Predictability of aggregate and firm-level returns

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Abstract

Recent studies find that the aggregate implied cost of capital (ICC) can predict market returns. This paper shows, however, that firm-level ICC does not display a similar predictability. The lack of predictability of firm-level ICC is due neither to the potential bias in analyst forecasts nor to small firms and firms with low-analyst coverage. Although the aggregation process increases the predictive power of ICC, the predictability gain is only observed among large firms. Using the stock-return decomposition of Campbell (1991), I show that the coefficients of firm-level predictive regressions are lower, and decay faster than that suggested by the autocorrelation structure of ICC. The decomposition also implies that the predictive ability of firm-level ICC is obscured by a negative correlation between ICC and future cash-flow news. An analysis using unexpected earnings growth as a proxy for cash-flow news suggests that this negative relation at the firm level is due to a delayed response of market participants to current cash-flow news.

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1. Introduction

Whether stock returns are predictable has been the central question in finance literature. Researchers have examined a broad range of variables that may have explanatory power in predicting future realized returns.[1] One of those variables that has received much attention recently is the implied cost of capital (ICC). The ICC is the rate of return that equates a stock's current price to the present value of the future expected cash flow to its shareholders. Pástor, Sinha, and Swaminathan (2008) show that under plausible assumptions, the ICC is perfectly correlated with the conditional expected return. Li, Ng, and Swaminathan (2012) compare the explanatory power of the ICC with other forecasting variables in predicting future market returns. They find that the aggregate ICC strongly predicts both short-run and long-run stock returns and the predictive power of the ICC is superior to other forecasting variables.

In this paper, I examine whether the predictability of returns depends on the level of aggregation. Recent literature suggests that the relation between forecasting variables and realized returns may vary based on the level of aggregation. For example, Kothari, Lewellen, and Warner (2006) document a negative contemporaneous relation between the market returns and the aggregate earnings changes but a positive relation between firm-level returns and firm-level earnings changes. Sadka and Sadka (2009) offer an explanation for this finding. They suggest that the aggregation process makes the earnings change more predictable, and this predictable aggregate earnings change is negatively correlated with conditional expected returns, which results in a negative relation between earnings changes and market returns. In addition, Vuolteenaho (2002) shows that firm-level returns are driven more by cash-flow news, while the expected-return news is more important in explaining the variation of market return.

Motivated by this literature, I study the predictability of firm-level returns using ICC. First, I show that while the aggregate ICC strongly predicts future realized returns (Li, Ng, and Swaminathan (2012)), firm-level ICC does not display a similar predictive power. The coefficients of the aggregate-level regressions are statistically and economically significant for most forecasting hori-

[1] There is a large literature on predicting returns using forecasting variables. Most forecasting variables are divided into two categories: Valuation ratios and business cycle variables. Examples of valuation ratios are dividend-to-price ratio (Campbell and Shiller (1988) and Fama and French (1988)), book-to-market ratio (Pontiff and Schall (1998)), and the payout yield (Boudoukh, Michaely, Richardson, and Roberts (2007)). And a partial list of business cycle variables are the term spread and default spread (Campbell (1987)), the net equity issuance (Baker and Wurglar (2000)), inflation (Campbell and Vuolteenaho (2004)), consumption-to-wealth ratio (Lettau and Ludvigson (2001)), and investment-to-capital ratio (Cochrane (1991))

zons. The coefficients are stable at about three over the 60-month forecasting period, suggesting that an 1% increase in ICC in the current month is associated with a 3% increase in the realized return per month over the next 60-month horizon. On the other hand, the average coefficient of firm-level predictive regressions decreases quickly and converges to zero as the forecasting horizon increases. The cross-sectional mean (median) of the coefficients of firm-level time-series regressions is 2.26 (0.94) for a one-month horizon, but decrease to 0.60 (0.47) for a 12-month and 0.15 (0.26) for a 60-month horizon. In addition, the within-group R^2 of firm-level panel regressions is below 1% for all the forecasting horizons. Multivariate analyses using book-to-market and return-on-equity in addition to the ICC provide a similar implication regarding firm-level predictability. Robustness analyses show that the lack of predictability of firm-level ICC is due neither to the potential bias in analyst forecasts nor to small firms and firms with low-analyst coverage.

Second, I show that although the aggregation process generally increases the predictive power of ICC, the predictability gain is only observed among large firms. Size-sorted portfolio results show that the benefit of the aggregation with respect to predictability depends on the firm size. For the group of big firms, when more firms are included in a portfolio, the portfolio ICC is better able to predict the portfolio returns. However, within the group of small firms, this predictability gain obtained by including more firms is marginal.

To explain the contrasting results between the aggregate and firm-level predictability, I investigate the mechanism through which the ICC predicts future stock returns. First, modifying the stock-return decomposition of Campbell (1991), I show that realized returns can be decomposed into cash-flow news and the changes in ICC. Campbell (1991) shows that the stock market return for the period $t+1$ is decomposed into three components: the expected return at time t, the cash-flow news at $t+1$, and the expected-return news at $t+1$. Using this decomposition and the definition of ICC (given in Pástor, Sinha, and Swaminathan (2008)), I show that returns at $t+1$ are decomposed into the cash-flow news at $t+1$ and the change in ICC from t to $t+1$. Further, K-period returns can be decomposed into the sum of the cash-flow news during the period t to $t+K$ and the change in ICC from t to $t+K$.

Second, I show that from the above decomposition, the coefficients of predictive regressions on the ICC can be decomposed into the autocorrelation of ICC and the correlation between future cash-flow news and the ICC. Therefore, the correlation between the ICC at t and the cash-flow news at $t+k$ can be recursively estimated from the autocorrelations of ICC and the OLS estimates of predictive regressions. From this decomposition, I show that the ability of ICC to predict future returns is affected by the correlation between the ICC and future cash-flow news. Specifically, the predictability of firm-level ICC is obscured by the highly negative correlation between the ICC and the future cash-flow news for short-term horizons. In an efficient market, since the correlation between future cash-flow news and the ICC should be zero, the predictability of returns using the ICC is solely determined by the autocorrelation structure of ICC. However, the coefficients of firm-level predictive regressions are lower, and decay faster than that suggested by the autocorrelation of firm-level ICC. Therefore, the decomposition implies a negative correlation between the ICC and future cash-flow news at the firm level.

To reassert the implication of the decomposition, I use earnings surprises as a proxy for future cash-flow news. Specifically, I regress earnings surprises at $t + 1$ on the ICC at t. While the aggregate-level regression provides no evidence for the relation between the ICC and future earnings surprises, the panel and cross-sectional regressions show that the ICC strongly predicts negative earnings surprises at the firm level. These regression results are consistent with the implication of the predictive regressions – the negative relation between the ICC and future cash-flow.

The negative correlation between the ICC and future cash-flow news at the firm level is puzzling, since by definition, the cash-flow news is the changes in the expectation for the future cash flows that are not predictable from the current information set. Three possible explanations can be offered. First, there may be a statistical bias in the firm-level regression coefficients due to imprecisely measured firm-level ICC. Specifically, if there is a measurement error in ICC, the coefficients of predictive regressions would have a downward bias. To examine this possibility, I use various samples that exclude firms that are likely to have high measurement errors in the ICC estimates. Since the measurement errors in ICC are likely to be higher for small firms or firms with low analyst coverage, I use following samples that exclude these firms; the sample of S&P500, the sample of large firms (Size Quintile 4 and 5), and the sample of firms with at least 5 analyst coverages. However, the negative correlation pattern is robust to these samples, indicating that the firm-level results are not likely to be driven by the statistical bias. Second, as the literature shows that analyst forecasts could be biased (for example, La Porta (1996) and Lim (2001)), the potential bias in analyst forecasts may be the cause of the negative correlation. However, the correlation pattern is robust to the sample of firms with low analyst forecast errors. The firm-level results are also robust to using alternative measures of ICC, which controls for the analyst forecast bias. Therefore, the negative correlation is not likely to be driven by the potential bias in analyst forecasts.

Finally, the third possible explanation, advanced here, is that the negative correlation at the firm level between the ICC and the future cash-flow news is due to under-reaction of market participants to the current cash-flow news. Sadka and Sadka (2009) show that a higher expected earnings growth for the period $t+1$ is associated with a lower expected return at t. Thus, when investors expect a higher future earnings growth, they also demand a lower risk premium, therefore a lower expected return. This implies a negative relation between the cash-flow news at t and the expected return at t. On the other hand, Bernard and Thomas (1990) provide evidence that market participants underreact to the current earnings news and are constantly surprised by the components that are predictable by previous earnings announcements. Therefore, future cash-flow news may be positively related with the current cash-flow news due to this under-reaction. Combining these two empirical regularities suggests a negative relation between the cash-flow news at $t+1$ and the expected return at t. Thus, assuming the ICC is a reasonable proxy for the expected return, the negative correlation between the ICC and the future cash-flow news is due to under-reaction to the current cash-flow news.

I investigate the above explanation using earnings surprises as a proxy for cash-flow news. Specifically, I examine the relation between cash-flow news at t and expected returns at t. For that, returns at $t+1$, as a proxy for expected return at t, are regressed on earnings surprises at t. If the expected return is negatively related with the contemporaneous cash-flow news, a positive earnings surprise would predict a low return in the next period. The panel regression results are consistent with this explanation. These regression results are consistent with the explanation that the negative correlation at the firm level between the ICC and future cash-flow news is due to the under-reaction of market participants to the current cash-flow news.

This paper makes several contributions to the literature on the return predictability using ICC. First, I document that the predictive power of ICC depends on the level of aggregation. While the aggregate ICC strongly predicts future returns, the firm-level ICC does not display the ability to predict firm-level returns. I also show that the predictability gain through the aggregation process is observed only among big firms. Second, using the stock-return decomposition of Campbell (1991), I show that the ability of ICC to predict future returns is affected by the correlation between the ICC and future cash-flow news. In particular, the lack of predictability at the firm level is due to the negative correlation between the ICC and future cash-flow news. Regression results using earnings surprise as a proxy for cash-flow news show that the negative correlation is due to a delayed response of market participants to the current cash-flow news at the firm level.

Bernard and Thomas (1990) provide evidence that the market is constantly surprised by the components that are predictable by the autocorrelation structure of earnings. Abarbanell and Bernard (1992) show that analysts also do not fully utilize the autocorrelation structure of earnings in their forecasts, although the extent of analysts' under-reaction is smaller than that of the market. Cohen, Gompers, and Vuolteenaho (2002) argue that the under-reaction is due to the positive relation between cash-flow news and expected return news. The main results of the paper provide evidence concerning market inefficiency that is similar to earlier findings in the literature. The negative correlation between the firm-level ICC and future cash-flow news may be due to the market's under-utilization of the available information regarding future cash flow. Contrary to Cohen, Gompers, and Vuolteenaho (2002), this paper shows that firm-level stock prices underreact to cash-flow news despite a negative correlation between cash-flow news and expected return news.

This paper is also related to the literature on the earnings-return relationship. Kothari, Lewellen, and Warner (2006) show that the earnings changes are positively correlated with returns at the firm level, while the aggregate earnings changes are negatively correlated with the aggregate returns. The strong predictability of ICC at the aggregate level and no predictability at the firm level are reminiscent of the literature.

The paper is organized as follows: In the next section, I describe the sample and the estimation method of the ICC. Section 3 explains the empirical methods and stock return decomposition using ICC. Section 4 provides the results of forecasting regressions of returns on the ICC. Section 5 examines the reasons why the ICC predicts returns at the aggregate level but not at the firm level. Section 6 provides concluding remarks.

2. Data and Variables

2.1. Data

The first dataset, obtained from the CRSP, includes monthly stock returns, prices, number of shares outstanding, and other market characteristics of common shares traded on the NYSE, AMEX, and

Nasdaq. The second dataset, obtained from IBES, is used for mean, standard deviation, and other statistics of monthly-updated analyst forecasts. Finally, firms' financial statements are obtained from Compustat. Due to the availability of IBES data, the sample period is from 1981 to 2010.

2.2. The Implied Cost of Capital

The ICC is the internal rate of return that equates the current stock price to the discounted future free cash flow to its equity holders. Specifically, the ICC for stock i at time t is defined by the following simple stock valuation equation,

$$P_{i,t} = \sum_{k=1}^{\infty} \frac{E_t[CF^e_{i,t+k}]}{E_t[R_{i,t+k}]^k} = \sum_{k=1}^{\infty} \frac{E_t[CF^e_{i,t+k}]}{(R^e_{i,t})^k}, \tag{1}$$

where $E_t[CF^e_{i,t+k}]$ is expected future free cash flows to equity and $E_t[R_{i,t+k}]$ is the time-varying (gross) expected return for the period $t+k$. The internal rate of return, $R^e_{i,t}$, is the (gross) ICC for firm i at time t. If future expected returns are time varying, the expected return for time t is not necessarily equivalent to $R^e_{i,t}$. However, Pástor, Sinha, and Swaminathan (2008) show that if future expected returns follow an AR process, $R^e_{i,t}$ is perfectly correlated with the expected return for period t.

Estimating $R^e_{i,t}$ is a challenging task because future free cash flows to equity can only be estimated based on the information set available at time t. The validity of an ICC estimate is therefore subject to the reasonableness of the assumptions made in estimating future free cash flows. The free cash flow to equity captures the total cash flow available to shareholders, net of stock repurchases and new equity issues. In particular, it is equivalent to the following expression:

$$E_t(CF^e_{i,t+k}) = FE_{i,t+k} \times (1 - b_{i,t+k}), \tag{2}$$

where $FE_{i,t+k}$ is the forecasted earnings of firm i for period $t+k$, and $b_{i,t+k}$ is the plowback rate for $t+k$. (The plowback rate is the proportion of earnings that is reinvested in the firm.) Thus one minus the plowback rate is the payout ratio to the shareholders. The payout ratio is adjusted for stock repurchase and new equity issues. Notice that according to Equation (2), the estimation of the ICC is then equivalent to the estimation of future earnings and future plowback rates. I briefly explain the estimation method for these variables below.[2]

[2] For the estimation of ICC, I closely follow the approach of Pástor, Sinha, and Swaminathan (2008), Lee, Ng, and Swaminathan (2009), and Li, Ng, and Swaminathan (2012). For a more detailed explanation of the methodology, see Pástor, Sinha, and Swaminathan (2008) whose notations and equations I borrow in this section.

Earnings: At each month during year t, future earnings, $FE_{i,t+k}$, are forecasted over a finite horizon, up to the terminal period $t+T$ ($T = 15$). And, a terminal value is computed based on the forecasted earning at $t+T+1$. Specifically, $FE_{i,t+1}$ and $FE_{i,t+2}$ are obtained from the mean analyst forecast of EPS as provided by IBES. From year $t+3$ to $t+T+1$, forecasted earnings are calculated based on the previous-year forecasted earnings and the forecasted growth rate for the year. Thus, the earnings at $t+k$ are given by

$$FE_{i,t+k} = FE_{i,t+k-1} \times g_{i,t+k}, \tag{3}$$

where $k >= 3$. The analyst-consensus, long-term growth rate obtained from IBES is used for $g_{i,t+3}$. From $t+4$ to $t+T+1$, the growth rate is assumed to be mean-reverting to the steady-state growth rate g, at the exponential rate of decline. The steady-state growth rate is assumed to be the nominal long-run GDP growth rate which is estimated from a rolling average of annual nominal GDP growth up to year t.

Plowback rate: For year $t+1$ to $t+3$, plowback rate, $b_{i,t+k}$, is estimated using the most recent payout ratio, $p_{i,t} \equiv D_{i,t}/NI_{i,t}$, where $D_{i,t}$ is total dividends and $NI_{i,t}$ is the net income of firm i. If $p_{i,t}$ is above one or below -0.5, then the industry median payout ratio is used. For $t+4$ to $t+T$, the plowback rate is assumed to decline linearly to its steady state value, b_i. The steady state value of the plowback rate is computed from the sustainable growth rate formula. Specifically, it is given by $g = ROI_i \times b_i$, where ROI_i is set to be the ICC for firm i at t, $r^e_{i,t}$.

Terminal value at $t+T$ is computed as a perpetuity of the forecasted earnings for $t+T+1$. As such, the implied cost of capital is obtained from the following equation:

$$P_{i,t} = \sum_{k=1}^{T} \frac{FE_{i,t+k}(1 - b_{i,t+k})}{(R^e_{i,t})^k} + \frac{FE_{i,t+T+1}}{(R^e_{i,t} - 1)(R^e_{i,t})^T} \tag{4}$$

Note that the computation of steady state plowback rates requires iterations. Thus, if the ICC of a firm does not converge after 50 iterations, the firm is excluded from the sample. Firms having negative or multiple solutions to IRR are also excluded. Also, the top and bottom 0.5% of ICC estimates are deleted.

3. Empirical Methods

This section describes the methodologies for the empirical analyses. Specifically, I develop a framework that shows the channel through which the ICC predicts realized returns.

3.1. Forecasting Regressions of Returns on ICC

For the empirical analyses, I employ the following multi-period forecasting regression (Fama and French (1988))

$$\frac{1}{K}\sum_{k=1}^{K} r_{t+k} = \alpha + \beta_K X_t + u_{t+K,t}, \tag{5}$$

where r_{t+k} is the log of gross return at $t+k$ and X_t is the forecasting variable at t. In this paper, X_t is the log of ICC (r_t^e). I estimate these regressions up to 60-month horizons, therefore $K = 1$ to 60.

Using this regression framework, Li, Ng, and Swaminathan (2012) show that the aggregate ICC strongly predicts future realized market returns. They also provide evidence that the aggregate ICC is a superior predictor to financial ratios, such as dividend-to-price ratio and book-to-market ratio, and to business cycle variables, such as consumption-to-wealth ratio and investment-to-capital ratio. However, it is well known in the literature that the driving forces of the market returns are different from those of firm-level returns. For example, Voulteenaho (2002) shows that the cash-flow news is more important in explaining the variation of firm-level returns, while the market return is driven more by the expected-return news. Kothari, Lewellen, and Warner (2006) document that earnings changes are positively correlated with contemporaneous returns at the firm level, while the market return is negative related with the aggregate earnings changes. Therefore, to examine whether the predictability depends on the aggregation level, I estimate Regression (5) both for the aggregate and the firm-level returns. For firm-level analyses, I also run the following panel regressions

$$\frac{1}{K}\sum_{k=1}^{K} r_{i,t+k} = \alpha_i + \beta_K r_{i,t}^e + u_{i,t+K,t}. \tag{6}$$

These panel regressions assume that the coefficients are constant across firms. Firm fixed effects are included to absorb cross-sectional variations. I also include r_{t-1}, book-to-market ratio, bm_t, and return on equity, ROE_t, for multivariate analyses. Returns and the ICC are calculated as of three months after fiscal quarter end to insure that accounting information become publicly available.

The estimation of above regression model involves with the use of overlapping observations, which induces serial correlation in the regression residuals. The traditional way to correct for this autocorrelation is to use the GMM standard errors with the Newey-West type correction. However, Boudoukh, Richardson, and Whitelaw (2008) point out that this asymptotic t-statistics with Newey-West correction tend to be overstated, if the forecasting variables are persistent. Instead of relying on the asymptotic t-statistics, they propose a Monte Carlo study under the null of no predictability. Following their suggestion, I conduct Monte Carlo simulations under the assumption that returns are White noises and the ICC follows an AR(1). The data generating processes are as follow.

$$\begin{aligned} r_t &= \mu + u_t \\ r_t^e &= \alpha + \rho r_{t-1}^e + \epsilon_t \end{aligned} \tag{7}$$

The simulation involves 5,000 replications. For each set of simulated time-series data, Regression (5) is estimated. Then, the simulated p-values are obtained by comparing the coefficients of Regression (5) with the empirical distribution of the coefficient generated by simulations. For panel regressions in (6), the standard errors are estimated following the generalized Hodrick (1992) (Ang and Bekaert (2007)).

Additionally, the coefficients of Regressions (5) for various horizons are likely to be correlated, since the regressions use the same data for multiple overlapping horizons. Therefore, Boudoukh, Richardson, and Whitelaw (2008) also consider a test for joint hypothesis that $\beta_1 = \cdots = \beta_k = \cdots = \beta_K = 0$. The test statistics are given by

$$W = T\hat{\beta}' V(\hat{\beta})^{-1}\hat{\beta} \tag{8}$$

where $\hat{\beta} = (\hat{\beta}_1, \cdots, \hat{\beta}_k, \cdots, \hat{\beta}_K)$ and $V(\hat{\beta})$ is the covariance matrix of the $\hat{\beta}$ estimators. W follows χ^2 distribution with K degree of freedom.

3.2. Decomposition of β_K of Forecasting Regressions

In this subsection, I study the mechanism through with the ICC predicts future returns. The decomposition method of Campbell (1991) is useful to understand the mechanism. Using the decomposition, the stock price can be written as[3]

$$p_t = \frac{\kappa}{1-\rho} + (1-\rho)\sum_{k=0}^{\infty}\rho^k E_t[d_{t+1+k}] - \sum_{k=0}^{\infty}\rho^k E_t[r_{t+1+k}], \tag{9}$$

where p_t is the log price at t, d_t is the log of dividend, and r_t is the log of gross return. Using the definition of ICC given by Pástor, Sinha, and Swaminathan (2008), Equation (9) can be rewritten as

$$p_t = \frac{\kappa}{1-\rho} + (1-\rho)\sum_{k=0}^{\infty}\rho^k E_t[d_{t+1+k}] - r_t^e \sum_{k=0}^{\infty}\rho^k, \tag{10}$$

where r_t^e is the log of gross ICC. Taking the first difference of Equation (9) and using the definition of ICC in Equation (10), returns at $t+1$ are decomposed as

$$\begin{aligned} r_{t+1} &= E_t[r_{t+1}] + \big(E_{t+1} - E_t\big)\Big[\sum_{k=1}^{\infty}\rho^k \Delta d_{t+k}\Big] - \big(E_{t+1} - E_t\big)\Big[\sum_{k=1}^{\infty}\rho^k r_{t+1+k}\Big] \\ &= \eta_{t+1}^{CF} - \sum_{k=1}^{\infty}\rho^k E_{t+1}[r_{t+1+k}] + \sum_{k=0}^{\infty}\rho^k E_t[r_{t+1+k}] \\ &= \eta_{t+1}^{CF} - \frac{1}{1-\rho} r_{t+1}^e + \frac{1}{1-\rho} r_t^e, \end{aligned} \tag{11}$$

where η_{t+1}^{CF} is the cash-flow news at $t+1$, defined as $\big(E_{t+1} - E_t\big)\Big[\sum_{k=1}^{\infty}\rho^k \Delta d_{t+k}\Big]$. Note, the last equality in Equations (11) comes from the definition of ICC. Equation (11) shows that a return can be decomposed into the cash-flow news component and the change in ICC. And, the information in the change in ICC includes the the expected return at t and the expected-return news.

Equation (11) gives an interesting intuition about β_K in Equation (5). From Equation (11), multi-period returns can be written as

$$\frac{1}{K}\sum_{k=1}^{K} r_{t+k} = \frac{1}{K}\sum_{k=1}^{K}\eta_{t+k}^{CF} - \frac{1}{K(1-\rho)}\big(r_{t+K}^e - r_t^e\big). \tag{12}$$

Therefore, K-period returns are decomposed into the sum of cash-flow news during the period and the change in the ICC for the period. From this, the OLS estimate from the regression of

[3]From here, I suppress subscript i for an individual firm since following analyses apply both to the aggregate and the firm-level variables.

K-period returns on ICC (Equation (5)) can be written as

$$\begin{aligned}\hat{\beta}_K &= Cov\big(\frac{1}{K}\sum_{k=1}^{K} r_{t+k}, r_t^e\big)\Big/ Var\big(r_t^e\big)\\ &= \frac{Cov\big(\sum_{k=1}^{K}\eta_{t+k}^{CF}, r_t^e\big)}{K\cdot Var\big(r_t^e\big)} - \frac{1}{K(1-\rho)}\frac{Cov\big(r_{t+K}^e, r_t^e\big)}{Var\big(r_t^e\big)} + \frac{1}{K(1-\rho)}\frac{Var\big(r_t^e\big)}{Var\big(r_t^e\big)}\\ &= \frac{1}{K}\frac{\sigma(\eta^{CF})}{\sigma(r^e)}\sum_{k=1}^{K} Cor\big(\eta_{t+k}^{CF}, r_t^e\big) + \frac{1}{K(1-\rho)}\Big(1 - Cor\big(r_{t+K}^e, r_t^e\big)\Big). \qquad (13)\end{aligned}$$

Therefore, the regression coefficient is determined by the correlation between future cash-flow news and the ICC and the autocorrelation structure of the ICC. To get better intuition, consider an one-month forecasting horizon. Then $\hat{\beta}_1 = \frac{\sigma(\eta^{CF})}{\sigma(r^e)} Cor\big(\eta_{t+1}^{CF}, r_t^e\big) + \frac{1}{(1-\rho)}\Big(1 - Cor\big(r_{t+1}^e, r_t^e\big)\Big)$. Thus, the coefficient is determined by the correlation between the cash-flow news at $t+1$ and the ICC at t and the first order autocorrelation of the ICC. In an efficient market, since $Cor\big(\eta_{t+1}^{CF}, r_t^e\big)$ should be zero, the coefficient is solely determined by the autocorrelation of the ICC.

Note that the changes in ICC contain the information about the one-period conditional expected return and the expected-return news during the forecasting period. For example, from Equation (11), the one-period change in ICC is given by $\frac{1}{(1-\rho)}\big(r_{t+1}^e - r_t^e\big) = E_t[r_{t+1}] - \eta_{t+1}^R$, where η_{t+1}^R is the expected-return news at $t+1$. Therefore, if expected returns are persistent, the ICC would also be persistent.

3.3. Implied Correlation between Future Cash-Flow News and ICC

If the market is efficient, the correlation between future cash-flow news and the ICC is zero by definition. If $Cor\big(\eta_{t+k}^{CF}, r_t^e\big)$ is not zero for some k, this may indicate that market participants do not utilize the information contained in r_t^e to estimate future cash flows, and are constantly surprised by observing the cash-flow component of realized returns that are predictable from r_t^e. Rearranging Equation (13), the correlation between future cash-flow news at K and ICC at t is given by

$$Cor\big(\eta_{t+K}^{CF}, r_t^e\big) = K\frac{\sigma(r^e)}{\sigma(\eta^{CF})}\Big[\hat{\beta}_K - \frac{1}{K(1-\rho)}\Big(1 - Cor\big(r_{t+K}^e, r_t^e\big)\Big)\Big] - \sum_{k=1}^{K-1} Cor\big(\eta_{t+k}^{CF}, r_t^e\big). \qquad (14)$$

Therefore, the implied correlation between the future cash-flow news and the ICC can be estimated recursively using OLS estimates and the autocorrelation of ICC.

If market participants utilize all the available information to estimate future cash flows, the correlation between η_{t+k}^{CF} and r_t^e should be zero. Therefore, the non-zero correlation for some k

may imply the inefficiency of stock price. In the next section, I find that the firm-level correlations implied by forecasting regressions are not zero, particularly negative, for short-term horizons. Thus, I will investigate the potential reasons of this negative correlation.

4. Forecasting Regression Results

In this section, I run the forecasting regressions of multi-period returns on ICC at the aggregate level, as well as at the firm and portfolio level. I show that the predictive power of ICC depends on the level of aggregation.

4.1. Summary Statistics

Figure 1 shows the time trend in ICC at the aggregate level. Specifically, Figure 1 plots the time trends of the value-weighted ICC, the risk free rate (one-month T-bill rate), and the value-weighted implied risk premium (IRP). The IRP is obtained by subtracting the risk free rate from the ICC. The trend in Figure 1 displays a very similar pattern that is reported in Li, Ng, and Swaminathan (2012)[4]. There are some noticeable hikes in the ICC and the IRP. For example, after October 1987, there is a significant jump both in the ICC and the IRP caused by the price drop due to the stock market crash. Also, the IRP reaches to its highest point at March 2009 when stock market experienced its deepest downturn and the T-bill rate was near zero.

Table 1 reports the summary statistics of the variables for the empirical analyses. Panel A shows the descriptive statistics of the aggregate return and the aggregate ICC, while Panel B shows the summary statistics of the pooled sample for the firm-level analyses. Panel C reports the auto-correlations of returns and ICC both at the aggregate and the firm level. The value-weighted and equally-weighted market returns are obtained from CRSP.

Panel A shows that the means of monthly market return and monthly aggregate ICC are of similar magnitude. The time-series averages of value-weighted (equally-weighted) returns and the value-weighted (equally-weighted) ICC are 0.95% and 0.88% (1.13% and 1.18%), respectively, implying that the average ICC closely approximates the average realized return at the aggregate

[4] Li, Ng, and Swaminathan (2012) use only S&P500 firms to obtain the IRP, while this paper uses all the available firms in IBES. The average number of firms that are used to calculate IRP is about 360 in Li, Ng, and Swaminathan (2012), while it is 2,165 in this paper. Nevertheless, the time-trend pattern in IRP plotted in Figure 1 is very similar with that in Li, Ng, and Swaminathan (2012)

level. As expected, however, the ICC displays a much smaller standard deviation than realized return. The standard deviation of value-weighted (equally-weighted) market return is about 4.6% (5.5%), while the standard deviations of both the value-weighted and equally-weighted ICC are about 0.1%.

Panel B shows that the mean of firm-level ICC also closely approximates the mean of firm-level returns. The monthly average return in the pooled sample is 1.18%, while the average ICC is 1.15%. Similar to the aggregate level, the standard deviation of firm-level returns is much higher than that of firm-level ICC. Panel B also reports that compared to the entire CRSP sample for period 1981 – 2010, firms in this sample tend to be larger and have lower book-to-market ratio. The average market capitalization in the pooled sample is $2,516 million, while it is $1,278 million in the entire CRSP sample. The average book-to-market ratio is 2.21, which is lower compared to 4.68 in the entire CRSP sample.

Panel C reports the autocorrelation structure of returns and ICC. To calculate the k^{th} autocorrelation of firm-level ICC or returns, firms with less than $k + 24$ observations are excluded. Panel C shows that there is no obvious pattern in the autocorrelation of returns except that there is a strongly positive one-month autocorrelation in the aggregate level. The aggregate ICC, however, displays persistent autocorrelations. Interestingly, the equally-weighted ICC shows higher persistence in the long-run. The 60-month autocorrelation of equally-weighted ICC is 0.465, while it is 0.231 for the value-weighted ICC. Panel C also show that the firm-level ICC display less persistent autocorrelation than the aggregate ICC. The autocorrelation in the pooled sample shows a higher persistence than the cross-sectional mean of firm-level autocorrelation, which eventually become indistinguishable from zero. However, the cross-sectional means of firm-level autocorrelation has similar decaying pattern with the autocorrelation in the pooled sample.

4.2. Aggregate-level Results

Table 2 summarizes the forecasting regression results of the aggregate returns on the aggregate ICC (Equation (5)). The dependent variables are the continuously compounded returns per month for the period t to $t + K$ (for K =1 to 60), calculated from monthly value-weighted market returns obtained from CRSP. The explanatory variables are the value-weighted ICC at time t. Figure 2 graphically presents the results the aggregate-level regressions. Each panel plots the coefficients, the simulated p-values, and R^2 for different forecasting periods.

The results shown in Table 2 and Figure 2 are consistent with Li, Ng, and Swaminathan (2012). The aggregate ICC has positive and significant coefficients for most forecasting horizons. The coefficients are about or close to three for most forecasting horizons. This implies that an 1% increase in the ICC in the current month is associated with a 3% increase in the realized return per month over next 60-month horizon. This association is economically significant. As expected, p-values of asymptotic t-statistics with Newey-West correction becomes more significant as K increases, from 10.8% for one-month to 0.0% for 60-month period. The asymptotic p-values for all forecasting horizons, except $K = 1, 7$, and 8, are significant at 10% and are significant at less than 5% for above the 12-month horizon.[5] However, the simulated p-values from the Monte Carlo simulation (Equation (7)) are less significant, above 10% for the horizons up to 12 months, except for $K = 2$ and 3. Nevertheless, forecasting horizons above 12 months show significant simulated p-values at 10% level. In addition, the Wald statistics (Equation (8)) are significant at 10% level for all the forecasting horizons (significant at 5% except $K = 2, 11, 12$, and 18). Also, R^2s increase with horizons from 0.4% for one-month to 36% for 60-month period. Overall, the significance of forecasting power using the aggregate ICC increases as the horizon increases. In sum, the results in Table 2 and Figure 2 confirm the findings of Li, Ng, and Swaminathan (2012), showing the aggregate ICC has a significant forecasting power.

4.3. Firm-Level Regressions

Table 3 reports the results of firm-level analyses using a simple forecasting regression model. Panel A reports the summary statistics of the cross-section of individual forecasting regression results, while Panel B reports the results of the panel regression with firm fixed effect. K-period returns of each individual firm are regressed on the ICC of the firm at t using Equations (5) and (6). To obtain the regression results of the K-period returns, firms with less than $K + 24$ observations are excluded. Figure 3 compares the mean and the median of the coefficients, t-values, and R^2 of individual firm-level time-series regressions in Equation (5) with the market-level coefficient, t-value, and R^2.

Table 3 and Figure 3 show that the patterns in the firm-level returns and ICC are clearly differ-

[5]Since a one-sided test is appropriate, the 5% critical value is 1.65 and 10% critical value is 1.28.

ent from those found in the aggregate level. Both the mean and the median coefficients have clear downward trends, while the aggregate-level coefficients are stable at about three. The mean of the coefficients is compatible with the aggregate-level regressions for one-month forecasting horizon, but they decrease below one quickly and eventually become close to zero for long-term forecasting horizons. The median coefficients of firm-level regressions are below one for all forecasting horizons. Although the magnitude of the coefficients is not compatible with time-series regressions, the coefficients of the panel regression show a similar decreasing trend. This result suggests that at the firm level, economic magnitude of the association between the ICC and returns decreases very quickly as the horizon increases.

At the firm level, the mean and median t-values are below the critical value at 10% level and are mostly flat over different forecasting horizons. Thus, for the majority of firms, the ICC does not have significant explanatory power in forecasting returns. For the panel regression, the asymptotic t-values are significant. However, p-values for the Wald statistics are insignificant, indicating that the coefficients for overlapping horizons are correlated. On the other hand, the mean and median R^2 are actually higher than R^2 of the aggregate-level regressions for short forecasting horizons. For example, the mean (median) R^2 for 12-month forecasting horizon is 12% (5%), while R^2 for the aggregate-level regression is 4% for the horizon. However, the trends are reversed. The increasing trends in both mean and median R^2 slow down, and become eventually flattened as the horizon increases. This pattern suggests that unlike the aggregate level, using longer horizon returns does not results in more predictive power of ICC at the firm level.

The different implications of the firm-level regression results from the aggregate-level results are reminiscent of Kothari, Lewellen, and Warner (2006), who document a negative contemporaneous relation between the market returns and the aggregate earnings changes but a positive relation between firm-level returns and firm-level earnings changes. Vuolteenaho (2002) also documents the main driving force of stock returns depends on the aggregation level. He shows that firm-level returns are driven more by cash-flow news, while the expected-return news is more important in explaining the market return variation. Therefore, in the next section, I examine what explains this contrasting results between firm-level forecasting regressions and aggregate-level regressions.

4.4. Does the Aggregation Process Increase the Predictability?

In this subsection, I examine whether the aggregation process increases the predictability of ICC. Specifically, I study whether the predictability gain through the aggregation depends on firm size. Table 4 presents the results of the forecasting regressions of size-sorted portfolio. Panel A reports the portfolio results for firms in the size Quintile 5, while Panel B shows the results for firms in Quintile 1. To form a size-sorted portfolio, stocks are sorted into quintiles based on the market capitalization at the end of previous month. Within each quintile, stocks are further sorted into N portfolios according to their sizes. The value-weighted portfolio returns are regressed on value-weighted portfolio ICC using the Equation (5). Then, the average coefficients, t-statistics and R^2 of N portfolios are reported. Figure 5 is a graphical presentation of portfolio-level regressions. The first column shows the results of portfolios in Quintile 5, while the second column shows the results of portfolios in Quintile 1.

The results shown in Table 5 and Figure 4 suggest that the predictive power of ICC indeed comes from large firms. The average coefficient of portfolios in Quintile 5 increase as more firms are included in a portfolio. For example, when 20 portfolios are formed within Quintile 5, the average coefficient of 20 portfolios for the 60-month horizon is 0.90. On the other hand, the coefficient is 3.14 when the entire firms in Quintile 5 are used to form a portfolio. The average t-values and R^2 have a similar pattern within Quintile 5. The more firms are included in a portfolio, the better the portfolio ICC is able to predict future portfolio returns.

However, this predictability gain is not observed in the group of small firms. Adding more firms in a portfolio increases the level of the coefficients only marginally for short-term horizon periods. Also, within Quintile 1, the average t-statistics and R^2 of portfolios do not vary much depending on the level of aggregation. Therefore, the size-sorted portfolio results suggest that the aggregation process increase the predictability of the ICC only for big firms.

5. Implied Correlation between ICC and Future Cash-flow News

5.1. Pattern in the Implied Correlations

The previous section shows that the predictability of the aggregate ICC is different from that of firm-level ICC. In this section, I examine what causes the difference in the predictive power between the aggregate and firm-level ICC. Specifically, I study the firm-level correlation between ICC and future cash-flow news is different from the aggregate-level correlation.

Table 6 and Figure 6 report the implied correlations between future cash-flow news at period $t + K$ and the ICC at t. The implied correlation between the cash-flow news and the ICC is obtained using Equation (14). The average firm-level implied correlations are obtained using the coefficients of the panel regressions and the autocorrelations of the ICC in the pooled sample.[6]

To calculate the correlations in Equation (14), a couple of parameter values should be determined. First, ρ is assumed to be 0.996, following the predictability literature.[7] Second, the volatility ratio, $\sigma(r^e)\Big/\sigma(\eta^{CF})$, is estimated to be 0.025. Depending on how it is measured, the volatility of cash-flow news is 20 to 200 times larger than that of ICC.[8] However, because the volatility ratio is just a scalar that affects the correlations only proportionately, the choice of the ratio does not change the pattern in Table 6 and Figure 6. Here, I choose 0.025 for the ratio so that the maximum correlation is below the unity.

Table 6 shows that the firm-level correlations display a quite different pattern from the aggregate-level correlations. First, the magnitude of negative correlations for short-term forecasting periods is much higher in the firm level than in the aggregate level. The correlation between ICC and one-month ahead cash-flow news is -0.630 in the firm level, while the aggregate-level correlation is -0.079. More importantly, however, while the aggregate-level correlations do not display any specific pattern, the firm-level correlations show a pattern similar to an AR process; The correlations are strongly negative for first few months, but they decay proportionately to zero.

The patterns reported in Table 6 are seen more clearly in Figure 6. The first panel shows the aggregate-level correlations, and the second low plots the firm-level correlations. Although there seem to be some seasonality, it is hard to find any specific pattern in the aggregate-level correlations. On the other hand, the firm-level correlations clearly show a pattern of an AR process. The decay rate is exponential and the correlation between the ICC at t and future cash-flow news at $t + K$ approaches to zero as K increases. Although the firm-level correlation between current month ICC and one-month ahead cash-flow news is of the magnitude of eight times the aggregate-

[6]The average firm-level implied correlations obtained from firm-level time-series regressions have a very similar pattern.

[7]For example, Vuolteenaho (2002) and Cohen, Polk, and Vuolteenaho (2003) use ρ = 0.96 for annual data, which means 0.996 for monthly data.

[8]For example, while the standard deviation of the value-weighted ICC is 0.12%, the standard deviation of the growth in 12-month moving average dividend is 2.83%. The standard deviation of quarterly aggregate earnings growth 17.7%.

level correlation, the firm-level correlations quickly decrease and are not distinguishable from zero for longer horizons. The difference between the aggregate and the firm level is striking and may explain the reasons why firm-level ICC does not predict the future returns. I will further explore the reasons why firm-level correlation is negative in the next subsection.

5.2. Why is the Firm-level Correlation Negative?

Equation (13) shows that the coefficient of the forecasting regression is determined by the correlation between the ICC and the future cash-flow news, as well as the persistence of the ICC. Equations (11) and (12) show that the changes in ICC contain the information about the one-period conditional expected return and the expected-return news during the forecasting period. Therefore, if expected returns are persistent, the ICC should also display the persistence. Thus, the strong predictability of ICC suggests that ICC is a good proxy for conditional expected returns.

Therefore, the aggregate-level results suggest that the aggregate ICC is a good proxy for expected returns. However, the return predictability is not observed in the firm-level regressions. Assuming the ICC is a reasonable proxy for the conditional expected return, the lack of predictability of ICC is due to the negative correlation between the ICC and future cash-flow news. In other words, although a high ICC means a higher ex-ante return, a high ICC is associated with negative cash-flow news, which results in low correlation between realized return and the ICC. However, future cash-flow news are, by definition, unpredictable using current information set which includes ICC. If current stock prices are efficient, we expect the correlation between future cash-flow news and the ICC is zero. Therefore, the negative correlation is puzzling.

There are three possible explanations to this negative correlation at the firm level. First, there is a statistical bias in β of the firm-level forecasting regressions. Equation (14) shows that the correlation between future cash-flow news and the ICC is estimated from β and the autocorrelation of ICC. Therefore, if β is biased, the correlation is not precisely estimated. Specifically, if ICC is estimated with a measurement error, there would be an attenuation bias in β, which in turn causes the downward bias in the correlation estimate. To investigate this possibility, I use various samples that exclude firms that are likely to have high measurement errors in the ICC estimates. Since the measurement errors in ICC are likely to be higher for small firms or firms with low analyst coverage, I use following samples that exclude these firms; the sample of S&P500, the sample of large firms (Size Quintile 4 and 5), and the sample of firms with at least 5 analyst coverages. The results are reported in the Table A1. Table A1 shows almost identical results with Table 3, showing that the negative correlation pattern is robust to these samples. Therefore, the firm-level negative correlation between future cash-flow news and the ICC is not likely to be driven by the statistical bias.

Second, the potential bias in analyst forecasts may be the cause of the negative correlation. The literature provides ample evidence indicating that analysts could be biased (for example, La Porta (1996) and Lim (2001)). However, Li, Ng, and Swaminathan (2012) shows that the predictability of ICC in the aggregate level is not driven by the collective bias in analysts' forecasts. Nevertheless, to check whether the negative correlation is caused by the bias in analyst forecasts, the following robustness checks are conducted. First, I check whether the correlation pattern is robust to the sample of firms with low analyst forecast errors. Second, I use alternative measures of ICC, controlling for the analyst forecast bias. Specifically, ICC_low is estimated using the lowest forecast instead of the consensus forecast. Also, ICC_rank is estimated using analyst forecast adjusted by recent forecast errors (Chen, Da, and Zhao (2012)). Table A2 reports that the firm-level results are robust to various ways of controlling for the bias in the analyst forecasts. Therefore, the negative correlation is not likely to be driven by the potential bias in analyst forecasts.

Finally, the negative correlation may be due to inefficient market price in the firm level. This explanation is similar to Bernard and Thomas (1990), who document that the stock prices do not fully reflect the information that are contained in the current earnings announcement. Specifically, they show that investors are constantly surprised by earnings changes that are predictable by autocorrelation structure of earnings. If firm-level prices do not fully reflect all the information regarding future cash flows, the realization of future cash flows may be systematically associated with the current ICC. I investigate this possibility carefully in the following subsection.

5.3. Under-reaction to the Current Cash-Flow News

In this subsection, I examine whether the negative correlation at the firm level between the ICC and future cash-flow news is due to the inefficient response of market participant to the current cash-flow news. Consider the following model where stock prices do not fully reflect the implication of the current cash-flow news:

$$Cov(\eta_{t+1}^{CF}, r_t^e) = Cov(\rho\eta_t^{CF} + u_t, E_t(r_{t+1}) + \epsilon_t) = \rho Cov(\eta_t^{CF}, E_t(r_{t+1})) \tag{15}$$

where ρ is considered as the coefficient of timely response. In an efficient market, ρ should be zero. A positive ρ implies the under-reaction of market participants, while a negative ρ implies the over-reaction. It is difficult to directly observe ρ, since cash-flow news are usually measured as residuals from a regression. However, the sign of ρ can be obtained by determining the signs of terms in Equation (15), namely $Cov(\eta_{t+1}^{CF}, r_t^e)$ and $Cov(\eta_t^{CF}, E_t(r_{t+1}))$.

First, although the firm-level forecasting regression results and the decomposition of β_K imply that $Cov(\eta_{t+1}^{CF}, r_t^e)$ is negative, I examine the sign of $Cov(\eta_{t+1}^{CF}, r_t^e)$ directly from a regression model using a proxy for cash-flow news. I use unexpected earnings growth as a proxy for cash-flow news. The regression model is as follows:

$$dE_t = \alpha + \beta r_t^e + \gamma_1 dE_{t-1} + \gamma_2 dE_{t-2} + \gamma_3 dE_{t-3} + \gamma_4 dE_{t-4} + \epsilon_t \tag{16}$$

where $dE_t = (E_t - E_{t-4})/P_{t-4}$, which is seasonally differenced earnings, equal to earnings this quarter minus earnings four quarters ago, scaled by market equity at the end of four quarter ago. The explanatory variables include the lagged dependent variables up to 4th lag. Including the lagged dependent variables is to orthogonalize the unexpected components of earnings from the earnings growth that is predictable from previous earnings announcement. Therefore, the regression is equivalent to a regression of residuals of an AR(4) model on the ICC. The regression model is estimated both at the aggregate and firm level.

Table 7 reports the results of Regression (16). Table 6 shows that the results are consistent with the decomposition; close-to-zero correlation at the aggregate and the negative correlation at the firm level. While the aggregate-level ICC do not predict the aggregate earnings growth, firm-level ICC is significantly related with future unexpected earnings. This negative relation is robust to different specifications, including firm fixed effect and Fama-MacBeth regressions. Table 6 also shows that the negative relation between firm-level ICC and the future unexpected earnings is not due to analyst forecast errors. Controlling for the forecast error for the fiscal quarter $t-1$ does not have effect on the negative relation. In addition, the table shows the predictive ability of firm-level ICC on future earnings surprise is stronger for small firms. While the coefficient on the interaction between the dummy for big firms and the ICC is positive (and significant for the model with the firm fixed effect), the interaction between the dummy for small firm and the ICC is significantly negative for all the specification. In sum, the results confirm the firm-level negative relation between future cash-flow news and the ICC.

Second, I examine the sign of $Cov(\eta_t^{CF}, E_t(r_{t+1}))$ to infer the sign of ρ. Evidence in the literature suggests that $Cov(\eta_t^{CF}, E_t(r_{t+1}))$ is negative. For example, Sadka and Sadka (2009) show that at the aggregate level, expected future earnings changes are negatively related with the expected return at t. Since a positive cash-flow news at t is likely to increase expected future earnings growth, I expect that the contemporaneous relation between the cash-flow news and the expected return is negative. To examine the relation between the expected return and the current cash-flow news, I use realized return at quarter $t+1$ as a proxy for the expected return at t, and unexpected earnings growth for the quarter $t-1$ as a proxy for cash-flow news at t. Specifically, I run the following regression:

$$r_{t+1} = \alpha + \beta dE_{t-1} + \gamma_1 dE_{t-2} + \gamma_2 dE_{t-3} + \gamma_3 dE_{t-4} + \gamma_4 dE_{t-5} + \epsilon_t. \tag{17}$$

I run the above regression both at the aggregate and firm level. For, the firm-level regression, I run a panel regression with the firm fixed effect. The regression above is equivalent to the regression of r_{t+1} on the residuals of the AR(4) model.

Table 8 reports the regression results. Both the aggregate and firm-level regressions show a negative coefficient on the cash-flow news at t, although the coefficient for the aggregate-level regression is not significant. This is likely due to the fact that the aggregate-level earnings growth is more predictable than the firm-level growth. Nevertheless, the firm-level regressions confirm that there is a strong negative relation between the expected return and the current cash-flow news.

Overall, evidence in Tables 7 and 8 show that ρ is positive for firm-level cash-flow news. This implies that firm-level stock prices do not fully reflect the implication of current cash-flow news. Therefore, the negative relation between future cash-flow news and the ICC is likely to be due to a delayed response of market participants to the firm-level cash-flow news.

6. Conclusion

The contribution of this paper is as follows. First, I show that predictability of stock returns using ICC depends on the aggregation level. While the aggregate ICC strongly predicts short- and long-run realized returns, the firm-level ICC do not have the predictive power for firm-level returns. Although the aggregation process increases the predictive power of ICC, the predictability gain is only observed among large firms. However, the lack of predictability of firm-level ICC is not due to small firm, or the potential bias in analyst forecasts.

Second, I show that the difference between the aggregate and the firm-level ICC with respect to return predictability is due to the different correlation structure between ICC and future cash-flow news. While the correlation between future cash-flow news and the ICC is close to zero at the aggregate level, the firm-level correlation is strongly negative for short-term forecasting horizons. Therefore, the firm-level predictability is dampened by this negative correlation between future cash-flow news and the ICC. Finally, the negative correlation at the firm level implies that the stock prices may under-react to the current cash-flow news. Panel regressions using unexpected earnings growth as a proxy for cash-flow news, I provide evidence consistent with this under-reaction hypothesis.

References

Ang, Andrew and Geert Bekaert, 2007, Stock return predictability: Is it there? *Review of Financial Studies* 20, 651-707

Abarbanell, Jeffery S. and Victor L. Bernard, 1992, Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior, *The Journal of Finance* 67, 1181-1207.

Baker, Malcolm and Jeffrey Wurgler, 2000, The equity share in new issues and aggregate stock returns, 2000, *The Journal of Finance* 55, 2219-2257.

Bernard, Victor L. and Jacob K. Thomas, 1990, Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, *Journal of Accounting and Economics* 13, 305-340.

Boudoukh, Jacob, Roni Michaely, Matthew Richardson, and Michael Roberts, 2007, On the importance of measuring payout yield: Implications for empirical asset pricing, *The Journal of Finance* 62, 877-915.

Boudoukh, Jacob, Matthew Richardson, and Robert F. Whitelaw, 2008, The myth of long-horizon predictability, *Review of Financial Studies* 21, 1577-1605.

Campbell, John Y., 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373-399.

Campbell, John Y., 1991, A variance decomposition for stock returns, *Economic Journal* 101, 157-179

Campbell, John Y. and Robert J. Shiller, 1988, The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, 195-228.

Campbell, John Y. and Tuomo Vuolteenaho, 2004, Inflation illusion and stock prices, *American Economic Review* 94, 19-23.

Chen, Long, Zhi Da, and Xinlei Zhao, 2012, What drives stock price movement? working paper

Cochrane, John H., 1991, Production-based asset pricing and the link between stock returns and economic fluctuations, *The Journal of Finance* 46, 209-237.

Cohen, Randolph B., Paul A. Gompers, and Tuomo Vuolteenaho, 2002, Who underreacts to cash-flow news? evidence from trading between individuals and institutions, *Journal of Financial Economics* 66, 409-462.

Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2003, The value spread, *The Journal of Finance* 58, 609-641.

Fama, Eugene F. and Kenneth R. French, 1988, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3-25.

Kothari, S.P., Jonathan W. Lewellen, and Jerold B. Warner, 2006, Stock returns, aggregate earnings surprises, and behavioral finance, *Journal of Financial Economics* 15, 143-171.

La Porta, Rafael, 1996, Expectations and the cross-section of stock returns, *The Journal of Finance* 51, 1715-1742

Lee, Charles M.C., David Ng, and Bhaskaran Swaminathan, 2009, Testing international asset pricing models using implied cost of capital, *Journal of Financial and Quantitative Analysis* 44, 307-335.

Lettau, Martin and Sydney C. Ludvigson, 2001, Resurrecting (c)capm: A cross-sectional test when risk premia are time-varying, *Journal of Political Economy* 109, 1238-1287.

Li, Yan, David T. Ng, and Bhaskaran Swaminathan, 2012, Predicting market returns using aggregate implied cost of captial, working paper.

Lim, Terence, 2001, Rationality and analysts' forecast bias, *The Journal of Finance* 56, 369-385.

Pástor, Ľuboš, Meenakshi Sinha, and Bhaskaran Swaminathan, 2008, Estimating the intertemporal risk-return tradeoff using the implied cost of capital, *The Journal of Finance* 63, 2859-2897.

Pontiff, Jeffrey and Lawrence D. Schall, 1998, Book-to-market ratios as predictors of market returns, *Journal of Financial Economics* 49, 141-160.

Sadka, Gil and Ronnie Sadka, 2009, Predictability and the earnings-returns relation, *Journal of Financial Economics* 94, 87-106.

Vuolteenaho, Tuomo, 2002, What drives firm-level stock returns? *The Journal of Finance* 57, 233-264.

Table 1: Summary Statistics

This table provides summary statistics for stock returns and the ICC. Panel A shows the summary statistics of the aggregate returns and the aggregate ICC, while Panel B reports the firm-level returns and ICC in the pooled sample. Panel C reports the autocorrelations of returns and ICC at the aggregate level as well as at the firm level. Return is the monthly raw return. The ICC is the monthly implied cost of capital estimated following Pástor, Sinha, and Swaminathan (2008). The sample period is 1981–2010.

Panel A: Aggregate ICC and Returns

Variables	Avg. N	Mean	Std	Q1	Median	Q3
Return - VW	6,973	0.0095	0.0459	-0.0173	0.0142	0.0397
Return - EW	6,973	0.0113	0.0550	-0.0203	0.0154	0.0431
ICC - VW	2,165	0.0088	0.0012	0.0079	0.0085	0.0093
ICC - EW	2,165	0.0118	0.0014	0.0110	0.0117	0.0126

Panel B: Pooled Sample

Variables	N	Mean	Std	Q1	Median	Q3
Return	779,397	0.0118	0.1359	-0.0556	0.0069	0.0724
ICC	779,397	0.0115	0.0078	0.0067	0.0091	0.0136
Market Cap ($mil)	779,397	2,516	12,034	107	341	1,210
B/M	665,184	2.21	35.35	0.35	0.58	0.93

Panel C: Autocorrelation

	Aggregate Level				Firm Level			
Lag	Value Weighted		Equally Weighted		Pooled Sample		Cross-Sectional Mean	
	Return	ICC	Return	ICC	Return	ICC	Return	ICC
1	0.1087	0.9716	0.2679	0.9748	0.0057	0.8720	-0.0261	0.7186
2	-0.0281	0.9444	-0.0061	0.9473	-0.0113	0.7773	-0.0319	0.5302
3	0.0117	0.9193	-0.0099	0.9227	0.0015	0.7028	-0.0169	0.3952
4	-0.0017	0.8978	-0.0307	0.9016	-0.0085	0.6482	-0.0238	0.3034
5	0.0404	0.8807	-0.0370	0.8877	-0.0118	0.6055	-0.0223	0.2375
6	-0.0357	0.8675	-0.0764	0.8811	-0.0104	0.5706	-0.0215	0.1906
12	0.0072	0.8016	0.0038	0.8418	-0.0004	0.4619	-0.0055	0.0804
24	0.0539	0.5998	0.0825	0.7423	0.0069	0.3579	0.0044	0.0116
36	-0.0404	0.4485	0.0228	0.6425	-0.0010	0.2924	-0.0016	-0.0198
48	0.0162	0.3707	0.0749	0.5727	0.0039	0.2510	0.0022	-0.0150
60	-0.1053	0.2309	-0.0444	0.4651	-0.0068	0.2363	-0.0099	-0.0166

Table 2: Aggregate-level Regressions

This table summarizes the forecasting regression results of the aggregate returns on the aggregate ICC. The dependent variables are the continuously compounded returns per month for the period *t* to *t+j* (for *j*=1 to 60), calculated from monthly value-weighted market returns obtained from CRSP. The explanatory variables are the value-weighted ICC at time *t*. A monthly firm-level ICC is estimated following Pástor, Sinha, and Swaminathan (2008). Asymtotic *p*-value are based on GMM standard errors with Newey-West correction. The simulated *p*-values are obtained by comparing the regression coefficients with the empirical distribution generated from 5,000 trials of a Monte Carlo simulation under the assumption of no predictability and an AR(1) process of ICC. The *p*-values of the Wald statistics, which test the joint hypothesis of $\beta_1 = \cdots = \beta_j = \cdots = \beta_J$, are also reported. The sample period is 1981–2010.

Horizon	β	Asym. *p*	Sim. *p*	Wald (*p*)	R^2
1	2.519	0.108	0.115	0.209	0.4%
2	2.977	0.022	0.086	0.052	1.1%
3	2.802	0.037	0.098	0.025	1.4%
4	2.493	0.066	0.119	0.016	1.4%
5	2.305	0.091	0.135	0.031	1.5%
6	2.293	0.099	0.135	0.025	1.8%
7	2.254	0.108	0.137	0.042	2.0%
8	2.294	0.106	0.130	0.044	2.3%
9	2.418	0.094	0.118	0.030	2.9%
10	2.478	0.084	0.112	0.043	3.3%
11	2.479	0.078	0.111	0.058	3.7%
12	2.514	0.069	0.106	0.052	4.1%
18	3.083	0.015	0.063	0.057	9.4%
24	3.004	0.015	0.063	0.032	12.2%
36	2.834	0.007	0.056	0.011	17.3%
48	2.851	0.001	0.046	0.003	25.9%
60	2.888	0.000	0.035	0.006	35.7%

Table 3: Firm-level Analyses– Simple Regressions

This table provides the results of firm-level forecasting regressions using the ICC as a forecasting variable. Panel A reports summary statistics of the cross-section of firm-level time-series regression results. Panel B shows the results of the panel regression with a firm fixed effect. The dependent variables are firm-level continuously compounded returns per month for the period *t* to *t+j* (for *j*=1 to 60). The explanatory variables are the firm-level ICC at time *t*. A monthly firm-level ICC is estimated following Pástor, Sinha, and Swaminathan (2008). To obtain the regression results of the *j*-period returns, firms with less than *j*+24 observations are excluded. Aymtotic *t*-values for individual time-series regressions are obtained using GMM standard errors with Newey-West correction. Asymtotic *t*-values for the panel regressions are obtained using the generalized Hodrick (1992). For the panel regressions, both the within groups R^2 and the between groups R^2 are reported. The sample period is 1981–2010.

Panel A: Distribution of Time Series Regressions

Horizon	Variable	Mean	Std	Q1	Median	Q3
1	β	2.256	8.493	-1.179	0.937	4.017
	t -value	[0.38]	[1.19]	[-0.36]	[0.37]	[1.11]
	R^2	2.46%	4.15%	0.18%	0.84%	2.90%
3	β	1.436	6.336	-1.164	0.698	3.244
	t -value	[0.43]	[1.69]	[-0.61]	[0.43]	[1.46]
	R^2	4.92%	7.44%	0.40%	1.97%	6.08%
6	β	0.926	4.971	-1.058	0.536	2.556
	t -value	[0.47]	[2.07]	[-0.71]	[0.42]	[1.59]
	R^2	6.85%	9.67%	0.63%	2.85%	9.17%
12	β	0.595	3.565	-0.785	0.472	1.946
	t -value	[0.65]	[2.85]	[-0.76]	[0.52]	[1.88]
	R^2	8.39%	11.10%	0.85%	3.87%	11.61%
24	β	0.393	2.868	-0.505	0.360	1.434
	t -value	[0.85]	[3.03]	[-0.73]	[0.69]	[2.21]
	R^2	9.80%	12.20%	1.15%	5.00%	13.95%
36	β	0.181	2.178	-0.520	0.260	1.130
	t -value	[0.93]	[3.30]	[-0.86]	[0.76]	[2.41]
	R^2	10.54%	12.67%	1.36%	5.72%	14.94%
48	β	0.093	1.947	-0.444	0.207	0.893
	t -value	[0.92]	[3.42]	[-0.94]	[0.72]	[2.54]
	R^2	11.01%	13.01%	1.36%	5.94%	16.07%
60	β	0.145	1.618	-0.304	0.259	0.817
	t -value	[1.04]	[3.41]	[-0.85]	[0.88]	[2.65]
	R^2	11.40%	13.09%	1.54%	6.39%	16.87%

Panel B: Panel Regression Results

Horizon	β	t-value	Within R^2	Between R^2
1	0.419	[2.94]	0.03%	11.62%
3	0.323	[3.71]	0.06%	12.71%
6	0.273	[4.35]	0.08%	12.73%
12	0.278	[7.17]	0.18%	12.24%
24	0.281	[13.64]	0.41%	11.43%
36	0.244	[14.44]	0.52%	11.98%
48	0.219	[15.09]	0.63%	10.95%
60	0.218	[17.65]	0.86%	13.84%

Table 4: Firm-level Analyses– Multivariate Regressions

This table provides the results of firm-level forecasting regressions using multiple forecasting variables. Panel A reports summary statistics of the cross-section of firm-level time-series regression results. Panel B shows the results of the panel regression with a firm fixed effect. The dependent variables are firm-level continuously compounded returns per quarter for the period *t* to *t+j* (for *j*=1 to 20). The explanatory variables are the firm-level ICC at quarter *t,* the continuously compounded returns for *t,* book-to-market ratio at quarter *t,* return on equity at quarter *t*. Returns and the ICC are calculated as of three months after fiscal quarter end to insure that accounting information become publicly available. A quarterly firm-level ICC is estimated following Pástor, Sinha, and Swaminathan (2008). Firms with less than *j*+20 (less than *j*+4) observations are excluded for the time-series regressions (panel regressions). Aymtotic *t*-values for individual time-series regressions are obtained using GMM standard errors with Newey-West correction. Asymtotic t-values for the panel regressions are obtained using the generalized Hodrick (1992). For the panel regressions, both the within groups R^2 and the between groups R^2 are reported. The sample period is 1981–2010.

Panel A: Distribution of Time Series Regressions

Horizon (Quarter)	Variable	ICC	Ret(t-1)	B/M	ROE	R^2
1	Mean	0.351	0.008	0.124	0.491	17.96%
		[0.09]	[0.02]	[1.08]	[0.16]	
	Median	0.232	0.008	0.103	0.165	14.94%
		[0.10]	[0.04]	[1.09]	[0.17]	
4	Mean	-0.156	0.017	0.092	0.212	28.74%
		[-0.02]	[0.08]	[1.94]	[0.16]	
	Median	0.007	0.009	0.086	0.053	26.04%
		[0.01]	[0.12]	[1.77]	[0.15]	
8	Mean	-0.202	0.007	0.067	0.141	35.60%
		[-0.08]	[0.01]	[2.51]	[0.11]	
	Median	-0.067	0.002	0.066	0.024	33.41%
		[-0.10]	[0.05]	[2.22]	[0.11]	
12	Mean	-0.237	0.007	0.056	0.113	39.50%
		[-0.11]	[0.12]	[3.16]	[0.09]	
	Median	-0.039	0.003	0.057	0.019	38.08%
		[-0.11]	[0.16]	[2.79]	[0.17]	
16	Mean	-0.180	0.006	0.048	0.095	42.14%
		[-0.11]	[0.32]	[3.94]	[0.04]	
	Median	-0.033	0.004	0.048	0.003	40.90%
		[-0.09]	[0.32]	[3.26]	[0.03]	
20	Mean	-0.175	0.000	0.041	0.081	44.46%
		[-0.22]	[-0.05]	[4.41]	[0.02]	
	Median	-0.030	0.000	0.042	0.000	43.21%
		[-0.11]	[-0.05]	[3.35]	[0.00]	

Panel B: Panel Regression Results

Horizon (Quarter)	ICC	Ret(t-1)	B/M	ROE	Within R^2	Between R^2
1	0.045	0.018	0.067	0.016	1.63%	57.61%
	[0.50]	[0.58]	[5.57]	[0.27]		
4	-0.011	0.009	0.059	-0.001	5.55%	42.76%
	[-0.28]	[0.79]	[13.23]	[-0.03]		
8	0.023	0.000	0.049	0.008	9.32%	25.67%
	[0.85]	[-0.06]	[19.03]	[1.02]		
12	0.036	0.003	0.043	-0.011	12.80%	17.50%
	[2.04]	[0.83]	[27.77]	[-1.81]		
16	0.036	0.005	0.039	-0.012	16.10%	13.58%
	[2.66]	[1.38]	[32.16]	[-2.37]		
20	0.036	0.000	0.036	-0.003	20.93%	12.13%
	[3.56]	[-0.14]	[36.88]	[-0.76]		

Table 5: Size-sorted Portfolio

This table reports the forecasting regression results of size-sorted portfolios. Panel A reports the portfolio results for firms in the size Quintile 5, while Panel B shows the results for firms in Quintile 1. Stocks are sorted into quintiles based on size each month. Within each quintile, stocks are further sorted into N portfolios according to their sizes. The value-weighted portfolio returns for the period *t* to *t+j* (for *j*=1 to 60) are regressed on value-weighted portflio ICC at time *t*. Then, the average coefficients and R^2 of N portfolios are reported. A monthly firm-level ICC is estimated following Pástor, Sinha, and Swaminathan (2008). *t*-statistics are obtained using GMM standard errors with Newey-West correction. The sample period is 1981–2010.

Panel A: Big firms (Quintile 5)

Forecasting	β				t-value				R^2			
Horizon	N=1	N=5	N=10	N=20	N=1	N=5	N=10	N=20	N=1	N=5	N=10	N=20
1	1.956	1.555	1.007	0.614	0.92	0.80	0.58	0.38	0.3%	0.3%	0.3%	0.4%
2	2.657	2.037	1.508	1.061	1.46	1.19	0.95	0.76	0.9%	0.6%	0.5%	0.5%
3	2.574	2.003	1.538	1.112	1.43	1.19	1.00	0.85	1.2%	0.8%	0.7%	0.6%
4	2.416	1.968	1.526	1.123	1.30	1.15	1.00	0.88	1.3%	1.0%	0.9%	0.7%
5	2.392	1.996	1.541	1.127	1.25	1.15	1.01	0.89	1.6%	1.3%	1.0%	0.8%
6	2.451	2.080	1.621	1.157	1.25	1.18	1.06	0.93	2.0%	1.6%	1.3%	0.9%
7	2.562	2.193	1.734	1.265	1.31	1.25	1.16	1.05	2.5%	2.0%	1.7%	1.1%
8	2.658	2.302	1.831	1.337	1.36	1.32	1.24	1.15	3.0%	2.5%	2.0%	1.4%
9	2.784	2.391	1.932	1.401	1.46	1.39	1.33	1.23	3.7%	3.0%	2.5%	1.7%
10	2.771	2.398	1.950	1.411	1.50	1.42	1.37	1.26	4.1%	3.4%	2.9%	1.9%
11	2.729	2.406	1.967	1.431	1.54	1.46	1.42	1.32	4.4%	3.8%	3.2%	2.2%
12	2.732	2.427	1.974	1.431	1.61	1.53	1.48	1.37	4.8%	4.2%	3.5%	2.4%
18	2.570	2.755	2.114	1.600	2.11	2.12	2.00	1.88	7.9%	8.5%	6.4%	4.2%
24	3.160	2.646	2.080	1.506	2.71	2.37	2.24	2.06	14.2%	11.5%	8.9%	5.4%
36	3.288	2.205	1.624	1.144	2.98	2.70	2.43	2.06	19.6%	13.8%	10.1%	5.8%
48	2.172	2.271	1.670	1.063	2.28	3.24	2.91	2.19	18.7%	20.7%	14.0%	7.4%
60	3.135	2.222	1.531	0.910	3.34	3.76	3.13	2.25	30.2%	26.2%	15.5%	7.9%

Panel B: Small firms (Quintile 1)

Forecasting	β				t-value				R^2			
Horizon	N=1	N=5	N=10	N=20	N=1	N=5	N=10	N=20	N=1	N=5	N=10	N=20
1	1.284	0.384	0.671	-0.161	0.82	0.23	0.54	-0.12	0.2%	0.0%	0.2%	0.1%
2	1.548	0.812	0.698	0.059	1.00	0.55	0.59	0.06	0.4%	0.2%	0.2%	0.1%
3	1.733	1.070	0.783	0.258	1.11	0.74	0.67	0.25	0.7%	0.5%	0.3%	0.2%
4	1.717	1.082	0.788	0.273	1.08	0.74	0.67	0.25	0.9%	0.6%	0.4%	0.2%
5	1.574	1.003	0.740	0.272	0.98	0.68	0.64	0.25	0.9%	0.7%	0.5%	0.2%
6	1.518	0.973	0.719	0.259	0.93	0.65	0.61	0.23	1.0%	0.8%	0.6%	0.3%
7	1.458	0.952	0.696	0.264	0.89	0.64	0.60	0.23	1.1%	0.9%	0.7%	0.5%
8	1.444	0.954	0.689	0.266	0.87	0.66	0.60	0.26	1.3%	1.1%	0.8%	0.5%
9	1.439	0.944	0.691	0.276	0.86	0.66	0.62	0.28	1.4%	1.1%	0.8%	0.5%
10	1.488	1.013	0.719	0.302	0.90	0.72	0.67	0.33	1.7%	1.3%	1.0%	0.6%
11	1.492	1.060	0.748	0.344	0.90	0.77	0.71	0.41	2.0%	1.5%	1.1%	0.7%
12	1.523	1.128	0.798	0.398	0.93	0.83	0.78	0.50	2.3%	1.7%	1.3%	0.8%
18	1.540	1.159	0.724	0.457	0.98	0.88	0.76	0.61	3.7%	2.2%	1.7%	0.9%
24	1.122	0.942	0.546	0.316	0.73	0.74	0.61	0.46	3.0%	1.8%	1.7%	0.9%
36	0.517	0.490	0.205	0.075	0.40	0.50	0.33	0.15	1.1%	0.7%	1.1%	0.7%
48	0.278	0.358	0.175	0.014	0.28	0.48	0.33	0.05	0.5%	0.6%	1.4%	0.7%
60	0.334	0.320	0.130	-0.021	0.42	0.53	0.33	-0.02	1.1%	0.9%	1.1%	0.5%

Table 6: Correlation between Future Cash-Flow News and ICC

This table reports the implied correlations between future cash-flow news and the ICC both at the aggregate and the firm level. The implied correlation between the cash-flow news at time *t+j* (for *j*=1 to 60) and the ICC at time *t* is obtained using Equation (13). The firm-level implied correlations are calculated based on the panel regression results. The sample period is 1981–2010.

Horizon	Aggregate Level		Firm Level (Panel)	
	Beta	Imp. Corr	Beta	Imp. Corr
1	2.519	-0.079	0.419	-0.630
2	2.977	-0.050	0.365	-0.466
3	2.802	-0.064	0.323	-0.366
4	2.493	-0.068	0.307	-0.266
5	2.305	-0.047	0.292	-0.208
6	2.293	-0.010	0.273	-0.170
7	2.254	0.007	0.267	-0.128
8	2.294	0.000	0.270	-0.106
9	2.418	0.017	0.270	-0.083
10	2.478	0.016	0.269	-0.070
11	2.479	0.025	0.272	-0.062
12	2.514	0.016	0.278	-0.053
18	3.083	0.022	0.295	-0.024
24	3.004	-0.012	0.281	-0.024
36	2.834	0.010	0.244	-0.020
48	2.851	0.027	0.219	-0.006
60	2.888	0.021	0.218	-0.001

Table 7: Earnings growth and ICC

This table reports the regression results of earnings growth on ICC both at the aggregate and firm level. Earnings growth (dE) is measured by seasonally differenced earnings, equal to earnings this quarter minus earnings four quarters ago, scaled by market equity at the end of four quarter ago. dE_{t-k} is k^{th} lag of earnings growth. Big is the dummy variable that takes one when a firm belongs to the size Quintile 5 and zero otherwise. Sm is the the dummy variable that takes one when a firm belongs to the size Quintile 1 and zero otherwise. Error is analyst forecast error for quarter *t-1* scaled by begining-of-the-quarter price. A quarterly firm-level ICC is estimated following Pástor, Sinha, and Swaminathan (2008). The sample period is 1981–2010.

Variables	Aggregate Level	Firm level								
		Pooled			Firm fixed effect			Fama-MacBeth		
		(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
ICC	-0.037	-0.059	-0.028	-0.062	-0.020	-0.003	-0.042	-0.052	-0.028	-0.040
	[-0.10]	[-9.60]	[-3.87]	[-8.37]	[-2.48]	[-0.35]	[-4.33]	[-3.84]	[-2.19]	[-2.15]
dE_{t-1}	0.578	0.206	0.205	0.191	0.145	0.145	0.135	0.236	0.236	0.211
	[6.59]	[90.18]	[89.90]	[73.75]	[62.45]	[62.28]	[51.14]	[17.37]	[17.31]	[14.55]
dE_{t-2}	0.020	0.096	0.096	0.077	0.060	0.059	0.043	0.129	0.129	0.094
	[0.19]	[40.13]	[40.10]	[28.62]	[24.67]	[24.59]	[15.70]	[11.79]	[11.78]	[7.96]
dE_{t-3}	0.132	0.048	0.049	0.040	0.018	0.018	0.013	0.059	0.059	0.057
	[1.29]	[20.63]	[20.67]	[15.15]	[7.66]	[7.65]	[5.06]	[7.09]	[7.13]	[6.32]
dE_{t-4}	-0.367	-0.300	-0.300	-0.308	-0.334	-0.334	-0.337	-0.354	-0.354	-0.369
	[-4.00]	[-128.34]	[-128.22]	[-116.24]	[-140.04]	[-140.03]	[-124.84]	[-18.64]	[-18.67]	[-15.24]
Big·ICC			0.015			0.060			0.007	
			[1.41]			[3.44]			[0.52]	
Sm·ICC			-0.064			-0.058			-0.047	
			[-8.24]			[-5.12]			[-3.74]	
Error				-0.002			-0.002			-0.206
				[-2.26]			[-2.44]			[-2.87]
R^2	43.5%	13.4%	13.5%	12.7%	22.1%	22.2%	21.9%			

Table 8: Quarterly Returns and Earnings Growth

This table reports the regression results of quarterly returns on earnings growth both at the aggregate and firm level. Earnings growth (dE) is measured by seasonally differenced earnings, equal to earnings this quarter minus earnings four quarters ago, scaled by market equity at the end of four quarter ago. dE_{t-k} is k^{th} lag of earnings growth. The dependent variable is return at quarter *t+1* to insure that earnings growth for quarter *t-1* is publicly available information. The sample period is 1981–2010.

Variable	Aggregate Level			Firm Level (Panel)		
	(1)	(2)	(3)	(1)	(2)	(3)
dE_{t-1}	-0.728	-2.234	-2.423	-0.030	-0.055	-0.044
	[-0.56]	[-1.24]	[-1.33]	[-3.39]	[-5.05]	[-4.04]
dE_{t-2}		0.607	0.820		-0.003	-0.005
		[0.32]	[0.43]		[-0.24]	[-0.52]
dE_{t-3}		1.942	1.912		0.043	0.043
		[1.03]	[1.01]		[4.17]	[4.14]
dE_{t-4}		1.276	1.229		0.004	0.005
		[0.51]	[0.49]		[0.39]	[0.48]
dE_{t-5}		-2.153	-2.279		-0.006	-0.003
		[-0.88]	[-0.92]		[-0.53]	[-0.24]
ret_t			0.076			-0.032
			[0.80]			[-12.72]
R^2	0.3%	2.7%	3.2%	8.9%	8.4%	8.5%

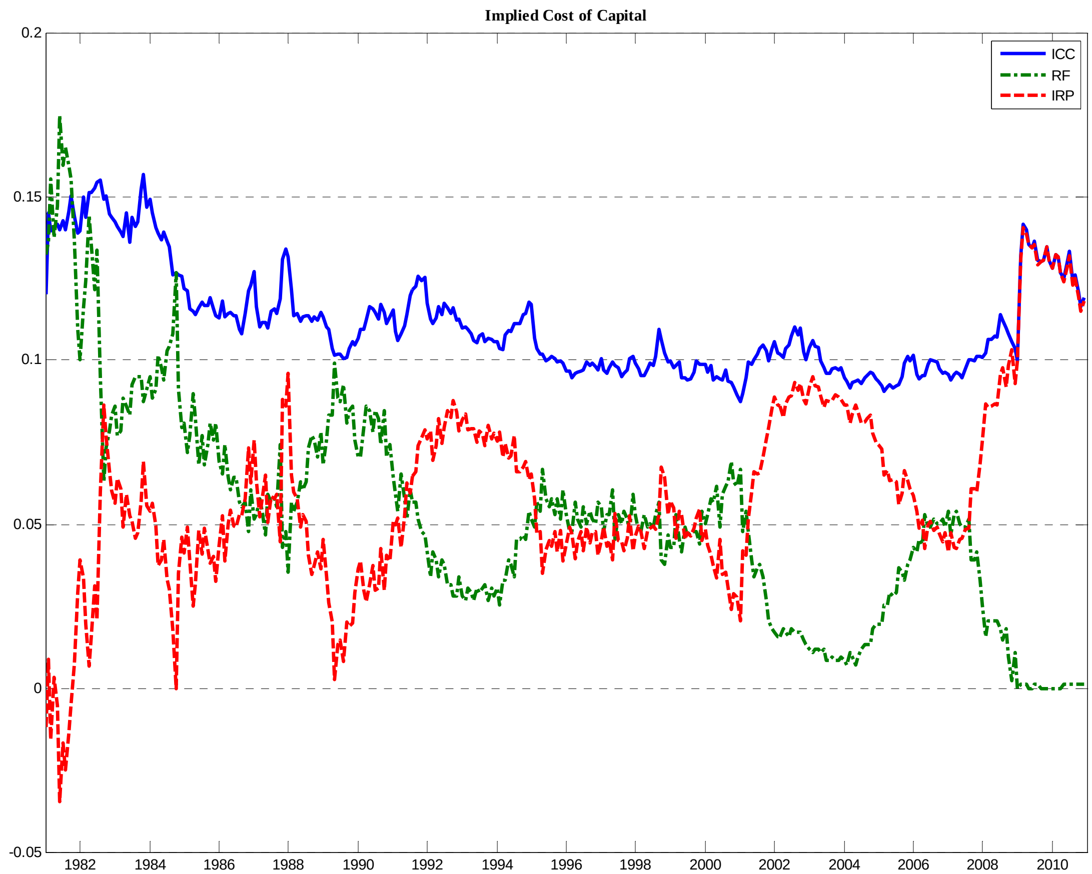

Figure 1. Time Trend of Implied Cost of Captial. The figure plots the time trends of the value-weighted implied cost of capital, the risk free rate, and the value-weighted implied risk premium. The implied risk premium is obtained by subtracting the risk free rate from the implied cost of capital. The risk free rate is the one-month T-bill rate. A monthly firm-level ICC is estimated following Pástor, Sinha, and Swaminathan (2008). The sample period is 1981–2010.

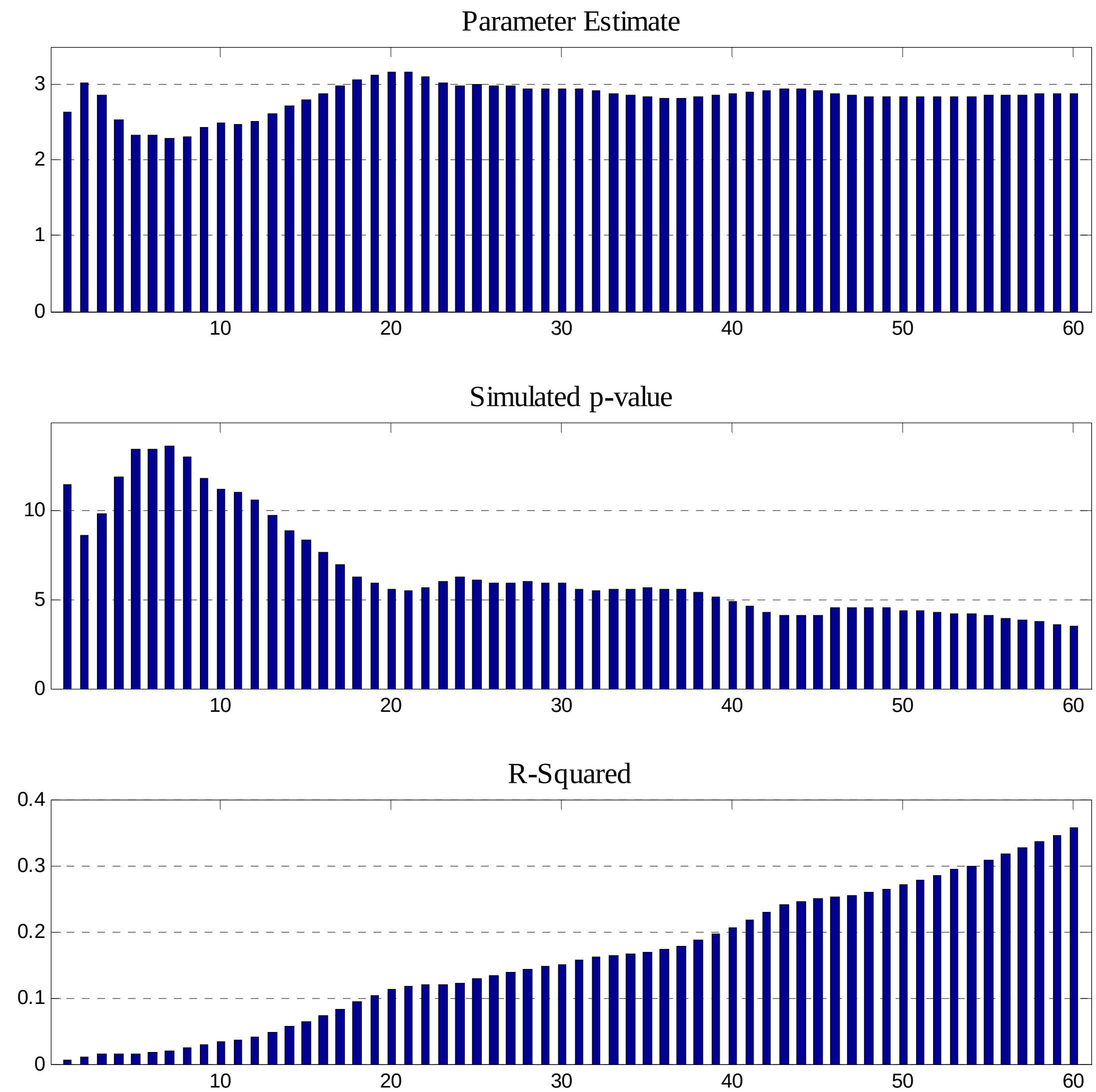

Figure 2. Aggregate-level Regressions. The figure plots the results of forecasting regressions of the aggregate returns on the aggregate ICC. Each panel shows the coefficients, the simulated *p*-values, and R^2 of the regressions. The dependent variables are the continuously compounded returns per month for the period *t* to *t+j* (for *j* =1 to 60), calculated from monthly value-weighted market returns obtained from CRSP. The explanatory variables are the value-weighted ICC at time *t*. A monthly firm-level ICC is estimated following Pástor, Sinha, and Swaminathan (2008). The simulated *p*-values are obtained by comparing the regression coefficients with the empirical distribution generated from 5,000 trials of a Monte Carlo simulation under the assumption of no predictability and an AR(1) process of ICC. The sample period is 1981–2010.

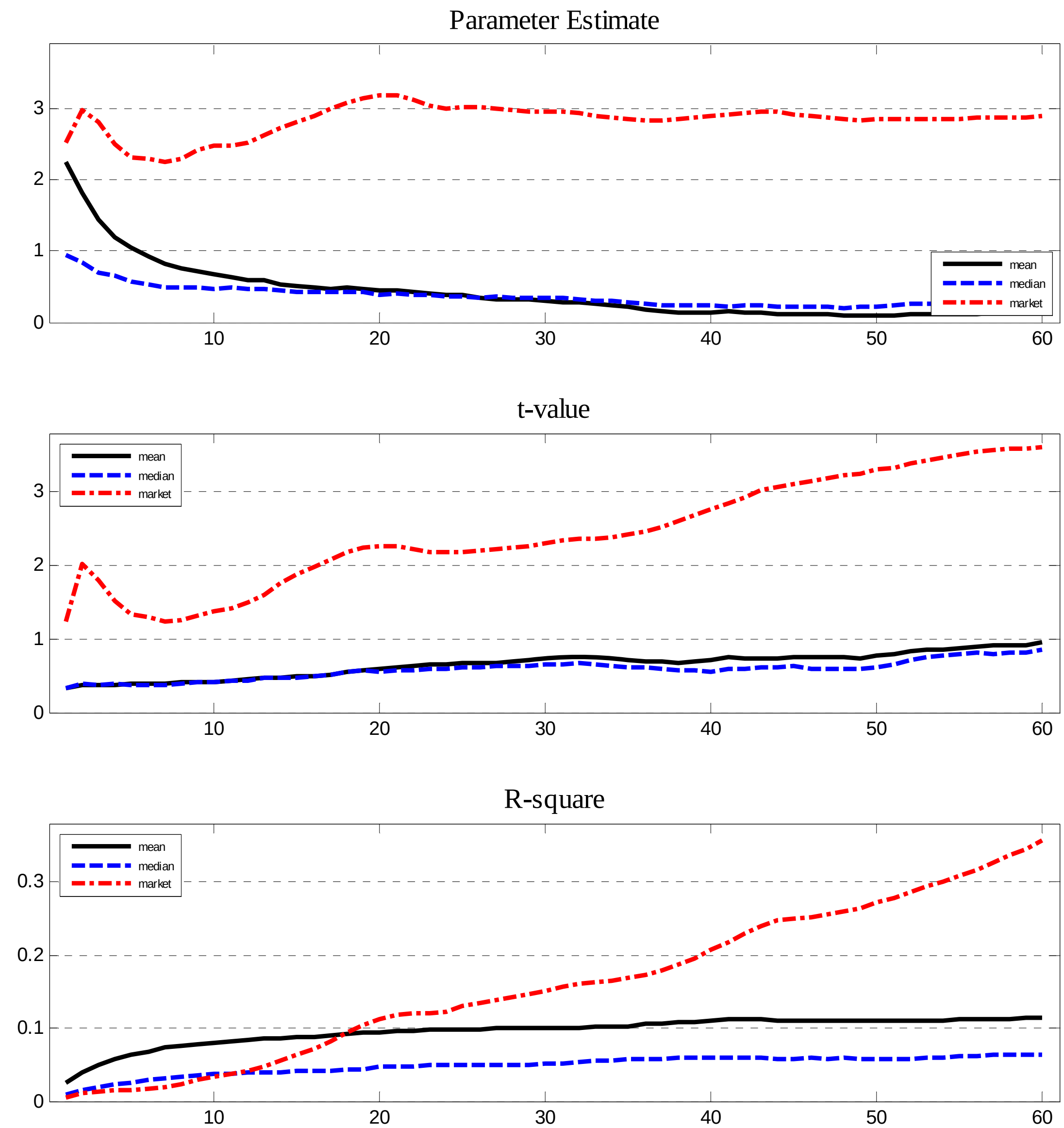

Figure 3. Firm-level Regressions. The figure plots the mean and the median of the cross-section of firm-level forecasting regression results. Each panel shows the mean and the median of the coefficients, the *t*-statistics, and R^2 of the firm-level regressions. The coefficient, the *t*-statistics, and R^2 of the aggregate-level regressions are also plotted for comparison. The dependent variables are the continuously compounded returns per month of each firm for the period t to $t+j$ (for j=1 to 60). The explanatory variables are the firm-level ICC at time t. A monthly firm-level ICC is estimated following Pástor, Sinha, and Swaminathan (2008). To obtain the regression results of the j-period returns, firms with less than j+24 observations are excluded. *t*-statistics are obtained using GMM standard errors with Newey-West correction. The sample period is 1981–2010.

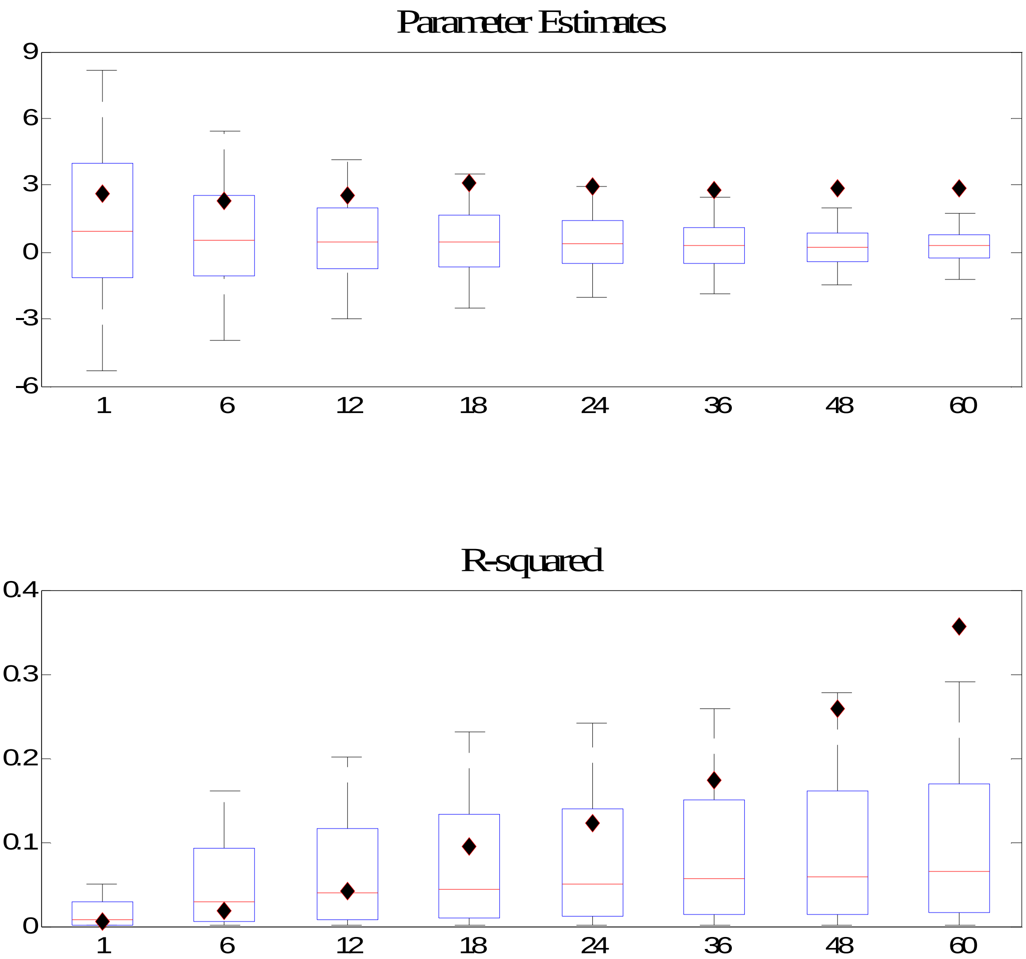

Figure 4. Distributions of Coefficient Estimates and R^2 of Firm-level Regressions. The figure provides boxplots of the distributions of firm-level predictive regressions for various forecasting horizons. The first panel reports the distribution of β and the second panel shows the distribution of R^2 of regressions. The boxes show the median, 25th, and 75th percentile. The whisker value is 0.8 of the interquartile range, which approximately coincides with 10th and 90th percentile, if the distribution is normal. The diamonds on boxes represent the β and R^2 of aggregate-level regressions for corresponding forecasting horizons. The sample period is 1981–2010.

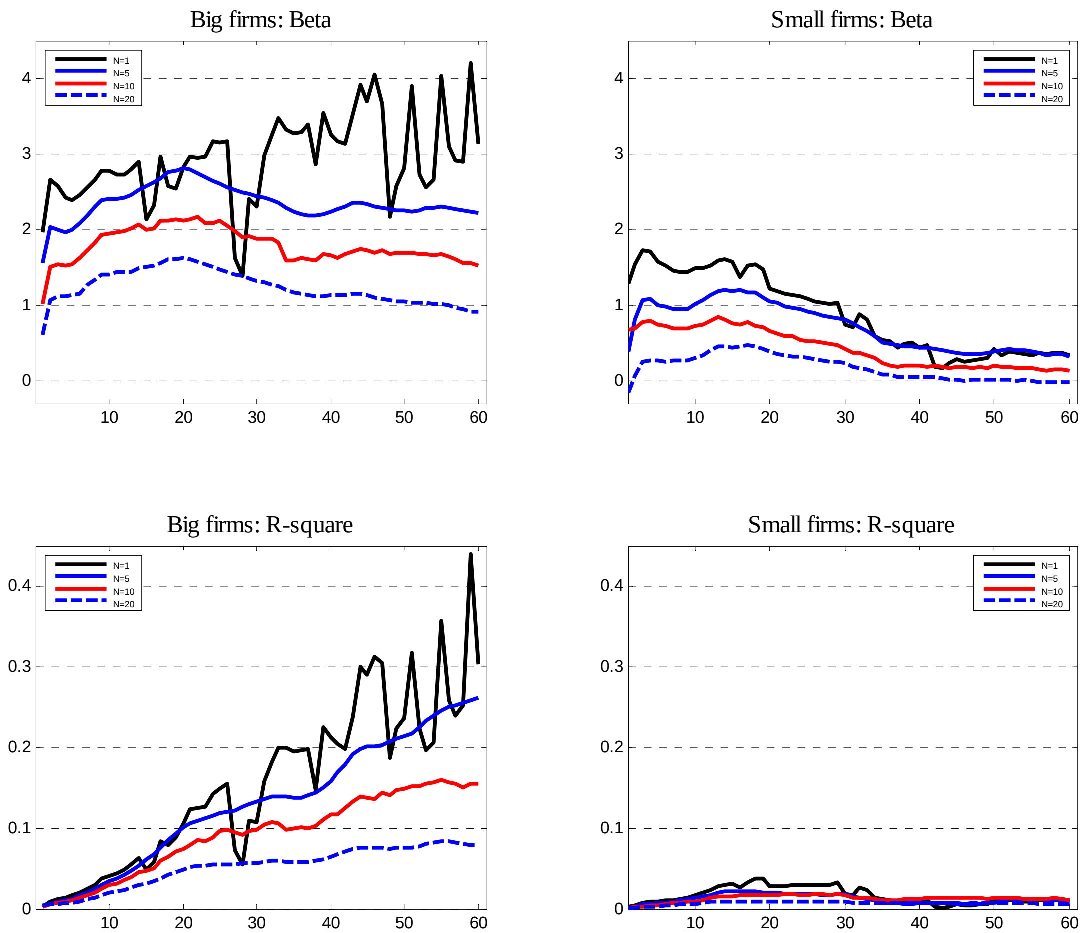

Figure 5. Size-sorted Portfolio. The figure plots the forecasting regression results of size-sorted portfolio. The first column reports the portfolio results for size Quintile 5 (big firms), while the second column shows the results for Quintile 1. Stocks are sorted into quintiles based on the size each month. Within each quintile, stocks are further sorted into N portfolios according to their size. Then, value-weighted portfolio returns for the period *t* to *t+j* (for *j*=1 to 60) are regressed on value-weighted portfolio ICC at time *t*. The figure reports the average coefficients and R^2 of forecasting regressions of N portfolios. A monthly firm-level ICC is estimated following Pástor, Sinha, and Swaminathan (2008). The sample period is 1981–2010.

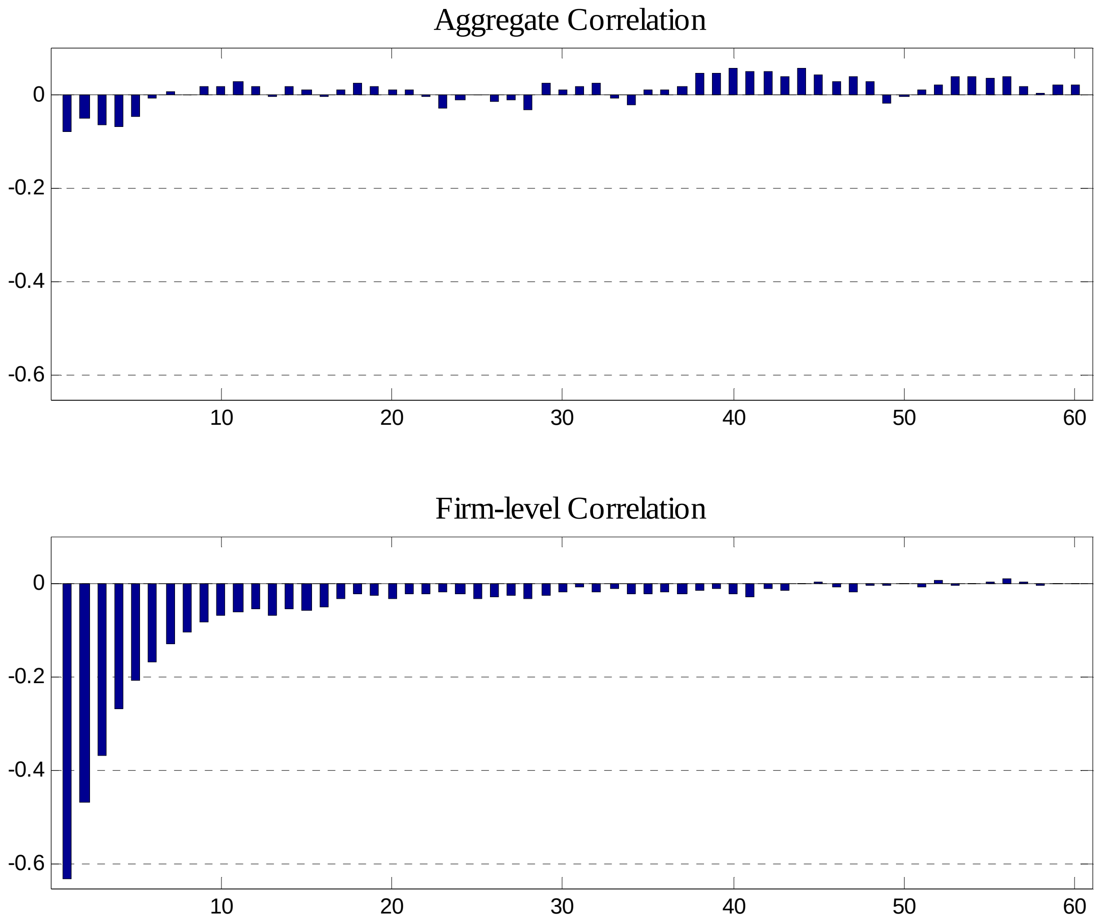

Figure 6. Correlation between the Implied Cost of Capital and Future Cash-Flow News. The figure plots the implied correlation between future cash-flow news and the ICC. The implied correlation between the cash-flow news at time $t+j$ (for j=1 to 60) and the ICC at time t is obtained using Equation (13). The first row shows the implied correlation at the aggregate level, while the second row plots the firm-level implied correlations. The firm-level implied correlations are calculated based on the panel regression results. The sample period is 1981–2010.

Table A1: Robustness of Firm-level Regressions

This table provides the firm-level forecasting regression results for various samples. The sample of S&P500 firms consists of firms in the S&P500 index at any point in time during the sample period. The sample of big firms includes firms with size Quintile 4 and Quintile 5. The sample of high-coverage firms includes firms for which at least five analysts provide earnings forecast. To obtain the regression results of the *j*-period returns, firms with less than *j*+24 observations are excluded. Aymtotic *t*-values are obtained using GMM standard errors with Newey-West correction. The sample period is 1981–2010.

	S&P500				Big Firms				High-Coverage Firms			
Horizon	β (mean)	β (median)	t-value	R^2	β (mean)	β (median)	t-value	R^2	β (mean)	β (median)	t-value	R^2
1	2.814	0.941	0.37	2.40%	2.340	0.845	0.27	2.35%	3.550	1.478	0.39	2.67%
2	2.109	0.774	0.36	3.53%	1.683	0.737	0.29	3.64%	2.690	1.247	0.44	4.16%
3	1.606	0.670	0.33	4.29%	1.145	0.542	0.26	4.60%	2.101	1.026	0.44	5.21%
4	1.499	0.609	0.35	5.01%	0.854	0.423	0.24	5.27%	1.653	0.868	0.43	6.01%
5	1.317	0.493	0.37	5.52%	0.600	0.341	0.21	5.88%	1.414	0.748	0.43	6.70%
6	1.190	0.507	0.38	5.97%	0.449	0.282	0.19	6.34%	1.247	0.683	0.43	7.24%
7	1.079	0.418	0.40	6.40%	0.344	0.242	0.18	6.65%	1.070	0.666	0.44	7.65%
8	0.989	0.459	0.42	6.51%	0.326	0.222	0.19	6.87%	0.982	0.643	0.45	7.84%
9	0.926	0.445	0.45	6.82%	0.243	0.187	0.18	7.06%	0.908	0.637	0.45	8.05%
10	0.853	0.428	0.47	7.28%	0.255	0.223	0.19	7.13%	0.843	0.594	0.45	8.19%
11	0.727	0.365	0.44	7.61%	0.222	0.193	0.20	7.41%	0.776	0.594	0.47	8.52%
12	0.673	0.363	0.41	7.97%	0.166	0.215	0.20	7.57%	0.713	0.566	0.48	8.75%
18	0.427	0.271	0.43	8.95%	0.059	0.173	0.23	8.82%	0.513	0.457	0.51	9.73%
24	0.342	0.199	0.52	9.73%	-0.050	0.127	0.23	9.49%	0.370	0.357	0.57	10.45%
36	0.081	0.116	0.40	11.63%	-0.156	0.043	0.20	10.31%	0.033	0.187	0.43	10.83%
48	-0.142	0.134	0.43	12.40%	-0.183	0.040	0.27	10.98%	-0.038	0.152	0.49	11.50%
60	-0.073	0.174	0.60	12.86%	-0.153	0.127	0.42	11.39%	-0.064	0.177	0.56	11.85%

Table A2: Firm-level Regressions Controlling for the Bias in Analysts' Forecasts

This table provides analyses on the effect of analyst forecast errors on the firm-level regression results. The first panel reports forecasting regression results for the sample of firms with low forecasting errors. Firms are ranked into quintiles, year by year, according to earnings forecast errors during the most recent fiscal year. Then firms with the highest forecasting errors (in the 4th and 5th quintile) are excluded in the sample. The second and the third panels use alternative ICC measures for firm-level analysis. ICC_low uses the lowest forecasts instead of the consensus forecasts. ICC_rank is obtained analyst forecast adjusted by recent forecast errors. To obtain ICC_low and ICC_rank, firms with three analyst coverage are excluded. To obtain the regression results of the *j*-period returns, firms with less than *j*+24 observations are excluded. Aymtotic *t*-values are obtained using GMM standard errors with Newey-West correction. The sample period is 1981–2010.

	Excluding High-Error Firms				ICC_low				ICC_rank			
Horizon	β (mean)	β (median)	t-value	R^2	β (mean)	β (median)	t-value	R^2	β (mean)	β (median)	t-value	R^2
1	3.973	1.604	0.38	3.05%	2.373	1.298	0.35	2.51%	2.477	1.090	0.36	2.42%
2	2.471	1.251	0.39	4.21%	1.926	1.123	0.41	3.77%	2.023	1.004	0.42	3.68%
3	1.874	0.958	0.38	5.36%	1.553	0.935	0.41	4.69%	1.676	0.920	0.43	4.61%
4	1.442	0.800	0.35	6.30%	1.269	0.841	0.40	5.30%	1.410	0.818	0.42	5.35%
5	1.189	0.745	0.34	7.08%	1.088	0.721	0.39	5.78%	1.224	0.732	0.42	5.91%
6	1.005	0.675	0.33	7.73%	0.936	0.629	0.40	6.12%	1.090	0.627	0.43	6.32%
7	0.853	0.631	0.34	8.30%	0.804	0.571	0.40	6.42%	0.945	0.574	0.44	6.71%
8	0.755	0.612	0.35	8.70%	0.744	0.535	0.41	6.64%	0.869	0.559	0.45	7.06%
9	0.702	0.607	0.35	8.96%	0.680	0.514	0.42	6.83%	0.832	0.574	0.47	7.34%
10	0.632	0.570	0.34	9.25%	0.627	0.532	0.44	7.08%	0.755	0.512	0.45	7.51%
11	0.528	0.494	0.33	9.52%	0.588	0.525	0.45	7.31%	0.665	0.472	0.45	7.73%
12	0.538	0.479	0.33	9.69%	0.568	0.502	0.49	7.50%	0.620	0.439	0.46	7.99%
18	0.277	0.298	0.29	10.09%	0.439	0.421	0.54	8.25%	0.496	0.396	0.59	9.00%
24	0.097	0.295	0.31	10.73%	0.346	0.393	0.62	8.58%	0.353	0.363	0.62	9.47%
36	-0.066	0.151	0.27	11.40%	0.300	0.313	0.73	9.05%	0.204	0.250	0.61	9.76%
48	-0.180	0.048	0.31	12.48%	0.293	0.313	0.92	9.15%	0.080	0.209	0.66	10.42%
60	-0.192	0.070	0.17	11.83%	0.285	0.276	1.13	9.48%	0.129	0.208	0.95	10.52%