Predicting Time-varying Value Premium Using the Implied Cost of Capital: Implications for Countercyclical Risk, Mispricing and Style Investing

We estimate an implied value premium (*IVP*) using the implied cost of capital approach. The implied value premium is the difference between the implied costs of capital of value stocks and growth stocks and is a direct estimate of the difference in expected returns between value stocks and growth stocks. We use *IVP* to predict future realized value premium controlling for a variety of countercyclical measures of risk that have been used in the predictability literature. We find that *IVP* is the best predictor of realized value premium during the 1977-2011 time period from horizons ranging from one month to 36 months compared to the value spread, default spread, term spread, and consumption-to-wealth ratio. *IVP* strongly predicts (in the time-series) the difference in abnormal price reactions around future quarterly earnings announcements of value stocks and growth stocks, and the predictive power of *IVP* is stronger during periods of extreme mispricing. Since risk is unlikely to change unexpectedly over a matter of days, the ability of *IVP* to predict price reactions around earnings announcements is strongly supportive of the mispricing story as at least one major source of the predictable time variation in value premium. There is mixed evidence for the countercyclical risk explanation in the data.

JEL Classification: G12

Keywords: Implied Value Premium, Implied Cost of Capital, Predictability, Value Spread, Term Spread, Default Spread, Risk and Mispricing

1 Introduction

Asness, Friedman, Krail, and Liew (2000) and Cohen, Polk, and Vuolteenaho (2003) provide evidence of predictable time variation in the ex-post value premium—the return premium earned by value stocks over growth stocks. Specifically, high value spread (the spread in book-to-market ratios, or earnings-to-price ratios, between value stocks and growth stocks) predicts high value premium. There are two possible explanations for this time variation: time-varying relative mispricing (Lakonishok, Shleifer, and Vishny (1994) and Barberis and Shleifer (2003)) or time-varying relative risks (Zhang (2005)).[1] We explore these alternative explanations in this paper.

Our initial objective, however, is to examine the evidence on time-varying value premium. For this purpose, we use a measure of ex-ante value premium estimated using the implied cost of capital (*ICC*) approach. The ex-ante value premium (henceforth the implied value premium *IVP*) is the difference between the implied costs of capital of value stocks and growth stocks and is a direct estimate of the difference in their expected returns. Since the *ICC* methodology carefully controls for differences in earnings growth rates and payout ratios between value stocks and growth stocks, *IVP* is likely to be a more precise estimate of the ex-ante value premium than traditional value spreads. We use the implied value premium to forecast ex-post value premium.

We estimate *IVP* in two ways: (1) *IVP* based on value and growth portfolios constructed using book-to-market (B/M) ratios as in Fama and French (1993) and (2) *IVP* based on value and growth portfolios constructed using a composite measure of value comprising book-to-market (B/M), cash flow-to-price (C/P), and one-year ahead and two-year ahead forecast earnings-to-price ratios (FE_1/P and FE_2/P). We consider this alternate way of constructing value/growth portfolios to show that our results are not contingent on any specific definition of value.[2] Our sample consists of all firms with available analyst earnings forecasts from January 1977 to December 2011. We use these implied value premia to forecast three measures of ex-post value premium: (i) the Fama and French *HML* factor (Fama and French (1993, 1996)), (ii) a *HML* factor based on B/M ratios using only the firms in our sample and (iii) a *HML* factor based on the composite value measure also using only the firms in our sample.

We conduct long-horizon regression tests to evaluate the forecasting power of *IVP*. In these

[1]Berk, Green, and Naik (1999) develop a model of firm value as the sum of its assets-in-place and growth options and explain a number of stylized facts including the cross-sectional relationship between book-to-market ratio and returns, time-series relationship between aggregate book-to-market ratio and future market excess returns, and short-horizon reversal and longer horizon momentum. Their model does not focus on time-varying value premium.

[2]See Section 2.3 for more details on the construction of these measures.

regressions, we control for the value spread (*VS*), defined as the difference in log B/M ratios between value and growth stocks. We also control for a variety of business cycle proxies including the term spread (*Term*), the default spread (*Default*), and the consumption-to-wealth ratio (*Cay*). We find that *IVP* is the best predictor of *HML* in horizons ranging from 1 month to 36 months. The value spread, which predicts *HML* in univariate regressions, loses much of its predictive power in the presence of *IVP*. None of the business cycle variables have any predictive power for *HML*. Our results provide unambiguous evidence of time variation in the value premium and show that *IVP* is the best ex-ante proxy of this time variation.

What are the sources of the time-varying value premium? Lakonishok, Shleifer, and Vishny (1994) suggest mispricing as one source of value premium. They argue that value stocks become undervalued and growth stocks become overvalued due to investors' tendency to extrapolate past performance (growth rates in earnings, sales etc.) too far into the future. If investors' (biased) relative expectations about the future performance of value and growth stocks vary over time, the relative mispricing can also vary over time giving rise to predictable time-varying value premium. Barberis and Shleifer (2003) develop a model of *style investing* in which investors with extrapolative expectations switch between investment styles based on a style's past performance. If growth stocks had recently done well, the switchers would move into growth stocks and out of value stocks even if there were no bad news about value stocks. As more investors switch, growth stocks become overvalued relative to value stocks. Eventually, prices of both growth stocks and value stocks revert to fundamentals making these strategies profitable for rational investors. The value premium can vary over time as switchers make one style or the other too expensive over time.[3] With time-varying relative mispricing, the implied value premium would be high after a period of value underperformance and low after a period of value outperformance and would predict high and low realized value premium respectively.

Zhang (2005) suggests costly reversibility and countercyclical price of risk as the source of value premium. In downturns, value firms are unable to sell unproductive assets, have to cut dividends and, as a result, become riskier. Growth firms do not face the same issues as they have fewer assets-in-place. In good economic times, growth firms face very few constraints raising the capital needed to expand and, as a result, their dividends and returns may not be that sensitive

[3] For instance, at the beginning of 2000 after two years of strong performance by growth stocks, value stocks became cheap and growth stocks became too expensive and value outperformed growth over the next six years. At the beginning of 2007, value stocks were much less cheap and value underperformed growth subsequently. While switchers switch styles based on recent performance, rational investors are likely to switch based on the relative valuation between the two styles helping bring their prices back to fundamentals.

to economic conditions. Value firms do not need to expand as more of their unproductive assets become productive. Overall, costly reversibility can lead to value firms being much riskier than growth firms in downturns and only slightly more risky or even less risky than growth firms during expansions. Countercyclical price of risk, high in downturns and low in expansions, can amplify the effects of time-varying relative risk between value and growth firms, and cause the expected returns of value firms to rise significantly during downturns and fall during expansions relative to growth firms. This also implies value stocks should underperform growth stocks in downturns and outperform them during expansions. In other words, *HML* should be low in downturns and high in expansions. Zhang (2005) also shows that the interaction of time-varying risks and countercyclical price of risk can give rise to positive unconditional value premium consistent with prior empirical findings.[4]

First we explore the mispricing explanation. Specifically, we examine whether *IVP* can predict future quarterly earnings surprises. La Porta, Lakonishok, Shleifer, and Vishny (1997) find value stocks earn positive abnormal returns and growth stocks earn negative abnormal returns in the days surrounding their future quarterly earnings announcements. This is consistent with mispricing since it suggests value investors are positively surprised and growth investors are negatively surprised by the announced earnings. We extend this test to a time-series context. For each quarter, we compute a value-weighted or equally-weighted average of the cumulative abnormal returns (*CAR*) earned by the firms in the value and growth portfolios from day -2 to +2 around their quarterly earnings announcements. We subtract the *CAR* of the growth portfolio *CAR(L)* from the *CAR* of the value portfolio *CAR(H)* to compute *CAR(HML)*. We average the *CAR(HML)* over the next four quarters and use them as dependent variables in the forecasting regressions. *CAR(HML)* measures the relative earnings surprise between value and growth portfolios. Under the mispricing scenario, a high *IVP* implies that value stocks are undervalued relative to growth stocks. Therefore, a high *IVP* should predict a high *CAR(HML)*, i.e., more positive earnings surprises for value stocks than growth stocks, in the future. Our results show that *IVP* significantly predicts *CAR(HML)* over the next four quarters. In contrast, none of the risk variables are able to predict *CAR(HML)*. This provides strong evidence in support of the mispricing explanation. Further analysis shows that the

[4] Zhang (2005) proposes a risk-based explanation for the *time-varying* value premium. An extant large literature also propose risk-based explanations for the *cross-sectional* difference between value and growth stock returns. For instance, Fama and French (1993), Lettau and Ludvigson (2001), Lettau and Wachter (2007), Campbell, Polk, and Vuolteenaho (2010), Hansen, Heaton, and Li (2008), Bansal et al. (2012), Koijen, Lustig, and Van Nieuwerburgh (2012).

predictive power of *IVP* for future *CAR(HML)* is stronger during periods of extreme mispricing.[5]

Our finding that *Default*, *Term*, and *Cay* do not predict *HML* suggests that the time variation in value premium is not related to the variation in these business cycle variables. The countercyclical risk story suggests that the ex-ante value premium should be high in downturns and low in expansions and correspondingly value stocks should underperform in downturns and perhaps outperform in expansions. Figures 1 and 2 plot our implied value premium measures (based respectively on B/M and composite value), and Figure 3 plots the annual Fama-French HML factor, all from 1977 to 2011. As is clear from these plots, during the economic expansion of 1998-1999, value stocks underperformed growth stocks quite significantly, and the expected value premium was high. During the short eight month recession from March to November 2001, the expected value premium was low (not peaking until the end) and the realized value premium was high. Going further back to the recession from July 1981 to November 1982, value stocks outperformed growth stocks and the implied value premium was low not peaking until 1984. This is inconsistent with the countercyclical risk explanation. More recently, however, the expected value premium peaked during the December 2007-June 2009 recession and value stocks underperformed which is more consistent with the countercyclical risk theory. Clearly, the time variation in expected and realized value premium around downturns and expansions are not uniformly supportive of the countercyclical risk explanation.

To further explore the role of countercyclical risk, we examine whether *IVP* and *VS* are able to predict future growth rates in industrial production. If the value premium is countercyclical then it should be positively related to future economic activity, as high value premium in downturns is likely to be followed by future economic recovery. Our regression tests show that the implied value premium is unable to predict future industrial production growth in univariate tests although there is some evidence of predictability in multivariate tests that control for *VS* and other business cycle variables. *VS* is negatively related to future economic activity and among the business cycle variables, only *Term* has a statistically significant positive relationship with future growth in industrial production. Overall, the evidence presented in this paper does not provide much support for the countercyclical risk explanation, although we cannot entirely rule it out.

Our in-sample analysis showed that *IVP* is an excellent predictor of future realized value premium. We also examine the out-of-sample performance of the implied value premium, and our results show that during the two forecast periods we examine (April 1989-December 2011 and Jan-

[5]We identify periods of extreme mispricing as those when value underperforms growth which are relatively rare in the data and characterized by extremely high growth expectations for growth stocks as in 1998-1999.

uary 1995-December 2011), the implied value premium is also a reliable out-of-sample predictor of future realized value premium.[6] The implied value premium outperforms the value spread and the business cycle variables, and also contains distinct and important information beyond these variables. Our work contributes to the growing literature that uses valuation models to estimate expected stock returns (e.g., Blanchard, Shiller, and Siegel (1993), Lee, Myers, and Swaminathan (1999), Claus and Thomas (2001), Gebhardt, Lee, and Swaminathan (2001),Jagannathan, McGrattan, and Scherbina (2000), Constantinides (2002), Fama and French (2002), Rytchkov (2010), van Binsbergen and Koijen (2010), Wu and Zhang (2011), Mo (2012), and Li, Ng, and Swaminathan (2013)). Our paper also makes significant contributions to the literature on time-varying value premium. Chen, Petkova, and Zhang (2008) estimate expected value premium using the Gordon growth model following Fama and French (2002) and find that, unlike the equity premium, the expected value premium is mostly stable over time. Campello, Chen, and Zhang (2008) estimate the expected value premium using corporate bond yields and find evidence that the expected value premium is countercyclical but find no evidence that corporate bond yields predict realized value premium. Using a regime-switching model, Gulen, Xing, and Zhang (2008) provide evidence in support of time-varying value premium but find no evidence of out-of-sample predictability of future realized value premium.

In sum, there are two key results in our paper: (a) *IVP* is the best predictor of ex-post value premium providing strong evidence of time variation in value premium and (b) this predictability is strongly related to time-varying relative mispricing. Our results strongly support relative mispricing as at least one source of the time variation in value premium. Our results also have implications for style timing with respect to value and growth. We provide a measure of relative valuation between value and growth that is empirically superior to widely used value spreads both in-sample and out-of-sample. Our paper proceeds as follows. We describe the methodology to construct the implied value premium in Section 2. Section 3 discusses data and summary statistics. Section 4 presents the in-sample and out-of-sample analysis of the implied value premium for predicting future realized value premium. Section 5 concludes the paper.

[6]See Campbell (2000), Campbell and Thompson (2008), and Welch and Goyal (2008) for the recent literature on out-of-sample forecasting tests.

2 Construction of Implied Value Premium

In this section, we describe the methodology to construct the firm-level implied cost of capital. We then discuss how to construct the value and growth portfolios and obtain their respective expected returns from the firm-level implied cost of capital. The implied value premium is defined as the difference between the implied costs of capital for the value and growth portfolios.

2.1 Firm-level Implied Cost of Capital

Our estimation of firm-level implied cost of capital follows the approach of Li, Ng, and Swaminathan (2013).[7] The firm-level implied cost of capital (ICC) is constructed as the internal rate of return that equates the present value of future dividends/free cash flows to the current stock price. We use the term "dividends" interchangeably with free cash flows to equity (FCFE) to describe all cash flows available to equity.

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

There are two key assumptions in our empirical implementation of the free cash flow model: (a) short-run earnings growth rates converge in the long-run to the growth rate of the overall economy and (b) competition will drive economic profits on new investments to zero in the long-run (the marginal rate of return on investment—the ROI on the next dollar of investment—will converge to the cost of capital). As explained below, we use these assumptions to forecast earnings growth rates and free cash flows during the transition from the short-run to the long-run steady-state. We implement equation (1) 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 year $t+1$ using analyst forecasts. I/B/E/S analysts supply earnings per share (EPS) forecasts for the next two fiscal years, FY_1, and FY_2 respectively, for each firm in the I/B/E/S database. We construct a 12-month ahead earnings forecast FE_1 using the *median* FY_1 and FY_2

[7] Also see Pastor, Sinha, and Swaminathan (2008) and Lee, Ng, and Swaminathan (2009).

forecasts such that $FE_1 = w \times FY_1 + (1 - w) \times FY_2$, where w is the number of months remaining until the next fiscal year-end divided by 12 (we use median forecasts instead of mean in order to alleviate the effects of extreme forecasts especially on the optimistic side by individual analysts). (ii) We then use the growth rate implicit in FY_1 and FY_2 to forecast earnings for $t + 2$; that is, $g_2 = FY_2/FY_1 - 1$, and the two-year-ahead earnings forecast is given by $FE_2 = FE_1 (1 + g_2)$. Constructing FE_1 and FE_2 in this way ensures a smooth transition from FY_1 to FY_2 during the fiscal year and also ensures that our forecasts are always 12 months and 24 months ahead from the current month.[8] Firms with growth rates above 100% (below 2%) are given values of 100% (2%). (iii) We forecast earnings from year $t+3$ to year $t+T+1$ by assuming that the year $t+2$ earnings growth rate g_2 mean-reverts exponentially to steady-state values by year $t+T+2$. We assume that the steady-state growth rate starting in year $t+T+2$ is equal to the long-run nominal GDP growth rate, g, computed as a rolling average of annual nominal GDP growth rates. Specifically, earnings growth rates and earnings forecasts are computed for years $t+3$ to $t+T+1$ ($k = 3, ..., T+1$) using an exponential rate of mean reversion:

$$g_{t+k} = g_{t+k-1} \times \exp\left[\log\left(g/g_2\right)/T\right] \text{ and} \tag{3}$$
$$FE_{t+k} = FE_{t+k-1} \times \left(1 + g_{t+k}\right).$$

The exponential rate of mean-reversion is just linear interpolation in logs and provides a more rapid rate of mean reversion for very high growth rates. We forecast plowback rates using a two-stage approach. (i) We explicitly forecast plowback rate for years $t+1$ as one minus the most recent year's dividend payout ratio. We estimate the dividend payout ratio by dividing actual dividends from the most recent fiscal year by earnings over the same time period.[9] We exclude share repurchases and new equity issues 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 $t + 1$, b_1 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

[8]In addition to FY_1 and FY_2, I/B/E/S also provides the analysts forecasts' of the long-term earnings growth rate (Ltg). An alternative way of obtaining g_2 is to use Ltg. In untabulated results, we show that $g_2 = FY_2/FY_1 - 1$ is a better measure than $g_2 = Ltg$, because the former is a better predictor of the actual earnings' growth rate in year $t + 2$.

[9]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.

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 the cost of equity g/r_e. The intermediate plowback rates from $t+2$ to $t+T$ $(k = 2, ..., T)$ are computed as follows:

$$b_{t+k} = b_{t+k-1} - \frac{b_1 - b}{T}. \tag{4}$$

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 $t + T + 1$.[10] 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 analyses.

2.2 Value and Growth Portfolios

Initially, we construct value and growth portfolios using a two-way sort based on size and book-to-market ratios following the procedure in Fama and French (1993). In June of each year from 1976 to 2011, all NYSE stocks on CRSP are ranked on size (market capitalization). The median NYSE size is then used to split NYSE, Amex, and NASDAQ stocks into two portfolios, small and big (S and B). We also divide NYSE, Amex, and NASDAQ stocks into three book-to-market portfolios based on NYSE break points: stocks in the bottom 30% (L), middle 40% (M) and top 30% (H).

[10] 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.

The book equity is stockholder equity plus balance sheet-deferred taxes and investment tax credits plus post-retirement benefit liabilities minus the book value of preferred stock. Depending on data availability, we use redemption, liquidation, or par value, in this order, to represent the book value of preferred stock. Stockholder equity is the book value of common equity. If the book value of common equity is not available, stockholder equity is calculated as the book value of assets minus total liabilities. Book-to-market equity, B/M, is calculated as book equity for the fiscal year ending in calendar year $t-1$, divided by market equity at the end of December of $t-1$. Following Fama and French (1993), we do not use negative book firms, when calculating the breakpoints for B/M, or when forming the portfolios. The intersection of the two size portfolios and three B/M portfolios generates six portfolios (denoted S/L, B/L, S/M, B/M, S/H, and B/H). For instance, the S/L portfolio contains the small stocks that are also in the low book-to-market group, and the B/H portfolio contains the big stocks that are also in the high book-to-market group. The value portfolio (H) is an equal-weighted portfolio of S/H and B/H, (S/H + B/H)/2, and the growth portfolio (L) is an equal-weighted portfolio of S/L and B/L, (S/L + B/L)/2.

Although B/M is the most popular measure used to define value and growth in the academic literature, practitioners use a variety of other measures to define value and growth. A popular measure is cash flow-to-price ratio (C/P) where cash flows are defined as the sum of net income before extraordinary items and depreciation and amortization as in Lakonishok, Shleifer, and Vishny (1994). Similar to B/M, C/P is calculated as cash flows for the fiscal year ending in calendar year $t-1$, divided by market equity at the end of December of $t-1$. High C/P stocks are defined as value stocks and low C/P stocks are defined as growth stocks. Forecasted earnings-to-price ratios are also widely used by practitioners to identify value and growth stocks. We use two ratios: FE_1/P which is based on the one-year ahead earnings forecast and FE_2/P which is based on the two-year ahead earnings forecast. We use B/M, C/P, FE_1/P and FE_2/P to construct a composite measure of value based on the ranks of the individual measures. Firms are ranked from 0 to 1 based on each individual value measure where 0 represents the most expensive and 1 represents the least expensive. The composite rank is defined as $\frac{1}{3}RnkB/M + \frac{1}{3}(\frac{1}{2}RnkFE_1/P + \frac{1}{2}RnkFE_2/P) + \frac{1}{3}RnkC/P$, where $RnkB/M$, $RnkFE_1/P$, $RnkFE_2/P$, and $RnkC/P$ are the individual ranks.[11] In June of each year from 1976 to 2011, we construct the same two-way sort as in Fama and French (1993) but

[11]If a firm has missing or negative values for B/M, FE_1, FE_2, or C/P, then we construct the composite rank using whatever information is available, keeping in mind that we equal weight the three categories (B/M, earnings-to-price ratios and C/P), and equal weight within the earnings-to-price ratio category. For example, if a firm only has positive B/M, the composite rank is just based on its B/M rank; if a firm has both positive B/M and FE_1, then its composite rank is $\frac{1}{2}RnkB/M + \frac{1}{2}RnkFE_1$ and so on. For financial firms, we do not use C/P.

instead of using just the B/M ratio, we use our composite value rank to construct high (top 30%), medium (middle 40%) and low (bottom 30%) portfolios. The portfolio construction procedure is the same in all other aspects. (S/H + B/H)/2 is the value portfolio (H), (S/L + B/L)/2 is the growth portfolio (L), and *HML* = (S/H + B/H)/2 - (S/L + B/L)/2.

2.3 Implied Value Premium, Realized Value Premium and Value Spread

We construct the implied value premium as follows. Each month, we first compute the *ICC*s of S/L, B/L, S/H, and B/H by value-weighting the *ICC*s of their constituent firms using the month-end market capitalization. The *ICC* for H is a simple average of the *ICC*s of S/H and B/H, and the *ICC* for L is a simple average of the *ICC*s of S/L and B/L. The two measures of implied value premium based on B/M ratio and the composite value rank respectively can now be defined as:

$$IVP(B/M)_t = ICCH(B/M)_t - ICCL(B/M)_t,$$
$$IVP(comp)_t = ICCH(comp)_t - ICCL(comp)_t,$$

where $ICCH$ is the *ICC* for the value portfolio (H) and $ICCL$ is the *ICC* for the growth portfolio (L).

The returns of value and growth portfolios are computed in the same manner. The return of the value portfolio (H) is the average of the returns of S/H and B/H, where the returns of S/H and B/H are obtained by value-weighting the individual firm returns within each portfolio using the month-end market capitalization. The return of the growth portfolio (L) is computed by averaging the returns of S/L and B/L. The realized value premium, which we refer to as the constructed *HML*, is defined as

$$HML(B/M)_t = H(B/M)_t - L(B/M)_t,$$
$$HML(comp)_t = H(comp)_t - L(comp)_t.$$

If our implied value premium is a good ex-ante measure of the value premium, it should predict not only our constructed *HML*, but also the *HML* factor in the Fama-French three-factor model (Fama and French (1993, 1996)) with a positive sign. We obtain the *HML* factor from Kenneth French's website. The Fama-French *HML* factor is denoted as *HML(FF)* to differentiate it from our own constructed *HML*.

One important control variable we examine in our regression analysis is the value spread (VS) defined as the difference in the book-to-market ratios of value and growth portfolios. The value spread has been documented as an important predictor of the realized value premium (e.g., Asness, Friedman, Krail, and Liew (2000), Cohen, Polk, and Vuolteenaho (2003)). We obtain the book-to-market ratio for the value portfolio as the average of book-to-market ratios of S/H and B/H where the book-to-market ratios of S/H and B/H are obtained by value-weighting the firm-level book-to-market ratios within each portfolio using the end-month market capitalization. We obtain the book-to-market ratio for the growth portfolio in the same manner as the average of the book-to-market ratios of S/L and B/L.[12] The value spread is the difference in the natural logs of the book-to-market ratio between value portfolio and the growth portfolio:

$$VS_t = LogB/M(H)_t - LogB/M(L)_t.$$

The value spreads based on B/M and the composite value rank are denoted as *VS(B/M)* and *VS(comp)*, respectively.[13]

3 Data and Summary Statistics

3.1 Data

We obtain market capitalization and return data from CRSP, accounting data including common dividends, net income, book value of common equity, and fiscal year-end date from COMPUSTAT, and analyst earnings forecasts and share price from I/B/E/S. To ensure that we only use publicly available information, we obtain accounting data items for 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 begins 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.

The control variables used in the forecasting regressions include the business cycle variables:

[12]An alternative way of constructing the value spread is to first calculate the total book values and market values for the value and growth portfolios, respectively, and then obtain the corresponding portfolio level book-to-market ratios. The value spread is then defined as the log difference between the book-to-market ratios of the value portfolio and the growth portfolio. The value spread using this alternative method has a correlation of 0.99 with our main measure, and provide similar (untabulated) results.

[13]For the value and growth portfolios formed on the composite value rank, we also construct a value spread as the difference between the value ranks of the high (H) and low (L) portfolio, $Diff(comp)$. First we compute an average value rank for each of the four portfolios S/L, B/L, S/H, and B/H by averaging the composite value ranks of the individual firms in each portfolio. We then compute a value rank for the H portfolio as the average of the ranks for S/H and B/H and a rank for the L portfolio as the average of the ranks for S/L and B/L. The difference is $Diff(comp)$. Our main results remain robust to this alternative measure of the value spread.

term spread *(Term)*, default spread *(Default)*, and consumption-to-wealth ratio (*Cay*).[14] The term spread is the difference between Moody's AAA bond yield and the 1-month T-bill rate and represents the slope of the treasury yield curve. The 1-month T-bill rate is obtained from WRDS. The default spread is the difference in the yields of BAA and AAA-rated corporate bonds obtained from the economic research database at the Federal Reserve Bank at St. Louis (FRED). *Cay* is obtained from Martin Lettau's website. In addition to these control variables, we also examine the relationship between the implied value premium and monthly growth rates in industrial production gIP based on the seasonally-adjusted industrial production index obtained from FRED.[15]

3.2 Summary Statistics

Table 1 provides summary statistics for the various forecasting variables and returns. Panel A presents the summary statistics for the implied cost of capital/expected returns of the value portfolio, the growth portfolio, and the implied value premium. We subtract the yield on 1-month T-bill (from WRDS) from the *ICC*s of value and growth stocks to obtain the corresponding implied risk premia. For value and growth portfolios based on B/M, the average annual risk premia are 10.73% and 7.22%, with standard deviations of 3.25% and 2.19%. For value and growth portfolios based on the composite value rank, the average annual risk premia are 10.49% and 7.15%, with standard deviations of 3.08% and 2.22%. In terms of the implied value premium, *IVP(B/M)* has a mean of 3.51% and a standard deviation of 2.23%, and *IVP(comp)* has a mean of 3.34% and a standard deviation of 2.06%. In Panel B, we report the realized risk premia for the constructed value and growth portfolios, H and L, constructed *HML* and the Fama-French *HML*. The constructed *HML(B/M)* has a mean of 3.59%, and a standard deviation of 9.92%; the constructed *HML(comp)* has a mean of 3.91%, and a standard deviation of 10.55%; and the Fama-French *HML* factor *HML(FF)* has a mean of 3.68% and a standard deviation of 10.55%. As is obvious, all three *HML* measures have similar means and standard deviations. Not surprisingly, they are also highly correlated with one another (0.91 to 0.94 in Panel D). For all three measures of realized value premium, the sum of autocorrelations at long horizons are negative, which suggests there is long-term mean reversion in the ex-post value premium.

Also, the average implied value premium in Panel A is about the same magnitude as the ex-post

[14] See Lettau and Ludvigson (2001).

[15] In unreported results, we also examined two other measures of growth in industrial production $gIP3$ which is the industrial production growth for a three-month period around the current month, and $gIP5$ which is the industrial production growth rate for a five-month period around the current month. These alternative measures provide similar results to gIP.

value premium in Panel B during our sample period. The mean of *IVP(B/M)* and *IVP(comp)* are 3.51% and 3.34% respectively, which is comparable to the means of the three *HML* factors which are in the range of 3.59% to 3.91%. Moreover, the implied risk premia of the H and L portfolios are also similar in magnitude to the ex-post risk premia of the H and L portfolios. Overall, the implied value premium seems to track the ex-post value premium fairly well at least in terms of their means. The implied value premium is also quite persistent. The first-order autocorrelations for *IVP(B/M)* and *IVP(comp)* are 0.93.[16]

Panel D shows that both *IVP(B/M)* and *IVP(comp)* are positively correlated with the value spread and the business cycle variables, suggesting that the time variation in the implied value premium is related to the business cycle. We have plotted the time-series of the two implied value premium measures *IVP(B/M)* and *IVP(comp)* in Figures 1 and 2. We also highlight the implied value premia on some notable dates and mark the NBER recession periods in shaded areas. *IVP(B/M)* and *IVP(comp)* exhibit strikingly similar time variation and mean reversion. We explore the relationship between *IVP* and economic conditions in more detail later. The implied value premium was high in January 2000, low in June 2007 and high in March 2009. Value stocks underperformed growth stocks during 1999-2000, outperformed growth stocks from 2000 to 2007, and have underperformed since then with the exception of 2009.

4 Predictability of Implied Value Premium

In our predictability tests, we conduct both univariate and multivariate regression tests involving the implied value premium. Our initial objective is to examine whether *IVP* predicts *HML* and compare its predictive power, if any, to that of the value spread and the business cycle variables. We then turn to examining the sources of the time variation in the value premium, in particular, whether it is due to mispricing, risk or both.

4.1 Univariate Regressions

We examine the univariate predictive power of the implied value premium *IVP* for *HML* based on the following multi-period forecasting regression:

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

[16]Unit root tests strongly reject the null of a unit root in both *IVP* measures.

where b is the slope coefficient and K is the forecasting horizon in months or quarters, and u_{t+K} is the regression residual. Y_{t+k} is either the Fama-French *HML* factor (*HML(FF)*) or our constructed *HML* (*HML(B/M)* or *HML(comp)*). X_t is the implied value premium (*IVP(B/M)* or *IVP(comp)*), the value spread or the business cycle variables.

We estimate the forecasting regression at various horizons: $K = 1$, 12, 24, and 36 months for monthly regressions, and $K = 1$, 2, 3, 4 quarters for quarterly regressions. One problem with the regression in (7) is the use of overlapping observations, which induces serial correlation in the regression residuals. Specifically, under both the null hypothesis of no predictability and the alternative hypotheses that fully account for time-varying expected returns, the regression residuals are autocorrelated up to certain lags. 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 (Newey and West (1987)). We use $K - 1$ lags to calculate the Newey-West standard errors, and we call the resulting statistic the Z-statistic.

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. To avoid these problems, we generate small sample distributions of the test statistics using Monte Carlo simulations (see Hodrick (1992), Nelson and Kim (1993), Swaminathan (1996) and Lee, Myers, and Swaminathan (1999)). The Appendix describes our Monte Carlo simulation methodology. Finally, 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 at different horizons, to test the null hypothesis that the slopes at different horizons are jointly zero. We also conduct Monte Carlo simulations to compute the statistical significance of the average slope estimate.

If the implied value premium is an ex-ante measure of future realized value premium, then it should predict *HML* with a positive sign and, therefore, the slope coefficient associated with *IVP(B/M)* or *IVP(comp)* in (7) should be positive. We also expect a positive sign for the value spread since Cohen, Polk, and Vuolteenaho (2003) find that the value spread positively predicts future realized value premium. If the value premium is countercyclical as argued in rational theories, then business cycle variables should also positively predict future realized value premium. Therefore, a one-sided test of the null hypothesis is appropriate for all forecasting variables.

Table 2 presents the regression results of (7) using the implied value premium (*IVP(B/M)* and *IVP(comp)*), value spread (*VS(B/M)* and *VS(comp)*), and other predictors. Panel A presents the results for predicting *HML(FF)*. Panel B presents the results for predicting *HML(B/M)* and Panel C presents the results for predicting *HML(comp)*. We provide these results only to show that our results are robust to predicting value factors constructed with a smaller sample of firms. In Panels B and C, we also omit the predictability results involving the business cycle variables to save space and to avoid repetitiveness.

The regression results provide strong evidence that the implied value premium predicts future realized value premium with a positive sign. The slope coefficients of *IVP(B/M)* and *IVP(comp)* are uniformly positive and significant at the 1% or the 5% (based on the simulated p-values) level at every horizon. Not surprisingly, the average slope statistics are all strongly significant at the 1% level or better. The adjusted R-squares associated with these regressions are also high. For example, in Panel A, the adjusted R-square of *IVP(B/M)* is 1% at the 1-month horizon, 27% at the 12-month horizon, and 35% at the 36-month horizon. In Panel B, the adjusted R-squares of *IVP(B/M)* for predicting *HML(B/M)* are similar, with 2% at the 1-month horizon, 30% at the 12-month horizon, and 40% at the 36-month horizon. The results in Panel C involving *IVP(comp)* are even stronger with R-squares ranging from 1% at the 1-month horizon to 48% at the 36-month horizon. The results are also economically significant. In Panel A, at the 1-month horizon, a one-standard-deviation increase in *IVP(B/M)* (2.23%) translates into an annualized increase of about 4.4% (2.23%$\times$1.96) for *HML(FF)*, and in Panel B an annualized increase of about 5% (2.23%$\times$2.23) for *HML(B/M)*.

Among other variables, the value spread *VS(B/M)* is a significant predictor of the *HML(FF)* in Panel A at the 24-month and 36-month horizons, and the p-value for the average slope coefficient is 0.04. *VS(comp)* is also a significant predictor of both *HML(FF)* and *HML(comp)* at long horizons, with p-values of 0.03 and 0.07 for the average slope coefficient (Panels B and C). None of the business cycle variables are able to predict *HML(FF)* reliably. Overall, the implied value premium is the strongest predictor of future realized value premium in univariate regressions.

4.2 Multivariate Regressions

In this section, we examine whether the implied value premium continues to predict future realized value premium in the presence of value spread and the business cycle variables. Table 3 presents the multivariate regression results. Panels A and B provide monthly regression results involving *IVP*, the value spread, the term spread, and the default spread, and Panels C and D provide the quarterly regressions involving *IVP* and *Cay*. The dependent variable is *HML(FF)* in all panels. In untabulated results, we have also examined the robustness of our findings using the constructed HML factors *HML(B/M)* and *HML(comp)* as dependent variables and find similar results. We do not show them on a table to conserve space.

The results show that the implied value premium predicts future realized value premium strongly, even after controlling for the value spread and the business cycle variables. In every panel from Panel A to Panel D, the implied value premium has positive slope coefficients that are significant at every horizon. The average slope statistics are all significant at the 1% level or better. The value spread, on the other hand, is significant only at longer horizons although the slope coefficients are mostly positive. The evidence clearly shows that the value spread does not perform well in the presence of the implied value premium. The business cycle variables have no predictive power in the presence of the implied value premium, and the slope coefficients are not even uniformly positive.

To summarize, the multivariate regression results provide strong evidence that the implied value premium remains a strong predictor of future realized value premium even in the presence of the value spread and other widely used business cycle variables. The other variables do not fare well in the presence of the implied value premium. The unavoidable conclusion is that the implied value premium is the best predictor of ex-post value premium.

4.3 Mispricing or Risk?

In this section, we investigate the sources behind the strong predictive power of the implied value premium. In particular, we would like to understand whether the predictability is due to time variation the relative mispricing between value and growth stocks or due to time variation in the relative riskiness of value and growth stocks. As discussed in the introduction, the work of Lakonishok, Shleifer, and Vishny (1994) and Barberis and Shleifer (2003) suggest mispricing varies over time due to time-varying extrapolative expectations of investors. Zhang (2005) suggests that the relative risks of value and growth firms vary with the business cycle with value stocks being riskier than growth stocks in economic downturns.

4.3.1 Predicting Price Reactions around Quarterly Earnings Announcements

In Section 4.2, we reported that the implied value premium continues to predict future realized value premium after controlling for business cycle variables (Table 3). This implies that the implied value premium may also contain a mispricing component. We now turn to directly testing the mispricing implications of the predictive power of *IVP*.

Earnings announcements are important events, which bring new information to the market regarding the fundamental values of firms. Therefore, if value and growth stocks are mispriced, the mispricing is most likely to be resolved during earnings announcements. La Porta, Lakonishok, Shleifer, and Vishny (1997) find value stocks earn positive abnormal returns and growth stocks earn negative abnormal returns in the days surrounding their future quarterly earnings announcements. This is consistent with mispricing since it suggests value investors are positively surprised and growth investors are negatively surprised by the announced earnings. We extend this test to a time-series context. For each quarter, we compute a value-weighted or equally-weighted average of the cumulative (market-adjusted) abnormal returns (*CAR*) earned by the firms in the value and growth portfolios from day -2 to +2 around their quarterly earnings announcements. We subtract the *CAR* of the growth portfolio (*CAR(L)*) from the *CAR* of the value portfolio (*CAR(H)*) to compute *CAR(HML)*. We average the *CAR(HML)* over the next four quarters and use them as dependent variables in the forecasting regressions. *CAR(HML)* measures the relative earnings surprise between value and growth portfolios. Under the mispricing scenario, a high *IVP*, which implies value stocks are undervalued relative to growth stocks, should predict a high *CAR(HML)*, i.e., more positive earnings surprises for value stocks than growth stocks, in the future. Since *CAR* represents returns over a few days, neither risk nor the price of risk is likely to change significantly over such a short window. Thus, tests based on *CAR*s are direct tests of mispricing.

We consider three measures of *CAR(HML)*: (i) *CAR(HML(FF))* for the Fama and French value and growth portfolios (Fama and French (1993)), (ii) *CAR(HML(B/M))* for value and growth portfolios formed by B/M ratio using only the firms in our sample, and (iii) *CAR(HML(comp))* for value and growth portfolios formed by the composite value rank also using only the firms in our sample. The quarterly earnings announcement dates are obtained from the quarterly COMPUSTAT file. The daily stock returns for stocks and the market are obtained from the daily CRSP files. We use the WRDS value-weighted market return with dividend as our measure of market return. The quarterly values of implied value premium and other forecasting variables are the monthly values at the end of each quarter.[17] The sample extends from the first quarter of 1977 to the last quarter of 2011. We report results for both the value-weighted and the equally-weighted *CAR(HML)*. When calculating the value-weighted *CAR(HML)* at quarter t, we use the firm-level market value at the end of quarter $t-1$.

We conduct forecasting regressions to examine whether a high *IVP* predicts a high *CAR(HML)* as suggested by the mispricing scenario. The dependent variable in our regressions, as discussed earlier, is the average quarterly *CAR(HML)* over the four quarters.[18]

The results from univariate regressions are provided in Table 4. We find that *IVP* strongly predicts future *CAR(HML)*. The results are strong irrespective of whether we use *CAR(HML)* computed for Fama-French portfolios *CAR(HML(FF))* (Panels A and B), *CAR(HML)* computed for B/M portfolios *CAR(HML(B/M))* (Panel C), or *CAR(HML)* for composite value portfolios, *CAR(HML(comp))* (Panel D). The predictive power of *IVP* remains strong regardless of whether we use the value-weighted *CAR(HML)* or the equal-weighted *CAR(HML)*, and whether we use *IVP(B/M)* or *IVP(comp)*. The slope coefficients of *IVP(B/M)* and *IVP(comp)* are positive and highly significant at every horizon. The average slopes are also highly significant. The adjusted R-squares are in the range of 19% to 28% at the 4-quarter horizon. In untabulated results, we show that only *VS(B/M)* and *VS(comp)* have some predictive power for *CAR(HML)*. None of the risk variables *Term*, *Default*, or *Cay* have any predictive power for *CAR(HML)*: their slope coefficients are not statistically significant, and the adjusted R-squares associated with these regressions are close to 0%.

Table 5 presents multivariate regression results that control for the other forecasting variables. The predictive power of *IVP(B/M)* and *IVP(comp)* for *CAR(HML)* continues to remain strong even in the presence of other forecasting variables. Although the value spread has some predictive power in univariate regressions, neither *VS(B/M)* nor *VS(comp)* is significant in the presence of *IVP(B/M)* or *IVP(comp)*, indicating that the implied value premium is superior to the value spread in capturing the relative mispricing between value and growth stocks. Among other variables, only *Default* has some ability to predict future *CAR(HML)* although *Default* is not significant in the univariate regression. Overall, the results in Tables 4 and 5 provide strong support for the

[17]The results are similar if we obtain the quarterly values of these variables by averaging their monthly values within each quarter.

[18]Essentially, we are running the regression in equation (7) but we set $Y_t = CAR(HML)_t$.

hypothesis that relative mispricing between value and growth is at least one major source of the time variation in value premium.

Next, we turn to examining whether the predictability of future CAR is stronger in periods when mispricing is likely to be most severe. We identify periods of value underperformance as instances of extreme mispricing. Periods of value underperformance are relatively rare in the data. On average, value outperforms growth by about 3.5% to 4% a year (see Panel B of Table 1). During 1977 to 2011 (see Figure 3), value underperformed growth in 13 calendar years (37%) and outperformed growth in 24 calendar years (63%). Based on monthly data, value underperformed growth in 40% of the 6-month periods and 42% of the 12-month periods. Periods of value underperformance and growth outperformance are periods when growth expectations for growth stocks are likely to be particularly extreme and the extrapolation bias particularly acute (as for instance in 1998-1999). Our hypothesis is that the predictive power of *IVP* should be stronger during these periods as the extreme expectations are corrected during subsequent quarterly earnings announcements. To investigate this hypothesis, we define a dummy variable D_t which takes the value 1 if the realized Fama-French *HML* factor (*HML(FF)*) in the recent two quarters is negative. We then conduct the following regression:

$$\sum_{k=1}^{K} \frac{CAR(HML)_{t+k}}{K} = a + b \times IVP_t + c \times (IVP_t \cdot D_t) + u_{t+K}.$$

We expect a positive sign for c.

Table 6 provides the regression results. In every panel, coefficient c corresponding to the interaction term of *IVP* and the dummy variable is positive and statistically significant, indicating that the predictive power of *IVP* for *CAR(HML)* is indeed much stronger in periods of extreme mispricing when value stocks have recently underperformed growth stocks. Periods of extreme mispricing are followed by periods of strong correction. In this regression, coefficient b corresponding to *IVP* represents the predictive power of *IVP* in relatively normal periods when the mispricing is not as severe. The results show that *IVP* still predicts future *CAR* positively in these other periods though not as strongly as in periods of extreme mispricing which is consistent with the mispricing hypothesis.

Our analysis on *CAR(HML)* thus far has provided strong evidence that *IVP* contains a mispricing component. Evidently, investors' tendency to extrapolate the past too far into the future and switch between styles based on recent performance play a major role in the pricing and performance of value and growth stocks.

4.3.2 Countercyclical Risk

We now turn to examining the risk explanation. Figures 1 and 2 plot the NBER recession periods in shaded areas. During our sample period, there were five recessions: January 1980-July 1980, July 1981-November 1982, July 1990-March 1991, March 2001-November 2001, and December 2007-June 2009. The second and the last recession period span longer (16 and 18 months, respectively), while the other recessions generally lasted less than a year. Figure 3 plots the annual Fama-French HML factor also from 1977 to 2011. As is clear from these plots, during the economic expansion of 1998-1999, value stocks underperformed growth stocks quite significantly, and the expected value premium was high. During the short eight month recession from March to November 2001, the expected value premium was low (not peaking until the end) and the realized value premium was high. Going further back to the recession from July 1981 to November 1982, value stocks outperformed growth stocks and the implied value premium was low not peaking until 1984. These results are inconsistent with the countercyclical risk explanation. More recently, however, the expected value premium peaked during the December 2007-June 2009 recession and value stocks underperformed which is more consistent with the countercyclical risk theory. The contemporaneous correlation between *IVP(B/M)* (*IVP(comp)*) and a dummy variable for the NBER recession is 0.23 (0.36)(*p*-values 0.00) which indicates there is potentially some countercyclical time variation in the implied value premium. Overall though the time variations in expected and realized value premium around economic downturns and expansions are not uniformly supportive of the countercyclical risk explanation.

If the implied value premium is countercyclical then it should predict proxies of future economic activity with a positive sign. This is because *IVP* is high in economic downturns which are likely to be followed by economic recovery and hence the positive sign. In Table 7, we regress future cumulative growth rates in industrial production on the implied value premium, value spread, term and default spreads and the consumption-to-wealth ratio.[19] Table 7 provides the regression results. Panel A provides univariate regression results of *IVP* predicting *gIP*. Panels B and C provide results from regressing future industrial production growth rates on *IVP(B/M)* or *IVP(comp)*, *VS(B/M)*, *Term*, and *Default*. Panels D and E provide results from regressing future quarterly industrial production growth rates on *IVP(B/M)* or *IVP(comp)* and *Cay*.

The univariate regressions in Panel A show that the implied value premium is unable to predict future industrial production growth although the slope coefficients are mostly positive. The ad-

[19] Essentially, we are running the regression in equation (7) but we set $Y_t = gIP_t$.

justed R-squares are low and none of the slope coefficients are significant. Multivariate regressions in Panel B, C, D, and E that control for other forecasting variables, however, provide stronger evidence of predictability. The results show, in general, that *IVP* is able to predict *gIP* significantly at the 1-month and the 36-month horizons in the presence of other predictors. *VS* has the wrong sign in predicting *gIP* which is inconsistent with the countercyclical risk explanation. The best predictor of *gIP* is the term spread which predicts *gIP* at every horizon. None of the other forecasting variables are able to predict *gIP*. Overall, the evidence in our paper does not unambiguously support the countercyclical risk explanation although we cannot rule it out entirely.

4.4 Robustness

This section provides robustness checks using alternative standard errors to assess statistical significance and using alternative specifications of the *ICC* model to construct *IVP*, and further analyzes the impact of any analyst forecast bias on our results. To save space, we report results only for the implied value premium measure *IVP(B/M)*. The results using *IVP(comp)* are very similar and are available upon request.

4.4.1 Analysis Based on Hodrick (1992) Standard Errors

Our calculation of $Z(b)$ is based on the Newey-West standard errors, which are biased in small samples (see discussions in Section 4.1). Therefore, we draw inferences based on the simulated p-values of $Z(b)$, which are obtained by comparing $Z(b)$ to its empirical distributions under the null. An alternative standard error was developed by Hodrick (1992), which, as shown in Ang and Bekaert (2007), is less biased than the Newey-West (1987) standard errors in small samples and has lower type I error at long horizons. We use this alternate standard error to conduct statistical inference and confirm the robustness of our predictability findings.

Panel A of Table 8 shows the results of regressing *HML(FF)* and *HML(B/M)* on *IVP(B/M)*, where the Z-statistics and the simulated p-values in these results are calculated based on the Hodrick (1992) standard errors. Although the magnitudes of $Z(b)$ are smaller than their Newey-West counterparts (Table 2), they are still highly significant with the simulated p-values all being smaller than 0.01. These results show that the predictive power of the implied value premium is not sensitive to the choice of standard errors.

4.4.2 Alternate Specifications of the *ICC* Model

We value-weight the firm-level *ICC*s for the value and growth firms, respectively, and take their difference to obtain the implied value premium (*HML(B/M)* and *HML(comp)*). As a robustness check, we equally-weight the firm-level *ICC*s to obtain the implied value premium, and examine its predictive power for future realized value premium. Panel B of Table 8 shows that the resulting *HML(B/M)* and *HML(comp)* continue to strongly predict the Fama-French HML factor.

Our primary measure of implied value premium is based on cash flow forecasts up to 15 years, i.e., $T = 15$ in Equation (6). To examine the robustness of our results, we estimate the implied value premium (based on B/M portfolios) with $T = 10$ and $T = 20$. With $T = 10$, the implied cost of capital for the value portfolio is 14.45%, and that for the growth portfolio is 10.76%, both lower than their counterparts for $T = 15$. However, the implied value premium which is the difference between the two values is largely unaffected, with a mean of 3.69% and a standard deviation of 2.15%. With $T = 20$, the *ICC* for the value portfolio increases to 17.11%, and that of the growth portfolio increases to 13.39%, both higher than the *ICC*s for $T = 15$. The implied value premium now has a mean of 3.72% and a standard deviation of 2.54%. These results show changing the horizon has very little effect on the implied value premium. In unreported regression results we find that the predictive power of *IVP(B/M)* is robust to these alternate horizons.

Another possible concern about our methodology is whether using the same time horizon for growth and value stocks would give rise to a bias in our estimate of ex-ante value premium. If growth stocks take a longer time to revert to the GDP growth rate than value stocks, then using the same horizon for both could lead to too low a *ICC* for growth stocks and too high a *ICC* for value stocks.[20] This, in turn, could lead to an estimate of implied value premium that is too high on average. However, this appears unlikely. The average implied value premium is very close in magnitude to the realized value premium during our sample period, which suggests that the bias, if any, is negligible. Also, any such bias in the *ICC* estimation is unlikely to be time-varying. Even if it is time-varying, there is little reason to believe that this can give rise to our predictability findings. As a robustness check, we construct our *IVP* measure by assuming a longer horizon for growth stocks (T=20) and a shorter horizon for value stocks (T=15). This new measure with asymmetric forecasting horizons for value and growth stocks produce similar results to those in Tables 2 and 3.

[20]For example, Dechow, Sloan, and Soliman (2004) report that equity duration is negatively correlated with book-to-market ratios.

Due to the difficulty of determining the likelihood of recurrence for repurchases and new equity issues, our measure of *IVP(B/M)* excludes repurchases and new equity issues. As a robustness check, we have computed *IVP(B/M)* by incorporating repurchases and new equity issues in estimating the *ICC*. The new *IVP(B/M)* measure has a correlation of 0.98 with our original measure, and its predictive power for future realized value premium is also similar to that reported in Table 2.

4.4.3 Analyst Forecast Bias

Our calculation of implied value premium uses analysts' forecasts of future earnings, which might be biased. In particular, several studies find that analyst forecasts tend to be optimistic. We now show that the predictive power of the implied value premium (we focus on *IVP(B/M)*) is not driven by analyst forecast optimism bias. If analysts are differentially optimistic about value versus growth stocks during recession and expansion, it could lead to a possible relationship between the implied value premium and future realized value premium.

To investigate whether analyst forecast optimism bias affects the predictability of *IVP(B/M)*, we use the growth rate implicit in the FY_2 and FY_1 forecasts. For both value and growth portfolios, for each firm, each month we use $g_2 = FY_2/FY_1 - 1$ as our measure of firm-level time-varying analyst optimism bias. We then compute the value-weighted average of the firm-level g_2 for value and growth firms to obtain their aggregate growth rates. The difference in aggregate growth rates between value and growth stocks is our measure of analysts' relative optimism between value and growth, AE.[21]

Panel B of Table 8 examines the predictive power of*IVP(B/M)* for *HML(FF)* after controlling for AE. The results show that *IVP(B/M)* continues to positively forecast future realized value premium at all horizons. The slope coefficients are comparable to those in Table 2 and statistically significant at every horizon. These results show that the predictive power of the implied value premium is not driven by analyst forecast optimism.

4.5 Out-of-Sample Analysis

So far, we have provided strong in-sample evidence that the implied value premium is an excellent predictor of ex-post value premium. Recently, evaluating the out-of-sample performance of return

[21] Note that the time variation in the implied growth rate could also be due to the business cycle. We are agnostic as to what causes this time variation and only interested in examining whether this time variation adversely affects the predictive power of *IVP(B/M)*.

prediction variables has received much attention in the literature (e.g., Spiegel (2008) and Welch and Goyal (2008)). In this section, we evaluate the performance of the implied value premium in out-of-sample settings.

4.5.1 Econometric Specification

We start with the following predictive regression model:

$$r_{t+1} = \alpha_i + \beta_i x_{i,t} + \varepsilon_{i,t+1}, \tag{8}$$

where r_{t+1} is the Fama-French *HML* factor *HML(FF)* at month t, $x_{i,t}$ is the ith monthly predictive variable, which includes the implied value premium measure (*IVP(B/M)* and *IVP(comp)*), as well as other variables, namely, the value spread (*VS(B/M)* and *VS(comp)*), the term spread ($Term$), and the default spread (*Default*). $\varepsilon_{i,t+1}$ 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 value premium. 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 (8) 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 (8) 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 value premium $\{\hat{r}_{i,t+1}\}_{t=m}^{T-1}$. Following Campbell and Thompson (2008), Welch and Goyal (2008), and Rapach, Strauss, and Zhou (2010), we use the historical average realized value premium 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 value premium, then $\hat{r}_{i,t+1}$ should be closer to the true value premium than $\overline{r}_{t+1}$. We now introduce the forecast evaluation method.

4.5.2 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 similar 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 (8) 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 $R^2_{os} > 0$. Since our approach is equivalent to comparing forecasts from nested models (setting $\beta_i = 0$ in (8) reduces our predictive regression using x_i to the benchmark model using the historical average), we use the adjusted-MSPE statistic of Clark and West (2007):[22]

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

The adjusted-MSPE f_{t+1} is then regressed on a constant and the t-statistic corresponding to the constant is estimated. The p-value of R^2_{os} is obtained from the one-sided t-statistic (upper-tail) based on the standard normal distribution.[23]

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

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

[22]The most popular method for testing these kinds of hypotheses is the Diebold and Mariano (1995) and West (1996) statistic, which has a standard normal distribution. However, as pointed out by Clark and McCracken (2001) and McCracken (2007), the Diebold and Mariano (1995) and West (1996) statistic has a nonstandard normal distribution when comparing forecasts from nested models. Hence we use the adjusted statistic.

[23]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.

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

4.5.3 Out-of-sample forecasting results

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 also important to have a long-enough period for the model to be evaluated. In our experiment, we examine two specifications. In the first case, the forecast period is from April 1989 to December 2011, and in the second case, the forecast period is from January 1995 to December 2011. So the two forecast periods correspond to 2/3 and 1/2 of the entire sample. Due to the fact that corporate earnings display short-run cyclical noise (Campbell and Shiller (1988, 1998)), we use a 1-year smoothed *IVP(B/M)* and *IVP(comp)* as our out-of-sample predictor. Similarly, we perform a 1-year moving average of *VS(B/M)* and *VS(comp)* as well.

Panel A of Table 9 provides the R^2_{os} test results. We observe that the two implied value premium measures are the best out-of-sample predictors in both forecasting periods. For *IVP(B/M)*, the R^2_{os} is 3.62% in the first forecast period, and 2.41% in the second forecast period. Both R^2_{os} are statistically significant at the 1% level. For *IVP(comp)*, the R^2_{os} is 2.66% in the first forecast period, and 1.79% in the second forecast period, and they are also significant at the 1% level. Campbell and Thompson (2008) argue that for monthly data, even small positive R^2_{os} values such as 0.5% can signal an economically meaningful degree of return predictability for a mean-variance investor, which provides a simple assessment of forecastability in practice. Against this benchmark, the out-of-sample forecasting performance of the implied value premium is quite impressive. None of other variables produces a positive R^2_{os} in either forecasting period, indicating that they cannot beat the naive historical average predictor. To get a visual impression of how each model performs over the forecasting period, Figure 4 plots the differences between cumulative squared prediction error for the historical average forecast and the cumulative squared prediction error for the forecasting models using *IVP(B/M)* and other predictive variables, for the forecast period of January 1995 to December 2011. If a curve lies above the horizon line of zero, 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 positive; the closer a forecasting model is to this ideal, the better the performance of this model. In Figure 4, the difference between the prediction error of the historical average forecast and the cumulative squared prediction error for the *IVP(B/M)* forecast stays above zero for the vast majority of the time, and the slope of the difference stays positive for longer periods than for other forecasting variables. The difference between the prediction error of the historical average forecast and the cumulative squared prediction error for other variables stays below zero for most of the time, suggesting that these variables cannot beat the historical average, which is consistent with the R^2_{os} test in Table 9.

We further examine whether *IVP(B/M)* and *IVP(comp)* contain distinct information from that contained in existing variables such as the value spread. The Harvey, Leybourne, and Newbold (1998) test results are presented in Panels B and C of Table 9. We strongly reject the null hypothesis that *IVP(B/M)* (*IVP(comp)*) is encompassed by another variable for all variables at the 1% (5%) level in both forecasting periods. On the other hand, we cannot reject the null hypothesis that *IVP(B/M)* (*IVP(comp)*) encompasses other forecasting variables at conventional levels. Among other variables, the term spread and default spread contain different information from the value spread.

5 Conclusion

This paper estimates the implied value premium using the implied cost of capital approach which carefully controls for differences in growth rates and payout ratios between value stocks and growth stocks. Our results showed that the implied value premium is the best predictor of ex-post value premium during 1977 to 2011 and that it vastly outperformed the value spread, default spread, term spread, and the consumption-to-wealth ratio. Additional tests provided strong evidence in support of mispricing. We found that the implied value premium strongly predicts future differences in cumulative abnormal returns around quarterly earnings announcements between value stocks and growth stocks. Since risk and the price of risk are unlikely to change materially over a few days, these results support the notion that value stocks are undervalued and growth stocks are overvalued and that their relative valuation varies over time in a predictable manner. Specifically, this suggests that sometimes value stocks become quite cheap compared to growth stocks (as in early 2000) and at other times not as cheap (as in early 2007). Such time variation has implications for style timing as it recommends buying value stocks when they are cheap and abandoning them when they are not as cheap. Our results (both in-sample and out-of-sample) suggest that the implied value premium is a vastly superior measure of style timing than widely used measures of the spread in valuations between value and growth stocks.

6 Appendix

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 univariate regression using *IVP(B/M)* to predict *HML(B/M)*. The simulation method is conducted in the same way for other regressions. Define $Z_t = (HML(B/M)_t, IVP(B/M)_t)'$, where Z_t is a 2×1 column vector. We first fit a first-order VAR to Z_t using the following specification:

$$Z_{t+1} = A_0 + A_1 Z_t + u_{t+1}, \tag{9}$$

where A_0 is a 2×1 vector of intercepts and A_1 is a 2×2 matrix of VAR coefficients, and u_{t+1} is a 2×1 vector of VAR residuals. The point estimates in (9) are used to generate artificial data for the Monte Carlo simulations. We impose the null hypothesis of no predictability on $HML(B/M)_t$ 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 $HML(B/M)_t$ 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, $(HML(B/M)_t, IVP(B/M)_t)$. 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 $HML(B/M)_t$ are scaled to match its historical standard errors. These artificial data are then used to run multivariate 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 1. Summary Statistics

Panel A reports the summary statistics for the implied cost of capital (*ICC*) of the high B/M portfolio minus the one-month T-bill yield (*ICCH(B/M)-tbill*), the *ICC* of the low B/M portfolio minus the one-month T-bill yield (*ICCL(B/M)-tbill*), the *ICC* of the high composite value portfolio minus the one-month T-bill yield (*ICCH(comp)-tbill*), the *ICC* of the low composite value portfolio minus the one-month T-bill yield (*ICCL(comp)-tbill*), the implied value premium based on B/M (*IVP(B/M)*) which is calculated as *ICCH(B/M)* minus *ICCL(B/M)*, and the implied value premium based on the composite value rank (*IVP(comp)*) calculated as *ICCH(comp)* minus *ICCL(comp)*. The composite value rank is constructed based on B/M, C/P, FE_1/P, and FE_2/P. Panel B reports the summary statistics for the realized returns of the high B/M portfolio subtracting the one-month T-bill rate (*H(B/M)-tbill*), the low B/M portfolio subtracting the one-month T-bill rate (*L(B/M)-tbill*), the realized returns of the high composite value portfolio minus the one-month T-bill rate (*H(comp)-tbill*), the realized returns of the low composite value portfolio minus the one-month T-bill rate (*L(comp)-tbill*), the realized returns of high B/M minus low B/M portfolios (*HML(B/M)*), the realized returns of the high composite value portfolio minus the low composite value portfolio (*HML(comp)*), and the Fama and French *HML* factor (*HML(FF)*) obtained from Kenneth French's website. The autocorrelations in Panel B are calculated as the sum of individual autocorrelations up to that lag. Panel C reports the summary statistics of other predictors of the value premium, including the value spread based on B/M (*VS(B/M)*), the value spread based on the composite value rank (*VS(comp)*), the term spread (*Term*), the default spread (*Default*), and the consumption-to-wealth ratio (*Cay*). Panel D reports the pairwise correlations among the implied value premium and other predictors of the value premium; the *p*-values of the correlations are provided in parentheses. *gIP* is the monthly industrial production growth rate. Panel D also reports the correlation between the three measures of realized value premium, namely, *HML(B/M)*, *HML(comp)* and *HML(FF)*. All variables except *Cay* have monthly data spanning from January 1977 to December 2011; *Cay* has quarterly data from 1977.Q1 to 2011.Q3. The monthly values of *IVP(B/M)*, *IVP(comp)*, *VS(B/M)*, *VS(comp)*, *Term*, *Default* and *gIP* at the end of each quarter are used to calculate their correlations with *Cay*. All variables except the value spread are expressed in annual percentage terms.

Panel A: Expected Returns

	Mean	*Std*	*Max*	*Min*	Autocorrelation at Lag 1	12	24	36	48	60
ICCH(B/M)-tbill	10.73	3.25	21.94	4.32	0.94	0.48	-0.05	-0.36	-0.34	-0.13
ICCL(B/M)-tbill	7.22	2.19	12.50	-0.42	0.92	0.45	0.05	-0.22	-0.28	-0.05
ICCH(comp)-tbill	10.49	3.08	21.28	3.92	0.94	0.46	-0.05	-0.32	-0.37	-0.20
ICCL(comp)-tbill	7.15	2.22	12.52	-1.00	0.93	0.46	0.05	-0.22	-0.28	-0.05
IVP(B/M)	3.51	2.23	10.97	-0.12	0.93	0.52	0.11	-0.17	-0.26	-0.25
IVP(comp)	3.34	2.06	9.93	-0.21	0.93	0.54	0.08	-0.16	-0.31	-0.36

Panel B: Realized Returns

	Mean	*Std*	Autocorrelation at Lag 1	12	24	36	48	60
H(B/M)-tbill	11.57	16.73	0.15	-0.04	-0.34	-0.28	-0.33	-0.39
L(B/M)-tbill	7.98	19.03	0.10	-0.18	-0.45	-0.35	-0.45	-0.50
H(comp)-tbill	11.87	17.06	0.17	-0.01	-0.31	-0.26	-0.36	-0.47
L(comp)-tbill	7.97	19.16	0.09	-0.14	-0.44	-0.38	-0.45	-0.50
HML(B/M)	3.59	9.92	0.13	0.32	-0.05	-0.30	-0.15	0.09
HML(comp)	3.91	10.53	0.14	0.53	0.19	-0.30	-0.17	0.07
HML(FF)	3.68	10.55	0.16	0.35	-0.11	-0.29	-0.30	-0.14

Panel C: Other Predictors

	Mean	*Std*	Autocorrelation at Lag 1	12	24	36	48	60
VS(B/M)	1.38	0.16	0.97	0.65	0.46	0.37	0.29	0.16
VS(comp)	1.26	0.18	0.96	0.58	0.22	0.09	0.01	-0.10
Term	3.06	1.59	0.91	0.43	0.08	-0.27	-0.36	-0.14
Default	1.11	0.48	0.96	0.47	0.29	0.19	0.08	0.08
Cay	0.27	1.97	0.94	0.58	0.29	-0.17	-0.35	-0.49

Panel D: Correlations Among Various Variables

	IVP(B/M)	*IVP(comp)*	*VS(B/M)*	*VS(comp)*	*Term*	*Default*	*gIP*
IVP(comp)	0.92						
	(0.00)						
VS(B/M)	0.08	0.19					
	(0.11)	(0.00)					
VS(comp)	0.23	0.35	0.85				
	(0.00)	(0.00)	(0.00)				
Term	0.26	0.19	0.11	0.00			
	(0.00)	(0.00)	(0.02)	(0.97)			
Default	0.42	0.48	-0.23	-0.12	0.15		
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)		
gIP	-0.01	-0.08	0.01	-0.05	0.01	-0.35	
	(0.85)	(0.11)	(0.84)	(0.33)	(0.79)	(0.00)	
Cay	0.13	0.12	0.09	0.29	0.02	-0.24	0.00
	(0.14)	(0.15)	(0.30)	(0.00)	(0.85)	(0.00)	(0.96)

	HML(FF)	*HML(B/M)*
HML(B/M)	0.94	
	(0.00)	
HML(comp)	0.91	0.94
	(0.00)	(0.00)

Table 2. Univariate Regressions on Predicting Future Realized Value Premium.

This table reports the univariate regressions of using various variables to predict future realized value premium. The dependent variable is the realized value premium, which is *HML(FF)* in Panel A, *HML(B/M)* in Panel B, and *HML(comp)* in Panel C. *HML(FF)* is the Fama-French *HML* factor, and *HML(B/M)* and *HML(comp)* are our constructed *HML* based on B/M and the composite value rank, respectively. The independent variable in Panel A is the implied value premium (*IVP(B/M)* or *IVP(comp)*), the value spread (*VS(B/M)* or *VS(comp)*), the term spread (*Term*), the default spread (*Default*), or the consumption-to-wealth ratio (*Cay*). The independent variable in Panel B is the implied value premium (*IVP(B/M)*) or the value spread (*VS(B/M)*). The independent variable in Panel C is the implied value premium (*IVP(comp)*) or the value spread (*VS(comp)*). The regression with *Cay* uses quarterly data from 1977.Q1 to 2011.Q3; all other regressions use monthly data from January 1977 to December 2011. b is the slope coefficient from the OLS regressions. avg. is the average slope coefficient across all horizons. $Z(b)$ 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 the Z-statistics (*pval*) and the average slope coefficient are simulated using data 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 the Appendix.

Panel A: Predicting the Fama-French *HML* (Y=*HML(FF)*)

	IVP(B/M)				*IVP(comp)*				*VS(B/M)*			
Month	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$
1	1.96	2.50	0.01	0.01	1.74	1.98	0.03	0.01	0.17	0.90	0.28	0.01
12	2.98	5.12	0.00	0.27	2.74	4.26	0.00	0.19	0.27	1.80	0.16	0.11
24	2.24	5.72	0.00	0.32	2.52	5.01	0.00	0.35	0.24	2.78	0.08	0.20
36	1.68	6.47	0.00	0.35	2.03	6.75	0.00	0.42	0.20	3.39	0.05	0.25
avg.	2.28		0.00		2.26		0.00		0.22		0.04	
	VS(comp)				*Term*				*Default*			
Month	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$
1	0.13	0.69	0.34	0.00	-0.21	-0.20	0.58	0.00	-3.92	-0.86	0.80	0.00
12	0.25	1.78	0.16	0.12	1.15	1.04	0.20	0.02	1.45	0.52	0.35	0.00
24	0.24	3.96	0.02	0.24	1.17	1.44	0.13	0.04	3.62	1.27	0.18	0.04
36	0.20	9.21	0.00	0.32	0.22	0.37	0.38	0.00	3.53	1.35	0.18	0.06
avg.	0.21		0.03		0.54		0.24		0.72		0.42	

	Cay			
Quarter	*b*	$Z(b)$	*pval*	$adj.R^2$
1	-0.13	-0.62	0.66	0.00
2	-0.08	-0.43	0.57	0.00
3	-0.03	-0.18	0.47	0.00
4	-0.02	-0.12	0.45	0.00
avg.	-0.07		0.51	

Panel B: Predicting the Constructed *HML* (Y=*HML(B/M)*)

	IVP(B/M)				*VS(B/M)*			
Month	*b*	$Z(b)$	*pval*	$adj.R^2$	*b*	$Z(b)$	*pval*	$adj.R^2$
1	2.23	3.06	0.00	0.02	0.12	0.72	0.35	0.00
12	2.93	6.24	0.00	0.30	0.18	1.30	0.26	0.06
24	2.20	6.35	0.00	0.35	0.15	1.68	0.22	0.08
36	1.71	6.62	0.00	0.40	0.10	1.69	0.24	0.07
avg.	2.32		0.00		5.32		0.15	

Panel C: Predicting the Constructed *HML* (Y=*HML(comp)*)

	IVP(comp)				*VS(comp)*			
Month	*b*	$Z(b)$	*pval*	$adj.R^2$	*b*	$Z(b)$	*pval*	$adj.R^2$
1	1.81	2.15	0.02	0.01	0.07	0.34	0.49	0.00
12	2.94	4.62	0.00	0.20	0.18	1.24	0.28	0.05
24	2.87	4.82	0.00	0.36	0.23	3.30	0.04	0.17
36	2.53	6.49	0.00	0.48	0.20	6.93	0.00	0.24
avg.	2.54		0.00		0.17		0.07	

Table 3. Multivariate Regressions on Predicting Future Realized Value Premium.

This table reports the multivariate regressions of the realized value premium on the implied value premium (*IVP(B/M)* or *IVP(comp)*) and other control variables. The dependent variable is the Fama-French *HML* factor (*HML(FF)*). In Panels A and B, the independent variables are the implied value premium (*IVP(B/M)* or *IVP(comp)*), the value spread (*VS(B/M)* or *VS(comp)*), the term spread (*Term*), and the default spread (*Default*). In Panels C and D, the independent variables are the implied value premium (*IVP(B/M)* or *IVP(comp)*) and the consumption-to-wealth ratio (*Cay*). Regressions in Panels A and B use monthly data from January 1977 to December 2011, and regressions in Panels C and D use quarterly data from 1977.Q1 and 2011.Q3. b, c, d, and e are the slope coefficients from the OLS regressions. avg. is the average slope coefficient across all horizons. $Z(b)$, $Z(c)$, $Z(d)$, and $Z(e)$ are 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-value of the Z-statistics (*pval*) is simulated using data 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 the Appendix.

Panel A: Predicting the Fama-French *HML* Using *IVP(B/M)* and Other Predictors

	IVP(B/M)			*VS(B/M)*			*Term*			*Default*			
Month	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	d	$Z(d)$	*pval*	e	$Z(e)$	*pval*	$adj.R^2$
1	2.85	2.88	0.00	0.09	0.48	0.49	-0.99	-0.83	0.77	-8.26	-1.59	0.93	0.02
12	3.15	6.76	0.00	0.21	1.61	0.22	-0.16	-0.19	0.54	-2.93	-1.79	0.89	0.36
24	1.93	5.93	0.00	0.23	3.47	0.05	0.06	0.12	0.45	1.63	0.71	0.31	0.48
36	1.41	4.89	0.00	0.21	6.31	0.01	-0.64	-2.03	0.89	3.06	1.34	0.19	0.61
avg.	2.48		0.00	0.19		0.08	-0.49		0.70	-2.35		0.75	

Panel B: Predicting the Fama-French *HML* Using *IVP(comp)* and Other Predictors

	IVP(comp)			*VS(comp)*			*Term*			*Default*			
Month	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	d	$Z(d)$	*pval*	e	$Z(e)$	*pval*	$adj.R^2$
1	2.99	2.57	0.01	-0.02	-0.11	0.67	-0.50	-0.47	0.67	-9.93	-1.85	0.94	0.01
12	2.69	4.55	0.00	0.13	0.86	0.38	0.61	0.66	0.29	-3.84	-2.17	0.91	0.25
24	1.92	4.05	0.01	0.16	2.09	0.15	0.58	1.03	0.25	0.09	0.05	0.44	0.45
36	1.40	3.33	0.02	0.15	4.21	0.01	-0.22	-0.51	0.66	1.74	0.78	0.26	0.56
avg.	2.25		0.00	0.10		0.25	0.11		0.44	-3.45		0.81	

Panel C: Predicting the Fama-French *HML* Using *IVP(B/M)* and *Cay*

	IVP(B/M)			*Cay*			
Quarter	*b*	*Z*(*b*)	*pval*	*c*	*Z*(*c*)	*pval*	*adj.*R^2
1	7.08	2.36	0.02	-0.22	-1.04	0.78	0.03
2	8.86	3.63	0.00	-0.19	-1.09	0.74	0.11
3	9.37	4.01	0.00	-0.14	-0.83	0.65	0.19
4	9.54	4.56	0.00	-0.13	-0.75	0.62	0.27
avg.	8.71		0.00	-0.17		0.63	

Panel D: Predicting the Fama-French *HML* Using *IVP(comp)* and *Cay*

	IVP(comp)			*Cay*			
Quarter	*b*	*Z*(*b*)	*pval*	*c*	*Z*(*c*)	*pval*	*adj.*R^2
1	5.62	1.79	0.06	-0.20	-0.93	0.74	0.01
2	6.98	2.68	0.03	-0.16	-0.89	0.67	0.06
3	7.99	3.29	0.01	-0.12	-0.67	0.60	0.12
4	8.67	4.13	0.00	-0.11	-0.62	0.57	0.20
avg.	7.31		0.01	-0.15		0.59	

Table 4. Univariate Regressions on Predicting Future Cumulative Abnormal Returns Around Earnings Announcements.

This table reports the regression results when the implied value premium (*IVP(B/M)* or *IVP(comp)*) is used to predict the relative earnings surprise between value and growth portfolios (*CAR(HML)*) around future earnings announcements, using quarterly data from 1977.Q1 to 2011.Q4. For each quarter, we compute a value-weighted or equally-weighted average of the cumulative (market-adjusted) abnormal returns (*CAR*) earned by the firms in the value and growth portfolios from day -2 to +2 around their quarterly earnings announcements. We subtract the *CAR* of the growth portfolio *CAR(L)* from the *CAR* of the value portfolio *CAR(H)* to compute *CAR(HML)*. We average the *CAR(HML)* over the next four quarters and use them as dependent variables in the forecasting regressions. *CAR(HML)* measures the relative earnings surprise between value and growth portfolios. *CAR(HML(FF))* is the *CAR(HML)* for the value and growth portfolios formed based on the universe of all firms as in Fama and French (1993). *CAR(HML(B/M))* and *CAR(HML(comp))* are the corresponding *CAR(HML)*s of the value and growth portfolios formed based on B/M and the composite value rank, respectively, and these portfolios include only those firms that are used to calculate our *IVP* measures. Panels A and B provide univariate regressions of future *CAR(HML(FF))* on *IVP(B/M)* and *IVP(comp)*, respectively. Panel C regresses future *CAR(HML(B/M))* on *IVP(B/M)*, and Panel D regresses future *CAR(HML(comp))* on *IVP(comp)*. b is the slope coefficient from the OLS regressions. avg. is the average slope coefficient across all horizons. $Z(b)$ 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-value of the Z-statistics ($pval$) is simulated using data 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 the Appendix.

Panel A: Predicting *CAR(HML(FF))* Using *IVP(B/M)*

	Y= Value-weighted *CAR(HML)*				Y= Equally-weighted *CAR(HML)*			
Quarter	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	1.73	2.60	0.01	0.05	1.85	3.41	0.00	0.07
2	1.74	3.04	0.01	0.09	1.93	3.88	0.00	0.13
3	1.66	3.13	0.01	0.11	1.88	3.99	0.00	0.18
4	1.48	3.12	0.02	0.12	1.75	4.24	0.00	0.22
avg.	1.65		0.01		1.85		0.00	

Panel B: Predicting *CAR(HML(FF))* Using *IVP(comp)*

	Y= Value-weighted *CAR(HML)*				Y= Equally-weighted *CAR(HML)*			
Quarter	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	1.91	2.91	0.00	0.05	1.81	3.31	0.00	0.06
2	1.76	2.91	0.01	0.08	1.91	3.70	0.00	0.11
3	1.77	3.03	0.02	0.11	1.95	3.87	0.00	0.17
4	1.58	2.77	0.03	0.12	1.95	4.17	0.01	0.24
avg.	1.75		0.01		1.91		0.00	

Panel C: Predicting *CAR(HML(B/M))* Using *IVP(B/M)*								
	$Y=$ Value-weighted *CAR(HML)*				$Y=$ Equally-weighted *CAR(HML)*			
Quarter	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$
1	2.13	2.82	0.01	0.06	2.18	3.91	0.00	0.09
2	2.11	3.11	0.01	0.10	2.24	4.65	0.00	0.17
3	2.11	3.26	0.01	0.14	2.22	4.86	0.00	0.23
4	1.90	3.15	0.02	0.14	2.09	4.93	0.00	0.28
avg.	2.06		0.00		2.18		0.00	

Panel D: Predicting *CAR(HML(comp))* Using *IVP(comp)*								
	$Y=$ Value-weighted *CAR(HML)*				$Y=$ Equally-weighted *CAR(HML)*			
Quarter	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$
1	2.18	2.84	0.01	0.05	1.81	2.73	0.00	0.04
2	2.07	3.37	0.01	0.08	1.90	3.53	0.00	0.09
3	2.20	3.61	0.01	0.14	1.96	3.88	0.00	0.15
4	2.03	3.37	0.01	0.15	1.85	4.00	0.01	0.19
avg.	2.12		0.01		1.88		0.00	

Table 5. Multivariate Regressions on Predicting Future Cumulative Abnormal Returns Around Earnings Announcements.

This table provides the multivariate regression results of predicting the relative earnings surprise between value and growth portfolios (*CAR(HML)*) around future earnings announcements, using quarterly data from 1977.Q1 to 2011.Q4. Panels A and B regress future value-weighted *CAR(HML(FF))* on the implied value premium (*IVP(B/M)* or *IVP(comp)*), the value spread (*VS(B/M)* or *VS(comp)*), the term spread (*Term*), the default spread (*Default*), and the consumption-to-wealth ratio (*Cay*). Panel C regresses future value-weighted *CAR(HML(B/M))* on *IVP(B/M)*, *VS(B/M)*, *Term*, *Default*, and *Cay*. Panel D regresses future value-weighted *CAR(HML(comp))* on *IVP(comp)*, *VS(comp)*, *Term*, *Default*, and *Cay*. b, c, d, e, and f are the slope coefficients from the OLS regressions. avg. is the average slope coefficient across all horizons. $Z(b)$, $Z(c)$, $Z(d)$, $Z(e)$ and $Z(f)$ are 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-value of the Z-statistics (*pval*) is simulated using data 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 the Appendix.

Panel A: Predicting *CAR(HML(FF))* Using *IVP(B/M)* and Other Predictors

X=(*IVP(B/M)*, *VS(B/M)*, *Term*, *Default*, *Cay*)

	IVP(B/M)			*VS(B/M)*			*Term*		
Quarter	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	d	$Z(d)$	*pval*
1	2.79	2.91	0.00	0.15	1.29	0.19	-2.46	-2.75	0.99
2	2.63	3.56	0.00	0.16	1.67	0.17	-1.88	-2.41	0.97
3	2.40	3.92	0.00	0.14	1.57	0.21	-1.78	-2.42	0.96
4	2.13	3.93	0.01	0.13	1.49	0.24	-1.74	-2.26	0.95
avg.	2.49		0.00	0.15		0.15	-1.97		1.00

	Default			*Cay*			
Quarter	e	$Z(e)$	*pval*	f	$Z(f)$	*pval*	$adj.R^2$
1	5.25	0.95	0.24	-0.96	-1.31	0.81	0.11
2	5.05	1.34	0.18	-0.86	-1.22	0.75	0.20
3	3.86	1.51	0.16	-0.52	-0.73	0.58	0.25
4	3.01	1.31	0.21	-0.40	-0.56	0.54	0.26
avg.	4.30		0.12	-0.68		0.67	

Panel B: Predicting *CAR(HML(FF))* Using *IVP(comp)* and Other Predictors

X=(*IVP(comp)*, *VS(comp)*, *Term*, *Default*, *Cay*)

	IVP(comp)			*VS(comp)*			*Term*		
Quarter	*b*	*Z*(*b*)	*pval*	*c*	*Z*(*c*)	*pval*	*d*	*Z*(*d*)	*pval*
1	2.75	2.36	0.01	0.15	1.22	0.21	-1.91	-2.25	0.98
2	2.31	2.60	0.02	0.17	1.78	0.15	-1.30	-1.82	0.93
3	2.24	3.32	0.01	0.15	1.70	0.18	-1.28	-1.94	0.94
4	1.94	3.19	0.01	0.14	1.87	0.16	-1.28	-1.85	0.92
avg.	2.31		0.00	0.15		0.10	-1.44		0.97

	Default			*Cay*			
Quarter	*e*	*Z*(*e*)	*pval*	*f*	*Z*(*f*)	*pval*	*adj.*R^2
1	7.06	1.19	0.17	-1.30	-1.66	0.90	0.12
2	6.28	1.49	0.15	-1.17	-1.58	0.83	0.20
3	5.23	1.86	0.11	-0.83	-1.11	0.71	0.26
4	4.12	1.62	0.15	-0.69	-0.93	0.66	0.28
avg.	5.67		0.06	-1.00		0.78	

Panel C: Predicting *CAR(HML(B/M))* Using *IVP(B/M)* and Other Predictors

X=(*IVP(B/M)*, *VS(B/M)*, *Term*, *Default*, *Cay*)

	IVP(B/M)			*VS(B/M)*			*Term*		
Quarter	*b*	*Z*(*b*)	*pval*	*c*	*Z*(*c*)	*pval*	*d*	*Z*(*d*)	*pval*
1	3.22	3.36	0.00	0.15	1.13	0.25	-1.78	-1.77	0.95
2	3.11	3.92	0.00	0.15	1.42	0.23	-1.32	-1.52	0.89
3	2.98	4.04	0.00	0.13	1.27	0.28	-1.37	-1.61	0.89
4	2.60	3.70	0.01	0.11	1.20	0.31	-1.30	-1.46	0.86
avg.	2.98		0.00	0.14		0.21	-1.44		0.95

	Default			*Cay*			
Quarter	*e*	*Z*(*e*)	*pval*	*f*	*Z*(*f*)	*pval*	*adj.*R^2
1	8.22	1.73	0.07	-0.42	-0.52	0.59	0.11
2	8.34	2.39	0.04	-0.43	-0.58	0.58	0.21
3	7.00	2.39	0.05	-0.15	-0.20	0.46	0.26
4	5.26	1.91	0.10	0.08	0.11	0.37	0.25
avg.	7.20		0.03	-0.23		0.49	

Panel D: Predicting *CAR(HML(comp))* Using *IVP(comp)* and Other Predictors

X=(*IVP(comp)*, *VS(comp)*, *Term*, *Default*, *Cay*)

	IVP(comp)			*VS(comp)*			*Term*		
Quarter	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	d	$Z(d)$	*pval*
1	3.40	2.59	0.01	0.05	0.42	0.49	-1.06	-1.04	0.84
2	2.97	3.20	0.01	0.08	0.94	0.35	-0.58	-0.68	0.73
3	3.03	3.95	0.00	0.05	0.67	0.45	-0.61	-0.82	0.76
4	2.65	3.51	0.01	0.05	0.82	0.41	-0.59	-0.76	0.73
avg.	3.01		0.00	0.06		0.45	-0.71		0.79

	Default			*Cay*			
Quarter	e	$Z(e)$	*pval*	f	$Z(f)$	*pval*	$adj.R^2$
1	10.76	1.63	0.08	-0.42	-0.44	0.61	0.08
2	9.69	2.13	0.06	-0.24	-0.29	0.54	0.16
3	8.49	2.69	0.03	0.11	0.14	0.40	0.23
4	6.54	2.31	0.06	0.32	0.42	0.33	0.24
avg.	8.87		0.02	-0.06		0.47	

Table 6. Further Analysis on the Mispricing Component of *IVP*.

This table analyzes whether the predictive power of the implied value premium for the relative earnings surprise between value and growth is stronger when value stocks recently underperformed growth stocks. The dummy variable D takes the value 1 if the average of the Fama-French HML factor (*HML(FF)*) in the past two quarters is negative. Panel A regresses *CAR(HML(FF))* on *IVP(B/M)* and the interaction of *IVP(B/M)* with the dummy variable D. Panel B regresses *CAR(HML(FF))* on *IVP(comp)* and the interaction of *IVP(comp)* with the dummy variable D. Panel C regresses *CAR(HML(B/M))* on *IVP(B/M)* and the interaction of *IVP(B/M)* with the dummy variable D. Panel D regresses *CAR(HML(comp))* on *IVP(comp)* and the interaction of *IVP(comp)* with the dummy variable D. The monthly values of *IVP(B/M)* and *IVP(comp)* at the end of each quarter are used as their quarterly values. The quarterly *HML(FF)* is the average of its monthly values within each quarter. b and c are the slope coefficients from the OLS regressions. avg. is the average slope coefficient across all horizons. $Z(b)$ and $Z(c)$ are 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-value of the Z-statistics (*pval*) is simulated using data 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 the Appendix.

Panel A: Predicting *CAR(HML(FF))* Using *IVP(B/M)* and *IVP(B/M)*D*

	IVP(B/M)			*IVP(B/M)*D*			
Quarter	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	0.71	0.99	0.18	1.93	2.52	0.01	0.08
2	0.84	1.68	0.09	1.76	3.06	0.01	0.14
3	0.78	1.87	0.08	1.70	3.37	0.00	0.20
4	0.72	1.92	0.08	1.47	3.06	0.01	0.20
avg.	0.76		0.14	1.72		0.00	

Panel B: Predicting *CAR(HML(FF))* Using *IVP(comp)* and *IVP(comp)*D*

	IVP(comp)			*IVP(comp)*D*			
Quarter	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	0.66	0.85	0.21	1.95	2.42	0.02	0.08
2	0.65	1.20	0.16	1.76	2.88	0.01	0.13
3	0.72	1.47	0.13	1.66	3.06	0.01	0.18
4	0.64	1.31	0.16	1.47	2.92	0.02	0.19
avg.	0.67		0.19	1.71		0.00	

Panel C: Predicting *CAR(HML(B/M))* Using *IVP(B/M)* and *IVP(B/M)*D*							
	IVP(B/M)			*IVP(B/M)*D*			
Quarter	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	1.19	1.37	0.09	1.78	2.01	0.04	0.07
2	1.16	2.00	0.05	1.89	2.87	0.01	0.15
3	1.10	2.31	0.04	1.94	3.43	0.00	0.22
4	1.06	2.23	0.05	1.62	3.12	0.01	0.21
avg.	1.13		0.07	1.81		0.00	

Panel D: Predicting *CAR(HML(comp))* Using *IVP(comp)* and *IVP(comp)*D*							
	IVP(comp)			*IVP(comp)*D*			
Quarter	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	1.33	1.26	0.12	1.30	1.29	0.13	0.05
2	1.24	1.72	0.09	1.33	1.98	0.06	0.10
3	1.26	1.98	0.07	1.48	2.74	0.02	0.17
4	1.16	1.96	0.08	1.38	2.90	0.01	0.20
avg.	1.25		0.11	1.37		0.03	

Table 7. Predicting Future Industrial Production Growth Rates.

This table examines the predictive power of the implied value premium for future industrial production growth in multivariate regressions. Panel A provides the univariate regression of future industrial production growth rates on the implied value premium (*IVP(B/M)* or *IVP(comp)*), Panel B presents the results of regressing further industrial production growth rates on the implied value premium (*IVP(B/M)*), the value spread (*VS(B/M)*), the term spread (*Term*), and the default spread (*Default*), Panel C provides the multivariate regression on the implied value premium (*IVP(comp)*), the value spread (*VS(comp)*), the term spread (*Term*), and the default spread (*Default*), Panel D provides the bivariate regression on *IVP(B/M)* and the consumption-to-wealth ratio (*Cay*), and Panel E provides the bivariate regression on *IVP(comp)* and *Cay*. Panels A, B and C use monthly data from January 1977 to December 2011, and Panels D and E use quarterly data from 1977.Q1 to 2011.Q3. b, c, d, and e are the slope coefficients from the OLS regressions. avg. is the average slope coefficient across all horizons. $Z(b)$, $Z(c)$, $Z(d)$, and $Z(e)$ 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-value of the Z-statistics (*pval*) is bootstrapped using data 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 the Appendix.

Panel A: Univariate Regression of Predicting Future Industrial Production Growth

	Y= Industrial Production Growth *gIP*, X= *IVP(B/M)*				Y= Industrial Production Growth *gIP*, X= *IVP(comp)*			
Month	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$
1	0.01	0.03	0.49	0.00	-0.30	-1.48	0.93	0.01
6	0.15	0.57	0.33	0.00	-0.17	-0.81	0.75	0.00
12	0.28	0.85	0.26	0.02	-0.09	-0.32	0.60	0.00
24	0.35	1.27	0.19	0.06	0.05	0.16	0.46	0.00
36	0.38	1.85	0.11	0.12	0.17	0.72	0.30	0.02
avg.	0.24		0.05		-0.07		0.69	

Panel B: Multivariate Regression with *IVP(B/M)* and Other Predictors

Y = Industrial Production Growth *gIP*, X = (*IVP(B/M)*, *VS(B/M)*, *Term*, *Default*)

	IVP(B/M)			*VS(B/M)*			*Term*			*Default*			
Month	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	d	$Z(d)$	*pval*	e	$Z(e)$	*pval*	$adj.R^2$
1	0.64	3.02	0.00	-0.07	-3.14	1.00	0.68	2.42	0.01	-7.98	-6.81	1.00	0.16
12	0.45	1.17	0.20	-0.06	-1.95	0.91	0.81	3.11	0.02	-3.27	-2.66	0.98	0.19
24	0.36	1.44	0.15	-0.04	-2.11	0.91	0.89	5.89	0.00	-1.66	-2.31	0.95	0.27
36	0.37	2.20	0.07	-0.02	-0.92	0.71	0.75	4.19	0.01	-1.22	-1.67	0.88	0.33
avg.	0.47		0.00	-0.05		0.99	0.77		0.00	-3.84		1.00	

Panel C: Multivariate Regression with *IVP(comp)* and Other Predictors

Y = Industrial Production Growth *gIP*, X = (*IVP(comp)*, *VS(comp)*, *Term*, *Default*)

	IVP(comp)			*VS(comp)*			*Term*			*Default*			
Month	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	d	$Z(d)$	*pval*	e	$Z(e)$	*pval*	$adj.R^2$
1	0.75	2.72	0.00	-0.08	-3.57	1.00	0.66	2.28	0.02	-8.07	-6.67	1.00	0.15
12	0.60	1.53	0.12	-0.06	-2.37	0.95	0.79	3.37	0.01	-3.45	-2.77	0.97	0.19
24	0.41	1.50	0.14	-0.04	-2.16	0.92	0.89	5.13	0.00	-1.66	-2.06	0.93	0.25
36	0.39	2.22	0.06	-0.01	-0.62	0.66	0.78	4.22	0.01	-1.18	-1.43	0.86	0.30
avg.	0.56		0.00	-0.05		1.00	0.76		0.00	-3.91		1.00	

Panel D: Bivariate Regression with *IVP(B/M)* and *Cay*

Y = Industrial Production Growth *gIP*, X = (*IVP(B/M)*, *Cay*)

	IVP(B/M)			*Cay*			
Quarter	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	0.59	1.61	0.07	0.00	-0.17	0.56	0.01
2	0.63	1.66	0.10	0.00	0.06	0.48	0.03
3	0.68	1.56	0.13	0.01	0.28	0.41	0.06
4	0.63	1.40	0.16	0.01	0.43	0.37	0.07
avg.	0.63		0.02	0.00		0.45	

Panel E: Bivariate Regression with *IVP(comp)* and *Cay*

Y = Industrial Production Growth *gIP*, X = (*IVP(comp)*, *Cay*)

	IVP(comp)			*Cay*			
Quarter	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	0.27	0.71	0.28	0.00	0.00	0.49	-0.01
2	0.38	0.95	0.26	0.00	0.20	0.43	0.00
3	0.46	1.03	0.26	0.01	0.39	0.37	0.02
4	0.43	0.91	0.29	0.01	0.52	0.34	0.02
avg.	0.38		0.16	0.01		0.40	

Table 8. Further Analyses on the Implied Value Premium.

Panel A reports two univariate regressions of using the implied value premium *IVP(B/M)* to predict future realized value premium (*HML(FF)* and *HML(B/M)*), where the Z-statistics and their simulated p-values are obtained based on the Hodrick (1992) standard errors. Panel B reports the two univariate regressions of using *IVP(B/M)* and *IVP(comp)* to predict *HML(FF)*, when *IVP(B/M)* and *IVP(comp)* are obtained by equally-weighting the firm-level *ICC*s. Panel C reports the bivariate regression result when *HML(FF)* is regressed on *IVP(B/M)* and *AE*, where *AE* is the difference of analysts' forecast optimism between the value portfolio and the growth portfolio. All regressions use monthly data from January 1977 to December 2011. b and c are the slope coefficients from the OLS regressions. avg. is the average slope coefficient across all horizons. $Z(b)$ and $Z(c)$ are the asymptotic Z-statistics computed using the GMM standard errors with Newey-West correction in Panel B, and are computed using the Hodrick (1992) standard errors in Panel A. 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-value of the Z-statistics ($pval$) is simulated using data 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 the Appendix.

Panel A: Regressions Based on Hodrick (1992) Standard Errors

	Y = HML(FF), X = IVP(B/M)				Y = HML(B/M), X = IVP(B/M)			
Month	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	1.96	2.50	0.01	0.01	2.23	3.06	0.00	0.02
6	2.54	3.32	0.00	0.10	2.51	3.42	0.00	0.12
12	2.98	4.14	0.00	0.27	2.93	4.21	0.00	0.30
24	2.24	3.28	0.00	0.32	2.20	3.47	0.00	0.35
36	1.68	2.89	0.01	0.35	1.71	3.17	0.00	0.40
avg.	2.28		0.00		2.32		0.00	

Panel B: Predicting *HML(FF)* with Equally-weighted *IVP(B/M)* and *IVP(comp)*

	Y = HML(FF), X = IVP(B/M)				Y = HML(FF), X = IVP(comp)			
Month	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	2.27	2.71	0.01	0.02	1.85	2.03	0.03	0.01
6	2.55	3.82	0.00	0.09	2.05	2.62	0.03	0.05
12	2.79	5.51	0.00	0.21	2.74	4.63	0.00	0.18
24	2.25	6.02	0.00	0.29	2.51	5.21	0.00	0.32
36	1.79	7.92	0.00	0.36	2.03	8.37	0.00	0.40
avg.	2.33		0.00		2.24		0.00	

Panel C: Bivariate Regression with *IVP(B/M)* and Difference in Analysts' Forecast Optimism							
Y = *HML(FF)*, X = (*IVP(B/M)*, *AE*)							
	IVP(B/M)			*AE*			
Month	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	$adj.R^2$
1	2.15	2.66	0.01	-0.02	-1.73	0.96	0.02
12	3.05	5.23	0.00	-0.01	-1.38	0.86	0.27
24	2.25	5.78	0.00	0.00	-0.42	0.63	0.32
36	1.71	6.26	0.00	0.00	-0.98	0.76	0.35
avg.	2.29		0.00	-0.01		0.89	

Table 9. Out-of-sample Analysis.

This table summarizes the out-of-sample analysis of forecasting models using different forecasting variables. Panel A reports the R^2_{os} statistic of Campbell and Thompson (2008). Panels B and C report the p-values of the forecasting encompassing test statistic of Harvey, Leybourne, and Newbold (1998) (HLN statistic). We consider two forecast periods, namely, April 1989-December 2011 and January 1995-December 2011. In these tests, we perform a 1-year moving average for *IVP(B/M)*, *IVP(comp)*, *VS(B/M)*, and *VS(comp)*. The dependent variable is the Fama-French *HML* (*HML(FF)*). 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. The HLN statistic corresponds to a one-sided (upper-tail) test of the null hypothesis that the forecast from the row variable (R) encompasses the forecast from the column variable (C) against the alternative hypothesis that the forecast from the row variable (R) does not encompass the forecast from the column variable (C).

Panel A: Out-of-Sample R^2_{os} Test					
Forecast Period: 1989.04-2011.12			Forecast Period: 1995.01-2011.12		
	R^2_{os}	*pval*		R^2_{os}	*pval*
IVP(B/M)	3.62	0.00	*IVP(B/M)*	2.41	0.00
IVP(comp)	2.66	0.00	*IVP(comp)*	1.79	0.00
VS(B/M)	-4.19		*VS(B/M)*	-1.65	
VS(comp)	-3.11		*VS(comp)*	-0.71	
Term	-0.24		*Term*	-0.44	
Default	-0.22		*Default*	-0.18	

Panel B: Forecasting Encompassing Test				
Forecast Period: 1989.04-2011.12				
	Column Variables (C)			
Row Variables (R)	*IVP(B/M)*	*VS(B/M)*	*Term*	*Default*
IVP(B/M)		0.59	0.66	0.59
VS(B/M)	0.00		0.00	0.00
Term	0.00	0.64		0.39
Default	0.00	0.58	0.43	
Forecast Period: 1995.01-2011.12				
	Column Variables (C)			
Row Variables (R)	*IVP(B/M)*	*VS(B/M)*	*Term*	*Default*
IVP(B/M)		0.73	0.59	0.50
VS(B/M)	0.00		0.03	0.02
Term	0.00	0.63		0.39
Default	0.00	0.60	0.43	

Panel C: Forecasting Encompassing Test				
Forecast Period: 1989.04-2011.12				
	Column Variables (C)			
Row Variables (R)	*IVP(comp)*	*VS(comp)*	*Term*	*Default*
IVP(comp)		0.32	0.57	0.48
VS(comp)	0.00		0.10	0.08
Term	0.00	0.42		0.29
Default	0.00	0.44	0.57	
Forecast Period: 1995.01-2011.12				
	Column Variables (C)			
Row Variables (R)	*IVP(comp)*	*VS(comp)*	*Term*	*Default*
IVP(comp)		0.49	0.51	0.41
VS(comp)	0.05		0.28	0.23
Term	0.01	0.34		0.29
Default	0.01	0.36	0.57	

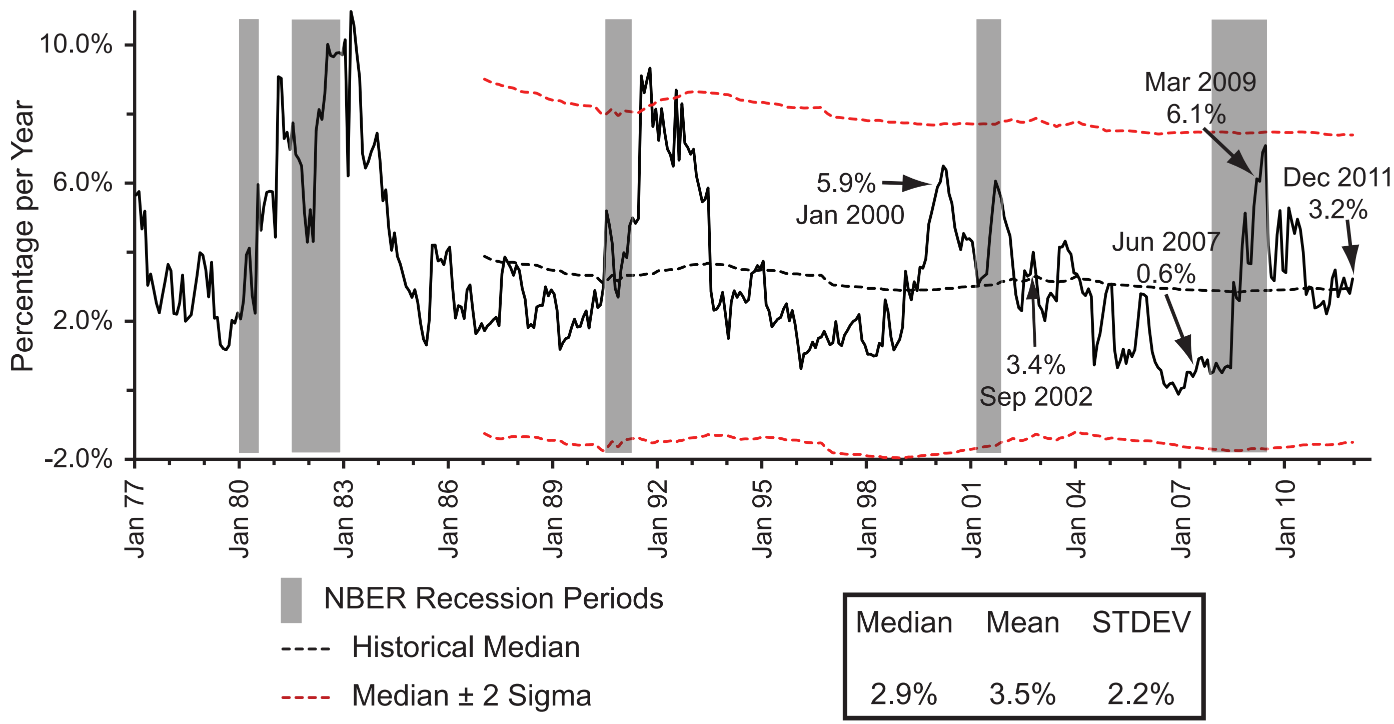

Figure 1: Implied Value Premium *IVP(B/M)* (January 1977-December 2011). This figure plots the time series of implied value premium constructed from a two-way sort based on size and B/M. *IVP(B/M)* is expressed in annualized percentages. The three horizontal dashed curves correspond to the rolling median and the two-standard-deviation bands calculated using all historic data starting from January 1987. The shaded areas indicate the NBER recession periods. The numbers associated with the arrows are the implied value premium for recent important dates. The historical mean, median and standard deviations of *IVP(B/M)* are provided in the box under the graph.

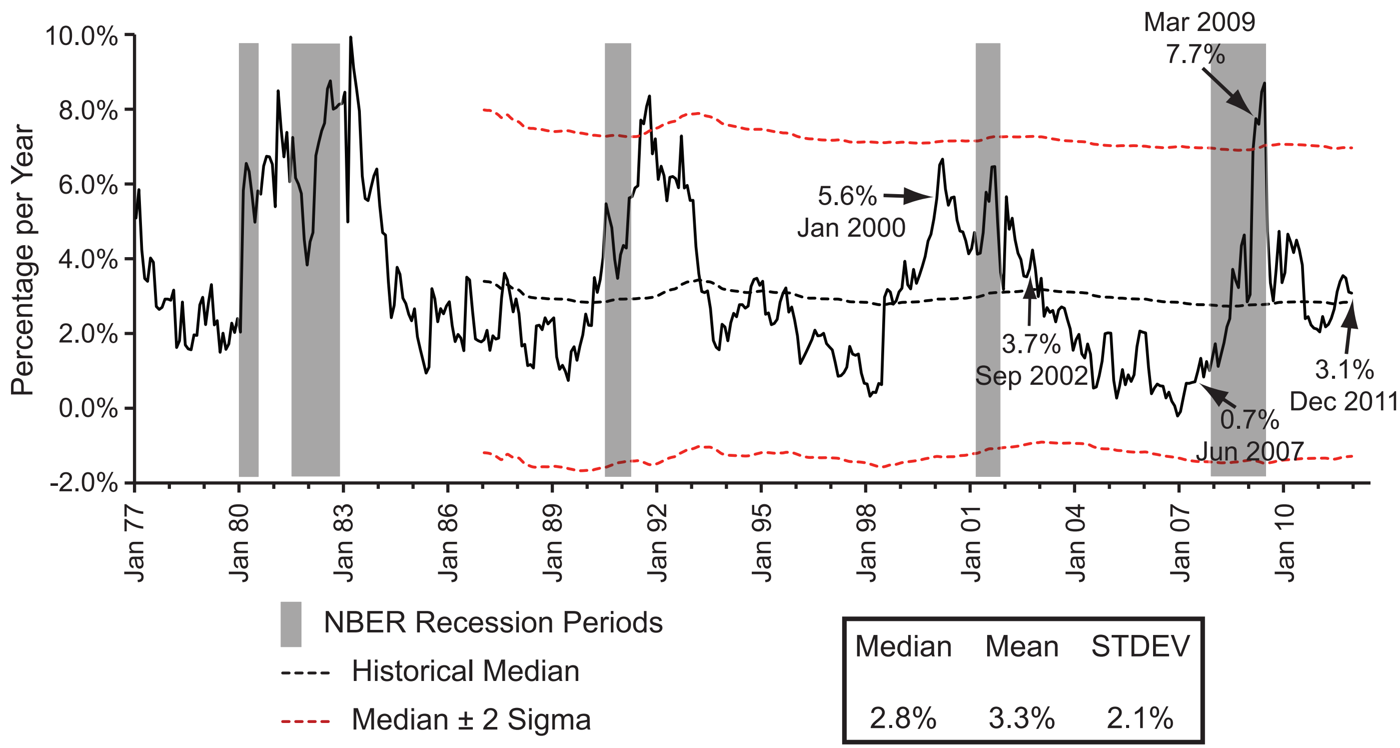

Figure 2: Implied Value Premium *IVP(comp)* (January 1977-December 2011). This figure plots the time series of implied value premium constructed from a two-way sort on size and a composite measure based on B/M, C/P, FE_1/P and FE_2/P. *IVP(comp)* is expressed in annualized percentages. The three horizontal dashed curves correspond to the rolling median and the two-standard-deviation bands calculated using all historic data starting from January 1987. The shaded areas indicate the NBER recession periods. The numbers associated with the arrows are the implied value premium for recent important dates. The historical mean, median and standard deviations of *IVP(comp)* are provided in the box under the graph.

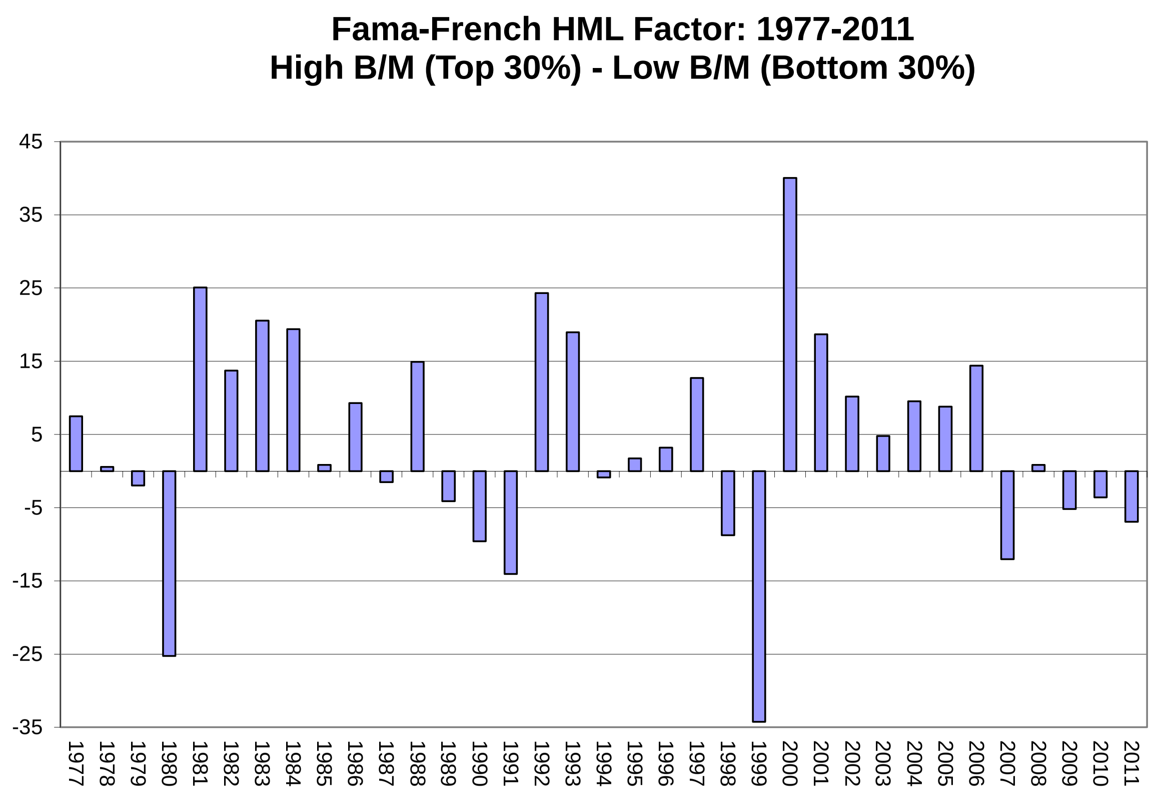

Figure 3: Annual Fama-French HML Factor (1977-2011). The data are taken from Kenneth French's website.

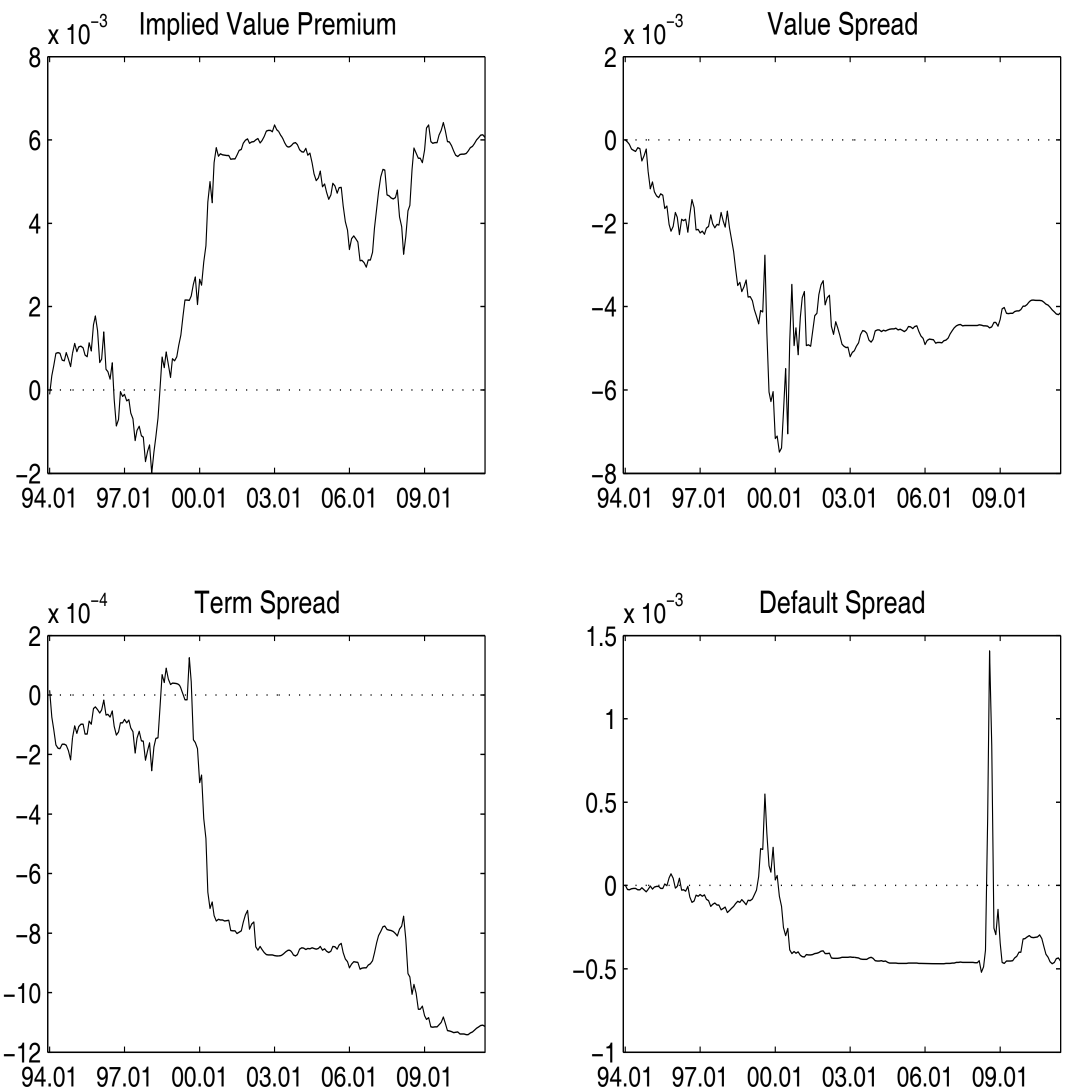

Figure 4: Cumulative Prediction Errors for Forecasting Variables (January 1995-December 2011). This figure plots the cumulative square prediction error of the Fama-French *HML* for the historical average benchmark forecasting model minus the cumulative square prediction error for the forecasting model using the implied value premium (*IVP(B/M)*), value spread (*VS(B/M)*), term spread, and default spread, respectively.