Predicting Market Returns Using Aggregate Implied Cost of Capital[☆]

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Abstract

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Keywords: Implied Cost of Capital, Market Predictability, Valuation Ratios

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Abstract

Theoretically, the implied cost of capital (*ICC*) is a good proxy for time-varying expected returns. We find that aggregate *ICC* strongly predicts future excess market returns at horizons ranging from one month to four years. This predictive power persists even in the presence of popular valuation ratios and business cycle variables, both in-sample and out-of-sample, and is robust to alternative implementations. We also find that *ICC*s of size and B/M portfolios predict corresponding portfolio returns.

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1. Introduction

The issue of return predictability is of great interest to academics and practitioners. Traditional academic literature has focused on the usefulness of valuation ratios such as dividend-to-price ratio, book-to-market ratio, earnings-to-price ratio and payout yield in predicting future returns (e.g., Fama and Schwert (1977), Campbell (1987), Campbell and Shiller (1988), Fama and French (1988a), Kothari and Shanken (1997), and Boudoukh et al. (2007)). Various business cycle variables have also been proposed as forecasting variables (e.g., Campbell (1987) and Fama and French (1989)). Whether return predictability exists is still an on-going debate. For instance, Ang and Bekaert (2007) find that the dividend yield does not have any long horizon predictive power once standard errors that are less biased in small samples are used to conduct statistical inference. Boudoukh, Richardson, and Whitelaw (2008) show that long horizon tests are not more powerful than short horizon tests, and find that only net payout yield and net equity issuance have the ability to predict returns under joint predictability tests. Cochrane (2008), however, argues that the absence of dividend growth predictability is stronger evidence for return predictability than the presence of return predictability itself. Welch and Goyal (2008) question the existence on stock return predictability using out of sample tests, but subsequent studies by Rapach, Strauss, and Zhou (2010), Henkel, Martin, and Nardari (2011), and Dangl and Halling (2012) re-affirm the evidence on predictability. Our paper strengthens the empirical evidence on predictability by introducing a new predictor, the aggregate implied cost of capital (*ICC*), that performs better than existing forecasting variables.

The *ICC* is estimated as the expected return that equates a stock's current price to the present value of its expected future free cash flows where, empirically, the free cash flows are estimated using a combination of short-term analyst earnings forecasts, long-term growth rates projected from the short-term forecasts, and historical payout ratios. The *ICC* has historically been used to estimate the unconditional equity premium, compute individual firm cost of equity, and address various other cross-sectional asset pricing issues.[1] Pastor, Sinha, and Swaminathan (2008) use the *ICC* in a time-series setting and show theoretically that the aggregate *ICC* is a good proxy for time-varying expected returns. They use the aggregate *ICC* to examine the inter-temporal asset pricing relationship between expected returns and volatility, and find a positive relationship between the two. If the aggregate *ICC* is a good proxy of time-varying expected returns, it should also predict future market returns. In addition, since the *ICC* is based on a theoretically justifiable valuation model that takes into account future growth opportunities, it is of interest to know whether *ICC* performs better in predicting future

[1] There is a large literature on the *ICC*. See Richardson, Tuna, and Wysocki (2010) for a literature review.

returns than traditional valuation ratios such as dividend yield and earnings yield. These are the issues we examine in this paper.

Our paper also has potential implications for the *ICC* literature. A key requirement for the usefulness of the *ICC* is to show that the *ICC positively* predicts future returns. Existing cross-sectional studies on the *ICC* have been unable to conclusively establish such a positive relationship (see Easton and Monahan (2005), Richardson, Tuna, and Wysocki (2010), and Hou, van Dijk, and Zhang (2012)). The absence of such evidence, however, might be due more to the noise in computing individual firm *ICC*s under the various methods used in the literature than to any theoretical problems with the *ICC* approach (see Lee, So, and Wang (2010)). The aggregate *ICC* is likely to be less noisy (since it is computed by averaging individual firm *ICC*s) and, therefore, might be more successful in predicting future returns.

We estimate the aggregate *ICC* by value-weighting the *ICC*s of firms in the S&P 500 index each month. We then subtract the one-month T-bill yield from the aggregate *ICC* to compute the excess *ICC* (the implied risk premium) and use it to forecast future excess market returns. For the sake of exposition, however, we refer to excess *ICC* as *ICC* throughout the paper. We use the standard forecasting regression methodology to examine the predictive power of the *ICC*. Our results, based on monthly data from January 1977 to December 2011, show that the *ICC* is a strong predictor of future market returns over the next four years, with adjusted R^2 ranging from 7% at the 1-year horizon to 31% at the 4-year horizon. Specifically, high *ICC* predicts high returns. The predictive power of the *ICC* remains strong even after we control for widely-used valuation ratios such as the earnings-to-price ratio, dividend-to-price ratio, book-to-market ratio, and payout yield, and business cycle variables such as the term spread, default spread, long-term government bond yield, and the T-bill rate. In contrast, valuation ratios and business cycle variables perform poorly during this sample period.

Our results are robust to a host of other checks. Since long horizon forecasting regressions are rife with small sample biases, we use Monte Carlo simulations to assess the statistical significance of our regression statistics (e.g., Hodrick (1992) and Stambaugh (1999)). The predictive power of the *ICC* remains strong even under these stringent simulated p-values. Our results also hold when we construct the *ICC* in alternative ways and under reasonable perturbations to the forecasting horizons of the free cash flow model.

We contend above that the aggregate *ICC* is likely to be less noisy since it is computed by averaging the firm level *ICC*s thereby reducing the estimation errors present in firm level *ICC*s. Indeed, we find that the aggregate *ICC* is a strong time-series predictor of future market returns in contrast to mixed evidence on the cross-sectional predictive power of individual firm *ICC*s. If aggregation helps reduce estimation errors at the aggregate market level, it should also work at the portfolio level. Consistent with this intuition, we find that the *ICC*s of size and book-to-market portfolios strongly predict corresponding size and B/M portfolio returns.

Recently, out-of-sample forecasting tests have received much attention in the literature (see Welch and Goyal (2008)). We perform a variety of out-of-sample tests and find that the *ICC* is also an excellent out-of-sample predictor of future market returns. During 1998-2011, the period we use to evaluate out-of-sample performance, the *ICC* delivers higher out-of-sample R^2 than its competitors, and provides positive utility gains of more than 4% per year to a mean-variance investor. Since Rapach, Strauss, and Zhou (2010) argue that it is important to combine individual predictors in the out-of-sample setting, we conduct a forecasting encompassing test, which provides strong evidence that the *ICC* contains distinct information above and beyond that contained in existing predictors.

The key reason for the *ICC*'s superior performance is that the *ICC* is estimated from a theoretically justifiable discounted cash flow valuation model that takes into account future growth opportunities that are ignored by traditional valuation ratios. Overall, our paper makes three contributions to the literature: (a) we provide strong evidence in favor of aggregate stock market predictability, (b) we introduce a new forecasting variable, the *ICC*, which forecasts future returns better than existing forecasting variables, both in-sample and out-of-sample, and (c) we also validate the usefulness of the *ICC* approach by showing that the *ICC* can positively predict future returns.

Our paper proceeds as follows. We describe the methodology for constructing the aggregate *ICC* in Section 2. Section 3 provides the data source and summary statistics. Section 4 and Section 5 present in-sample and out-of-sample return predictions, respectively. Section 6 concludes the paper.

2. Empirical Methodology

In this section, we first explain why the implied cost of capital is a good proxy for expected returns. We then describe its construction.

2.1. ICC as a Measure of Expected Return

The implied cost of capital is the value of r_e that solves the infinite horizon dividend discount model:

$$P_t = \sum_{k=1}^{\infty} \frac{E_t\left(D_{t+k}\right)}{\left(1+r_e\right)^k}, \tag{1}$$

where P_t is the stock price and D_t is the dividend at time t.

Campbell, Lo, and MacKinlay (1996) (7.1.24) provide a log-linear approximation of the dividend discount model which allows us to express the log dividend-price ratio as:

$$d_t - p_t = -\frac{k}{1-\rho} + E_t\left(\sum_{j=0}^{\infty}\rho^j r_{t+1+j}\right) - E_t\left(\sum_{j=0}^{\infty}\rho^j \bigtriangleup d_{t+1+j}\right), \tag{2}$$

where r_t is the log stock return at time t, d_t is the log dividends at time t, and $\rho = 1/(1+\exp(\overline{d-p})$, $k = \log(\rho) - (1-\rho)\log(1/\rho - 1)$, and $\overline{d-p}$ is the average log dividend-to-price ratio. Analogous to Pastor, Sinha, and Swaminathan (2008), we define the *ICC* as the value of $r_{e,t}$ that solves equation (2):

$$r_{e,t} = k + (1-\rho)(d_t - p_t) + (1-\rho)E_t\left(\sum_{j=0}^{\infty}\rho^j \bigtriangleup d_{t+1+j}\right).$$

Thus, the *ICC* contains information about both dividend yield and future dividend growth. Pastor, Sinha, and Swaminathan (2008) demonstrate that if the conditional expected return follows an AR(1) process, the *ICC* is perfectly correlated with the conditional expected return and, is therefore an excellent proxy of it. They use the *ICC* empirically to examine the inter-temporal asset pricing relationship between expected returns and volatility, and find a positive relation between the conditional mean and variance of stock returns both at the country level and the global level among the G-7 countries.

2.2. Construction of the Aggregate ICC

Our empirical construction of the implied cost of capital closely follows Pastor, Sinha, and Swaminathan (2008) and Lee, Ng, and Swaminathan (2009), but we also show later that using alternative ways of constructing the *ICC* lead to similar conclusions (see Section 4.2.3). We first estimate the firm-level *ICC* by implementing the following empirically tractable finite horizon model of (1):

$$P_t = \sum_{k=1}^{T}\frac{FE_{t+k}\times(1-b_{t+k})}{(1+r_e)^k} + \frac{FE_{t+T+1}}{r_e(1+r_e)^T}, \tag{3}$$

where P_t is the stock price at month t, FE_{t+k} and b_{t+k} are the earnings forecasts and the plowback rate forecasts for year $t+k$, respectively, and T is the forecasting horizon. $FE_{t+k}\times(1-b_{t+k})$ is the dividend/free cash flow for year $t+k$.[2] The first term on the right hand side of equation (3) captures the present value of free cash flows up to a terminal period $t+T$, and the second term captures the present value of free cash flows beyond the terminal period. Following Pastor, Sinha, and Swaminathan (2008), we use a 15-year horizon ($T = 15$) to implement the model in equation (3).

[2] We use the term "dividends" interchangeably with free cash flows to equity to describe all cash flows available to equity.

We forecast earnings up to year $t+T$ in three stages. (i) We explicitly forecast earnings (in dollars) for year $t+1$ using analyst forecasts. I/B/E/S analysts supply earnings per share (EPS) forecasts for the next two fiscal years, FY_1 and FY_2, respectively, for each firm in the I/B/E/S database. We construct a 12-month ahead earnings forecast FE_1 using the median FY_1 and FY_2 forecasts such that $FE_1 = w \times FY_1 + (1-w) \times FY_2$, where w is the number of months remaining until the next fiscal year-end divided by 12. We use median forecasts instead of mean forecasts in order to alleviate the effects of extreme forecasts. (ii) We then use the growth rate implicit in FY_1 and FY_2 to forecast earnings for year $t+2$; that is, $g_2 = FY_2/FY_1 - 1$, and the two-year-ahead earnings forecast is given by $FE_2 = FE_1 \times (1+g_2)$. Constructing FE_1 and FE_2 in this way ensures a smooth transition from FY_1 to FY_2 during the fiscal year, and also ensures that our forecasts are always 12 months and 24 months ahead of the current month. Firms with growth rates above 100% (below 2%) are given values of 100% (2%). (iii) We forecast earnings from year $t+3$ to year $t+T+1$ by assuming that the year $t+2$ earnings growth rate g_2 mean-reverts *exponentially* to steady-state values by year $t+T+2$. We assume that the steady-state growth rate starting in year $t+T+2$ is equal to the long-run nominal GDP growth rate, g, computed as a rolling average of annual nominal GDP growth rates. Specifically, earnings growth rates and earnings forecasts for years $t+3$ to $t+T+1$ are computed as follows ($k = 3, ..., T+1$):

$$\begin{aligned} g_{t+k} &= g_{t+k-1} \times \exp\left[\log\left(g/g_2\right)/T\right] \text{ and} \\ FE_{t+k} &= FE_{t+k-1} \times \left(1+g_{t+k}\right). \end{aligned} \tag{4}$$

We forecast plowback rates b_{t+k} as follows. We first explicitly forecast the plowback rate for year $t+1$, b_1, as one minus the most recent year's dividend payout ratio, which is estimated by dividing actual dividends from the most recent fiscal year by earnings over the same time period.[3] We then assume that the plowback rate in year $t+1$, b_1, reverts linearly to a steady-state value b by year $t+T+1$. Hence, the intermediate plowback rates from $t+2$ to $t+T$ ($k = 2, ..., T$) are computed as $b_{t+k} = b_{t+k-1} - \frac{b_1 - b}{T}$. The steady-state value b is derived from the sustainable growth rate formula, which assumes that the product of the return on new investments and the plowback rate $ROI * b$ is equal to the growth rate in earnings g. In the steady state, because competition will drive returns on

[3] Payout ratios of less than zero (greater than one) are assigned a value of zero (one). If earnings are negative, the plowback rate is computed as the median ratio across all firms in the corresponding industry-size portfolio. The industry-size portfolios are formed each year by first sorting firms into 49 industries based on the Fama–French classification and then forming three portfolios with an equal number of firms based on their respective market caps within each industry. In our primary approach, we exclude share repurchases and new equity issues due to the practical problems associated with determining the likelihood of their recurrence in future periods.

these investments down to the cost of equity, we further impose the condition that ROI equals r_e for new investments. The steady-state plowback rate b is then obtained as g/r_e.

The terminal value in equation (3) is computed as the present value of a perpetuity, which is equal to the ratio of the year $t+T+1$ earnings forecast (FE_{t+T+1}) divided by the cost of equity $\frac{FE_{t+T+1}}{r_e}$.[4] The resulting r_e from equation (3) is the firm-level *ICC* measure used in our empirical analysis.

Each month from January 1977 to December 2011, we compute the aggregate *ICC* as the value-weighted average of the *ICC*s of all firms that are in the S&P 500 as of that month.[5] Consistent with prior literature, we forecast future market excess returns using excess *ICC*. As mentioned earlier, we use the term *ICC* to denote excess *ICC* throughout the paper. "Returns" refer to excess returns.

3. Data and Summary Statistics

We obtain market capitalization and return data from CRSP, accounting data such as common dividends, net income, book value of common equity, and fiscal year-end date from COMPUSTAT, and analyst earnings forecasts and share price from I/B/E/S. To ensure that we use only publicly available information, we obtain accounting data items for the most recent fiscal year, ending at least 3 months prior to the month-end when the *ICC* is computed. Data on nominal GDP growth rates are obtained from the Bureau of Economic Analysis. Our GDP data begins in 1930. For each year, we compute the steady-state GDP growth rate as the historical average of GDP growth rates using annual data up to that year.

We use the CRSP NYSE/AMEX/Nasdaq value-weighted returns including dividends from WRDS as our primary measure of aggregate market returns.[6] We compare the performance of the *ICC* to various forecasting variables that have been proposed in the literature. The first group are the traditional valuation ratios: dividend-to-price-ratio (D/P), earnings-to-price ratio (E/P), book-to-market ratio (B/M), and the payout yield (P/Y). In addition to these valuation ratios, we also consider commonly used business cycle variables. As with the *ICC*, all monthly predictors are computed as of the end of the month.

- *Dividend-to-price ratio* (D/P) is the value-weighted average of firm-level dividend-to-price ratios for S&P 500 firms, where the firm-level D/P is obtained by dividing the total dividends from

[4] Note that the use of the no-growth perpetuity formula does not imply that earnings or cash flows do not grow after period $t+T$. Rather, it simply means that any new investments after year $t+T$ earn zero economic profits. In other words, any growth in earnings or cash flows after year T is value-irrelevant.

[5] We also construct alternative measures of the aggregate *ICC* in Section 4.2.3. To mitigate the effect of outliers, each month we delete extreme *ICC*s, which lie outside the five standard deviations of their monthly cross-sectional distributions. However, the results are robust to not trimming outliers.

[6] Results based on other measures of the aggregate market return such as the S&P 500 return yield similar results.

the most recent fiscal year-end (ending at least 3 months prior) by market capitalization at the end of the month.[7]

- *Earnings-to-price ratio* (E/P) is the value-weighted average of firm-level earnings-to-price ratios for S&P 500 firms, where the firm-level E/P is obtained by dividing earnings from the most recent fiscal year-end (ending at least 3 months prior) by market capitalization at the end of the month.

- *Book-to-market ratio* (B/M) is the value-weighted average of firm-level ratio of book value to market value for S&P 500 firms, where the firm-level B/M is obtained by dividing the total book value of equity from the most recent fiscal year-end (ending at least 3 months prior) by market capitalization at the end of the month.

- *Payout Yield* (P/Y) is the sum of dividends and repurchases divided by contemporaneous year-end market capitalization (Boudoukh et al. (2007)), obtained from Michael R. Roberts' website.

- *Term spread (Term)* is the difference between AAA rated corporate bond yields and the one-month T-bill yield, where the one-month T-bill yield is the average yield on the one-month Treasury bill obtained from WRDS and AAA rated corporate bond yields are obtained from the economic research database at the Federal Reserve Bank in St. Louis (FRED).

- *Default spread (Default)* is the difference between BAA and AAA rated corporate bond yields, both obtained from FRED.

- *T-bill rate (Tbill)* is the one-month T-bill rate obtained from Kenneth French's website.

- *Long-term treasury yield (Yield)* is the 30-year treasury yield obtained from WRDS.

All variables span from January 1977 to December 2011 except P/Y, which spans from January 1977 to December 2010. It is also worth noting that P/Y is provided in logarithm.

[INSERT TABLE 1 HERE]

Table 1 presents univariate summary statistics for all forecasting variables. The average annualized *ICC* (market risk premium) is 7.07% and its standard deviation is 2.68%. The first order autocorrelation of the *ICC* is 0.95 which declines to 0.10 after 24 months, and to -0.20 after 36 months. In contrast, the valuation ratios E/P, D/P, and B/M are much more persistent, with first-order autocorrelations between 0.98 and 0.99 that hover above 0.40 even after 60 months. In unreported results, we show that unit root tests strongly reject the null of a unit root for *ICC*, but not for the valuation ratios. The *ICC* is a much more stationary process that exhibits faster mean reversion. Table 1 also shows that the ex-post risk premium computed from value-weighted excess market returns, *Vwretd*, is 6.28% which is comparable to the average *ICC* of 7.07%.[8] The sum of autocorrelations at long

[7] Fama and French (1988a) construct D/P based on the value-weighted market return with and without dividends. This alternative measure of D/P has a correlation of 0.96 with our constructed measure, and yields very similar results.

[8] The excess return *Vwretd* is not continuously compounded; we use continuously compounded returns only in the regressions.

horizons are negative for *Vwretd* which suggests there is long-term mean reversion in stock returns. In unreported results, we find that the *ICC* is positively correlated with each of the valuation ratios, which suggests that they share common information about time-varying expected returns. The *ICC* is also significantly positively correlated with *Term* and *Default*, which suggests that the *ICC* also varies with the business cycle.

[INSERT FIGURE 1 HERE]

Figure 1 plots the *ICC* over time, together with its median and two-standard-deviation bands calculated based on the median using all historical data, starting from January 1987. It also marks the NBER recession periods in shaded areas and some notable dates and the risk premia on those dates. Consistent with existing theories (e.g., Campbell and Cochrane (1999) and Barberis, Huang, and Santos (2001)), there is some evidence of a countercyclical behavior on the part of the *ICC* particularly during recessions when it tends to be high. The *ICC* reached a high of 12.8% in March 2009 at the depth of the market downturn. At the end of 2011, the *ICC* remained at a high level of 9.7%.

4. In-sample Return Predictions

4.1. Forecasting Regression Methodology

We begin with the multiperiod forecasting regression test in Fama and French (1988a,b, 1989):

$$\sum_{k=1}^{K} \frac{r_{t+k}}{K} = a + b \times X_t + u_{t+K,t}, \tag{5}$$

where r_{t+k} is the continuously compounded excess return per month defined as the difference between the monthly continuously compounded return on the value-weighted market return, including dividends from WRDS, and the monthly continuously compounded one-month T-bill rate (i.e., continuously compounded *Vwretd*).[9] Quarterly returns are defined in the same way. X_t is a $1 \times k$ row vector of explanatory variables (excluding the intercept), b is a $k \times 1$ vector of slope coefficients, K is the forecasting horizon, and $u_{t+K,t}$ is the regression residual.

We conduct these regressions for five different horizons: in monthly regressions, $K = 1$, 12, 24, 36, and 48 months, and in quarterly regressions, $K = 1$, 4, 8, 12, and 16 quarters. One problem with this regression test is the use of overlapping observations, which induces serial correlation in the

[9] The continuously compounded *Vwretd* and *Vwretd* have a correlation of 0.9989, and our results are robust to using *Vwretd*.

regression residuals, which are also likely to be conditionally heteroskedastic. We correct for both the induced autocorrelation and the conditional heteroskedasticity by using the GMM standard errors with Newey-West correction with $K - 1$ moving average lags (e.g., Hansen (1982) and Newey and West (1987)).[10] We call the resulting test statistic the asymptotic Z-statistic. Since the forecasting regressions use the same data at various horizons, the regression slopes will be correlated. Following Richardson and Stock (1989), we compute the average slope statistic, which is the arithmetic average of regression slopes across different horizons, to test the null hypothesis that the slopes at different horizons are jointly zero.

While the asymptotic Z-statistics are consistent, they potentially suffer from small sample biases. Therefore, we generate finite sample distributions of $Z(b)$ and the average slopes under the null of no predictability and calculate the p-values based on their empirical distributions. Monte Carlo experiments require a data-generating process that produces artificial data whose time-series properties are consistent with those in the actual data. Therefore, we generate artificial data using a Vector Autoregression (VAR), and our simulation procedure closely follows Hodrick (1992), Swaminathan (1996), and Lee, Myers, and Swaminathan (1999). The Appendix describes the details of our simulation methodology.

4.2. Forecasting Regression Results

In this section we discuss the results from our forecasting regressions involving *ICC*. We first compare *ICC* to various valuation ratios, and then compare *ICC* to business cycle variables. Finally, we conduct a variety of robustness checks.

4.2.1. Regression Results with Valuation Ratios

Univariate Regression Results. In this section, we examine the univariate forecasting power of *ICC* and commonly used valuation ratios, by setting X = *ICC*, *D/P*, *E/P*, *B/M*, or *P/Y* in equation (5). High *ICC* represents high ex-ante risk premium, and hence we expect high *ICC* to predict high excess market returns. Prior literature has shown that high valuation ratios (*E/P*, *D/P*, and *B/M*) predict high stock returns. Boudoukh et al. (2007) find that Payout Yield (*P/Y*) is a better forecasting variable than dividend yield and that it positively predicts future returns. Thus, for all regressions, a one-sided test of the null hypothesis is appropriate.

[INSERT TABLE 2 HERE]

[10]We also conduct a robustness check using the standard errors suggested by Hodrick (1992), and confirm that our results are not sensitive to the choice of standard errors.

Panels A-D of Table 2 present univariate regression results for *ICC*, *D/P*, *E/P*, and *B/M*, respectively, using monthly data from January 1977 to December 2011. Panel E provides univariate regression results for *P/Y*, using monthly data from January 1977 to December 2010.

We observe that, as expected, all variables have positive slope coefficients. Because a one-sided test is appropriate, the conventional 5% critical value is 1.65. Using this cut-off, *ICC* is statistically significant at all horizons with the smallest Z-statistics being 1.85 at the 1-month horizon. Among the valuation ratios, only *D/P* and *P/Y* have Z-statistics larger than 1.65 in any of the horizons. The adjusted R^2 of *ICC* is also much larger than that of the valuation ratios: *ICC* explains 1% of future market returns at the 1-month horizon, and 31% at the 4-year horizon. For all variables, the adjusted R^2 increases with horizons. As pointed out by Cochrane (2005), the increase in the magnitude of the adjusted R^2 with the forecasting horizon is due to the persistence of the regressors.

However, when judged by simulated p-values, *D/P* is no longer significant, and its simulated p-values are all above 0.221. Since *D/P* is not statistically significant at any individual horizons, it is not surprising that it is not significant in the joint horizon test either, with a simulated p-value for the average slope estimate of just 0.349. This finding is consistent with our discussion in Section 4.1 on the importance of using simulated p-values to assess the statistical significance of forecasting variables. That *D/P* does not predict future market returns is also consistent with recent studies (e.g., Ang and Bekaert (2007) and Boudoukh, Richardson, and Whitelaw (2008)).

Unlike traditional valuation measures, *ICC* is statistically significant based on both conventional critical values and simulated p-values (at the 10% significance level or better) at all horizons. Not surprisingly, the average slope statistic of 1.75 is highly significant with a simulated p-value of 0.02. This suggests that on average, an increase of 1% in *ICC* in the current month is associated with an annualized increase of 1.75% in the excess market return over the next four years, which is quite economically significant. Among all the valuation ratios, the payout yield *P/Y* performs the best in univariate tests with some forecasting power at the 3-year and 4-year forecasting horizons. The average slope, however, is not significant (p-value 0.156).

Bivariate Regression Results. Because *ICC* is positively correlated with traditional valuation ratios, it is important to know whether *ICC* still forecasts future market returns in their presence. Given the high correlations among these valuation ratios (above 0.95), to avoid multicollinearity issues, we run bivariate regressions with *ICC* as one of the regressors, and one of the valuation ratios as the other regressor. Based on equation (5), X is one of the following four sets of regressors: (1) *ICC* and *D/P*, (2) *ICC* and *E/P*, (3) *ICC* and *B/M*, and (4) *ICC* and *P/Y*. Again, we expect the slope coefficients of all forecasting variables to be positive, and therefore, one-sided tests of the null of no predictability are appropriate.

[INSERT TABLE 3 HERE]

Table 3 presents the bivariate regression results. The results in Panels A to D show that *ICC* continues to strongly predict future returns, even in the presence of the other valuation measures. The slope coefficients of *ICC* are significant at most horizons and the average slope coefficients (in the range of 1.50 to 1.63) are all highly significant with simulated p-values ranging from 0.043 to 0.051. In contrast, traditional valuation measures have little or no predictive power in the presence of *ICC*. The slope coefficients are insignificant at all horizons and, not surprisingly, the average slope statistics are also insignificant. The results provide strong evidence that *ICC* is a better predictor of future returns than traditional valuation measures. We next turn to evaluating the forecasting performance of *ICC* in the presence of (countercyclical) forecasting variables that proxy for the business cycle.

4.2.2. Regression Results with Business Cycle Variables

Fama and French (1989) find that business cycle variables such as the default spread and term spread predict stock returns. Given the high positive correlations between *ICC* and default and term spreads, it is important to determine whether *ICC* has the ability to forecast future excess returns in the presence of these variables. Ang and Bekaert (2007) show that the short rate negatively predicts future returns at shorter horizons. While dividend yield does not have predictive power per se, it predicts future market returns in a bivariate regression with the short rate. Therefore, we also examine the predictive power of *ICC* in the presence of the one-month T-bill rate (*Tbill*). Finally, we also control for the 30-year treasury yield (*Yield*).

Panels F-I of Table 2 present univariate regression results for *Term*, *Default*, *Tbill*, and *Yield*. Since *Term*, *Default,* and *Yield* move countercyclically with the business cycle, we expect positive signs for these variables. For *Tbill*, we expect a negative sign at shorter horizons. Thus, for these regressions, a one-sided upper or lower tail test of the null hypothesis is appropriate.

The regression results indicate that *Term* is a strong predictor of future market returns at longer horizons. It has statistically significant predictive power beyond the 2-year horizon based on simulated p-values, and the average slope coefficient is also significant (p-value 0.067). *Default*, however, is not a statistically significant predictor of future returns. Slope coefficients of *Tbill* and *Yield* both have the expected signs in most horizons although none of them are statistically significant.

Panels E-H of Table 3 present the bivariate regression results with X = (*ICC*, *Term*), (*ICC*, *Default*), (*ICC*, *Tbill*) and (*ICC*, *Yield*), respectively. In all of these regressions, *ICC* strongly and positively predicts future market returns. In the presence of *Term*, *ICC* is statistically significant at the 1-month and 4-year horizons (p-values 0.009 and 0.039), and the average slope statistic is still highly significant (p-value 0.019). *Term*, however, is unable to predict future market returns in the presence of *ICC*. In fact, the slope coefficients corresponding to *Term* turn negative. It appears that the information common to the two variables is being absorbed by *ICC*. *ICC* remains highly significant at all horizons in the presence of *Default*, *Tbill,* or *Yield*, and its average slope remains highly significant with p-values ranging from 0.010 to 0.021. In contrast, none of these variables is significant in the presence of *ICC*. The slope coefficients corresponding to *Default* turn negative, while those of *Tbill* turn positive (Panels F and G). The slope coefficients corresponding to *Yield* remain mostly positive but only marginally significant at the 4-year horizon. Overall, these results provide strong evidence that the predictive power of *ICC* is not subsumed by the information in the business cycle variables.

In unreported results, we find that *ICC* continues to forecast future returns in the presence of several other forecasting variables that have been examined in the literature, including net equity expansion, inflation, stock variance, lagged excess market returns, the sentiment measure, consumption-to-wealth ratio and investment-to-capital ratio. Furthermore, we find that the *ICC* is superior to the forecasted earnings-to-price ratio, FE_1/P, which is constructed based on analyst forecasts but does not contain growth beyond the first year. This shows that there is additional information in the long-term growth rates projected from short-term earnings forecasts that are used to compute the *ICC*. Finally, we compare the performance of *ICC* to Shiller (2006)'s price-to-ten year average earnings ratio in predicting future returns, and find that the *ICC* performs better.[11]

4.2.3. Robustness

We conduct a variety of robustness checks in this section. First, we estimate *ICC* using free cash flow models with finite horizons of $T = 10$ and $T = 20$ (recall that our main approach uses $T = 15$ in equation (3)). While the horizons affect the average risk premium (the mean of *ICC* is 5.32% for $T = 10$ and 8.05% for $T = 20$), the regression results are unaffected, both in univariate and in multivariate regressions. Table 4 presents the univariate regression results for *ICC_T10* and *ICC_T20* when they are estimated for $T = 10$ and $T = 20$, respectively. In both regressions, *ICC* is statistically significant in all forecasting horizons, and its average slope is also significant (p-value 0.012 if $T = 10$, and p-value 0.027 if $T = 20$).

[11] These results are shown in the working paper version of our paper (Li, Ng, and Swaminathan (2012)) and are also available from the authors upon request.

[INSERT TABLE 4 HERE]

Due to difficulty in determining the likelihood of recurrence for repurchases and new equity issues, our main measure of *ICC* excludes repurchases and new equity issues. As another robustness check, we construct *ICC* by incorporating repurchases and new equity issues, and provide the univariate regression on this alternative *ICC* measure (*ICC_repurchase*) in Table 4. *ICC_repurchase* still positively forecasts future returns and is significant at all horizons, and is also significant in the joint horizon test (p-value 0.017).

So far, our measure of excess *ICC* is obtained by value-weighting the firm-level *ICC*s for the S&P 500 index firms to obtain the aggregate *ICC*, and then subtracting the one-month T-bill yield from the aggregate *ICC*. We now consider three alternative ways of constructing the excess *ICC*. First, we equally-weight the firm-level *ICC*s for the S&P 500 firms to obtain the aggregate *ICC*, and then subtract the one-month T-bill yield to construct an equally-weighted excess *ICC* measure (*ICC_equal*). Secondly, rather than using the firms in the S&P 500 index, we compute the value-weighted *ICC* using all firms in the sample. The implied cost of capital (*ICC_all*) is then obtained by subtracting the one-month T-bill yield from the aggregate *ICC* based on all firms.[12] Finally, rather than subtract the one-month T-bill yield from the aggregate *ICC* based on S&P 500, we subtract the 30-year treasury yield to obtain the implied risk premium with respect to long-term interest rates (*ICC_yield*). Note that, in this case, we should ideally use the excess of market returns over 30-year bond returns as the dependent variable. Nevertheless, for comparability, we still use the excess of market returns over T-bill returns as the dependent variable.

Table 4 provides the univariate regression results for the three alternative measures of *ICC*. The results show that all three measures of excess *ICC* positively predict future market returns at all forecasting horizons. In particular, *ICC_all* provides very similar results to our main measure of *ICC*: it is significant at every individual horizon, as well as in the joint horizon test. *ICC_equal* is significant at all horizons except the 1-year horizon. *ICC_yield* has statistical significance at the 1-month and 4-year horizons. The average slope statistic is highly significant for all three measures, with p-values being 0.015, 0.038, and 0.033 for *ICC_all*, *ICC_equal*, and *ICC_yield*.

In addition to the methodology used in this paper, there are several other procedures used in the literature to compute *ICC*. Rather than going through all of them, we pick a procedure recommended by Easton (2004) that directly computes the aggregate *ICC* using a regression approach. Table 4

[12] We also show that our results are robust to constructing *ICC* using the firms in the Dow Jones Industrial Index. These results are available upon request.

reports results using *ICC* from this alternate approach. The evidence suggests that this alternate *ICC* also predicts future returns strongly.

4.3. Return Predictability for Portfolios Sorted by Size and Book-to-Market Ratios

Our results thus far show that the aggregate *ICC* is successful in predicting future returns in the time-series, while the existing evidence in the *ICC* literature on cross-sectional predictability is mixed. This is consistent with our intuition that if we reduce the estimation errors at the firm level, the *ICC* for the market portfolio should be more effective in predicting future stock returns. If this is correct, then this should work at the portfolio level, too, and *ICC*s of portfolios should be able to predict corresponding portfolio returns. In this section, therefore, as an additional robustness check, we examine the predictive power of *ICC* among portfolios sorted by size and book-to-market ratios.[13]

In June of each year from 1977 to 2011, we rank all NYSE, Amex, and NASDAQ stocks on size (market capitalization) and form three size portfolios, namely, Small Size, Medium Size, and Large Size. The breakpoints used to form these portfolios are based on the market capitalization of the NYSE stocks: bottom 30% (Small Size), middle 40% (Medium Size), and top 30% (Large Size). The Small Size portfolio contains stocks with the smallest market capitalization, and the Large Size portfolio contains stocks with the largest market capitalization. We form the book-to-market portfolios in a similar fashion. In June of each year from 1977 to 2011, we divide NYSE, Amex, and NASDAQ stocks into three book-to-market portfolios based on NYSE break points: bottom 30% (Low B/M), middle 40% (Medium B/M), and top 30% (High B/M). The Low B/M portfolio contains stocks with the lowest B/M ratio, and the High B/M portfolio contains stocks with the highest B/M ratio. Book equity is stockholder equity plus balance sheet-deferred taxes and investment tax credits plus post-retirement benefit liabilities minus the book value of preferred stock.[14] We compute portfolio returns by value-weighting the individual stock returns, and the portfolio *ICC* by value-weighting the individual firm *ICC*s. Similarly, we obtain the portfolio-level D/P, E/P, and B/M as the corresponding value-weighted averages of individual firm values.

The returns of these portfolios display the usual cross-sectional pattern. Small-cap stocks earn higher returns than large-cap stocks: the average annual returns of Small Size, Medium Size, and Large

[13]We thank an anonymous referee for suggesting the tests in this section.

[14]Depending on data availability, we use redemption, liquidation, or par value, in this order, to represent the book value of preferred stock. Stockholder equity is the book value of common equity. If the book value of common equity is not available, stockholder equity is calculated as the book value of assets minus total liabilities. Book-to-market equity, B/M, is calculated as book equity for the fiscal year ending in calendar year $t-1$, divided by market equity at the end of December of $t-1$. Following Fama and French (1993), we do not use negative book firms when calculating the breakpoints for B/M, or when forming the portfolios.

Size portfolios are 19.53%, 15.63%, and 11.89%, respectively. Value stocks earn higher returns than growth stocks: the average annual returns of Low B/M, Medium B/M, and High B/M portfolios are 11.51%, 13.80%, and 15.25%, respectively. Consistent with the realized returns, the expected returns (*ICC*) of these portfolios display similar patterns. The expected returns of Small Size, Medium Size, and Large Size portfolios are 16.48%, 14.03%, and 12.43%, respectively, and the expected returns of Low B/M, Medium B/M, and High B/M portfolios are 11.37%, 13.89%, and 15.88%, respectively.

We now conduct univariate regressions using portfolio-level *ICC*s to predict portfolio returns. Similar to our aggregate analysis, we subtract the risk-free rate from both portfolio returns and portfolio *ICC*s. As a comparison, we also examine the predictive power of portfolio-level valuation ratios to predict portfolio returns.

[INSERT TABLE 5 HERE]

Table 5 reports the univariate regression results for the three size portfolios, and the three B/M portfolios. We find that *ICC* has strong predictive power for all six portfolios. The slope coefficients are all positive and significant at the 10% level or better in most of the horizons. The average slope coefficients range from 1.06 to 2.10, and they are all highly significant with p-values ranging from 0.014 to 0.038. Among the valuation ratios, only E/P and B/M have some predictive power for the Small Size portfolio. Overall, we find that by reducing estimation errors at the firm level through aggregation, *ICC*s of size and B/M portfolios are also excellent predictors of corresponding portfolio returns.[15]

5. Out-of-Sample Return Predictions

In a recent paper, Welch and Goyal (2008) show that a long list of predictors used in the literature is unable to deliver consistently superior out-of-sample forecasts of the U.S. equity premium relative to a simple forecast based on the historical average. In this section, we evaluate the out-of-sample performance of *ICC* to see how it fares relative to traditional valuation ratios and business cycle variables.

[15] We have conducted bivariate regression tests involving *ICC* and each of the valuation ratios. We have also replicated our findings with equal-weighted portfolio returns. The predictive power of *ICC* is similar or even stronger in these regressions. These results are available upon request. We have also conducted out-of-sample tests at the portfolio level and verified that *ICC* is substantially better than traditional valuation ratios in predicting future market returns.

5.1. Econometric Specification

We start with the following predictive regression model:

$$r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{i,t+1}, \tag{6}$$

where r_{t+1} is the continuously compounded excess return per month defined as the difference between the monthly continuously compounded return on the value-weighted market index from WRDS, and the monthly continuously compounded one-month T-bill rate; $x_{i,t}$ is the ith monthly forecasting variable, i.e., ICC_t, D/P_t, E/P_t, B/M_t, $Term_t$, $Default_t$, $Tbill_t$, or $Yield_t$; and $\varepsilon_{i,t+1}$ is the error term. We divide the entire sample T into two periods: an estimation period composed of the first m observations and an out-of-sample forecast period composed of the remaining $q = T - m$ observations. The initial out-of-sample forecast based on the predictive variable $x_{i,t}$ is generated by

$$\hat{r}_{i,m+1} = \hat{\alpha}_{i,m} + \hat{\beta}_{i,m} x_{i,m},$$

where $\hat{\alpha}_{i,m}$ and $\hat{\beta}_{i,m}$ are estimated from an OLS regression of equation (6) using observations from 1 to m. The second out-of-sample forecast is generated according to

$$\hat{r}_{i,m+2} = \hat{\alpha}_{i,m+1} + \hat{\beta}_{i,m+1} x_{i,m+1},$$

where $\hat{\alpha}_{i,m+1}$ and $\hat{\beta}_{i,m+1}$ are obtained by estimating (6) using observations from 1 to $m+1$. Proceeding in this manner through the end of the forecast period, for each predictive variable x_i, we can obtain a time series of predicted market returns $\{\hat{r}_{i,t+1}\}_{t=m}^{T-1}$.

Following Campbell and Thompson (2008), Welch and Goyal (2008), and Rapach, Strauss, and Zhou (2010), we use the historical average excess market returns $\overline{r}_{t+1} = \sum_{j=1}^{t} r_j$ as a benchmark forecasting model. If the predictive variable x_i contains useful information in forecasting future market returns, then $\hat{r}_{i,t+1}$ should be closer to the true market return than $\overline{r}_{t+1}$. We now introduce the forecast evaluation method.

5.2. Forecast Evaluation

We compare the performance of alternative predictive variables using the out-of-sample R^2 statistics, R^2_{os}:

$$R^2_{os} = 1 - \frac{\sum_{k=1}^{q} \left(r_{m+k} - \hat{r}_{i,m+k}\right)^2}{\sum_{k=1}^{q} \left(r_{m+k} - \overline{r}_{m+k}\right)^2}.$$

The R^2_{os} statistic measures the reduction in mean squared prediction error (MSPE) for the predictive regression (6) using a particular forecasting variable relative to the historical average forecast. For different predictive variables x_i, we can obtain different out-of-sample forecasts $\hat{r}_{i,m+k}$ and thus different

R^2_{os}. If a forecast variable beats the historical average forecast, then $R^2_{os} > 0$. A predictive variable that has a higher R^2_{os} performs better in the out-of-sample forecasting test.

We formally test whether a predictive regression model using x_i has a statistically lower MSPE than the historical average model by testing the null of $R^2_{os} \leq 0$ against the alternative of $R^2_{os} > 0$. Since our approach is equivalent to comparing forecasts from nested models (setting $\beta_i = 0$ in (6) reduces our predictive regression using x_i to the benchmark model using the historical average), we use the adjusted-MSPE statistic of Clark and West (2007):[16]

$$f_{t+1} = (r_{t+1} - \overline{r}_{t+1})^2 - \left[\left((r_{t+1} - \hat{r}_{i,t+1})^2\right) - \left((\overline{r}_{t+1} - \hat{r}_{i,t+1})^2\right)\right].$$

The adjusted-MSPE f_{t+1} is then regressed on a constant and the t-statistic corresponding to the constant is estimated. The p-value of R^2_{os} is obtained from a one-sided t-statistic (upper-tail), based on the standard normal distribution.

To explicitly account for the risk borne by an investor over the out-of-sample period, we also calculate the realized utility gains for a mean-variance investor (e.g., Marquering and Verbeek (2004), Campbell and Thompson (2008), Welch and Goyal (2008), Wachter and Warusawitharana (2009), and Rapach, Strauss, and Zhou (2010)). Based on forecasts of expected return and variance, a mean-variance investor with a relative risk aversion of γ optimally allocates her portfolio monthly between stocks and risk-free assets.[17] Her allocation to stocks in period $t+1$ using historical average as the estimate of expected return is:

$$w_{1,t} = \left(\frac{1}{\gamma}\right)\left(\frac{\overline{r}_{t+1}}{\hat{\sigma}^2_{t+1}}\right). \tag{7}$$

Her allocation to stocks using forecasts from the predictive regression model is:

$$w_{2,t} = \left(\frac{1}{\gamma}\right)\left(\frac{\hat{r}_{i,t+1}}{\hat{\sigma}^2_{t+1}}\right). \tag{8}$$

In both portfolio decisions, $\hat{\sigma}^2_{t+1}$ is the forecast for the variance of stock returns. We estimate $\hat{\sigma}^2_{t+1}$ using a ten-year rolling window of monthly returns.

The investor's average utility level over the out-of-sample period based on historical average is:

$$U_1 = \mu_1 - \frac{1}{2}\gamma\hat{\sigma}^2_1, \tag{9}$$

[16] The most popular method for testing these kinds of hypotheses is the Diebold and Mariano (1995) and West (1996) statistic, which has a standard normal distribution. However, as pointed out by Clark and McCracken (2001) and McCracken (2007), the Diebold and Mariano (1995) and West (1996) statistic has a nonstandard normal distribution when comparing forecasts from nested models. Hence we use the Clark and West (2007)'s adjusted-MSPE statistic, which in Monte Carlo simulations performs reasonably well in terms of size and power when comparing forecasts from nested linear predictive models.

[17] Following Campbell and Thompson (2008), we constrain the portfolio weight on stocks to lie between 0% and 150% (inclusive) each month.

where μ_1 and $\hat{\sigma}_1^2$ correspond to the sample mean and variance of the return on the portfolio formed based on (7) over the out-of-sample period. The utility level can also be viewed as the certainty equivalent return for the mean-variance investor.

The investor's average utility level over the out-of-sample period based on forecasts from the predictive regression is:

$$U_2 = \mu_2 - \frac{1}{2}\gamma\hat{\sigma}_2^2, \tag{10}$$

where μ_2 and $\hat{\sigma}_2^2$ correspond to the sample mean and variance for the return on the portfolio formed based on (8) over the out-of-sample period.

We measure the utility gain of using a particular predictive variable as the difference between (10) and (9). We multiply this difference by 1200 to express it in average annualized percentage return. This utility gain can be viewed as the portfolio management fee that an investor with mean-variance preferences would be willing to pay to access a particular forecasting variable. We report the results based on $\gamma = 3$.

In order to explore the information content of *ICC* relative to other forecasting variables, we also follow Rapach, Strauss, and Zhou (2010) to conduct a forecast encompassing test due to Harvey, Leybourne, and Newbold (1998). The null hypothesis is that the model i forecast encompasses the model j forecast against the one-sided alternative that the model i forecast does not encompass the model j forecast. Define $g_{t+1} = \left(\hat{\varepsilon}_{i,t+1} - \hat{\varepsilon}_{j,t+1}\right)\hat{\varepsilon}_{i,t+1}$, where $\hat{\varepsilon}_{i,t+1}$ $\left(\hat{\varepsilon}_{j,t+1}\right)$ is the forecast error based on predictive variable i (j), i.e, $\hat{\varepsilon}_{i,t+1} = r_{t+1} - \hat{r}_{i,t+1}$, and $\hat{\varepsilon}_{j,t+1} = r_{t+1} - \hat{r}_{j,t+1}$. The Harvey, Leybourne, and Newbold (1998) test can then be conducted as follows:

$$HLN = q/\left(q-1\right)\left[\hat{V}\left(\overline{g}\right)^{-1/2}\right]\overline{g},$$

where $\overline{g} = 1/q\sum_{k=1}^{q} g_{t+k}$, and $\hat{V}\left(\overline{g}\right) = \left(1/q^2\right)\sum_{k=1}^{q}\left(g_{t+k} - \overline{g}\right)^2$. The statistical significance of the test statistic is assessed according to the t_{q-1} distribution.

5.3. Out-of-sample Forecasting Results

Existing studies by Welch and Goyal (2008) and Rapach, Strauss, and Zhou (2010) show that many commonly used forecasting variables perform poorly, starting in the late 1990s. So we choose the out-of-sample forecast periods from January 1998 to December 2011. In our in-sample analysis, we find that the predictive power of *ICC* becomes stronger at longer horizons. In out-of-sample tests, since we predict only the next month's return, it is desirable to include predictors from the past, and, therefore, we propose a 2-year moving average of *ICC* as our out-of-sample forecasting variable.[18]

[INSERT FIGURE 2 HERE]

We first plot the differences between the cumulative squared prediction error for the historical average forecast and that for forecasting models using different predictive variables in Figure 2 for the forecast period of January 1998 to December 2011. This figure provides a visual representation of how each model performs over the forecasting period. If a curve lies above the horizontal line at zero, then the forecasting model outperforms the historical average model. As pointed out by Welch and Goyal (2008), the units on these plots are not intuitive, what matters is the slope of the curves: a positive slope indicates that a particular forecasting model consistently outperforms the historical average model, while a negative slope indicates the opposite. Among the various forecasting variables, *ICC* performs the best: it stays above zero for most periods and its slope is the closest to being always positive. The performance of D/P, E/P and B/M are mixed. The curves stay above zero only some of the time and the slopes are positive only for a relatively short window from the late 1990s to early 2000. The curves of the business cycle variables do not even rise above zero.

[INSERT TABLE 6 HERE]

Panel A of Table 6 reports the R^2_{os} statistics for each of the forecasting variables for the forecast period from January 1998 to December 2011. *ICC* produces a positive R^2_{os} of 1.22%, which is statistically significant based on the adjusted-MSPE statistic of Clark and West (2007). In contrast, valuation ratios D/P, E/P, and B/M produce much smaller and insignificant R^2_{os} (0.44%, 0.22%, and 0.26%), while business cycle variables yield negative R^2_{os}. This is consistent with the findings in Welch and Goyal (2008) that valuation ratios and business cycle variables have poor out-of-sample forecasting performances. These results are also consistent with what we observe in Figure 2.

Panel A of Table 6 also reports the utility gains from using a specific forecasting model against the historical average. *ICC* produces positive utility gains of more than 4.15% per year, indicating that mean-variance investors would be willing to pay more than 4% of annual fees for access to the information in *ICC* to form their optimal portfolios. Among other forecasting variables, valuation ratios produce some positive utility gains, but the economic magnitude of these utility gains is much smaller than that for *ICC*.

[18] In unreported results, we also use a 2-year moving average for valuation ratios such as D/P, E/P, and B/M. We find results similar to those found using their raw values, namely, they cannot beat the simple historical average.

We now turn to the question of whether *ICC* brings new information that is not contained in the existing variables. Panel B of Table 6 provides p-values corresponding to the Harvey, Leybourne, and Newbold (1998) forecast encompassing test statistic. The p-values correspond to an upper tail test of the null hypothesis that the forecast from the row variable (R) encompasses the forecast from the column variable (C) against the alternate hypothesis that it does not. The results show that we cannot reject the null that *ICC* encompasses the other forecasting variables while we can strongly reject the null that *ICC* is encompassed by other forecasting variables. This suggests that *ICC* is more informative than the other forecasting variables in predicting future returns. We also reject the null that valuation ratios are encompassed by *Term*, *Tbill*, and *Yield*.

6. Conclusion

In conclusion, our paper introduces *ICC* as a new forecasting variable to the predictability literature, one that substantially outperforms existing forecasting variables. Our results show that *ICC* is an excellent predictor of future market returns both in-sample and out-of-sample. In particular, our results provide unambiguous evidence of a positive relationship between *ICC* and future returns. This is important for the *ICC* literature because it validates the usefulness of the *ICC* approach. The superior performance of *ICC* is due to the fact that it is estimated from a theoretically justifiable valuation model that takes into account future growth rates and makes reasonable economic assumptions in estimating expected returns of individual stocks. The success of *ICC* in predicting future returns suggests that it can serve as an alternative forecasting variable in the asset allocation literature, which has traditionally relied on the dividend-to-price ratio as the key forecasting variable. We remain agnostic, however, as to the source of the predictability whether it is rational time varying expected returns and/or time-varying aggregate market mispricing.

Appendix: Monte Carlo Simulation Procedure

Following Hodrick (1992), Swaminathan (1996), and Lee, Myers, and Swaminathan (1999), we conduct a Monte Carlo simulation using a VAR procedure to assess the statistical significance of relevant statistics in each regression. We illustrate our procedure for the bivariate regression involving *ICC* and *D/P*, and the simulation method is conducted in the same way for other regressions.

Define $Z_t = (r_t,\ ICC_t, D/P_t)'$, where Z_t is a 3×1 column vector. We first estimate a first-order VAR to Z_t under the following specification:

$$Z_{t+1} = A_0 + A_1 Z_t + u_{t+1}, \tag{11}$$

where A_0 is a 3×1 vector of intercepts, A_1 is a 3×3 matrix of VAR coefficients, and u_{t+1} is a 3×1 vector of VAR residuals. The estimated VAR is used as the data generating process (DGP) for the simulation.

The point estimates in (11) are used to generate artificial data for the Monte Carlo simulations. The null hypothesis of no predictability on r_t is imposed in the VAR by setting the slope coefficients of the explanatory variables to zero, and the intercept in the equation of r_t to be its unconditional mean. Under the null hypothesis, we use the fitted VAR to generate T observations of the state variable vector, $(r_t,\ ICC_t,\ D/P_t)$. The initial observation for this vector is drawn from a multivariate normal distribution with mean and variance-covariance matrix equal to the historical mean and historical estimated variance-covariance matrix of the vector of state variables, respectively. Once the VAR is initiated, shocks for subsequent observations are generated by randomizing among the actual VAR residuals under sampling without replacement. The VAR residuals for r_t are scaled to match its historical standard errors. These artificial data are then used to run bivariate regressions and generate regression statistics. The process is repeated $5,000$ times to obtain empirical distributions of regression statistics. The Matlab numerical recipe mvnrnd is used to generate standard normal random variables.

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Table 1 Summary Statistics for Forecasting Variables

This table provides mean, standard deviation, and autocorrelations of forecasting variables used in the paper. The NYSE/AMEX/Nasdaq value-weighted market excess returns (*Vwretd*), the aggregate implied cost of capital subtracting one-month T-bill yield (*ICC*), the dividend-to-price ratio (D/P), the earnings-to-price ratio (E/P), the book-to-market ratio (B/M), the term spread (*Term*), the default spread (*Default*), the one-month T-bill rate (*Tbill*), and the 30-year treasury yield (*Yield*), are monthly data from January 1977 to December 2011; the payout yield (P/Y) (in logarithm) is monthly data from January 1977 to December 2010. All variables except B/M and P/Y are reported in annualized percentages. The autocorrelations for *Vwretd* represent the sum of autocorrelations up to the given lag while the autocorrelations for all other variables represent the autocorrelations at the specific lag. Detailed descriptions for these variables are provided in Section 3.

Mean, Standard Deviation and Autocorrelations								
			Autocorrelation at Lag					
Variable	Mean	Std. Dev.	1	12	24	36	48	60
ICC	7.07	2.68	0.95	0.56	0.10	-0.20	-0.25	-0.09
Vwretd	6.28	15.92	0.09	0.02	-0.24	-0.23	-0.36	-0.51
D/P	2.61	1.05	0.98	0.87	0.79	0.73	0.64	0.52
E/P	6.88	2.53	0.99	0.84	0.73	0.65	0.54	0.40
B/M	0.45	0.18	0.99	0.88	0.82	0.74	0.65	0.53
P/Y	-2.26	0.25	0.98	0.71	0.57	0.39	0.37	0.29
Term	3.06	1.59	0.91	0.43	0.08	-0.27	-0.36	-0.14
Default	1.11	0.48	0.96	0.47	0.29	0.19	0.08	0.08
Tbill	5.23	3.34	0.97	0.78	0.56	0.38	0.28	0.31
Yield	7.24	2.60	0.99	0.87	0.77	0.69	0.56	0.45

Table 2 Univariate Regressions for *ICC*, Valuation Ratios, and Business Cycle Variables

This table summarizes univariate forecasting regression results in equation (5). The dependent variable in these regressions is average monthly excess returns, and the independent variables are the implied cost of capital subtracting one-month T-bill yield (ICC), the dividend-to-price ratio (D/P), the earnings-to-price ratio (E/P), the book-to-market ratio (B/M), the payout yield (P/Y), the term spread ($Term$), the default spread ($Default$), the one-month T-bill rate ($Tbill$), and the 30-year treasury yield ($Yield$), in Panels A-I, respectively. P/Y is in logarithm form and spans January 1977 to December 2010. All other variables span January 1977 to December 2011. In forecasting horizons beyond one-month, the regressions use overlapping observations. b is the slope coefficient from the OLS regressions. avg. is the average slope coefficient. $Z(b)$ is the asymptotic Z-statistics computed using the GMM standard errors with $K-1$ Newey-West lag correction. The $adj.R^2$ is obtained from the OLS regression. The p-values of Z-statistics and the average slope coefficient are obtained by comparing the test statistics with their empirical distribution generated under the null of no predictability from 5,000 trials of a Monte Carlo simulation as described in the Appendix.

	Panel A: *ICC*				Panel B: *D/P*				Panel C: *E/P*			
K	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$
1	2.02	1.85	0.052	0.01	3.42	1.30	0.221	0.00	1.20	1.06	0.320	0.00
12	1.63	2.30	0.076	0.07	3.42	1.59	0.271	0.05	1.13	1.28	0.359	0.03
24	1.77	2.52	0.079	0.17	2.74	1.38	0.352	0.07	0.89	1.12	0.440	0.04
36	1.77	3.18	0.048	0.27	2.25	1.42	0.379	0.08	0.71	1.05	0.491	0.05
48	1.55	3.90	0.035	0.31	2.24	1.88	0.316	0.13	0.66	1.23	0.481	0.07
avg.	1.75		0.020		2.81		0.349		0.92		0.441	

	Panel D: *B/M*				Panel E: *P/Y*				Panel F: *Term*			
K	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$
1	0.16	1.04	0.365	0.00	0.79	0.75	0.245	0.00	0.96	0.53	0.312	0.00
12	0.17	1.40	0.365	0.03	1.13	1.42	0.161	0.04	1.79	1.53	0.129	0.03
24	0.13	1.17	0.470	0.05	1.18	1.85	0.119	0.11	2.17	2.36	0.056	0.10
36	0.11	1.18	0.499	0.06	0.96	2.33	0.089	0.13	2.07	3.17	0.019	0.14
48	0.10	1.37	0.485	0.08	0.86	2.99	0.064	0.16	1.64	3.01	0.037	0.14
avg.	0.13		0.519		0.98		0.156		1.73		0.067	

	Panel G: *Default*				Panel H: *Tbill*				Panel I: *Yield*			
K	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$
1	-2.29	-0.29	0.683	0.00	-0.39	-0.46	0.308	0.00	-0.25	-0.22	0.589	0.00
12	3.59	0.80	0.357	0.01	-0.28	-0.37	0.362	0.00	0.40	0.38	0.385	0.00
24	2.58	0.73	0.385	0.01	-0.24	-0.70	0.288	0.00	0.64	0.92	0.262	0.02
36	1.67	0.54	0.453	0.01	-0.07	-0.20	0.429	0.00	0.82	1.46	0.180	0.06
48	2.41	0.72	0.428	0.02	0.13	0.39	0.577	0.00	0.89	1.98	0.132	0.10
avg.	1.59		0.470		-0.17		0.380		0.50		0.354	

Table 3 Bivariate Regressions Involving *ICC*, Valuation Ratios, and Business Cycle Variables

This table summarizes bivariate forecasting regression results involving *ICC* and a control variable in equation (5). The control variables are dividend-to-price ratio (*D/P*), earnings-to-price ratio (*E/P*), book-to-market ratio (*B/M*), the payout yield (*P/Y*), the term spread (*Term*), the default spread (*Default*), the one-month T-bill rate (*Tbill*), and the 30-year treasury yield (*Yield*), in Panels A-H, respectively. The dependent variable in these regressions is average monthly excess returns. *P/Y* is in logarithm form and spans January 1977 to December 2010. All other variables span January 1977 to December 2011. In forecasting horizons beyond one-month, the regressions use overlapping observations. b and c are the slope coefficients from the OLS regressions. avg. is the average slope coefficient. $Z(b)$ and $Z(c)$ are the asymptotic Z-statistics computed using the GMM standard errors with $K-1$ Newey-West lag correction. The $adj.R^2$ is obtained from the OLS regression. The p-values of Z-statistics and the average slope coefficient are obtained by comparing the test statistics with their empirical distribution generated under the null of no predictability from 5,000 trials of a Monte Carlo simulation as described in the Appendix.

Panel A: Bivariate Regression Involving *ICC* and *D/P*

	ICC			*D/P*			
K	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	1.79	1.58	0.100	2.24	0.82	0.325	0.01
12	1.35	1.88	0.135	2.45	1.18	0.304	0.08
24	1.57	2.83	0.058	1.52	1.08	0.357	0.19
36	1.62	3.50	0.041	1.01	1.02	0.393	0.28
48	1.36	4.00	0.032	1.16	1.51	0.312	0.33
avg.	1.54		0.045	1.68		0.416	

Panel B: Bivariate Regression Involving *ICC* and *E/P*

	ICC			*E/P*			
K	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	1.87	1.70	0.085	0.79	0.70	0.381	0.01
12	1.46	2.08	0.112	0.81	1.01	0.369	0.08
24	1.66	2.75	0.071	0.50	0.95	0.400	0.18
36	1.69	3.50	0.044	0.35	0.89	0.433	0.27
48	1.46	4.17	0.034	0.36	1.17	0.391	0.32
avg.	1.63		0.043	0.56		0.478	

Panel C: Bivariate Regression Involving *ICC* and *B/M*

	ICC			*B/M*			
K	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	1.87	1.66	0.089	0.08	0.51	0.510	0.01
12	1.41	1.98	0.126	0.11	0.94	0.424	0.07
24	1.64	2.87	0.060	0.06	0.76	0.489	0.18
36	1.67	3.58	0.038	0.04	0.65	0.532	0.27
48	1.44	3.91	0.035	0.04	0.79	0.517	0.31
avg.	1.61		0.048	0.07		0.563	

Panel D: Bivariate Regression Involving *ICC* and *P/Y*

	ICC			*P/Y*			
K	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	2.16	1.88	0.053	0.06	0.05	0.513	0.01
12	1.22	1.82	0.139	0.68	0.85	0.297	0.07
24	1.26	2.08	0.130	0.73	1.23	0.238	0.17
36	1.59	3.16	0.057	0.41	1.29	0.243	0.29
48	1.28	3.45	0.056	0.41	1.77	0.186	0.32
avg.	1.50		0.051	0.46		0.344	

Panel E: Bivariate Regression Involving *ICC* and *Term*

	ICC			*Term*			
K	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	4.44	2.51	0.009	-5.06	-1.78	0.951	0.01
12	2.15	1.66	0.158	-1.10	-0.53	0.632	0.07
24	1.96	1.60	0.197	-0.40	-0.25	0.543	0.17
36	1.93	2.05	0.141	-0.31	-0.27	0.544	0.26
48	1.85	3.47	0.039	-0.62	-1.06	0.744	0.31
avg.	2.47		0.019	-1.50		0.801	

Panel F: Bivariate Regression Involving *ICC* and *Default*

	ICC			*Default*			
K	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	2.54	2.37	0.013	-7.62	-0.97	0.837	0.01
12	1.62	2.18	0.086	0.13	0.03	0.494	0.06
24	1.88	2.81	0.053	-1.45	-0.54	0.643	0.17
36	1.92	3.42	0.038	-2.06	-0.83	0.707	0.27
48	1.58	3.58	0.040	-0.64	-0.23	0.563	0.30
avg.	1.91		0.010	-2.33		0.698	

Panel G: Bivariate Regression Involving *ICC* and *Tbill*

	ICC			*Tbill*			
K	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	2.14	1.90	0.043	0.24	0.28	0.646	0.00
12	1.71	2.19	0.076	0.20	0.27	0.623	0.06
24	1.84	2.32	0.085	0.20	0.56	0.699	0.17
36	1.83	3.08	0.044	0.23	0.87	0.758	0.27
48	1.62	4.00	0.020	0.35	1.50	0.856	0.32
avg.	1.83		0.010	0.24		0.698	

Panel H: Bivariate Regression Involving *ICC* and *Yield*

	ICC			*Yield*			
K	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	2.02	1.85	0.052	-0.23	-0.21	0.482	0.00
12	1.62	2.25	0.082	0.34	0.37	0.312	0.06
24	1.73	2.56	0.078	0.47	0.91	0.201	0.18
36	1.67	3.22	0.056	0.49	1.36	0.145	0.28
48	1.41	3.80	0.039	0.53	1.75	0.118	0.34
avg.	1.69		0.021	0.32		0.302	

Table 4 Alternative *ICC* Specifications

This table provides univariate regression of (5) for alternative measures of *ICC*. *ICC_T10*, *ICC_T20*, and *ICC_repurchase* are obtained with forecasting horizon $T = 10$, $T = 20$, and net share repurchases, respectively. *ICC_equal* is the equally-weighted average of the firm-level *ICC* for firms in the S&P 500 index; *ICC_all* is the value-weighted average of the firm-level *ICC* for all firms in our sample universe, and *ICC_yield* is the value-weighted average of the firm-level *ICC* for firms in the S&P 500 index subtracting the 30-year treasury yield. This table also provides the regression results for *ICC* where *ICC* is calculated based on the method of Easton (2004). The dependent variable in these regressions is average monthly market excess returns. All regressions use data from January 1977 to December 2011. K is the forecasting horizon in months. In forecasting horizons beyond one-month, the regressions use overlapping observations. b is the slope coefficient from the OLS regressions. avg. is the average slope coefficient. $Z(b)$ is the asymptotic Z-statistics computed using the GMM standard errors with $K - 1$ Newey-West lag correction. The $adj.R^2$ is obtained from the OLS regression. The p-values of Z-statistics and the average slope coefficient are obtained by comparing the test statistics with their empirical distribution generated under the null of no predictability from 5,000 trials of a Monte Carlo simulation as described in the Appendix.

	ICC_T10				*ICC_T20*				*ICC_repurchase*			
K	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$
1	2.40	1.98	0.039	0.01	1.85	1.79	0.056	0.01	2.07	1.74	0.058	0.01
12	1.93	2.39	0.065	0.08	1.44	2.12	0.092	0.06	1.73	2.29	0.070	0.06
24	1.94	2.33	0.095	0.17	1.62	2.43	0.084	0.15	1.94	2.65	0.062	0.17
36	1.88	2.98	0.057	0.27	1.62	2.97	0.058	0.24	1.92	3.21	0.041	0.26
48	1.63	3.97	0.030	0.31	1.42	3.62	0.042	0.27	1.61	3.46	0.047	0.27
avg.	1.96		0.012		1.59		0.027		1.85		0.017	

	ICC_all				*ICC_equal*				*ICC_yield*			
K	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$
1	2.22	1.91	0.047	0.01	1.87	1.76	0.058	0.01	3.28	1.78	0.061	0.01
12	1.80	2.48	0.061	0.07	1.32	1.86	0.121	0.04	2.09	1.61	0.162	0.04
24	1.92	2.71	0.064	0.18	1.48	2.21	0.099	0.12	2.15	1.69	0.183	0.09
36	1.89	3.28	0.041	0.27	1.50	2.98	0.056	0.20	2.16	2.04	0.150	0.14
48	1.61	3.71	0.041	0.29	1.31	3.73	0.034	0.24	2.18	3.25	0.053	0.22
avg.	1.89		0.015		1.50		0.038		2.37		0.033	

	ICC Based on Easton (2004)			
K	b	$Z(b)$	*pval*	$adj.R^2$
1	2.07	1.74	0.058	0.01
12	1.73	2.29	0.070	0.06
24	1.94	2.65	0.062	0.17
36	1.92	3.21	0.041	0.26
48	1.61	3.46	0.047	0.27
avg.	1.85		0.017	

Table 5 Univariate Regressions for Size and B/M Portfolios.

This table summarizes univariate forecasting regression results for size and B/M portfolios. Small Size, Medium Size, and Large Size are the three size portfolios, and Low B/M, Median B/M, and High B/M are the three book-to-market portfolios. The dependent variable in these regressions is average monthly excess returns for the corresponding portfolio, and the independent variables are the implied cost of capital (ICC), the dividend-to-price ratio (D/P), the earnings-to-price ratio (E/P), and the book-to-market ratio (B/M) for the corresponding portfolio. All variables span January 1977 to December 2011. In forecasting horizons beyond one-month, the regressions use overlapping observations. b is the slope coefficient from the OLS regressions. avg. is the average slope coefficient. $Z(b)$ is the asymptotic Z-statistics computed using the GMM standard errors with $K-1$ Newey-West lag correction. The $adj.R^2$ is obtained from the OLS regression. The p-values of Z-statistics and the average slope coefficient are obtained by comparing the test statistics with their empirical distribution generated under the null of no predictability from 5,000 trials of a Monte Carlo simulation as described in the Appendix.

Panel A: Univariate Regressions for Small Size Portfolio

	ICC				*D/P*				*E/P*				*B/M*			
K	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	4.11	2.70	0.005	0.02	4.75	0.99	0.248	0.00	2.38	1.76	0.073	0.01	0.33	1.68	0.091	0.01
12	2.68	3.21	0.017	0.11	6.49	1.94	0.129	0.06	2.62	2.87	0.053	0.12	0.44	3.53	0.016	0.16
24	1.71	1.99	0.127	0.12	4.09	2.18	0.120	0.07	1.60	2.34	0.114	0.13	0.27	2.85	0.072	0.18
36	1.28	1.68	0.195	0.12	3.01	1.94	0.190	0.07	1.30	2.57	0.126	0.15	0.21	2.75	0.103	0.19
48	0.61	1.06	0.344	0.04	2.36	1.63	0.270	0.07	1.13	2.61	0.153	0.18	0.18	2.72	0.135	0.22
avg.	2.08		0.014		4.14		0.244		1.81		0.121		0.29		0.064	

Panel B: Univariate Regressions for Medium Size Portfolio

	ICC				*D/P*				*E/P*				*B/M*			
K	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	3.80	2.64	0.009	0.02	2.17	0.58	0.416	0.00	1.95	1.44	0.167	0.01	0.33	1.59	0.122	0.01
12	2.50	3.44	0.015	0.11	4.14	1.65	0.190	0.04	1.71	2.08	0.165	0.06	0.36	3.03	0.041	0.11
24	1.92	3.01	0.041	0.21	2.40	1.35	0.305	0.05	0.95	1.65	0.284	0.06	0.21	2.27	0.152	0.11
36	1.43	3.01	0.063	0.23	1.90	1.45	0.334	0.06	0.73	1.86	0.273	0.07	0.15	2.42	0.166	0.13
48	0.82	2.73	0.094	0.13	1.55	1.73	0.315	0.07	0.59	1.96	0.291	0.08	0.11	2.39	0.189	0.12
avg.	2.10		0.015		2.43		0.402		1.19		0.345		0.23		0.194	

Panel C: Univariate Regressions for Large Size Portfolio

	ICC				*D/P*				*E/P*				*B/M*			
K	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	1.77	1.67	0.073	0.01	2.87	1.13	0.280	0.00	0.94	0.85	0.352	0.00	0.13	0.83	0.403	0.00
12	1.42	2.07	0.089	0.05	2.74	1.35	0.326	0.03	0.84	0.98	0.408	0.02	0.13	1.10	0.422	0.02
24	1.59	2.37	0.095	0.14	2.21	1.15	0.423	0.05	0.64	0.83	0.485	0.02	0.10	0.87	0.515	0.03
36	1.70	3.08	0.060	0.22	1.89	1.16	0.472	0.06	0.52	0.75	0.525	0.03	0.09	0.84	0.548	0.03
48	1.54	3.85	0.035	0.25	1.95	1.47	0.444	0.09	0.51	0.85	0.539	0.04	0.08	0.93	0.559	0.05
avg.	1.60		0.025		2.33		0.418		0.69		0.424		0.11		0.497	

Panel D: Univariate Regressions for Low B/M Portfolio

	ICC				*D/P*				*E/P*				*B/M*			
K	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	2.51	1.99	0.041	0.01	2.97	0.76	0.358	0.00	1.47	0.93	0.328	0.00	0.15	0.61	0.460	0.00
12	1.71	1.96	0.115	0.05	3.05	1.02	0.354	0.02	1.36	1.13	0.367	0.02	0.17	0.84	0.453	0.01
24	1.66	2.03	0.123	0.11	1.77	0.62	0.480	0.02	0.90	0.79	0.473	0.02	0.09	0.48	0.589	0.01
36	1.77	2.57	0.083	0.17	1.20	0.49	0.537	0.01	0.65	0.64	0.556	0.02	0.08	0.46	0.617	0.01
48	1.59	2.62	0.092	0.18	1.16	0.51	0.547	0.02	0.56	0.62	0.592	0.02	0.06	0.41	0.634	0.01
avg.	1.85		0.029		2.03		0.452		0.99		0.460		0.11		0.579	

Panel E: Univariate Regressions for Medium B/M Portfolio																
	ICC				*D/P*				*E/P*				*B/M*			
K	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	1.40	1.45	0.108	0.01	1.20	0.49	0.455	0.00	0.44	0.43	0.551	0.00	0.09	0.59	0.459	0.00
12	1.20	1.85	0.119	0.04	1.74	0.96	0.391	0.01	0.50	0.68	0.527	0.01	0.15	1.43	0.274	0.03
24	1.51	3.35	0.023	0.16	1.27	0.86	0.443	0.02	0.18	0.35	0.660	0.00	0.10	1.14	0.397	0.03
36	1.51	4.01	0.021	0.28	0.97	0.78	0.488	0.02	-0.01	-0.03	0.774	0.00	0.07	0.85	0.515	0.03
48	1.16	3.82	0.036	0.25	1.14	1.05	0.458	0.05	0.02	0.04	0.757	0.00	0.05	0.68	0.590	0.02
avg.	1.36		0.038		1.27		0.501		0.22		0.671		0.09		0.474	

Panel F: Univariate Regressions for High B/M Portfolio																
	ICC				*D/P*				*E/P*				*B/M*			
K	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	0.95	1.17	0.168	0.00	2.35	1.33	0.175	0.00	0.62	0.68	0.347	0.00	0.07	0.62	0.407	0.00
12	1.30	2.93	0.020	0.08	2.72	1.67	0.186	0.06	0.67	1.03	0.299	0.02	0.13	1.56	0.231	0.04
24	1.22	3.13	0.022	0.18	2.14	1.68	0.240	0.09	0.67	1.37	0.252	0.04	0.12	1.72	0.245	0.09
36	0.99	3.24	0.032	0.21	1.98	1.97	0.223	0.15	0.72	1.85	0.184	0.09	0.10	1.80	0.243	0.12
48	0.87	2.98	0.054	0.24	1.88	2.43	0.189	0.21	0.70	2.11	0.171	0.14	0.10	1.82	0.284	0.18
avg.	1.06		0.023		2.21		0.215		0.68		0.221		0.10		0.248	

Table 6 Out-of-Sample Test

This table summarizes the out-of-sample analysis of forecasting models using different forecasting variables for the forecast period of January 1998 to December 2011. Panel A reports the R^2_{os} statistic of Campbell and Thompson (2008). Panel A also reports the utility gain (Ugain), which is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of three would be willing to pay to have access to the forecasting model using a particular forecasting variable relative to the historical average benchmark forecasting model; the weight on stocks in the investor's portfolio is constrained to lie between zero and 1.5 (inclusive). Panel B reports the p-values of the forecasting encompassing test statistic of Harvey, Leybourne, and Newbold (1998) (HLN statistic), which corresponds to a one-sided (upper-tail) test of the null hypothesis that the forecast from the row variable (R) encompasses the forecast from the column variable (C) against the alternative hypothesis that the forecast from the row variable (R) does not encompass the forecast from the column variable (C). The dependent variable in these regressions is monthly market excess returns. In these tests, we perform a 2-year moving average for *ICC*.

Panel A: Out-of-Sample R^2_{os} and Utility Gains

	R^2_{os}	*pval*	Ugain
IRP	1.22	0.06	4.15
D/P	0.44	0.16	1.38
E/P	0.22	0.27	0.40
B/M	0.26	0.23	0.57
Term	-0.53		-1.32
Default	-0.90		-1.33
Tbill	-1.18		-2.21
Yield	-1.62		-1.84

Panel B: Forecast Encompassing Test

	Column Variables (C)							
Row Variables (R)	*ICC*	*E/P*	*D/P*	*B/M*	*Term*	*Default*	*Tbill*	*Yield*
ICC		0.40	0.50	0.51	0.76	0.71	0.84	0.79
E/P	0.09		0.70	0.70	0.71	0.74	0.73	0.76
D/P	0.07	0.23		0.41	0.69	0.69	0.73	0.73
B/M	0.07	0.22	0.55		0.73	0.73	0.77	0.77
Term	0.03	0.07	0.10	0.09		0.53	0.74	0.66
Default	0.04	0.11	0.16	0.14	0.29		0.44	0.51
Tbill	0.01	0.03	0.04	0.03	0.10	0.28		0.67
Yield	0.01	0.02	0.04	0.03	0.09	0.18	0.19	

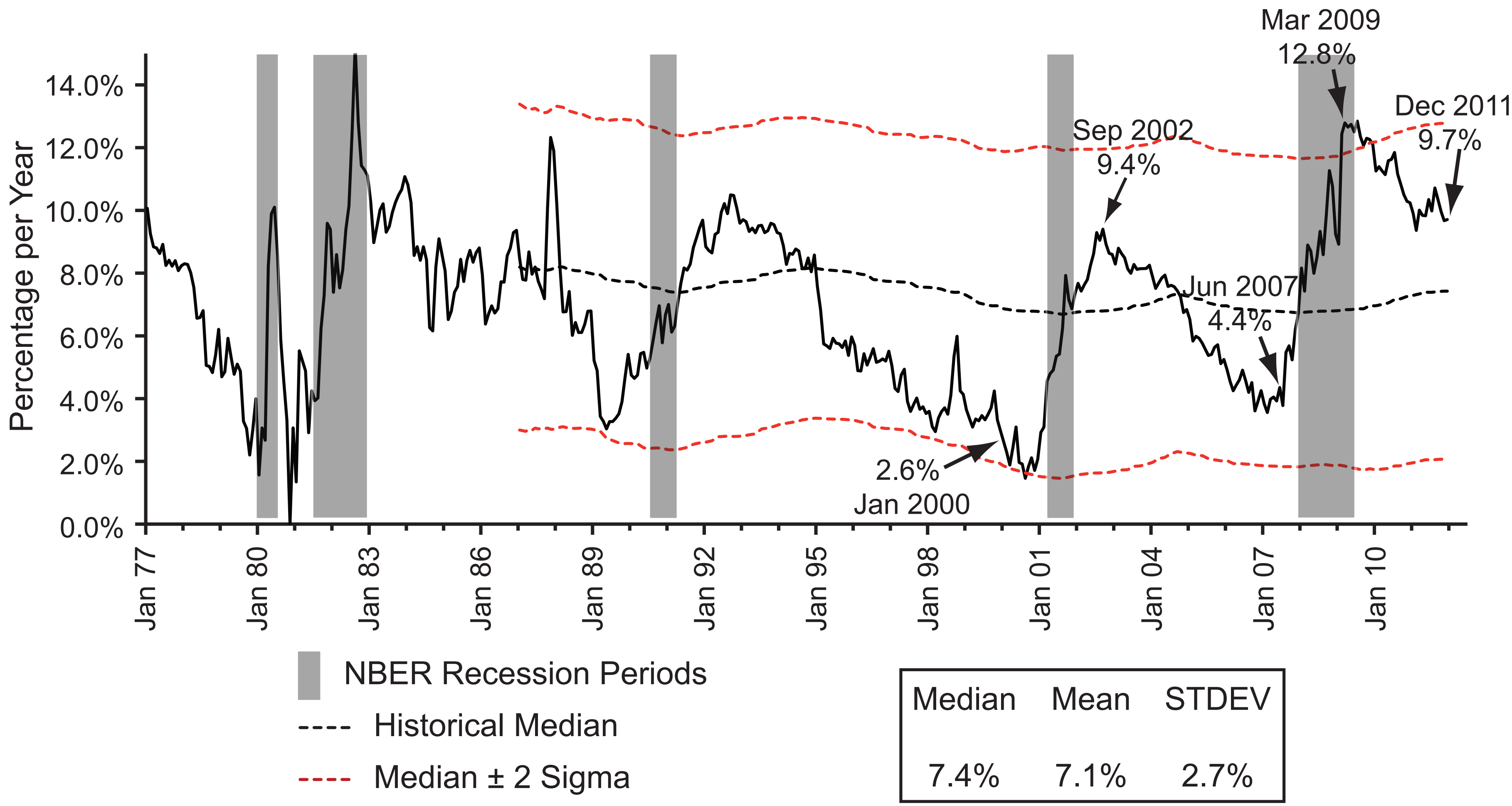

Figure 1: Aggregate Implied Cost of Capital (*ICC*). This figure depicts the value-weighted implied cost of capital constructed based on prevailing S&P 500 companies from January 1977 to December 2011 subtracting the one-month T-bill yield. *ICC* is expressed in annualized percentages. The three horizontal dashed curves correspond to the rolling median and the two-standard-deviation bands calculated using all historical data starting from January 1987. The shaded areas indicate the NBER recession periods. The numbers associated with the arrows are the *ICC*s for recent important dates. The historical mean, median and standard deviations of *ICC* are provided in the box under the graph.

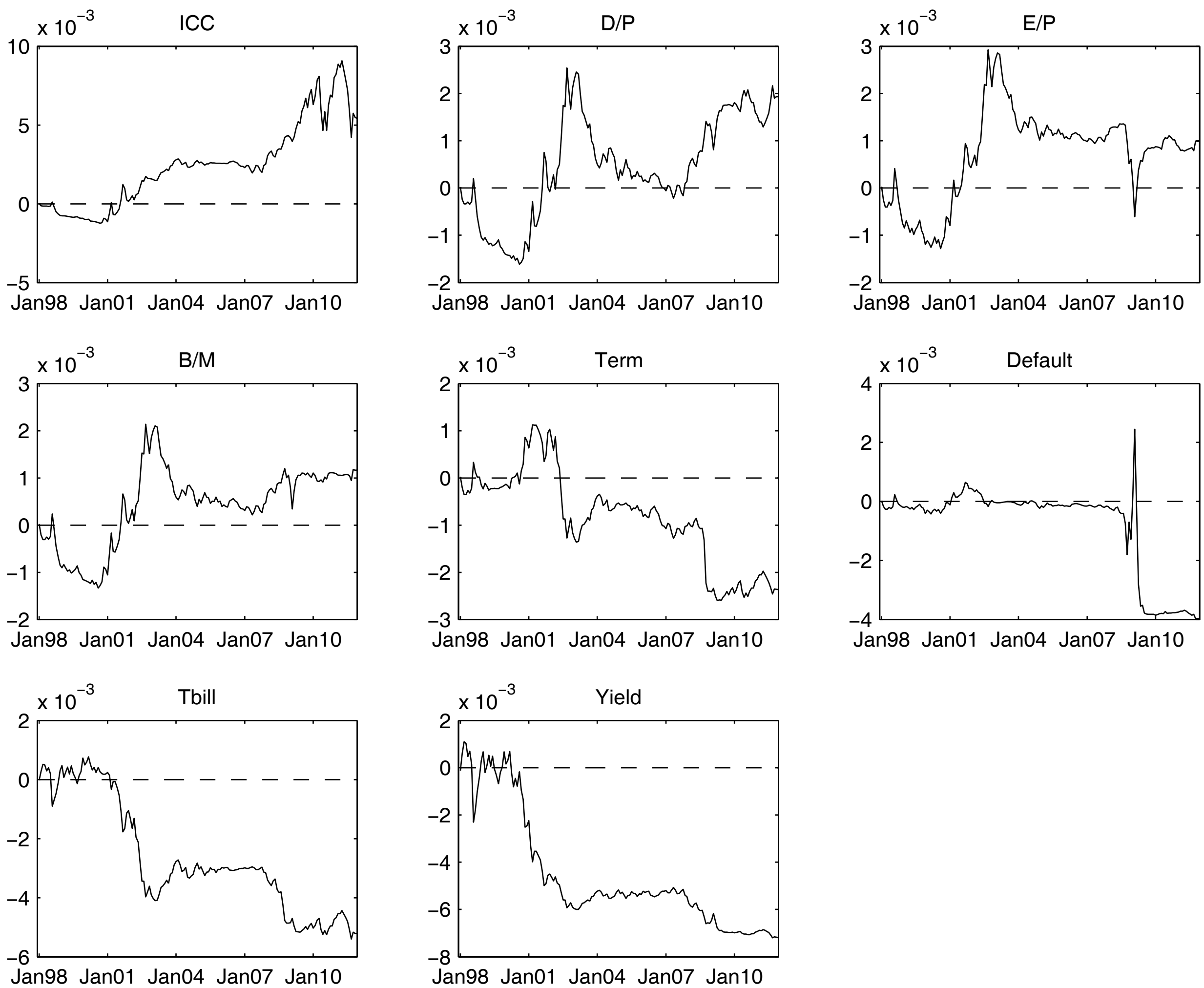

Figure 2: Cumulative squared prediction error for the historical average benchmark forecasting model minus the cumulative squared prediction error for the forecasting model using the implied cost of capital (ICC), dividend-to-price ratio (D/P), earnings-to-price ratio (E/P), book-to-market ratio (B/M), term spread ($Term$), default spread ($Default$), T-bill rate ($Tbill$), and 30-year treasury yield ($Yield$), during the forecast period of January 1998 to December 2011. The dotted line in each panel goes through zero.