)
1.030	0.057										
(4.96)	(1.68)										
0.999	0.070		0.008	0.203							
(1.49)	(2.38)		(0.17)	(2.37)							
1.115	0.086		0.010	0.174	-0.048	0.001	-0.515	-0.167	0.129	0.005	0.00004
(1.8)	(3.31)		(0.24)	(2.81)	(-2.59)	(0.19)	(-2.46)	(-2.5)	(2.52)	(2.26)	(0.06)
0.470	0.079	-0.185									
(1.63)	(2.22)	(-3.62)									
0.960	0.100	-0.124	-0.010	0.205	-0.040	0.003	-0.473	-0.119	0.131	0.004	-0.0003
(1.52)	(3.93)	(-3)	(-0.25)	(3.04)	(-2.25)	(0.41)	(-2.23)	(-1.9)	(2.38)	(1.7)	(-0.56)

Figure 1: Root mean square errors of predicted and realized ICCs

The predicted ICC is estimated based on the average cross-sectional regression coefficients of the past 36 months and the current beta variable at a monthly basis. The average return is computed using the next three years' return records, which is then subtracted from the predicted ICC. All the residual ICCs are squared and averaged each month. Likewise, we also compute the differences between the actual ICC at $t+1$ and the ex-post average return for comparison. The following plottings are from 1976 to 2011.

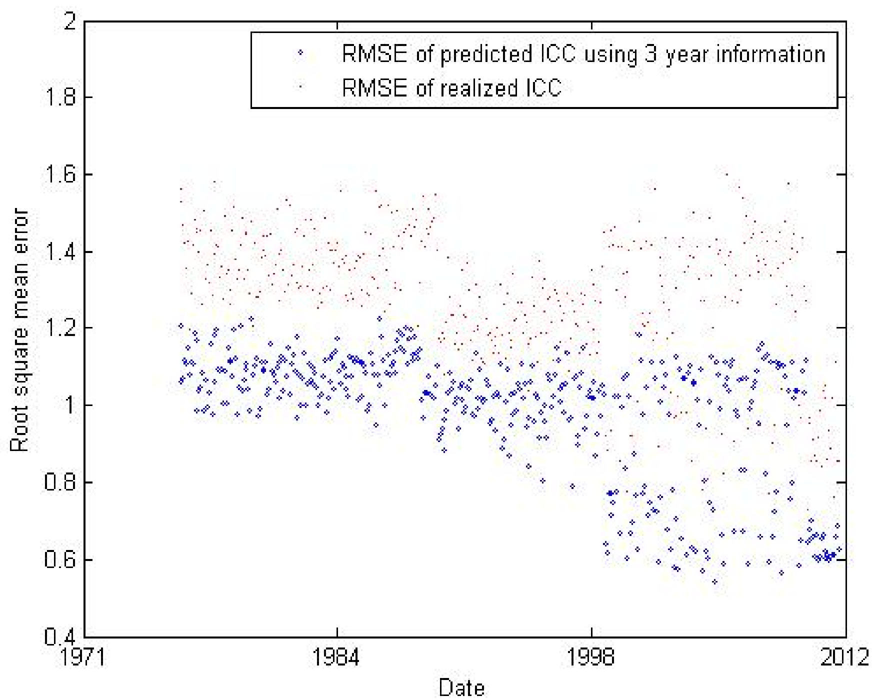

Figure 2: Predicted portfolio returns using adjusted beta

The adjusted beta is employed to predict each stock's next-month return. Both EW/VW Adjusted betas are calculated by adding the change of the relative ICC estimates from $t-1$ to t to the conventional beta, then multiplying the square of the relative ICC estimate change ratio. The relative ICC estimate's nominator is ICC premium, and the denominator is either equal- or value-weighted ICC premium calculated each month. Stock are also sorted into the 100 portfolios based on size and book-to-market, following Fama and French. The predicted portfolio returns are then calculated using equal weight of each firm, and plotted against the standard portfolio realized returns obtained from Kenneth French's website to examine the prediction power of the adjusted beta. The following plottings are from 1976 to 2011.