Predicting Market Returns Using Aggregate Implied Cost of Capital

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Theoretically, the aggregate implied cost of capital (ICC) computed using earnings forecasts is a good proxy for the conditional expected stock return. We empirically examine the ability of the aggregate implied risk premium (*IRP*), which is ICC minus the one-month T-bill yield, to predict future excess stock market returns. We find that the implied risk premium is a statistically and economically significant predictor of future excess returns, with an adjusted R^2 of 6.5% at the 1-year horizon and 31.9% at the 4-year horizon. The predictive power of *IRP* remains strong even in the presence of several well-known valuation ratios and predictors. The out-of-sample performance of *IRP* is superior to the risk premium computed from realized excess market returns and other predictors.

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Introduction

The implied cost of capital (ICC) is the expected return that equates a stock's current price to the present value of its expected future free cash flows. While most papers examine the role of ICC in cross-sectional settings, Pastor, Sinha, and Swaminathan (2008) use ICC in a time-series context to estimate the inter-temporal asset pricing relationship between expected returns and volatility.[2] They theoretically show that the aggregate ICC is perfectly correlated with the conditional expected stock return under plausible conditions. If the aggregate ICC is a good proxy for conditional expected returns, it should also be able to forecast future realized market returns.

In this paper, we examine the ability of the aggregate implied risk premium (IRP) to forecast future excess stock market returns. We estimate IRP as follows. First, we estimate the ICC for each stock in the S&P 500 index (as of that month) and then value-weight the individual ICCs to obtain the aggregate ICC. We then subtract the one-month T-bill yield from the aggregate ICC to compute the implied risk premium and use it to predict future excess market returns.

We find that the implied risk premium is a strong predictor of future excess market returns in forecasting horizons over the next five years with adjusted R^2 of 6.5% at the 1-year horizon and 31.9% at the 4-year horizon. In multivariate regressions, IRP continues to predict future returns in the presence of existing valuation ratios such as the earnings-to-price ratio, dividend-to-price ratio, book-to-market ratio, and the payout yield.[3] The predictive power of IRP remains strong even after controlling for other predictors that have been proposed in the literature, including the business cycle variables such as the term spread and default spread, the net equity issuance, inflation, stock market variance, long-term government bond yield, lagged stock returns, sentiment measures, consumption-to-wealth ratio, and investment-to-capital ratio.[4]

[2] There is a large literature on ICC. For example, ICC has been used to study the equity premium (Claus and Thomas (2001), Fama and French (2002)), test theories on betas (Kaplan and Ruback (1995), Botosan (1997), Gode and Mohanram (2003), Easton and Monahan (2005), Gebhardt, Lee, and Swaminathan (2001)), international asset pricing (Lee, Ng, and Swaminathan (2009)), default risk (Chava and Purnanandam (2010)), asset anomalies (Wu and Zhang (2011)), cross-sectional expected returns (Hou, van Dijk, and Zhang (2010)), stock return volatility (e.g., Friend, Westerfield, and Granito (1978)), and the cost of equity (Hail and Leuz (2006)). Botosan and Plumlee (2005), Lee, So, and Wang (2010) compare different ICC estimates.

[3] A partial list of references on the predictive power of valuation ratios includes Fama and Schwert (1977), Campbell (1987), Campbell and Shiller (1988), Fama and French (1988a, 1989), Kothari and Shanken (1997), Lamont (1998), Pontiff and Schall (1998), and Boudoukh, Michaely, Richardson, and Roberts (2007).

[4] A partial list of references includes: the term spread and default spread (Campbell (1987), Fama and French (1989)), the net equity issuance (Baker and Wurgler (2000)), inflation (Nelson (1976), Fama and Schwert (1977), Campbell and Vuolteenaho (2004)), stock market variance (Guo (2006)), long-term government bond yield (Campbell (1987), Keim and Stambaugh (1986)), lagged stock returns (Fama and French (1988b)), consumption-to-wealth ratio (Lettau and Ludvigson (2001)), investment-to-capital ratio (Cochrane (1991)), and the sentiment measures (Baker and Wurgler (2006)).

Given the well-known statistical issues in predictive regressions, we use a rigorous Monte Carlo procedure to assess the statistical significance of our regressions.[5] Consistent with the literature (e.g., Lee, Myers, and Swaminathan (1999), Stambaugh (1999), Boudoukh, Richardson, and Whitelaw (2008)), under the stringent simulated p-value, traditional valuation ratios largely lose their statistical significance, but the predictive power of *IRP* remains strong. Our findings are also robust to a host of checks, including alternative ways of constructing *IRP*, reasonable perturbations in forecast horizons, and an alternative measure of implied cost of capital proposed by Easton (2004). Several studies find that analyst forecasts tend to be systematically biased upward. We further construct a measure for analyst forecast optimism by comparing earnings forecasts to actual earnings and find that our results are not driven by analyst forecast optimism bias.

Recently, out-of-sample tests have received much attention in the literature. Notably, Welch and Goyal (2008) show that a long list of predictors from 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. To examine the out-of-sample performance of *IRP*, we perform a variety of out-of-sample tests and find that it is also an excellent out-of-sample predictor of future excess market returns in recent years. In the two forecast periods we examine (1998-2010 and 2003-2010), *IRP* delivers statistically and economically meaningful out-of-sample R^2, and provides positive utility gains of more than 7% a year to a mean-variance investor. Rapach, Strauss, and Zhou (2010) argue that it is important to combine individual predictors in the out-of-sample setting. We further conduct a forecasting encompassing test, which provides strong evidence that *IRP* contains distinct information above and beyond that contained in existing predictors.

Our paper contributes to the recent debate on the existence of aggregate stock market predictability. In particular, a large literature examines whether valuation ratios can forecast market returns, and has not reached a consensus.[6] Similar to existing valuation ratios, *IRP* measures stock prices relative to fundamentals and thus it should be positively related to expected returns. However, *IRP* offers much better in-sample and out-of-sample forecasting power than existing valuation ratios, because (a) *IRP* is estimated from a theoretically justifiable discounted cash flow valuation

[5] An active recent literature studies econometric methods for correcting the bias associated with predictive regressions and conducting valid inference (see, among others, Hodrick (1992), Cavanagh, Elliott, and Stock (1995), Stambaugh (1999), Lewellen (2004), Torous, Valkanov, and Yan (2004), Campbell and Yogo (2006), Polk, Thompson, and Vuolteenaho (2006), and Ang and Bekaert (2007)).

[6] See, among others, Stambaugh (1986, 1999), Fama and French (1988a), Bekaert and Hodrick (1992), Nelson and Kim (1993), Lamont (1998), Lewellen (2004), Ang and Bekaert (2007), Boudoukh, Michaely, Richardson, and Roberts (2007), Boudoukh, Richardson, and Whitelaw (2008), Cochrane (2008), Lettau and Nieuwerburgh (2008), Rytchkov (2008), Spiegel (2008), and Kelly and Pruitt (2011).

model and displays superior statistical properties such as faster mean reversion, making it a better proxy of expected returns and (b) there is a future growth component that is embedded in *IRP* but absent from traditional valuation ratios which improves its forecasting power. In our empirical analysis, we show that *IRP* is also superior to the forecasted earnings-to-price ratio, which is constructed based on analyst forecasts but does not contain growth beyond the first two years. Therefore, our approach is consistent with recent literature that has emphasized the importance of studying return predictability and dividend growth rate jointly (e.g., Fama and French (1988a), Campbell and Shiller (1988), Cochrane (2008), van Binsbergen and Koijen (2010), and Ferreira and Santa-Clara (2011)).

Our paper is related to Claus and Thomas (2001) who use a residual income model to estimate equity premium. While Claus and Thomas (2001) study the unconditional equity premium, we estimate time-varying conditional equity premium and examine its ability to predict excess market returns. By suggesting a new measure for expected returns, our work contributes to the time varying risk premium literature (e.g., Ferson and Harvey (1991, 1993, 1999), Pastor and Stambaugh (2009)). Our paper is also related in spirit to Lee, Myers, and Swaminathan (1999) (henceforth, LMS) who use the residual income valuation model to compute the intrinsic value of the Dow Jones Industrial Average. While LMS estimate intrinsic values, we estimate expected returns, which avoids the difficulties associated with estimating an appropriate cost of equity from standard asset pricing models. Compared with LMS who provide an in-sample comparison of the predictive power of the value-to-price ratio of the Dow and other valuation ratios, we evaluate both the in-sample and out-of-sample predictive power of *IRP* against a more comprehensive list of predictors that include new variables that have been proposed since. Finally, the data in LMS starts in the 1960s and ends in 1996. Since then we have experienced the bull market of the late 1990s, the subsequent bear market, and the financial crisis of 2007-2009. Our work evaluates the predictive performance of the ICC and the other predictive variables during a period covering these important episodes.

Our paper proceeds as follows. We describe the methodology for constructing the aggregate ICC and *IRP* in Section I. Section II provides the data source and summary statistics. Section III and Section IV present the in-sample and out-of-sample return predictions, respectively. Section V concludes the paper.

I Empirical Methodology

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

A. ICC as a Measure of Expected Return

The implied cost of capital is the value of r_e that solves

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

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

Campbell, Lo, and MacKinlay (1996)(7.1.24) show that

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

By the definition of r_e,

$$\begin{aligned} d_t - p_t &= -\frac{k}{1-\rho} + r_e E_t\left(\sum_{j=0}^{\infty} \rho^j\right) - E_t\left(\sum_{j=0}^{\infty} \rho^j \triangle d_{t+1+j}\right), \\ &= -\frac{k}{1-\rho} + r_e \frac{1}{1-\rho} - E_t\left(\sum_{j=0}^{\infty} \rho^j \triangle d_{t+1+j}\right), \end{aligned}$$

and thus

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

Thus, the ICC contains information about both the dividend yield and future dividend growth. Pastor, Sinha, and Swaminathan (2008) show that theoretically, ICC can detect an inter-temporal risk-return relationship that is difficult to detect in tests involving realized returns, demonstrating its empirical promise in tracking conditional expected returns.

B. Construction of Firm-Level ICC

Our construction of firm-level ICC follows the approach of Pastor, Sinha, and Swaminathan (2008) and Lee, Ng, and Swaminathan (2009). According to the free cash flow model, the firm-level ICC is constructed as the internal rate of return that equates the present value of future dividends to the current stock price. We use the term "dividends" quite generally to describe the free cash flow to equity (FCFE), which captures the total cash flow available to shareholders including stock repurchases net of new equity issues.

To implement equation (1), we need to explicitly forecast free cash flows for a finite horizon. More specifically, we forecast the free cash flows in two parts: i) the present value of free cash flows up to a terminal period $t+T$, and ii) a continuing value that captures free cash flows beyond the terminal period. We estimate free cash flows up to year $t+T$, as the product of annual earnings forecasts and one minus the plowback rate:

$$E_t\left(FCFE_{t+k}\right) = FE_{t+k} \times \left(1 - b_{t+k}\right), \tag{2}$$

where FE_{t+k} and b_{t+k} are the earnings forecasts and the plowback rate forecasts for year $t+k$, respectively.

We forecast earnings up to year $t+T$ in three stages. (i) We explicitly forecast earnings (in dollars) for years $t+1$ and $t+2$ using analyst forecasts. IBES analysts supply a one-year ahead forecast, FE_1, and a two-year-ahead forecast FE_2, of earnings per share (EPS) for each firm in the IBES database. (ii) We then use the growth rate implicit in the forecasts for years $t+1$ and $t+2$ to forecast earnings in year $t+3$; that is, $g_3 = FE_2/FE_1 - 1$, and the three-year-ahead earnings forecast is given by $FE_3 = FE_2\left(1+g_3\right)$.[7] Firms with growth rates above 100% (below 2%) are given values of 100% (2%). (iii) We forecast earnings from year $t+4$ to year $t+T+1$ by assuming that the year $t+3$ earnings growth rate g_3 reverts 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 the sum of the long-run real GDP growth rate (a rolling average of annual real GDP growth) and the long-run average rate of inflation based on the implicit GDP deflator. Specifically, earnings growth rates and earnings forecasts using the exponential rate of decline are computed as follows for years $t+4$ to $t+T+1$ ($k = 4, ..., T+1$):

$$\begin{aligned} g_{t+k} &= g_{t+k-1} \times \exp\left[\log\left(g/g_3\right)/\left(T-1\right)\right] \text{ and} \\ FE_{t+k} &= FE_{t+k-1} \times \left(1 + g_{t+k}\right). \end{aligned} \tag{3}$$

We forecast plowback rates using a two-stage approach. (i) We explicitly forecast plowback rates for years $t+1$ and $t+2$. For each firm, the plowback rate is computed as one minus that firm's dividend payout ratio. We estimate the dividend payout ratio by dividing actual dividends from the

[7] If both FE_2 and FE_1 are available and positive, then $g_3 = FE_2/FE_1 - 1$. Otherwise, we fill them using available data. For example, if $FE_1 > 0$ and the actual earning from the previous year (FE_0) is available and positive, then $LTG = FE_1/FE_0 - 1$, and $FE_2 = FE_1(1+LTG)$; if $FE_2 > 0$ and $FE_0 > 0$, then $LTG = (FE_2/FE_0 - 1)^{1/2}$, and $FE_1 = FE_0(1+LTG)$; if both FE_1 and FE_2 are missing or negative, but $FE_0 > 0$ and the IBES long-term earnings growth rate is available and positive, then we use the IBES long-term earnings growth rate to replace LTG, and fill FE_1 and FE_2.

most recent fiscal year by earnings over the same time period.[8] We exclude share repurchases due to the practical problems associated with determining the likelihood of their recurrence in future periods. Payout ratios of less than zero (greater than one) are assigned a value of zero (one). (ii) We assume that the plowback rate in year $t+2$, b_2 reverts linearly to a steady-state value by year $t+T+1$ computed from the sustainable growth rate formula. This formula assumes that, in the steady state, the product of the return on new investments and the plowback rate $ROE * b$ is equal to the growth rate in earnings g. We further impose the condition that, in the steady state, ROE equals r_e for new investments, because competition will drive returns on these investments down to the cost of equity.

Substituting ROE with cost of equity r_e in the sustainable growth rate formula and solving for plowback rate b provides the steady-state value for the plowback rate, which equals the steady-state growth rate divided by cost of equity g/r_e. The intermediate plowback rates from $t+3$ to $t+T$ ($k = 3, ..., T$) are computed as follows:

$$b_{t+k} = b_{t+k-1} - \frac{b_2 - b}{T-1}. \tag{4}$$

The terminal value TV is computed as the present value of a perpetuity equal to the ratio of the year $t+T+1$ earnings forecast divided by the cost of equity:

$$TV_{t+T} = \frac{FE_{t+T+1}}{r_e}, \tag{5}$$

where FE_{t+T+1} is the earnings forecast for year $t+T+1$.[9] It is easy to show that the Gordon growth model for TV will simplify to equation (5) when ROE equals r_e.

Substituting equations (2) to (5) into the infinite-horizon free cash flow valuation model in equation (1) provides the following empirically tractable finite horizon model:

$$P_t = \sum_{k=1}^{T} \frac{FE_{t+k} \times (1 - b_{t+k})}{(1+r_e)^k} + \frac{FE_{t+T+1}}{r_e (1+r_e)^T}. \tag{6}$$

Following Pastor, Sinha, and Swaminathan (2008), we use a 15-year horizon ($T = 15$) to implement the model in (6) and compute r_e as the rate of return that equates the present value of free cash flows to the current stock price. The resulting r_e is the firm-level ICC measure used in our empirical analysis.

[8] 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 market cap within each industry.

[9] 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.

C. Construction of the Aggregate ICC

Each month, the value-weighted aggregate ICC is constructed as:

$$ICC_t = \sum_{i=1}^{n} \frac{v_{i,t-1}}{\sum_{i=1}^{n} v_{i,t-1}} ICC_{i,t},$$

where i indexes firm, and t indexes time. $v_{i,t-1}$ is the market value for firm i at time $t-1$, and $ICC_{i,t}$ is the ICC for firm i at time t.

In our empirical analysis, since we forecast excess market returns, the predictive variable we use in our in-sample and out-of-sample forecast evaluations is the implied risk premium (IRP), obtained by subtracting the one-month T-bill yield from the aggregate ICC:

$$IRP_t = ICC_t - Tbill_t.$$

Our main measure of IRP is the value-weighted measure based on firms in the S&P 500 index, although we conduct a variety of robustness checks in Subsection III.

II Data and Sample Description

Our measure of ICC uses all prevailing firms in the S&P 500 index between January 1981 and December 2010. That is, when calculating the aggregate ICC at month t, we only use firms that belong to the index in that month. We obtain return data from CRSP, accounting data including common dividend, net income, book value of common equity, and fiscal year-end date from COMPUSTAT, and analyst forecasts from I/B/E/S. Monthly data on market capitalization are obtained from CRSP. To ensure we only use publicly available information, we obtain these items from the most recent fiscal year ending at least 3 months prior to the month in which ICC is computed. Data on nominal GDP growth rates are obtained from the Bureau of Economic Analysis. Our GDP data begin in 1930. Each year, we compute the steady-state GDP growth rate as the historical average of the GDP growth rates using annual data up to that year.

For the aggregate market return, we use the value-weighted market return including dividends from WRDS.[10] There is a long-standing literature focusing on the predictive power of the three valuation ratios including dividend-to-price-ratio (D/P), earnings-to-price ratio (E/P), and book-to-market ratio (B/M). Recently, Boudoukh, Michaely, Richardson, and Roberts (2007) propose payout yield as an alternative valuation measure and they show that while dividend yield fails to

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

predict future market returns, their new payout yield measure exhibits statistically and economically significant predictability. Since our new predictor *IRP* is similar to a valuation ratio, we are particularly interested in its forecasting performance with respect to the following valuation ratios:

- *Forecasted earnings-to-price ratio (FY/P).* Each month, we construct the aggregate FY/P by value-weighting the firm-level forecasted earnings-to-price ratio using the same firms in the S&P 500 index for which we calculate our aggregate ICC. We construct the firm-level forecasted earnings-to-price ratio by dividing the average of analysts' one-year-ahead (FE_1) and two-year-ahead (FE_2) earning forecasts by the current stock price.

- *Trailing earnings-to-price ratio (E/P).* Each month, we construct the aggregate E/P by value-weighting the firm-level E/P using the same firms in the S&P 500 index for which we calculate our aggregate ICC. We calculate the firm-level E/P by dividing earnings from the most recent fiscal year end (ending at least 3 months prior) by market capitalization.

- *Dividend-to-price ratio (D/P).* Each month, we construct the aggregate D/P by value-weighting the firm-level D/P using the same firms in the S&P 500 index for which we calculate our aggregate ICC. We calculate the firm-level D/P by dividing the total dividends from the most recent fiscal year end (ending at least 3 months prior) by market capitalization.[11]

- *Book-to-market ratio (B/M).* Each month, we construct the aggregate B/M by value-weighting the firm-level B/M using the same firms in the S&P 500 index for which we calculate our aggregate ICC. We calculate the firm-level B/M by dividing the total book value of equity from the most recent fiscal year end (ending at least 3 months prior) by market capitalization.

- *Payout Yield* (P/Y). The *payout yield* is the sum of dividend yield and repurchase yield, defined as the ratio of common share repurchases to year-end market capitalization.

Our constructed valuation ratios FY/P, E/P, D/P, and B/M are monthly data from January 1981 to December 2010. P/Y is monthly data from January 1981 to December 2008, obtained from the website of Michael Roberts. In addition to valuation ratios, we further investigate the forecasting power of *IRP* in the presence of a long list of other forecasting variables that have been proposed in the literature:

[11] In untabulated results, we use the dividend yield data provided by Michael Roberts used in Boudoukh, Michaely, Richardson, and Roberts (2007), in which the dividend yield is computed as the difference in the cum and ex-dividend returns to the CRSP value-weighted index. We find stronger predictability of *IRP* in the presence of this dividend yield measure.

- *Default spread (Default).* The *default spread* is the difference between yields on BAA and AAA-rated corporate bonds obtained from the economic research database at the Federal Reserve Bank at St. Louis (FRED). It is a measure of the ex-ante default risk in the economy.

- *Term spread (Term).* The *term spread* is the yield difference between Moody's Aaa bonds and the one-month T-bill rate representing the slope of the treasury yield curve. The one-month T-bill rate is the average yield on one-month Treasury bill obtained from WRDS.

- *Long-term yield* (*lty*). The 30-year government bond yield.

- *Net equity expansion (ntis).* The ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks.

- *Inflation (infl).* Inflation rate calculated based on the Consumer Price Index (all urban consumers).

- *Stock variance (svar).* Computed as the sum of squared daily returns on the S&P 500 index within a month.

- *Lagged excess market returns* (*vwretd*). Because we forecast excess returns in our empirical analysis, we subtract the one-month T-bill rate from the lagged monthly value-weighted market return with dividends to obtain *vwretd*.

- *Sentiment index 1 (senti1)* and *sentiment index 2 (senti2).* Two sentiment indices proposed in Baker and Wurgler (2006). They are based on the first principal component of six (standardized) sentiment proxies.

The business cycle variables including *Default* and *Term* span January 1981 to December 2010. Variables *ntis, infl,* and *svar* are obtained from Amit Goyal's website, *lty* and *vwretd* are obtained from WRDS, the two sentiment measures are taken from Jeffrey Wurgler's website; all these variables span January 1981 to December 2008.

Although the ICC is computed each month, we subtract the quarterly one-month T-bill yield from quarter-end ICC to compute the quarterly *IRP* measure, and examine the performance of *IRP* with respect to two quarterly forecasting variables:

- *Consumption-to-wealth ratio (cay)*: proposed in Lettau and Ludvigson (2001).

- *Investment-to-capital ratio (i/k)*: the ratio of aggregate (private nonresidential fixed) investment to aggregate capital for the whole economy. This is the variable proposed in Cochrane (1991).

cay and *i/k* are from Amit Goyal's website and they span the first quarter of 1981 to the fourth quarter of 2008. It should be noted that the construction of *cay* and the two sentiment indices uses future information, so they are not really forecasting variables.

[INSERT TABLE I HERE]

Table I presents univariate summary statistics on the above variables, with Panel A for *IRP*, *FY/P*, *E/P*, *D/P*, *B/M*, *Term*, and *Default* using monthly data from 1981.01 to 2010.12; Panel B for *IRP*, *P/Y*, *lty, ntis, infl*, *svar*, *vwretd*, *senti1*, and *senti2* using monthly data from 1981.01 to 2008.12*;* and Panel C for *IRP*, *cay*, and *i/k* using quarterly data from 1981.Q1 to 2008.Q4. In Panel A, the average annualized *IRP* is 6.74% and its standard deviation is 2.58%, whereas in Panel B, the average annualized *IRP* is 6.38% and its standard deviation is 2.27%. Therefore, both the mean and standard deviation of *IRP* have increased since 2008. Panel D provides the number of firms used to construct *IRP* each year, which increases over time.

As shown in Panel A, *IRP* exhibits faster mean reversion than other valuation ratios. Its first order autocorrelation is 0.95, and the autocorrelation declines to 0.04 after 24 months, and becomes −0.21 after 36 months (Panel A). The autocorrelations of all other valuation ratios, namely, *FY/P*, *E/P*, *D/P*, *B/M*, and *P/Y*, stay well above zero even after 60 months. These results suggest that *IRP* is more stationary than other valuation ratios. To formally test the stationarity of these variables, in Appendix A, we conduct formal unit root tests, and the results confirm that *IRP* is indeed more stationary than other valuation ratios. More specifically, we strongly reject the null of a unit root in *IRP* at the conventional levels, but for all other valuation ratios, we fail to reject the null that they contain a unit root.

Table II reports the correlation among the various measures. *IRP* is positively correlated with all the valuation ratios, which suggests that they share common information about time-varying expected returns. *IRP* is also significantly positively correlated with *Term* and *Default*, which suggests that *IRP* varies with the business cycle.

The high negative correlation (−0.68) between *IRP* and *i/k* (Panel D) suggests that the aggregate investment in the economy drops as the cost of capital rises. This is intuitive and as expected. Lettau and Ludvigson (2001) advocate *cay* as a conditioning variable that summarizes investor expectations of expected returns, and thus it is not surprising that *IRP* is positively correlated with *cay*. Overall, the results in Table II indicate that *IRP* has intuitive appeal as a measure of the conditional expected return.

[INSERT FIGURE 1 HERE]

Figure 1 plots *IRP* over time, together with its mean and two-standard-deviation bands using all historical data starting from January 1986. It also marks several important periods: the market crash of October 1987, the technology-driven bull market of 1998 and 1999, and the subsequent bear market and the financial crisis period of July 2007 to March 2009. The implied risk premium reached a high of 13.3% in March 2009 at the depth of the market downturn. At the end of 2010, the forward-looking implied risk premium was still above 10%.

[INSERT FIGURE 2 HERE]

Figure 2 plots *FY/P*, *E/P*, *D/P*, *B/M*, and *P/Y*. The plots suggest that there is some commonality in the way these valuation ratios vary over time. In comparison, *IRP* in Figure 1 appears more stationary.

III In-sample Return Predictions

A. Forecasting Regression Methodology

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

$$\sum_{k=1}^{K} \frac{r_{t+k}}{K} = a + b \times X_t + u_{t+K,t}, \tag{7}$$

where r_{t+k} is the continuously compounded excess return per month (quarter) defined as the difference between the monthly (quarterly) continuously compounded return on the value-weighted market return including dividends from WRDS and the monthly (quarterly) continuously compounded one-month T-bill rate. 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 different horizons: in monthly regressions, $K = 1$, 12, 24, 36, 48, and 60 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 regression residuals. Specifically, under both the null hypothesis of no predictability and alternative hypotheses that fully account for time-varying expected returns, the regression residuals are autocorrelated up to lag $K-1$. As a result, the regression standard errors from ordinary least squares (OLS) would be too low and the t-statistics too high. Moreover, the regression residuals are likely to be conditionally heteroskedastic. We correct for both the induced autocorrelation and the conditional heteroskedasticity using the Generalized Method of Moments (GMM) standard errors with the Newey-West correction (see Hansen and Hodrick (1980) and Newey and West (1987)) up to moving average lags $K-1$. We call the resulting test statistic the asymptotic Z-statistic. Moreover, since the forecasting regressions use the same data at various horizons, the regression slopes will be correlated. It is, therefore, not correct to draw inferences about predictability based on any one regression. To address this issue, Richardson and Stock (1989) propose a joint test based on the average slope coefficient. Following their paper, 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. To compute the statistical significance of the average slope estimate, we conduct Monte Carlo simulations, the details of which are described below.

As explained earlier, asymptotic Z-statistics are computed using the GMM standard errors. While these Z-statistics are consistent, they potentially suffer from small sample biases because of the following reasons. First, while the independent variables in the OLS regressions are predetermined they are not necessarily strictly exogenous. This is especially the case when we use valuation ratios, since valuation ratios are a function of current price. Stambaugh (1986, 1999) show that in these situations the OLS estimators of the slope coefficients are biased in small samples. Secondly, while the GMM standard errors consistently estimate the asymptotic variance-covariance matrix, Richardson and Smith (1991) show these standard errors are biased in small samples due to the sampling variation in estimating the autocovariances. Lastly, as demonstrated by Richardson and Smith (1991), the asymptotic distribution of the OLS estimators may not be well behaved if K is large relative to T, i.e., the degree of overlap is high relative to the sample size.

To account for these issues, 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). Appendix B describes the details of our simulation methodology.[12]

B. Forecasting Regression Results

In this section we discuss the results from our forecasting regressions involving *IRP*. We first compare *IRP* with the various valuation ratios, and we then compare *IRP* with a long list of forecasting variables that have been documented to predict future returns in the literature. Finally, we conduct various robustness checks.

B.1. Regression Results with Valuation Ratios

Univariate Regression Results We first examine the univariate regression results of *IRP* and other commonly used valuation ratios, by setting $X = IRP$, FY/P, E/P, D/P, B/M, or P/Y in equation (7). High *IRP* represents high ex-ante risk premium, and hence we expect high *IRP* to predict high excess market returns. Prior literature has shown that high valuation ratios (E/P, D/P, B/M) predict high stock returns. Similarly, we expect high FY/P to forecast high stock returns. Boudoukh, Michaely, Richardson, and Roberts (2007) show that *Payout Yield* (P/Y) is a better forecasting variable than the 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 III HERE]

Panels A-E of Table III present univariate regression results for *IRP*, FY/P, E/P, D/P, and B/M, respectively, using monthly data from 1981.01 to 2010.12. Panel F provides the univariate regression results for P/Y, using monthly data from 1981.01 to 2008.12. Because Boudoukh, Michaely, Richardson, and Roberts (2007) use the logarithm of P/Y in their regressions, to be consistent, in Panel F we also use the logarithm of P/Y as the regressor.

We observe that as expected, all variables have positive slope coefficients. Because a one-sided test is appropriate, the 5% critical value is 1.65 when we assess statistical significance based on conventional critical statistics. By this measure, all variables have some forecasting power, especially at longer horizons, and the adjusted R^2s also increase with horizons. That the conventional

[12] In our reported results below, the variables in the VAR vary with each regression. For example, in the univariate regression of (7) with only one predictive variable in X_t, the VAR contains two variables, namely, r_t and the predictive variable X_t. In a multivariate regression with two predictive variables in X_t, the VAR contains three variables, namely, r_t and the two predictive variables in X_t. In unreported results, for predictive variables with the same sample size, we also run a single VAR containing all variables and obtain similar conclusions.

significance of forecasting power increases with the forecasting horizon is due to the persistence of the regressors (see the proof in Cochrane (2005)). However, when judged by simulated p-values, the commonly used valuation ratios including E/P, D/P, and B/M are no longer significant; the forecasted earnings-to-price ratio (FY/P) is also not statistically significant. This finding is consistent with our discussion in Subsection III.A, and highlights the importance of using simulated p-values to assess the statistical significance of forecasting variables. Since E/P, D/P, B/M, and FY/P are not statistically significant at the individual horizons, it is not surprising that these variables are not significant in the joint horizon test: the simulated p-values of average slope estimates are 0.370, 0.446, 0.328, and 0.480 for E/P, D/P, B/M, and FY/P, respectively.

Unlike the traditional valuation measures, IRP is statistically significant both based on conventional $Z(b)$ and the simulated p-values. In particular, IRP is statistically significant at conventional levels for all forecasting horizons except the 2-year horizon. For IRP, the adjusted R^2 is 6.5% at the 1-year horizon, and it increases to 31.9% at the 4-year horizon. In comparison to FY/P, E/P, D/P, and B/M, IRP also has the highest R^2 at every forecasting horizon, indicating that IRP is able to explain a much larger portion of future market returns than commonly used valuation ratios. Moreover, the average slope coefficient of IRP across all horizons is 1.876, and it is highly significant (p-value 0.025). This suggests that on average, an increase of 1% in IRP in the current month is associated with an annualized increase of 1.876% in the excess market return over the next five years. Economically, this is very significant. Consistent with Boudoukh, Michaely, Richardson, and Roberts (2007), P/Y has strong forecasting power for future excess market returns: it is statistically significant at all horizons after a year, and the average slope estimate is also significant (p-value 0.096).

Bivariate Regression Results Because IRP is positively correlated with traditional valuation ratios, it is important to know whether IRP still forecasts future market returns in their presence. Given the high correlation among these valuation ratios (see Table II), to avoid multicollinearity issues, we run bivariate regressions according to equation (7), with X being one of the following five sets of regressors: (1) IRP and FY/P, (2) IRP and E/P, (3) IRP and D/P, (4) IRP and B/M, and (5) IRP and P/Y. In (5), we use logarithm of IRP 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 IV HERE]

Table IV presents the bivariate regression results. Panel A shows that *IRP* is still a statistically and economically significant forecasting variable in the presence of *FY/P*. The slope coefficients corresponding to *IRP* continue to be positive, and they are statistically significant at the 1-month, 3-year, and 4-year horizons according to the simulated *p*-values. The average slope coefficient across all forecasting horizons is 1.664 and statistically significant (*p*-value 0.087), suggesting that a 1% increase in *IRP* in the current month is associated with an annualized increase of 1.664% in the excess market return over the next five years. In contrast, *FY/P* is insignificant in both the individual horizon tests and the joint horizon test. This result suggests that *IRP* contains more information than *FY/P*, which forecasts only one-year-ahead and two-year-ahead earnings.

Panel B further confirms the predictive power of *IRP* in the presence of *E/P*. *IRP* is statistically significant at the 1-year, 3-year, and 4-year horizons, and the average slope coefficient is also significant (*p*-value 0.063). Panel C provides bivariate regression results of *IRP* and *D/P*. *IRP* continues to be significant at the 3-year and 4-year horizons while *D/P* is not statistically significant at any horizon. Panel D shows that *IRP* continues to predict future returns in the presence of *B/M*. Panel E shows that even in the presence of a strong predictor such as *P/Y*, *IRP* still strongly forecasts future market returns. The slope coefficients of *IRP* remain positive at all forecasting horizons, and they are statistically significant at all horizons after two years. In the presence of *IRP*, *P/Y* remain statistically significant only at the 3-year horizon and is no longer significant based on the joint average slope test (*p*-value 0.261).

Our analysis thus far has provided strong evidence that, in both univariate and bivariate regressions, *IRP* is the best predictor compared with the valuation ratios. Consistent with the existing findings in the literature (Stambaugh (1986, 1999), Nelson and Kim (1993), Boudoukh, Richardson, and Whitelaw (2008)), traditional valuation ratios such as *D/P*, *E/P* and *B/M* lose their significance when we use the simulated critical values to assess statistical significance. However, the *IRP* measure survives these more stringent simulated critical values.

Why does *IRP* perform better than traditional valuation ratios? Compared with traditional valuation ratios, *IRP* also contains important information about future growth, which leads to the superior predictive power of *IRP*. This can be clearly seen from the bivariate regression of *IRP* and *FY/P* in Panel A of Table IV: since *FY/P* is just the average of the next two years' earnings forecasts, the multiple regression shows that the information in *IRP*, not in *FY/P*, is still very important for predicting future returns. The insight that return predictability and dividend growth rate predictability are best studied jointly has been emphasized by Fama and French (1988a), Campbell and Shiller (1988), Cochrane (2008), van Binsbergen and Koijen (2010), and Ferreira and Santa-Clara (2011), among others. Subsection I.A theoretically shows that ICC (and thus *IRP*) contains information about both dividend yield and future dividend growth.

B.2. Regression Results with Other Forecasting Variables

In this subsection, we compare *IRP* to a host of other predictors that have been proposed in the literature, and examine whether *IRP* continues to forecast future excess returns in the presence of these measures. The first group of variables are the business cycle variables including the term spread (*Term*) and the default spread (*Default*); the second group of variables includes long-term yield (*lty*), net equity expansion (*ntis*), inflation (*infl*), stock variance (*svar*), and lagged excess market returns (*vwretd*); the third group of variables includes the sentiment measures in Baker and Wurgler (2006) (*senti1* and *senti2*); and the last group of variables includes consumption-to-wealth ratio (*cay*) and investment-to-capital ratio (*i/k*).

Univariate Regression Results

[INSERT TABLE V HERE]

Table V presents the univariate regression results based on (7) when X = *Term*, *Default, lty*, *ntis*, *infl*, *svar*, *vwretd*, *senti1*, *senti2*, *cay*, or *i/k.* In addition to these variables, we also provide a univariate regression for the quarterly *IRP*. Panel A presents the univariate regression results for *Term* and *Default.* Since *Term* and *Default* move countercyclically with the business cycle, we expect high default spread and high term spread to predict high stock returns. Thus, for these two regressions, a one-sided test of the null hypothesis is appropriate. The regression results indicate that *Term* is a strong predictor of future market returns. It is statistically significant at 1-year to 4-year horizons, according to the simulated p-values, and the average slope coefficient is also significant (p-value 0.070). On the other hand, *Default* is not a statistically significant predictor of future returns.

Panel B presents the univariate regression results for *lty*, *ntis*, *infl*, *svar*, and *vwretd.* We expect higher *lty* to predict higher future market returns. Baker and Wurgler (2000) show that *ntis* is a strong predictor of future market returns between 1928 and 1997. In particular, firms issue relatively more equity than debt just before periods of low market returns. So we expect negative coefficients for *ntis.* We do not have a definite sign for *infl*, *svar*, and *vwretd.* For example, for *vwretd*, we expect a positive sign within a year and a negative sign afterwards. Since we do not have a consistent sign for *infl*, *svar*, and *vwretd*, the average slope coefficient for these variables are not very informative. We nevertheless report it together with its p-value calculated based on the assumption that we expect a negative sign for *infl*, *svar*, and a positive sign for *vwretd*.

Consistent with our conjecture, *lty* has positive slope coefficients, although they are not statistically significant. In contrast to the findings in Baker and Wurgler (2000), we obtain positive slope coefficients for *ntis*. This is due to the time period we examine; if we only consider the time period of 1981.01-1997.12, the coefficients for *ntis* are negative and statistically significant at horizons less than a year. Higher inflation tends to predict lower future returns up to a year, and then higher returns at longer than a year. Higher stock variances tend to predict lower future returns. For *vwretd*, we observe the usual momentum effect up to a year, and then the reversal effect at longer horizons. None of these results are highly significant, however.

Panel C presents the univariate regression results for *senti1* and *senti2*. For both sentiment indices, we expect a negative sign, which is indeed what we find. The slope coefficients for both variables are negative across all horizons, and they are statistically significant only at the 1-month horizon.

Panel D presents the univariate regression results for *IRP*, *cay*, and *i/k* using quarterly data. We still expect *IRP* to positively forecast future returns, and this is indeed what we find. *IRP* is statistically significant at the 4-year horizons. Its average slope coefficient across four years is 5.495, suggesting that a 1% increase in *IRP* in the current quarter is associated with an annualized increase of 1.832% in the excess market return over the next four years.

Lettau and Ludvigson (2001) propose *cay* as a measure of time-varying expected returns with high *cay* predicting high returns. Therefore, we expect a positive sign for *cay*. Based on Cochrane (1991), we expect a negative sign for *i/k*. The regression results show that both *cay* and *i/k* have the expected signs; *cay* is significant at horizons less than one year, and *i/k* is significant at the 4-year horizon. We note again that because the sentiment measures (*senti1* and *senti2*) and *cay* use future information, they are not really forecasting variables; but we still compare *IRP* to them.

Multivariate regression results To examine the predictive power of *IRP* in the presence of these additional forecasting variables, we conduct multivariate regressions. First, we run bivariate regressions of *IRP* with business cycle variables and sentiment measures. That is, X is one of the four combinations: (1) *IRP* and *Term*, (2) *IRP* and *Default*, (3) *IRP* and *senti1*, and (4) *IRP* and *senti2*. To save space, we run the following two multivariate regressions of *IRP* with other variables:

$$\sum_{k=1}^{K} \frac{r_{t+k}}{K} = a + b \times IRP_t + c \times lty_t + d \times ntis_t + e \times infl_t + f \times svar_t + g \times vwretd_t + u_{t+K,t}, \quad (8)$$

and

$$\sum_{k=1}^{K} \frac{r_{t+k}}{K} = a + b \times IRP_t + c \times cay_t + d \times i/k_t + u_{t+K,t}. \quad (9)$$

[INSERT TABLE VI HERE]

Table VI presents the results. In all these regressions, we observe that *IRP* still positively predicts future market returns. Panel A reports two bivariate regressions, where the first one is *IRP* and *Term*, and the second one is *IRP* and *Default*. We observe that *IRP* remains statistically significant at the 1-month, 4-year, and 5-year horizons in the presence of *Term*; the average slope coefficient is also statistically significant (p-value 0.029). Although *Term* strongly predicts future returns with a positive sign in the univariate regression (Panel A of Table V), its coefficients become negative in the presence of *IRP* and become insignificant. The signs of *Default* are also mostly negative in the presence *IRP*. Panel B shows that even after controlling for *lty*, *ntis*, *infl*, *svar*, and *vwretd*, *IRP* remains statistically significant at the 4-year and 5-year horizons; its average slope coefficient is also significant (p-value 0.078).

Panel C shows that *IRP* strongly predicts future excess market returns even in the presence of both sentiment measures (which use ex-post information). In both bivariate regressions, *IRP* remains highly significant at the 1-year, 4-year, and 5-year horizons, and its average slope coefficient is also significant. The performance of the two sentiment measures is similar to that in the univariate regressions (Panel C of Table V), where they are significant at the 1-month horizon. These results indicate that *IRP* contains distinct information from the sentiment measures.

Panel D indicates that, in the presence of *cay* and *i/k*, *IRP* remains significant after two years. In the presence of *IRP*, *cay* is significant only at the 1-quarter horizon. Although *i/k* is significant in the univariate regression (Panel D of Table V), it loses its forecasting power in the multivariate regression. Given the high correlation between *IRP* and *i/k* (-0.68 in Panel D of Table II), it is not surprising that the presence of *IRP* diminishes the predictive power of *i/k* .

Overall, our analysis indicates that *IRP* has strong predictive power even in the presence of a variety of other forecasting variables.

B.3. Robustness Checks

Alternative ways of constructing *IRP* So far, our measure of implied risk premium is obtained by value-weighting the firm-level ICC 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. In this subsection, we consider three alternative ways of constructing the implied risk premium. First, we equally-weight the firm-level ICC 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 implied risk premium measure (*IRP_equ*). Second, we value-weight the firm-level ICC to obtain the aggregate ICC. Rather than subtracting the one-month T-bill yield from the aggregate ICC, we instead subtract the long-term government bond yield to obtain the implied risk premium (*IRP_yield*). Finally, rather than use the firms in the S&P 500 index, we compute the value-weighted ICC using only the firms in the Dow Jones Industrial Average. The third implied risk premium (*IRP_dj*) is then obtained by subtracting the one-month T-bill yield from the aggregate ICC based on Dow Jones companies.

[INSERT TABLE VII HERE]

Table VII provides the univariate regression results of using these three alternative measures of *IRP.* The results show that all three measures of implied risk premium positively predict future market returns at all forecasting horizons, and they all display statistical significance at some forecasting horizons. For example, *IRP_equ* is statistically significant at the 1-month, 4-year, and 5-year horizons. Moreover, all three measures have highly significant average slopes, with p-values being 0.052, 0.043, and 0.030 for *IRP_equ*, *IRP_yield,* and *IRP_dj,* respectively. At the 5-year horizon, *IRP_equ* explains 22.7% of future market returns, *IRP_yield* explains 29.0% of future market returns, and *IRP_dj* explains 26.6% of future market returns.

Alternative Model Specifications As another robustness check, we have also estimated *IRP* using free cash flow models with finite horizons of $T = 10$ and $T = 20$ (recall our main approach uses $T = 15$ in equation (6)). While the horizons affect the average risk premium (the mean of *IRP* is 5.63% for $T = 10$ and 7.62% for $T = 20$), the regression results are unaffected, both in univariate and in multivariate regressions. For example, using data from 1981.01 to 2010.12, the average slope coefficient across all horizons in the univariate regression of excess market returns on *IRP* is 2.035 for $T = 10$ and 1.743 for $T = 20$, respectively, and they are also statistically significant (p-value 0.025 if $T = 10$, and p-value 0.047 if $T = 20$). We have also estimated implied risk premium using the modified PEG approach of Easton (2004) and obtain results comparable to our main procedure. For example, using data from 1981.01 to 2010.12, the mean of *IRP* is 6.90%. The average slope coefficient across all horizons in the univariate regression is 2.067, and it is highly significant (p-value 0.020).

Analyst Forecast Biases Our calculation of *IRP* uses analysts' forecast of future earnings, which might be biased. Notably, several studies find that analyst forecasts tend to be optimistic. We now show that the predictive power of *IRP* is not driven by analyst forecast optimism. Our main finding is that *IRP* positively predicts future market returns. Optimistic analyst forecasts, all else equal, should lead to higher estimates of *IRP*; therefore, if our result is driven by analyst optimism, then analyst optimism bias should positively predict future market returns.

To investigate the predictive power of analyst optimism bias, we compute the following measure for each firm, each month: the ratio of the difference between the consensus 1-year-ahead analyst forecast of earnings per share (EPS) and the corresponding actual EPS to the 1-year-ahead forecast. Note that this is just the negative of the forecast error. Forecast optimism bias will lead to negative forecast errors and our optimism measure is just the negative of the forecast error. Therefore, for our *IRP* results to be explained by analyst optimism, a high value of our optimism measure should predict high returns and weaken/eliminate the predictive power of *IRP*. We value-weight the optimism biases across firms in each month to compute the aggregate analyst optimism. We then conduct univariate tests based on equation (7) to examine whether the aggregate analyst forecast optimism positively predicts future excess market returns.

[INSERT TABLE VIII HERE]

Panel A of Table VIII shows that this is not the case; on the contrary, analyst forecast optimism negatively predicts future market returns in horizons up to 24 months, although the results are not significant. This result can be understood as follows. If analysts provide too optimistic an estimate for the one-year-ahead earnings, and if the current market price does not fully account for this bias, then when the actual one-year-ahead earnings realizes, the market will be disappointed and the one-year-ahead market price will drop to reflect this market adjustment. In other words, a higher one-year-head analyst forecast optimism will forecast a negative market returns at the 12-month horizon. Therefore, if anything, analyst optimism should weaken our findings with respect to *IRP*.

To further explore whether the predictive power of *IRP* is robust to analyst forecast optimism, we estimate a bivariate regression involving the *IRP* and the aggregate analyst forecast optimism.

The results are provided in Panel B of Table VIII. We find that *IRP* continues to positively forecast future excess market returns at all horizons, and the statistical significance is also comparable to that provided in the univariate regression of Table III. This provides further evidence that our results are not driven by analyst optimism.

IV Out-of-Sample Return Predictions

Recently, evaluating the out-of-sample performance of return prediction variables has received much attention in the literature (see Spiegel (2008) and Welch and Goyal (2008) for more extensive surveys of the vast literature on return predictability). Most notably, 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 performance of *IRP* in out-of-sample forecast tests.

A. Econometric Specification

We start with the following predictive regression model:

$$r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{i,t+1}, \tag{10}$$

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 return including dividends from WRDS and the monthly continuously compounded one-month T-bill rate, $x_{i,t}$ is the ith monthly predictive variable corresponding to our *IRP* measure, *FY/P*, *E/P*, *D/P, B/M*, *Term*, *Default*, and $\varepsilon_{i,t+1}$ is the error term. Following Welch and Goyal (2008), we use a recursive method to estimate the model and generate out-of-sample forecasts of the market returns. Specifically, 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 obtained using ordinary least squares (OLS) by estimating (10) 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 (10) using observations from 1 to $m+1$. So when generating the next-period forecast, the forecaster uses all information up to the current period, which mimics the real-time forecasting situation. 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 $\{\hat{r}_{i,t+1}\}_{t=m}^{T-1}$.[13]

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 returns than $\overline{r}_{t+1}$. We now introduce the forecast evaluation method.

B. Forecast Evaluation

Following the literature, we compare the performance of alternative predictive variables using the out-of-sample R^2 statistics, R^2_{os}. This is akin to the familiar in-sample R^2, and is defined as

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

The R^2_{os} statistic measures the reduction in mean squared prediction error (MSPE) for the predictive regression (10) using a particular forecasting variable relative to the historical average forecast. For different predictive variables x_i, we can obtain different out-of-sample forecast $\hat{r}_{i,m+k}$ 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. This is equivalent to testing the null of $R^2_{os} \leq 0$ against the alternative of $R^2_{os} > 0$. The most popular method 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. This is true in our case: setting $\beta_i = 0$ in (10) reduces our predictive regression using x_i to the benchmark model using the historical average. Therefore, we use the adjusted version of the

[13] Alternatively, we can use a rolling method to estimate (10) and obtain the out-of-sample forecast. Specifically, we use observations from 1 to m to estimate the model and generate forecast at time $m+1$, and use observations from 2 to m+1 to estimate the model, and generate forecast at time $m+2$, and proceed in this manner. This rolling method is less sensitive to structural breaks in the data. Using the rolling method yields similar results.

Diebold and Mariano (1995) and West (1996) statistic in Clark and West (2007), which they call the adjusted-MSPE statistic. The adjusted-MSPE statistic is obtained by first defining

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

The adjusted-MSPE f_{t+1} is then regressed on a constant and the t-statistic corresponding to the constant estimated. The p-value of R^2_{os} is obtained from the one-sided t-statistic (upper-tail) based on the standard normal distribution. Clark and West (2007) demonstrate that, in Monte Carlo simulations, this adjusted-MSPE statistic performs reasonably well in terms of size and power when comparing forecasts from nested linear predictive models.

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 following existing studies (e.g., Marquering and Verbeek (2004), Campbell and Thompson (2008), Welch and Goyal (2008), Wachter and Warusawitharana (2009), and Rapach, Strauss, and Zhou (2010)). More specifically, based on the forecasts of expected return and expected variance of stocks, a mean-variance investor with relative risk aversion parameter γ makes her optimal portfolio decision by allocating her portfolio monthly between stocks and risk-free asset. If she forecasts the expected return using historical average, then her allocation to stocks in period $t + 1$ is:

$$w_{1,t} = \left(\frac{1}{\gamma} \right) \left(\frac{\overline{r}_{t+1}}{\hat{\sigma}^2_{t+1}} \right), \tag{11}$$

and if she forecasts the expected return using a particular predictive variable, then her allocation to stocks is:

$$w_{2,t} = \left(\frac{1}{\gamma} \right) \left(\frac{\hat{r}_{i,t+1}}{\hat{\sigma}^2_{t+1}} \right). \tag{12}$$

In both portfolio decisions, $\hat{\sigma}^2_{t+1}$ is the forecast for the variance of stock returns. Similar to Campbell and Thompson (2008) and Rapach, Strauss, and Zhou (2010), we assume that the investor obtains $\hat{\sigma}^2_{t+1}$ by using a ten-year rolling window of monthly returns.

If an investor uses historical average to make her portfolio decision, her average utility level over the out-of-sample period is (the utility level can also be viewed as the certainty equivalent return for the mean-variance investor):

$$U_1 = \mu_1 - \frac{1}{2} \gamma \hat{\sigma}^2_1, \tag{13}$$

where μ_1 and $\hat{\sigma}^2_1$ correspond to the sample mean and variance of the return on the portfolio formed based on (11) over the out-of-sample period.

If an investor uses a predictive variable to make her portfolio decision, then her average utility level over the out-of-sample period is:

$$U_2 = \mu_2 - \frac{1}{2}\gamma\hat{\sigma}_2^2, \tag{14}$$

where μ_2 and $\hat{\sigma}_2^2$ correspond to the sample mean and variance for the return on the portfolio formed based on (12) over the out-of-sample period.[14]

We measure the utility gain of using a particular predictive variable as the difference between (14) and (13). 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 *IRP* relative to other forecasting variables, we also follow Rapach, Strauss, and Zhou (2010) to conduct a forecasting 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 $g_{t+1} = (\hat{\varepsilon}_{i,t+1} - \hat{\varepsilon}_{j,t+1})\,\hat{\varepsilon}_{i,t+1}$, where $\hat{\varepsilon}_{i,t+1}$ ($\hat{\varepsilon}_{j,t+1}$) is the forecasting 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)'s test can 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.

C. Out-of-sample Forecasting Results

Existing studies of the out-of-sample forecasting performance of predictive variables are mainly conducted at lower frequencies, namely, at annual and quarterly frequencies. Because we construct *IRP* at the monthly frequency, we evaluate the performance of these variables at a relatively high frequency. In the out-of-sample forecasting scenario, how to choose the estimation and forecast periods is ultimately an ad-hoc choice, but the criteria are clear: it is important to have enough observations in the evaluation period to obtain reliable estimates of the predictive model, and it is

[14]Following Campbell and Thompson (2008), we constrain the portfolio weight on stocks to lie between 0% and 150% (inclusive) each month, although the results for *IRP* are also robust to the case where no constraint is imposed.

also important to have a long-enough period for the model to be evaluated. Therefore, we examine two specifications with two forecast periods: in the first case, the forecast period is from 1998.01 to 2010.12, and in the second case, the forecast period is from 2003.01 to 2010.12. The reason to choose the first forecast period is that existing studies such as Welch and Goyal (2008) and Rapach, Strauss, and Zhou (2010) have shown that many commonly used forecasting variables perform poorly starting in the late 1990s. In terms of the second forecasting period, we are interested in finding how various predictive variables performed during the recent housing boom and financial crisis period. Because the payout yield (P/Y) is available only up to 2008.12, we do not include this variable in our out-of-sample discussions.[15]

As argued in Campbell and Shiller (1988, 1998), aggregate corporate earnings display short-run cyclical noise, resulting in a short-run cyclical noise in *IRP*. When we conduct the in-sample analysis, this problem is less severe because we can forecast excess returns up to 60 months, and we do observe that the forecasting power of *IRP* increases with forecasting horizons, as reflected by the increasing adjusted R^2. However, this problem is particularly severe when we conduct the one-month-ahead out-of-sample forecast. Campbell and Shiller (1988, 1998) propose using the ratio of a 10-year moving average of earnings-to-prices to mitigate the noise due to short-run earnings fluctuations. Similar to Campbell and Shiller (1988, 1998), we propose a 3-year moving average of *IRP* as our out-of-sample forecasting variable. Similarly, we also do a 3-year moving average of other valuation ratios including FY/P, E/P, D/P, and B/M.

[INSERT FIGURE 3 HERE]

Before presenting the test statistics R^2_{os}, we first plot the differences between cumulative squared prediction error for the historical average forecast and the cumulative squared prediction error for the forecasting models using different predictive variables in Figure 3 for the forecast period of 2003.01-2010.12. This figure provides a visual representation of how each model performs over the forecasting period. If a curve lies above the horizon line, then the forecasting model using a particular predictive variable 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. If a forecasting model consistently beats the historical average model, then the corresponding curve will have a slope that is always

[15] In untabulated results, we examine the out-of-sample performance of the payout yield for the two forecast periods of 1998.01 to 2008.12 and 2003.01 to 2008.12, and we find that it cannot outperform the historical average model.

positive; the closer a forecasting model is to this ideal, the better the performance of this model. One notable thing from Figure 3 is that the performance of different forecasting variables were the most volatile during the recent financial crisis. Among all forecasting variables, *IRP* seems to perform the best: it stays above zero for most periods and its slope is closest to being positive.

[INSERT TABLE IX HERE]

Table IX reports the R^2_{os} statistics for each of the forecasting models using alternative predictive variables for two forecasting periods: 1998.01-2010.12 and 2003.01-2010.12. In both forecasting periods, *IRP* produces positive R^2_{os}. In the second forecasting period, the improvement of the forecast based on *IRP* relative to the historical average model is 2.9%. Campbell and Thompson (2008) argue that even very small positive R^2_{os} values, such as 0.5% for monthly data, can signal an economically meaningful degree of return predictability for a mean-variance investor, which provides a simple assessment of a variable's forecasting power in practice. The high R^2_{os} of *IRP* indicates that its out-of-sample forecasting performance is quite impressive. On the other hand, the forecasting models using other predictive variables all yield negative R^2_{os}, suggesting that these variables cannot beat the simple historical average forecast model. 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. In contrast, *IRP* consistently beat the historical average in the two forecasting periods we examine.

As discussed in Subsection IV.B, when R^2_{os} is greater than zero, statistical significance can be assessed with the adjusted-MSPE measure in Clark and West (2007). Since *IRP* is the only variable that produces a positive R^2_{os}, we obtain the p-value of its R^2_{os} based on the adjusted-MSPE measure of testing $R^2_{os} \leq 0$ against the alternative of $R^2_{os} > 0$. We see that *IRP* yields statistically significant R^2_{os} in both forecasting periods. These results are consistent with what we observe in Figure 3.

Table IX also reports the utility gains using a specific forecasting model versus using the historical average. *IRP* produces positive utility gains in both forecasting periods, indicating that mean-variance investors should be willing to pay for access to the information in *IRP* to form their optimal portfolios; the utility gain based on *IRP* is more than 7% a year. Among other forecasting variables, all variables produce some positive utility gains in the first forecast period; in the second forecast period, only *Term* and *Default* produce positive utility gains. Overall, the economic magnitude of the utility gains for other variables is much smaller than *IRP*.

[INSERT TABLE X HERE]

Rapach, Strauss, and Zhou (2010) show that, although individual economic variables may fail to deliver consistent out-of-sample forecasting gains relative to the historical average, combining individual forecasts could deliver significant out-of-sample gains relative to the historical average. Therefore, the more important question is whether *IRP* brings new information that is not contained in the existing variables. The Harvey, Leybourne, and Newbold (1998) test results in Table X show that *IRP* does indeed contain distinct information from existing forecasting variables. Panels A and B show that for *IRP*, in both forecasting periods, we can strongly reject the null hypothesis that *IRP* is encompassed by another valuation ratio at the 1% (or 5%) level; in contrast, we cannot reject the null hypothesis that *IRP* encompasses other valuation ratios at conventional levels. This indicates that *IRP* contains more information than other valuation ratios. For the business cycle variables, we still fail to reject the null that *IRP* encompasses *Term* and *Default*, while we strongly reject the null that *Term* encompasses *IRP* in both forecasting periods at the 5% level, and we marginally reject the null that *Default* encompasses *IRP*.

To summarize, our analysis shows that the out-of-sample forecast of the smoothed *IRP* for one-month ahead excess market return is quite impressive. More important, the results show that *IRP* contains important and distinct information not contained in other commonly used forecasting variables.

V Conclusion

In this paper, we find that the aggregate ICC is an excellent predictor of aggregate market returns both in-sample and out-of-sample, thus providing evidence that the aggregate ICC is an excellent proxy of time-varying expected returns. This significantly extends the findings of Pastor, Sinha, and Swaminathan (2008) who show theoretically that the aggregate ICC is a good proxy of time-varying expected returns and find that the aggregate ICC is able to detect the positive inter-temporal relationship between volatility and expected returns.

We estimate the aggregate ICC for the individual stocks in the S&P 500 index and use a value-weighted average of individual ICC as an estimate of market-wide expected returns. The aggregate implied risk premium is then obtained by subtracting the one-month T-bill yield from the aggregate ICC. This implied risk premium has intuitive properties in its relationship with measures of aggregate investment and consumption, strongly predicts future (excess) market returns, and has the best out-of-sample forecasting power among various predictor variables.

These results have implications for several different strands of the academic literature. Continuing on the work of Pastor, Sinha, and Swaminathan (2008), our work establishes the usefulness of ICC in aggregate time-series context especially with respect to predicting future returns, while most current work involving ICC focuses on cross-sectional relationships. Our results also significantly extend the predictability literature. While most current work has examined predictability using traditional valuation ratios such as book-to-market, dividend-to-price, and earnings-to-price ratios, we show that a measure of expected return estimated from a theoretically justifiable discounted cash flow model has superior forecasting power over such traditional measures. Finally, our work is also relevant to the behavioral finance literature since it shows that ICC is able to predict future market returns even in the presence of several macro-variables, which should capture business cycle information. Thus, the ICC may also be a good proxy of aggregate market mispricing.

Appendices

Appendix A

In this appendix, we formally test the stationarity of the various variables by conducting Phillips-Perron unit root tests (see Phillips (1987) and Perron (1988)). We run two types of Phillips-Perron unit root tests: regressions with an intercept but without a time-trend, and regressions with both an intercept and a time-trend. The two types of regressions are given below:

$$\begin{aligned} \text{Without time trend: } \Delta Y_t &= a + (c-1)\,Y_{t-1} + u_t, \\ \text{With time trend: } \Delta Y_t &= a + bt + (c-1)\,Y_{t-1} + u_t. \end{aligned} \tag{15}$$

The null hypothesis in both regressions is that the variable Y_t has a unit root; that is, $c = 1$. We report the test statistic based on the regression coefficient, $(c-1)$, which allows for serial correlation up to twelve lags in the regression residuals.

Table BI summarizes the results of the Phillips-Perron unit root tests. In Panels A and B, we strongly reject the null hypothesis of a unit root for *IRP*, but not for the traditional valuation ratios. This result is consistent with the autocorrelations reported in Panel A of Table I , i.e., it takes a shorter time for *IRP* to return to its mean than *FY/P*, *E/P*, *D/P*, *B/M*, and *P/Y*. For other forecasting variables in Panel B of Table V, we reject the null hypothesis of unit root for all variables except *lty*. Panel C shows that we cannot reject the null hypothesis that *cay*, and *i/k* contain a unit root.

[INSERT TABLE A.I HERE]

Appendix B

For each regression, we conduct a Monte Carlo simulation using a VAR procedure to assess the statistical significance of relevant statistics. We illustrate our procedure for the bivariate regression involving *IRP* and *FY/P*. The simulation method is conducted in the same way for other regressions.

Define $Z_t = (r_t,\ IRP_t, FY/P_t)'$, where Z_t is a 3×1 column vector. We first fit a first-order VAR to Z_t using the following specification:

$$Z_{t+1} = A_0 + A_1 Z_t + u_{t+1}, \tag{16}$$

where A_0 is a 3×1 vector of intercepts and 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 (16) are used to generate artificial data for the Monte Carlo simulations. We impose the null hypothesis of no predictability on r_t in the VAR. This is done by setting the slope coefficients on the explanatory variables to zero, and by setting the intercept in the equation of r_t to be its unconditional mean. We use the fitted VAR under the null hypothesis of no predictability to generate T observations of the state variable vector, $(r_t,\ IRP_t,\ FY/P_t)$. The initial observation for this vector is drawn from a multivariate normal distribution with mean equal to the historical mean and variance-covariance matrix equal to the historical estimated variance-covariance matrix of the vector of state variables. Once the VAR is initiated, shocks for subsequent observations are generated by randomizing (sampling without replacement) among the actual VAR residuals. 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. This 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 I
Summary Statistics of Forecasting Variables

This table provides summary statistics for the variables described in Section II. Panel A provides summary statistics for the implied risk premium (*IRP*), the forecasted earnings-to-price ratio (*FY/P*), the trailing earnings-to-price ratio (*E/P*), the dividend-to-price ratio (*D/P*), the book-to-market ratio (*B/M*), the term spread (*Term*), and the default spread (*Default*), using monthly data from 1981.01 to 2010.12. Panel B provides summary statistics for *IRP*, the payout yield (*P/Y*), long-term yield (*lty*), net equity expansion (*ntis*), inflation (*infl*), stock variance (*svar*), lagged excess market returns (*vwretd*), and two sentiment measures (*senti1* and *senti2*), using monthly data from 1981.01 to 2008.12. Panel C provides summary statistics for *IRP*, consumption-to-wealth ratio (*cay*), and investment-to-capital ratio (*i/k*), using quarterly data from 1981.Q1 to 2008.Q4. Panel D provides the number of firms in the S&P 500 index that is used to calculate *IRP*, *FY/P*, *E/P*, *D/P*, and *B/M*. All variables except *FY/P*, *E/P*, *D/P*, *B/M*, *P/Y*, *senti1*, and *senti2* are reported in annualized percentages. The implied risk premium (*IRP*) is our new forecasting variable calculated as the difference between the aggregate implied cost of capital and one-month T-bill yield. The detailed description for these variables are provided in Section II.

Panel A: Univariate Statistics for Forecasting Variables (1981.01-2010.12)

			Autocorrelation at Lag					
Variable	Mean	Std. Dev.	1	12	24	36	48	60
IRP	6.74	2.58	0.95	0.55	0.04	-0.21	-0.19	-0.06
FY/P	0.08	0.03	0.98	0.74	0.57	0.49	0.36	0.24
E/P	0.06	0.02	0.98	0.71	0.47	0.44	0.34	0.21
D/P	0.02	0.01	0.99	0.81	0.66	0.60	0.47	0.36
B/M	0.42	0.17	0.99	0.82	0.67	0.58	0.45	0.33
Term	3.22	1.46	0.91	0.34	-0.13	-0.39	-0.38	-0.09
Default	1.10	0.49	0.96	0.45	0.25	0.22	0.14	0.12

Panel B: Univariate Statistics for Forecasting Variables (1981.01-2008.12)

			Autocorrelation at Lag					
Variable	Mean	Std. Dev.	1	12	24	36	48	60
IRP	6.38	2.27	0.94	0.47	0.02	-0.16	-0.18	-0.12
P/Y	0.11	0.03	0.97	0.69	0.57	0.40	0.31	0.24
lty	7.34	0.74	0.98	0.77	0.64	0.57	0.41	0.30
ntis	8.38	7.34	0.97	0.43	0.18	0.08	0.01	-0.06
infl	3.19	1.15	0.51	0.21	0.26	0.29	0.19	0.17
svar	3.17	1.99	0.43	0.02	0.00	0.00	-0.03	0.00
vwretd	5.11	15.47	0.11	-0.03	0.07	-0.03	0.00	-0.09
senti1	0.32	0.68	0.97	0.58	0.24	0.18	0.09	-0.07
senti2	0.37	0.65	0.98	0.50	0.21	0.16	0.05	-0.12

Panel C: Univariate Statistics for Forecasting Variables (1981.Q1-2008.Q4)

			Autocorrelation at Lag					
Variable	Mean	Std. Dev.	1	12	24	36	48	60
IRP	6.42	2.21	0.85	-0.15	-0.09	0.19	-0.11	-0.15
cay	2.33	8.17	0.93	0.46	0.18	-0.27	-0.39	-0.34
i/k	14.48	1.34	0.97	0.14	-0.44	-0.27	0.02	0.11

Panel D: Number of Firms for *IRP*

Year	1981	1982	1983	1984	1985	1986	1987	1988
Obs.	301	294	303	317	323	316	317	323
Year	1989	1990	1991	1992	1993	1994	1995	1996
Obs.	319	317	315	318	325	331	336	343
Year	1997	1998	1999	2000	2001	2002	2003	2004
Obs.	356	362	372	391	388	392	404	421
Year	2005	2006	2007	2008	2009	2010		
Obs.	430	435	430	419	405	443		

Table II
Correlation Among Forecasting Variables

This table provides the correlation among the variables described in Section II. Panel A provides the correlation among the implied risk premium (*IRP*), the forecasted earnings-to-price ratio (*FY/P*), the trailing earnings-to-price ratio (*E/P*), the dividend-to-price ratio (*D/P*), the book-to-market ratio (*B/M*), the term spread (*Term*), and the default spread (*Default*), using monthly data from 1981.01 to 2010.12. Panel B provides the correlation among *IRP*, the payout yield (*P/Y*), long-term yield (*lty*), net equity expansion (*ntis*), inflation (*infl*), stock variance (*svar*), lagged excess market returns (*vwretd*), and two sentiment measures (*senti1* and *senti2*), using monthly data from 1981.01 to 2008.12. Panel C provides the correlation among *IRP*, consumption-to-wealth ratio (*cay*), and investment-to-capital ratio (*i/k*), using quarterly data from 1981.Q1 to 2008.Q4.

Panel A: Correlation Among Forecasting Variables (1981.01-2010.12)

Variable	*IRP*	*FY/P*	*E/P*	*D/P*	*B/M*	*Term*	*Default*
IRP	1.00	0.31	0.33	0.37	0.39	0.82	0.48
FY/P		1.00	0.96	0.95	0.97	-0.02	0.68
E/P			1.00	0.94	0.96	0.00	0.76
D/P				1.00	0.98	0.08	0.65
B/M					1.00	0.09	0.71
Term						1.00	0.24
Default							1.00

Panel B: Correlation Among Forecasting Variables (1981.01-2008.12)

Variable	*IRP*	*P/Y*	*lty*	*ntis*	*infl*	*svar*	*vwretd*	*senti1*	*senti2*
IRP	1.00	0.49	0.21	0.09	-0.13	0.17	-0.05	0.02	0.02
P/Y		1.00	0.59	-0.31	0.09	0.00	0.04	0.05	0.03
lty			1.00	0.04	0.29	-0.13	-0.02	0.55	0.50
ntis				1.00	0.06	-0.19	0.03	-0.10	-0.09
infl					1.00	-0.28	-0.05	0.13	0.08
svar						1.00	-0.42	0.00	0.00
vwretd							1.00	-0.11	-0.12
senti1								1.00	0.96
senti2									1.00

Panel C: Correlation Among Forecasting Variables (1981.01-2008.04)

Variable	*IRP*	*cay*	*i/k*
IRP	1.00	0.18	-0.68
cay	0.18	1.00	-0.22
i/k	-0.68	-0.22	1.00

Table III
Univariate Regressions for *IRP* and Valuation Ratios

This table summarizes the univariate forecasting regression results for equation (7). The dependent variable in these regressions is 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. The independent variables are the implied risk premium (IRP), the forecasted earnings-to-price ratio (FY/P), the trailing earnings-to-price ratio (E/P), the dividend-to-price ratio (D/P), the book-to-market ratio (B/M) and the payout yield (P/Y) in Panels A-F, respectively. The data span from 1981.01 to 2010.12 in Panels A-E, and span from 1981.01 to 2008.12 in Panel F. In Panel F, P/Y is in logarithm form. In all regressions, we are predicting monthly excess market returns in percentages. In Panels A-E, we obtain the corresponding monthly values for IRP, FY/P, E/P, D/P, and B/M measured in percentages. The rescaling of data does not affect the significance of slopes. In Panel F, Log(P/Y) is the logarithm of monthly P/Y not in percentages. Horizon is 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 Newey-West correction. These standard errors correct for the autocorrelation in regressions due to overlapping observations and for generalized heteroskedasticity. 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. The artificial data for the simulation are generated under the null using the VAR approach described in Appendix B.

	Panel A: IRP				Panel B: FY/P				Panel C: E/P			
Horizon	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	2.083	1.662	0.078	0.009	0.331	0.288	0.566	0.000	0.912	0.639	0.466	0.001
12	1.827	2.096	0.105	0.065	1.214	1.180	0.335	0.033	1.449	1.252	0.358	0.036
24	1.955	2.068	0.143	0.153	1.274	1.777	0.242	0.091	1.334	1.619	0.319	0.075
36	2.098	2.931	0.078	0.272	1.075	1.688	0.286	0.106	1.084	1.429	0.402	0.080
48	1.824	4.026	0.041	0.319	1.046	2.208	0.234	0.159	1.131	1.993	0.327	0.139
60	1.467	3.500	0.080	0.293	1.015	2.799	0.196	0.219	1.090	2.526	0.289	0.188
avg. b	1.876		0.025		0.993		0.370		1.167		0.446	

	Panel D: D/P				Panel E: B/M				Panel F: Log(P/Y)			
Horizon	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	3.106	0.995	0.353	0.003	0.134	0.734	0.467	0.002	1.112	1.157	0.138	0.006
12	4.239	1.649	0.277	0.058	0.203	1.362	0.369	0.039	1.362	2.263	0.063	0.097
24	3.850	1.858	0.277	0.119	0.186	1.594	0.356	0.081	1.300	2.404	0.078	0.235
36	3.207	1.961	0.301	0.135	0.158	1.584	0.402	0.096	0.913	2.648	0.080	0.180
48	3.251	2.825	0.205	0.218	0.156	2.141	0.343	0.149	0.703	3.162	0.065	0.161
60	3.081	3.617	0.163	0.283	0.151	2.732	0.283	0.203	0.570	3.252	0.080	0.152
avg. b	3.456		0.328		0.165		0.480		0.993		0.096	

Table IV
Bivariate Regressions Involving *IRP* and Valuation Ratios

This table summarizes the bivariate forecasting regression results involving the implied risk premium (IRP) and forecasted earnings-to-price ratio (FY/P) in Panel A, the implied risk premium (IRP) and trailing earnings-to-price ratio (E/P) in Panel B, the implied risk premium (IRP) and dividend-to-price ratio (D/P) in Panel C, the implied risk premium (IRP) and book-to-market ratio (B/M) in Panel D, and the implied risk premium (IRP) and the payout yield (P/Y) in Panel E. The data span from 1981.01 to 2010.12 in Panels A-D, and span from 1981.01 to 2008.12 in Panel E. In Panel E, both IRP and P/Y are in logarithm forms. The dependent variable in these regressions is 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. In all regressions, we are predicting monthly excess market returns in percentages. In Panels A-E, we obtain the corresponding monthly values for IRP, FY/P, E/P, D/P, and B/M measured in percentages. The rescaling of data does not affect the significance of slopes. In Panel E, Log(P/Y) is the logarithm of monthly P/Y not in percentages. Horizon is 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 Newey-West correction. These standard errors correct for the autocorrelation in regressions due to overlapping observations and for generalized heteroskedasticity. 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. The artificial data for the simulation are generated under the null using the VAR approach described in Appendix B.

Panel A: Bivariate Regression Involving IRP and FY/P

	IRP			FY/P			
Horizon	b	$Z(b)$	$pval$	c	$Z(c)$	$pval$	$adj.R^2$
1	2.189	1.745	0.068	-0.339	-0.302	0.689	0.004
12	1.570	1.681	0.173	0.734	0.749	0.374	0.070
24	1.623	1.979	0.155	0.778	1.714	0.194	0.178
36	1.869	2.940	0.082	0.527	1.407	0.274	0.289
48	1.565	4.013	0.043	0.598	2.121	0.194	0.361
60	1.168	2.885	0.120	0.690	2.744	0.153	0.378
avg.	1.664		0.087	0.498		0.457	

Panel B: Bivariate Regression Involving IRP and E/P

	IRP			E/P			
Horizon	b	$Z(b)$	$pval$	c	$Z(c)$	$pval$	$adj.R^2$
1	2.039	1.646	0.103	0.149	0.108	0.551	0.004
12	1.536	1.648	0.199	0.867	0.798	0.377	0.071
24	1.687	2.032	0.161	0.783	1.484	0.257	0.171
36	1.932	3.032	0.073	0.496	1.077	0.364	0.282
48	1.604	4.058	0.038	0.650	1.838	0.253	0.356
60	1.217	2.896	0.125	0.735	2.322	0.209	0.366
avg.	1.669		0.063	0.613		0.458	

Panel C: Bivariate Regression Involving *IRP* and *D/P*

	IRP			*D/P*			
Horizon	*b*	*Z(b)*	*pval*	*c*	*Z(c)*	*pval*	*adj.*R^2
1	1.902	1.449	0.134	1.277	0.397	0.518	0.004
12	1.348	1.338	0.266	2.878	1.051	0.380	0.082
24	1.492	1.892	0.197	2.430	1.668	0.268	0.187
36	1.794	2.870	0.101	1.480	1.445	0.339	0.290
48	1.441	3.785	0.061	1.896	2.347	0.226	0.375
60	1.042	2.622	0.164	2.136	2.981	0.192	0.400
avg.	1.503		0.104	2.016		0.483	

Panel D: Bivariate Regression Involving *IRP* and *B/M*

	IRP			*B/M*			
Horizon	*b*	*Z(b)*	*pval*	*c*	*Z(c)*	*pval*	*adj.*R^2
1	2.049	1.585	0.111	0.013	0.072	0.626	0.004
12	1.503	1.579	0.197	0.115	0.762	0.448	0.070
24	1.648	2.062	0.146	0.094	1.174	0.376	0.165
36	1.920	3.081	0.072	0.052	0.816	0.475	0.275
48	1.580	3.842	0.051	0.071	1.360	0.386	0.340
60	1.157	2.501	0.168	0.091	1.816	0.336	0.348
avg.	1.643		0.072	0.073		0.557	

Panel E: Bivariate Regression Involving Log(*IRP*) and Log(*P/Y*)

	Log(*IRP*)			Log(*P/Y*)			
Horizon	*b*	*Z(b)*	*pval*	*c*	*Z(c)*	*pval*	*adj.*R^2
1	0.202	0.317	0.435	0.958	0.922	0.206	0.000
12	0.742	1.881	0.124	0.814	1.235	0.208	0.132
24	0.638	2.380	0.084	0.826	1.874	0.124	0.305
36	0.703	3.069	0.051	0.386	2.209	0.106	0.311
48	0.672	3.437	0.045	0.200	1.419	0.243	0.346
60	0.631	2.913	0.084	0.094	0.611	0.421	0.380
avg.	0.598		0.106	0.546		0.261	

Table V
Univariate Regressions for Other Forecasting Variables

This table summarizes the monthly univariate regression results for the term spread (*Term*) and the default spread (*Default*) in Panel A (1981.01 to 2010.12), for the long-term yield (*lty*), the net equity expansion (*ntis*), inflation (*infl*), stock variance (*svar*), and lagged excess market return (*vwretd*) in Panel B (1981.01 to 2008.12), and for the two sentiment measures (*senti1* and *senti2*) in Panel C (1981.01 to 2008.12). Panel D provides the quarterly univariate regression results for the implied risk premium (*IRP*), the consumption-to-wealth ratio (*cay*), and investment-to-capital ratio (*i/k*) (1981.Q1 to 2008.Q4). The dependent variable in these regressions is continuously compounded excess return per month (per quarter) defined as the difference between the monthly (quarterly) continuously compounded return on the value-weighted market return including dividends from WRDS and the monthly (quarterly) continuously compounded one-month T-bill rate. In Panels A-C, we are predicting monthly excess returns in percentages. In Panels A-B, we obtain the corresponding monthly values for *Term*, *Default*, *lty*, *ntis*, *infl*, *svar*, and *vwretd* measured in percentages. In Panel C, sentiment measures are monthly values not in percentages. In Panel D, we are predicting quarterly excess market returns in percentages, and we obtain the corresponding quarterly values for *IRP*, *cay*, and *i/k* measured in percentages. The rescaling of data does not affect the significance of slopes. Horizon is in months in Panels A-C and in quarters in Panel D. In forecasting horizons beyond one-month (one-quarter), 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 Newey-West correction. These standard errors correct for the autocorrelation in regressions due to overlapping observations and for generalized heteroskedasticity. 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. The artificial data for the simulation are generated under the null using the VAR approach described in Appendix B.

Panel A: Univariate Regressions for Business Cycle Variables

	Term				*Default*			
Horizon	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$
1	0.640	0.321	0.403	0.000	-4.216	-0.491	0.761	0.001
12	2.529	1.916	0.087	0.043	4.236	0.920	0.327	0.014
24	2.578	2.141	0.076	0.105	2.361	0.698	0.428	0.010
36	2.532	2.717	0.047	0.160	1.969	0.485	0.505	0.008
48	2.055	3.162	0.033	0.156	2.999	0.825	0.434	0.031
60	1.361	1.866	0.142	0.089	3.514	1.129	0.388	0.062
avg. b	1.949		0.070		1.810		0.507	

Panel B: Univariate Regressions for *lty*, *ntis*, *infl*, *svar*, and *vwretd*

	lty				*ntis*				*infl*			
Horizon	*b*	*Z*(*b*)	*pval*	*adj.*R^2	*b*	*Z*(*b*)	*pval*	*adj.*R^2	*b*	*Z*(*b*)	*pval*	*adj.*R^2
1	0.113	0.092	0.506	0.000	0.089	0.655	0.748	0.002	-1.182	-1.497	0.076	0.007
12	0.620	0.581	0.373	0.009	0.055	0.543	0.657	0.006	-0.505	-1.098	0.183	0.011
24	0.819	1.318	0.220	0.042	0.081	1.241	0.805	0.030	0.051	0.289	0.610	0.000
36	0.605	1.033	0.303	0.034	0.047	1.057	0.749	0.016	0.013	0.083	0.542	0.000
48	0.676	1.319	0.279	0.059	0.044	0.864	0.703	0.020	0.078	0.544	0.680	0.001
60	0.724	1.742	0.240	0.092	0.052	1.149	0.738	0.041	0.202	1.604	0.902	0.012
avg. *b*	0.593		0.370		0.062		0.729		-0.224		0.174	

Panel B (continued)

	svar				*vwretd*			
Horizon	*b*	*Z*(*b*)	*pval*	*adj.*R^2	*b*	*Z*(*b*)	*pval*	*adj.*R^2
1	-1.228	-2.704	0.014	0.024	0.121	1.849	0.028	0.015
12	-0.033	-0.199	0.379	0.000	0.006	0.362	0.265	0.000
24	-0.050	-0.291	0.336	0.001	-0.008	-0.598	0.526	0.002
36	-0.189	-1.238	0.144	0.015	-0.003	-0.544	0.469	0.000
48	-0.130	-0.788	0.206	0.011	-0.006	-1.555	0.669	0.002
60	-0.099	-0.768	0.206	0.009	-0.010	-3.344	0.897	0.009
avg. *b*	-0.288		0.008		0.017		0.057	

Panel C: Univariate Regressions for Sentiment Measures

	senti1				*senti2*			
Horizon	*b*	*Z*(*b*)	*pval*	*adj.*R^2	*b*	*Z*(*b*)	*pval*	*adj.*R^2
1	-0.669	-1.809	0.035	0.010	-0.584	-1.483	0.047	0.007
12	-0.472	-1.493	0.138	0.059	-0.393	-1.253	0.138	0.036
24	-0.270	-1.055	0.244	0.051	-0.211	-0.794	0.232	0.028
36	-0.137	-0.808	0.311	0.020	-0.081	-0.475	0.307	0.006
48	-0.114	-0.819	0.315	0.021	-0.111	-0.876	0.241	0.018
60	-0.073	-0.557	0.383	0.012	-0.066	-0.518	0.321	0.009
avg. *b*	-0.289		0.184		-0.241		0.191	

Panel D: Univariate Regressions for Quarterly *IRP*, *cay* and *i/k*

	IRP				*cay*				*i/k*			
Horizon	*b*	*Z*(*b*)	*pval*	*adj.*R^2	*b*	*Z*(*b*)	*pval*	*adj.*R^2	*b*	*Z*(*b*)	*pval*	*adj.*R^2
1	4.496	0.919	0.254	0.009	0.694	2.446	0.019	0.027	-1.772	-0.689	0.342	0.005
4	6.182	1.801	0.141	0.069	0.589	2.184	0.102	0.081	-1.653	-0.817	0.365	0.017
8	5.940	1.801	0.166	0.172	0.564	2.289	0.126	0.181	-2.219	-1.096	0.330	0.086
12	5.642	2.235	0.143	0.235	0.621	2.376	0.157	0.293	-2.714	-1.944	0.198	0.202
16	5.215	3.361	0.072	0.313	0.581	2.841	0.140	0.339	-2.731	-3.228	0.096	0.320
avg. *b*	5.495		0.108		0.610		0.129		-2.218		0.340	

Table VI
Multivariate Regressions Involving *IRP* and Other Forecasting Variables

This table summarizes the multivariate regression results of *IRP* with forecasting variables other than valuation ratios. Panel A reports the bivariate regressions involving *IRP* and the term spread (*Term*), and *IRP* and the default spread (*Default*) (1981.01-2010.12), Panel B reports the multivariate regression involving *IRP*, the long-term yield (*lty*), net equity expansion (*ntis*), inflation (*infl*), stock variance (*svar*), and lagged market returns (*vwretd*) (1981.01-2008.12), and Panel C reports the bivariate regressions involving *IRP* with one sentiment measure (*senti1*), and *IRP* with the other sentiment measure (*senti2*) (1981.01-2010.12). Panel D reports the quarterly multivariate regression involving *IRP*, the consumption-to-wealth ratio (*cay*), and investment-to-capital ratio (*i/k*) (1981.Q1 to 2008.Q4). The dependent variable in these regressions is continuously compounded excess return per month (quarter) defined as the difference between the monthly (quarterly) continuously compounded return on the value-weighted market return including dividends from WRDS and the monthly (quarterly) continuously compounded one-month T-bill rate. In Panels A-C, we are predicting monthly excess returns in percentages, and we obtain the corresponding monthly values for *IRP*, *Term*, *Default*, *lty*, *ntis*, *infl*, *svar*, and *vwretd* measured in percentages; in Panel C, sentiment measures are monthly values not in percentages. In Panel D, we are predicting quarterly excess market returns in percentages, and we obtain the corresponding quarterly values for *IRP*, *cay*, and *i/k* measured in percentages. The rescaling of data does not affect the significance of slopes. Horizon is in months in Panels A-C and in quarters in Panel D. In forecasting horizons beyond one-month (one-quarter), 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 Newey-West correction. These standard errors correct for the autocorrelation in regressions due to overlapping observations and for generalized heteroskedasticity. 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. The artificial data for the simulation are generated under the null using the VAR approach described in Appendix B.

Panel A: Bivariate Regressions Involving *IRP* and Business Cycle Variables

	IRP			*Term*			
Horizon	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	5.454	2.526	0.015	-7.258	-2.109	0.977	0.016
12	1.843	1.006	0.313	-0.033	-0.012	0.476	0.060
24	1.873	1.039	0.336	0.162	0.066	0.450	0.148
36	2.258	1.802	0.207	-0.314	-0.172	0.512	0.268
48	2.234	3.345	0.067	-0.827	-0.909	0.692	0.324
60	2.251	3.787	0.061	-1.650	-2.647	0.939	0.336
avg.	2.652		0.029	-1.653		0.806	

	IRP			*Default*			
Horizon	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	3.211	2.641	0.009	-12.273	-1.423	0.930	0.013
12	1.875	2.046	0.120	-0.469	-0.104	0.546	0.060
24	2.214	2.297	0.115	-2.672	-0.868	0.743	0.158
36	2.367	3.358	0.048	-3.384	-1.053	0.768	0.287
48	1.927	3.819	0.046	-1.286	-0.408	0.625	0.320
60	1.435	2.454	0.166	0.407	0.129	0.509	0.289
avg.	2.172		0.018	-3.280		0.759	

Panel B: Multivariate Regression Involving *IRP*, *lty*, *ntis*, *infl*, *svar*, and *vwretd*

	IRP			*lty*			*ntis*		
Horizon	*b*	$Z(b)$	*pval*	*c*	$Z(c)$	*pval*	*d*	$Z(d)$	*pval*
1	1.477	0.993	0.274	0.142	0.120	0.436	0.017	0.132	0.491
12	1.879	1.602	0.215	0.331	0.337	0.392	0.009	0.077	0.467
24	1.585	1.503	0.273	0.481	1.186	0.232	0.049	0.763	0.628
36	1.759	2.099	0.196	0.172	0.640	0.350	0.011	0.202	0.494
48	1.640	3.142	0.102	0.247	1.015	0.311	0.012	0.302	0.511
60	1.473	3.391	0.103	0.239	1.277	0.288	0.024	0.908	0.616
avg.	1.636		0.078	0.269		0.395	0.020		0.087

Panel B (continued)

	infl			*svar*			*vwretd*			
Horizon	*e*	$Z(e)$	*pval*	*f*	$Z(f)$	*pval*	*g*	$Z(g)$	*pval*	$adj.R^2$
1	-1.722	-2.357	0.012	-1.403	-2.874	0.006	0.037	0.565	0.235	0.028
12	-0.489	-1.381	0.143	-0.080	-0.575	0.295	-0.001	-0.057	0.315	0.074
24	-0.012	-0.062	0.521	-0.111	-0.874	0.225	-0.008	-0.730	0.457	0.173
36	0.033	0.245	0.620	-0.258	-2.328	0.045	-0.012	-1.476	0.606	0.254
48	0.085	1.025	0.802	-0.190	-1.526	0.123	-0.012	-2.511	0.789	0.346
60	0.207	2.999	0.984	-0.162	-1.626	0.121	-0.013	-3.681	0.912	0.435
avg.	-0.316		0.518	-0.367		0.003	-0.001		0.341	

Panel C: Bivariate Regressions Involving *IRP* and Sentiment Measures

	IRP			*senti1*			
Horizon	*b*	$Z(b)$	*pval*	*c*	$Z(c)$	*pval*	$adj.R^2$
1	1.174	0.814	0.289	-0.676	-1.852	0.050	0.007
12	2.113	2.311	0.090	-0.489	-1.970	0.118	0.139
24	1.865	2.005	0.158	-0.283	-1.482	0.225	0.218
36	1.803	2.418	0.141	-0.142	-1.517	0.252	0.256
48	1.699	3.486	0.074	-0.115	-1.481	0.290	0.339
60	1.549	3.612	0.080	-0.080	-0.865	0.423	0.387
avg.	1.700		0.058	-0.298		0.246	

	IRP			*senti2*			
Horizon	*b*	$Z(b)$	*pval*	*c*	$Z(c)$	*pval*	$adj.R^2$
1	1.168	0.809	0.290	-0.593	-1.512	0.091	0.003
12	2.117	2.267	0.096	-0.417	-1.645	0.156	0.116
24	1.871	1.915	0.182	-0.233	-1.137	0.284	0.195
36	1.806	2.349	0.150	-0.094	-0.906	0.359	0.242
48	1.706	3.505	0.070	-0.119	-1.521	0.267	0.338
60	1.554	3.602	0.083	-0.081	-0.846	0.396	0.385
avg.	1.704		0.060	-0.256		0.288	

Panel D: Multivariate Regression Involving Quarterly *IRP*, *cay* and *i/k*

	IRP			*cay*			*i/k*			
Horizon	*b*	$Z(b)$	*pval*	*c*	$Z(c)$	*pval*	*d*	$Z(d)$	*pval*	$adj.R^2$
1	3.805	0.546	0.388	0.651	2.126	0.059	0.509	0.143	0.412	0.004
4	7.049	1.878	0.144	0.518	1.906	0.187	1.634	0.809	0.251	0.107
8	5.718	3.410	0.037	0.490	2.257	0.182	0.584	0.364	0.375	0.279
12	4.722	5.429	0.008	0.553	2.591	0.177	-0.133	-0.115	0.486	0.450
16	4.374	6.785	0.006	0.513	3.544	0.121	-0.222	-0.260	0.509	0.575
avg.	5.134		0.165	0.545		0.184	0.475		0.408	

Table VII
Predictability Analysis on Alternative Measures of *IRP*

This table provides the univariate return predictability analysis for three alternative measures of *IRP*: *IRP_equ*, *IRP_yield*, and *IRP_dj*, where *IRP_equ* is calculated based on equally-weighting firm-level *IRP* for firms in the S&P 500 index; *IRP_yield* calculated based on value-weighting firm-level *IRP* for firms in the S&P 500 index, but the firm-level *IRP* is calculated by subtracting the 30-year government bond yield from the firm-level ICC; *IRP_dj* is calculated by value-weighting the firm-level *IRP* for firms in the Dow Jones Industrial Moving Average. The dependent variable in these regressions is 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. All regressions use monthly data from 1981.01 to 2010.12. In all regressions, we are predicting monthly excess market returns in percentages, so we obtain the corresponding monthly percentage values for *IRP_equal*, *IRP_yield*, and *IRP_dj*. The rescaling of data does not affect the significance of slopes. Horizon is 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 Newey-West correction. These standard errors correct for the autocorrelation in regressions due to overlapping observations and for generalized heteroskedasticity. 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. The artificial data for the simulation are generated under the null using the VAR approach described in Appendix B.

	IRP_equal				*IRP_yield*				*IRP_dj*			
Horizon	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$
1	1.994	1.632	0.083	0.008	3.315	1.529	0.095	0.009	1.290	0.915	0.237	0.004
12	1.569	1.892	0.131	0.045	1.780	1.032	0.298	0.023	1.169	0.890	0.337	0.022
24	1.563	1.844	0.178	0.101	1.828	1.039	0.317	0.046	2.197	2.194	0.120	0.161
36	1.711	2.501	0.117	0.191	2.441	1.704	0.207	0.121	1.930	2.433	0.115	0.209
48	1.526	3.147	0.078	0.229	2.549	2.798	0.096	0.209	1.788	3.245	0.072	0.280
60	1.310	3.175	0.099	0.227	2.479	2.864	0.116	0.290	1.446	2.826	0.122	0.266
avg. b	1.612		0.052		2.399		0.043		1.637		0.030	

Table VIII
Analysis Involving Analyst Forecast Bias

This table provides the univariate return predictability analysis on the aggregate analyst forecast optimism (*AE*) in Panel A, and provides the bivariate return predictability analysis involving *IRP* and *AE* in Panel B. Both regressions use monthly data from 1981.01 to 2010.12. We compute the forecast optimism bias for each firm and month as the ratio of the difference between the consensus 1-year-ahead analyst forecast of earnings per share (EPS) and the corresponding actual EPS to the 1-year-ahead forecast. We value-weight the forecast optimism biases across firms in each month to compute the aggregate analyst forecast optimism bias. The dependent variable in these regressions is 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. For both regressions in Panels A-B, we are predicting monthly excess market returns in percentages, and we obtain monthly percentage values for both *IRP* and *AE*. The rescaling of data does not affect the significance of slopes. Horizon is 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 Newey-West correction. These standard errors correct for the autocorrelation in regressions due to overlapping observations and for generalized heteroskedasticity. 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. The artificial data for the simulation are generated under the null using the VAR approach described in Appendix B.

Panel A: Univariate Regression for *AE*

Horizon	b	$Z(b)$	$pval$	$adj.R^2$
1	0.095	0.803	0.316	0.001
12	-0.138	-1.780	0.869	0.025
24	-0.015	-0.417	0.618	0.001
36	0.070	0.625	0.375	0.007
48	0.105	1.132	0.275	0.025
60	0.122	1.596	0.200	0.049
avg. b	0.040		0.143	

Panel B: Bivariate Regression Involving *IRP* and *AE*

Horizon	b	$Z(b)$	$pval$	c	$Z(c)$	$pval$	$adj.R^2$
1	2.052	1.640	0.084	0.082	0.742	0.332	0.005
12	1.947	2.369	0.081	-0.160	-2.444	0.922	0.093
24	2.050	2.165	0.133	-0.058	-2.316	0.907	0.159
36	2.120	3.104	0.071	-0.021	-0.267	0.563	0.268
48	1.796	4.035	0.043	0.027	0.344	0.420	0.316
60	1.404	3.148	0.112	0.068	0.833	0.324	0.303
avg.	1.895		0.027	-0.010		0.624	

Table IX
Out-of-Sample Test

This table summarizes the out-of-sample test of forecasting models using different forecasting variables. The dependent variable in these regressions is 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. In these tests, we perform a 3-year moving average for *IRP*, *FY/P*, *E/P*, *D/P*, and *B/M*. Two forecasting periods are examined, with the first one from 1998.01 to 2010.12, and the second from 2003.01 to 2010.12. R^2_{os} is the Campbell and Thompson (2008) out-of-sample R^2 statistic. Statistical significance of R^2_{os} is obtained based on the p-value for the Clark and West (2007) out-of-sample adjusted-MSPE statistic; the statistic corresponds to a one-sided test of the null hypothesis that the competing forecasting model using a specific forecasting variable has equal expected squared prediction error relative to the historical average forecasting model against the alternative that the competing model has a lower expected squared prediction error than the historical average benchmark model. Utility gain (Ugain) 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).

	Forecast Period 1998.01-2010.12			Forecast Period 2003.01-2010.12		
	R^2_{os}	*pval*	Ugain	R^2_{os}	*pval*	Ugain
IRP	0.017	0.034	7.366	0.029	0.037	7.252
FY/P	-0.002		1.427	-0.005		-1.342
E/P	-0.003		0.995	-0.002		-1.142
D/P	-0.005		1.890	-0.005		-0.828
B/M	-0.004		1.099	-0.002		-0.482
Term	-0.009		0.285	-0.009		0.074
Default	-0.014		1.564	-0.024		3.217

Table X
Forecast Encompassing Test Results

This table reports p-values for the Harvey, Leybourne, and Newbold (1998) HLN statistic for the two forecasting periods, 1998.01-2010.12 and 2003.01-2010.12, in Panels A and B, respectively. In these tests, we perform a 3-year moving average for *IRP*, *FY/P*, *E/P*, *D/P*, and *B/M*. The statistic corresponds to a one-sided (upper-tail) test of the null hypothesis that the forecast given in the column heading encompasses the forecast given in the row heading against the alternative hypothesis that the forecast given in the column heading does not encompass the forecast given in the row heading.

Forecast Period: 1998.01-2010.12							
	IRP	*FY/P*	*E/P*	*D/P*	*B/M*	*Term*	*Default*
IRP		0.865	0.899	0.865	0.882	0.863	0.469
FY/P	0.013		0.608	0.769	0.739	0.718	0.342
E/P	0.010	0.340		0.668	0.696	0.674	0.332
D/P	0.009	0.167	0.240		0.306	0.527	0.311
B/M	0.011	0.209	0.263	0.602		0.671	0.330
Term	0.012	0.132	0.162	0.213	0.172		0.326
Default	0.086	0.190	0.193	0.203	0.203	0.250	

Forecast Period: 2003.01-2010.12							
	IRP	*FY/P*	*E/P*	*D/P*	*B/M*	*Term*	*Default*
IRP		0.838	0.854	0.809	0.814	0.792	0.440
FY/P	0.017		0.177	0.509	0.023	0.534	0.332
E/P	0.018	0.794		0.633	0.413	0.585	0.339
D/P	0.018	0.445	0.292		0.155	0.515	0.336
B/M	0.025	0.971	0.546	0.791		0.657	0.351
Term	0.027	0.294	0.250	0.258	0.209		0.352
Default	0.108	0.212	0.204	0.214	0.205	0.238	

Table A.I
Phillips-Perron Unit Root Tests

This table summarizes the results of Phillips-Perron unit root tests on three sets of variables: Panel A provides test results for *IRP*, *FY/P*, *E/P*, *D/P*, *B/M*, *Term*, and *Default*, using monthly data from 1981.01 to 2010.12. Panel B provides test results for *IRP*, *P/Y*, *ntis*, *infl*, *svar*, and *vwretd*, *senti1*, and *senti2*, using monthly data from 1981.01 to 2008.12. Panel C provides test results for *IRP*, *cay*, and *i/k* using quarterly data from 1981.01 to 2008.04. Two types of unit root tests specified in equation (15) are performed. T is the number of observations. The Phillips-Perron test allows for regression errors to be serially correlated and heteroskedastic. The test statistics are computed using serial correlation up to twelve lags in the regression residuals. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Phillips-Perron Unit Root Tests (1981.01-2010.12)

	Test Statistics		
Variables	without trend	with time trend	T
IRP	-19.48**	-19.44*	360
FY/P	-6.83	-9.55	360
D/P	-7.95	-9.80	360
E/P	-4.80	-9.53	360
B/M	-4.91	-6.64	360
Term	-30.95***	-30.98***	360
Default	-18.03**	-18.38*	360

Panel B: Phillips-Perron Unit Root Tests (1981.01-2008.12)

	Test Statistics		
Variables	without trend	with time trend	T
IRP	-24.18***	-26.45**	336
P/Y	-9.91	-15.12	336
lty	-2.84	-21.30*	336
ntis	-12.88*	-13.01	336
infl	-121.46***	-120.84***	336
svar	-216.96***	-220.48***	336
vwretd	-298.98***	-297.23***	336
senti1	-11.85*	-13.99	336
senti2	-13.70*	-16.40	336

Panel C: Phillips-Perron Unit Root Tests (1981.01-2008.04)

	Test Statistics		
Variables	without trend	with time trend	T
IRP	-17.57**	-18.41*	112
cay	-7.92	-11.38	112
i/k	-8.18	-8.22	112

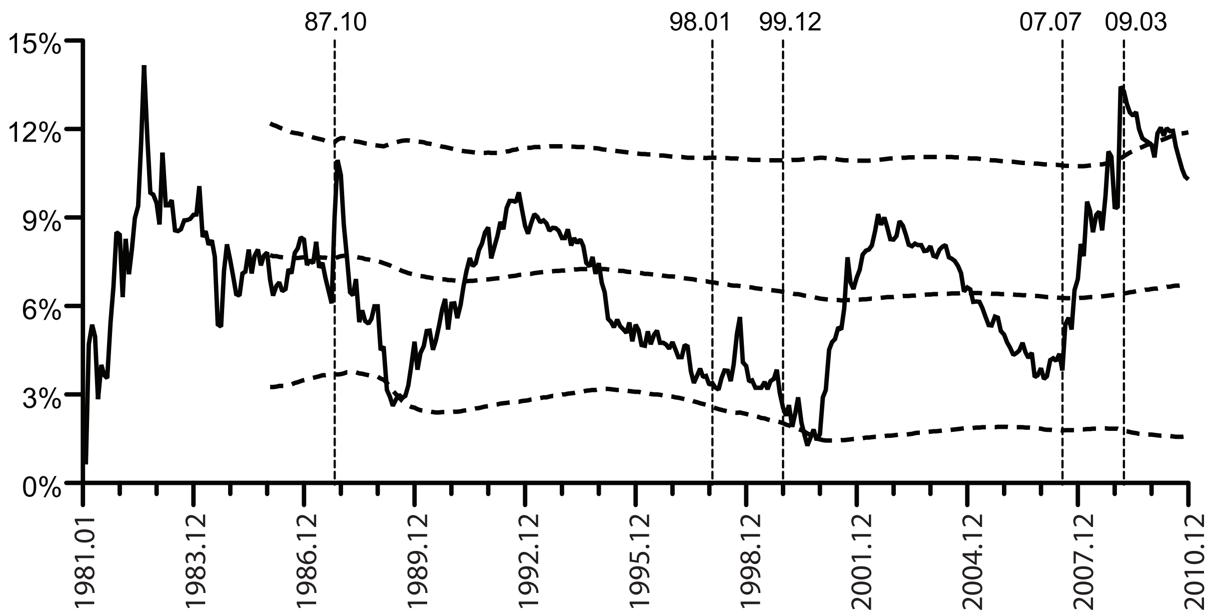

Figure 1. Implied risk premium (*IRP*). This figure depicts the value-weighted implied risk premium constructed based on prevailing S&P 500 companies from January 1981 to December 2010. *IRP* is expressed in annualized percentages. The three horizontal dashed curves correspond to the rolling mean and the two-standard-deviation bands calculated using all historic data starting from January 1986. Dotted vertical lines mark some interesting market periods, namely, 1987.10, 1998-1999, and 2007.07-2009.03.

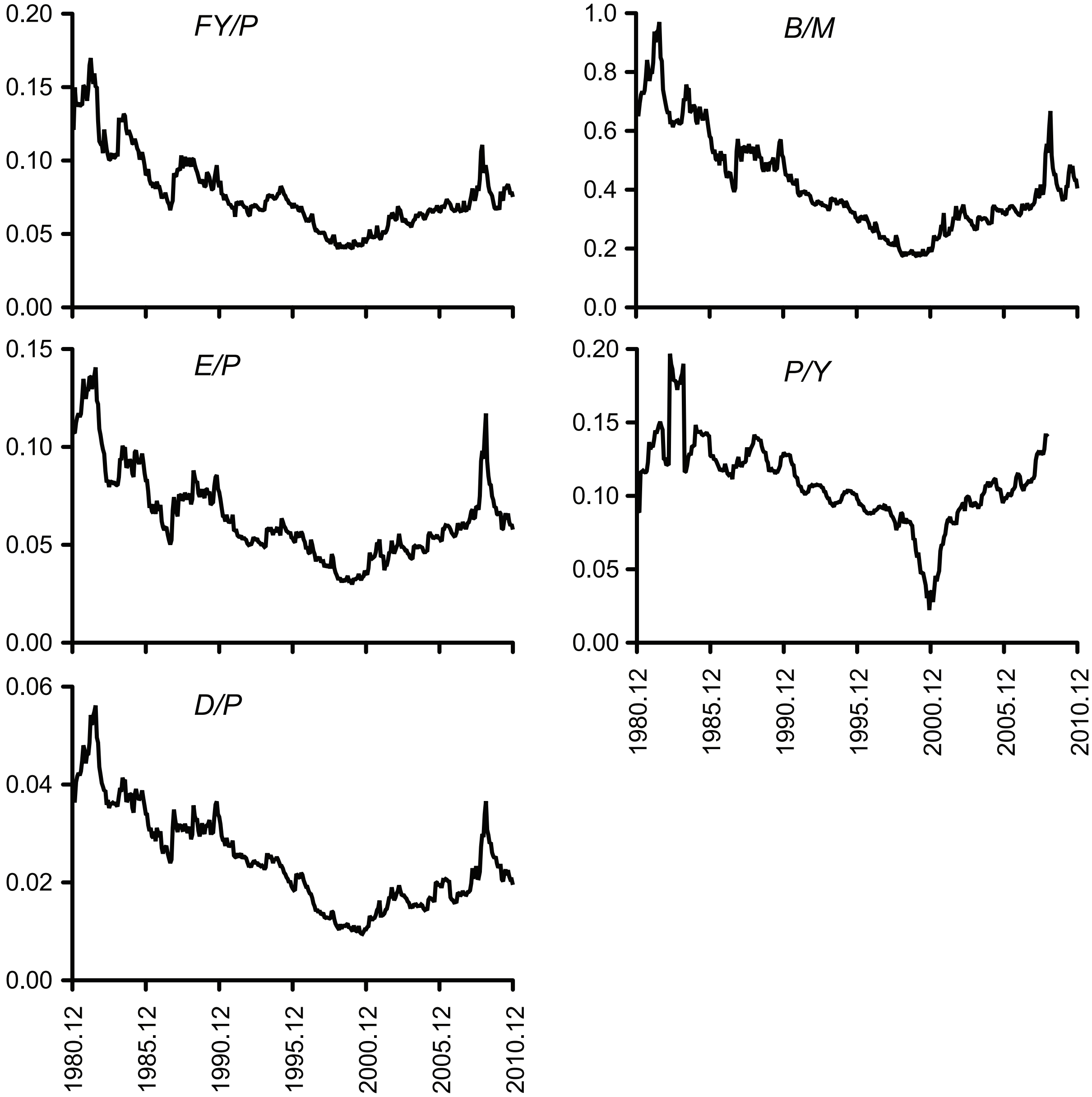

Figure 2. Other predictive variables. This figure depicts the forecasted earnings-to-price ratio (FY/P), trailing earnings-to-price ratio (E/P), dividend-to-price ratio (D/P) and book-to-market ratio (B/M) from January 1981 to December 2010, and the payout yield (P/Y) from January 1981 to December 2008. All panels share identical x-axis.

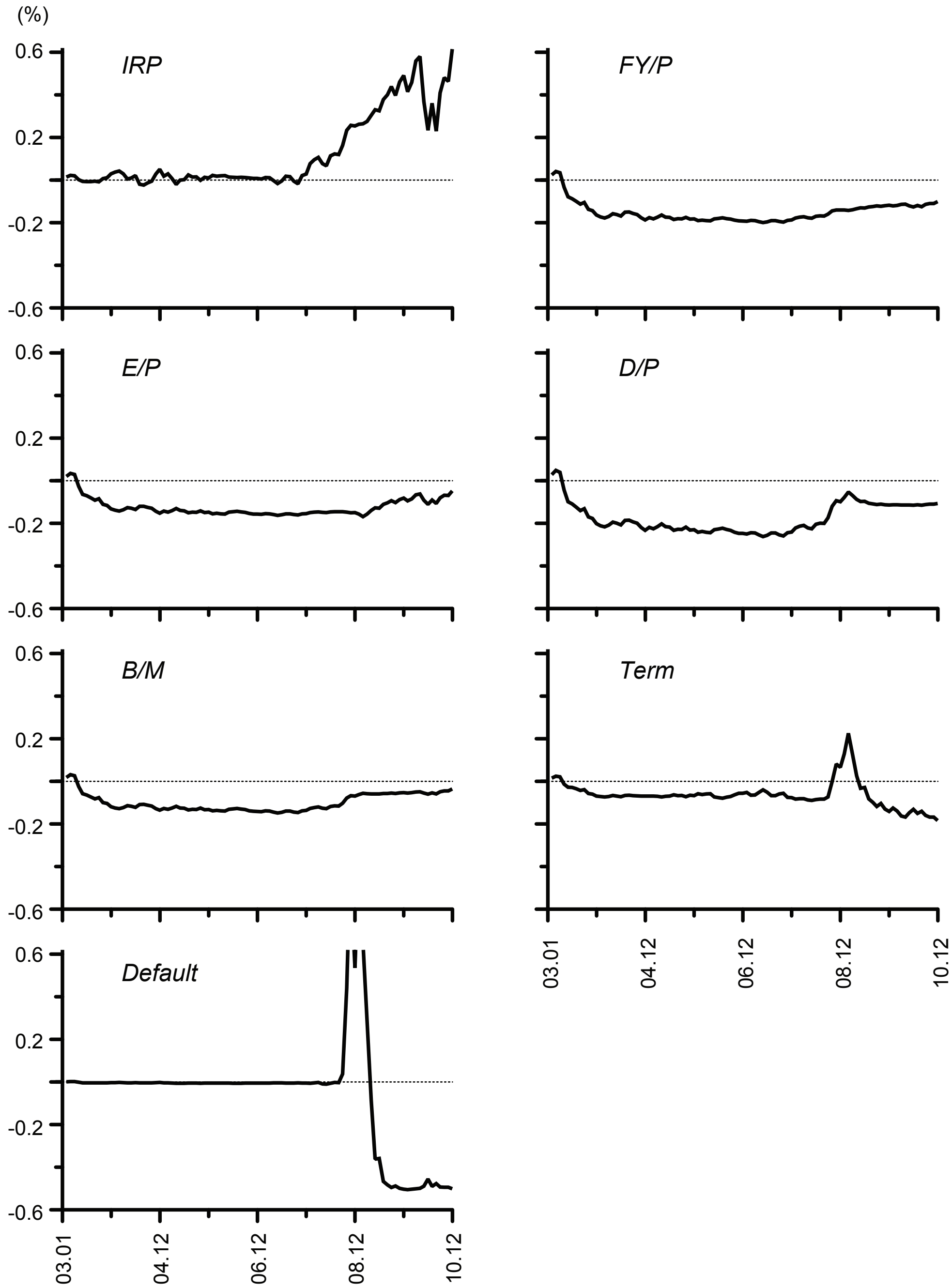

Figure 3. Cumulative squared prediction error for the historical average benchmark forecasting model minus the cumulative squared prediction error for the forecasting model using the implied risk premium (*IRP*), the forecasted earnings-to-price ratio (*FY/P*), trailing earnings-to-price ratio (*E/P*), dividend-to-price ratio (*D/P*), book-to-market ratio (*B/M*), term spread (*Term*) and default spread (*Default*) during the forecast period of 2003.01-2010.12. All panels share identical x-axis and y-axis. The dotted line in each panel goes through zero. The points for 2008.11, 2009.01, 2009.02 and 2009.03 of *Default* are 1.020, 1.023, 1.687 and 0.773, respectively. All four points are out of range.