Predicting Time-varying Value Premium Using the Implied Cost of Capital

Yan Li, David T. Ng, and Bhaskaran Swaminathan[1]

We estimate an implied value premium (*IVP*) using the implied cost of capital methodology. 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 find that *IVP* is the *best predictor* of ex-post value premium during the 1977-2012 time period at horizons ranging from one month to 36 months in univariate and multivariate forecasting regression tests. At the 12-month horizon, *IVP* is able to explain 18% to 29% of the variation in the ex-post value premium. Other forecasting variables such as value spread, default spread, term spread, and consumption-to-wealth ratio do not fare as well. *IVP* strongly predicts the difference in cumulative abnormal returns around future quarterly earnings announcements of value and growth stocks, and its predictive power is stronger during periods of extreme mispricing. *IVP* is unable to predict future macroeconomic activity. Overall our results are supportive of mispricing as at least a partial explanation for the predictable time variation in value premium.

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[1]Yan Li, liyanlpl@temple.edu, Department of Finance, Fox School of Business, Temple University, 425 Alter Hall, Philadelphia, PA 19122; David T. Ng, dtn4@cornell.edu, Dyson School of Applied Economics and Management, Cornell University, 310D Warren Hall, Ithaca, NY 14853; Bhaskaran Swaminathan, swami@lsvasset.com, LSV Asset Management, 155 North Wacker Dr., Chicago, IL 60606. We thank Hengjie Ai, Hendrik Bessembinder, Long Chen, Francis X. Diebold, Amy Dittmar, George Gao, Kewei Hou, Ming Huang, Marcin Kacperczyk, Andrew Karolyi, Qingzhong Ma, Lilian Ng, Nagpurnanand R. Prabhala, Amiyatosh Purnanandam, David Reeb, Michael R. Roberts, Oleg Rytchkov, Ramu Thiagarajan, Jun Tu, Jeffrey Wurgler, Lu Zhang, Xiaoyan Zhang, Yuzhao Zhang, and seminar participants at Cheung Kong Graduate School of Business, Cornell University, Hong Kong University of Science and Technology, Nanyang Technological University, National Taiwan University, National University of Singapore, Shanghai University of Finance and Economics, the Journal of Investment Management conference in Chicago in 2012, University of Hong Kong, University of Sydney, University of Technology in Sydney, Singapore Management University, and Syracuse University, for their helpful comments. Any errors are our own.

1 Introduction

Prior evidence shows that value stocks earn higher returns than growth stocks. Fama and French (1992, 1993) suggest that this is because value stocks face greater earnings distress risk than growth stocks. Lakonishok, Shleifer, and Vishny (1994) suggest that this is because value stocks are undervalued, and growth stocks are overvalued due to investors' extrapolation bias. There exists a vast literature addressing these contrasting hypotheses, focusing primarily on cross-sectional asset pricing tests based on *realized returns*.[2] In this paper, we attempt to shed light on the risk versus mispricing debate by focusing instead on the *time-variation* in value premium—the return premium earned by value stocks over growth stocks—using a direct measure of the *expected value premium*.[3]

There is indication of considerable time variation in the ex-post value premium in the U.S. (see Figure 1). Asness, Friedman, Krail, and Liew (2000) and Cohen, Polk, and Vuolteenaho (2003) provide empirical evidence that this time variation is predictable. Specifically, they find that a high value spread (the spread in book-to-market ratios, or earnings-to-price ratios, between value stocks and growth stocks), which is an ex-ante measure of the relative valuation between value and growth stocks, predicts high value premium in the future. This predictability might be due to either time-varying relative mispricing (Barberis and Shleifer (2003)) or time-varying relative risks (Zhang (2005)). We explore these alternative explanations in this paper.

Our initial objective, however, is to introduce an *ex-ante* measure of expected value premium using the implied cost of capital (ICC) methodology. 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, the implied value premium is likely to be a more precise estimate of the ex-ante value premium than the spreads in earnings yields, book-to-market ratios, etc that are widely used in the literature. We use the implied value premium to forecast the ex-post value premium and show that it is more effective in capturing the time-variation in the ex-post value premium.

We compute the implied value premium (IVP) in a couple of ways: (1) based on value and

[2]See Barberis and Thaler (2003), Cochrane (2007), and Campbell, Polk, and Vuolteenaho (2010) for the cross-sectional literature.

[3]Realized returns are noisy and do not necessarily converge to expected returns in finite samples. For example, Elton (1999) (p. 1199) argues that "realized returns are a very poor measure of expected returns." See Pastor, Sinha, and Swaminathan (2008) for related discussions.

growth portfolios constructed using book-to-market (B/M) ratios as in Fama and French (1993) and (2) based on value and growth portfolios constructed using a composite measure of value based on book-to-market (B/M) ratio, cash flow-to-price (C/P) ratio, and one-year ahead and two-year ahead forecasted earnings-to-price ratios (FE_1/P and FE_2/P). We use these alternate measures to show that our results are robust to different definitions of value and growth.[4] We use these *IVP*s 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. Our sample consists of all firms with available analyst earnings forecasts from January 1977 to December 2012.

We conduct long-horizon regression tests to evaluate the forecasting power of *IVP*. In these regressions, we control for the value spread (*VS*), defined as the difference in log B/M ratios between value and growth stocks, and a variety of business cycle proxies including the term spread (*Term*), the default spread (*Default*), and the consumption-to-wealth ratio (*Cay*).[5] We find that *IVP* is the best predictor of HML in horizons ranging from 1 month to 36 months during the 1977-2012 period. For instance, in univariate regressions at the 12-month horizon, *IVP* is able to explain 18% to 29% of the variation in HML. The value spread, which predicts HML in univariate regressions, does not fare well in multivariate regressions involving *IVP*, while none of the business cycle variables have any predictive power for HML in either univariate or multivariate tests. Our results thus establish *IVP* to be the best ex-ante measure of time-varying value premium.

What are the likely 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 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 will also vary over time giving rise to predictable time-varying value premium. Barberis and Shleifer (2003) formalize this idea in their model of style investing in which investors with extrapolative expectations switch between investment styles based on a style's past performance giving rise to time-varying relative mispricing.[6] With time-varying relative mispricing, the implied value premium would be high after

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

[5] All statistical inference is drawn by comparing the test statistic with its empirical distribution under the null derived from Monte Carlo simulations.

[6] If growth stocks have recently done well, the switchers would move into growth stocks and out of value stocks even if there is no bad news about value stocks. As more investors switch, growth stocks become overvalued relative

a period of value underperformance and low after a period of value outperformance predicting a high and low realized value premium subsequently.

Zhang (2005) suggests costly reversibility and countercyclical price of risk as the source of time-variation in 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 risks as they have fewer assets-in-place. During expansions, growth firms face fewer constraints raising the capital needed to expand and, as a result, their dividends and returns may not be as sensitive to economic conditions. Value firms have no need to expand as more of their unproductive assets become productive. Overall, costly reversibility can lead to value firms to become more risky than growth firms during downturns. Countercyclical price of risk, high in downturns and low in expansions, can amplify the effects of time-varying relative risk, and cause the expected returns of value firms to rise significantly during downturns and fall during expansions relative to growth firms. This implies value stocks should underperform growth stocks during downturns and outperform them during expansions. Consequently, HML should be low in downturns and high in expansions.[7]

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 average CAR of the growth portfolio from the average CAR of the value portfolio to compute *CAR(HML)*. We average the *CAR(HML)* over the next four

to value stocks. While switchers switch styles based on recent performance, rational investors are likely to switch based on the relative valuation between the two styles, profiting of the mispricing in the long-run and helping bring their prices back to fundamentals. Thus, the value premium can vary over time as switchers make one style or the other too expensive over time. At the beginning of 2000, for instance, 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.

[7]Zhang (2005) proposes a risk-based explanation for the *time-varying* value premium. He shows that the interaction of time-varying risks and countercyclical price of risk can give rise to positive unconditional 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), Berk, Green, and Naik (1999), Lettau and Ludvigson (2001), Lettau and Wachter (2007), Campbell, Polk, and Vuolteenaho (2010), Hansen, Heaton, and Li (2008), Bansal, Kiku, Shaliastovich, and Yaron (2012), and Koijen, Lustig, and Van Nieuwerburgh (2012).

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 higher *IVP* implies that value stocks are more 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. Since risk is unlikely to change unexpectedly over a matter of days, this result provides strong evidence in support of the mispricing explanation. Further analysis shows that the predictive power of *IVP* for future *CAR(HML)* is stronger during periods of extreme mispricing.[8]

The countercyclical risk hypothesis suggests that the expected value premium should be high in downturns and low in expansions and, therefore, value stocks should underperform in downturns and perhaps outperform in expansions. Figure 1 plots the annual Fama-French HML factor with an overlay of the NBER business cycles, and Figures 2 and 3 plot our implied value premium measures (based respectively on B/M and the composite value). Contrary to the predictions of the hypothesis, value stocks outperformed growth stocks during the recessions of July 1981-November 1982 and March 2001-November 2001 and underperformed during the economic expansion of 1998-1999. The implied value premium remained low during the 1981-82 and 2001 recessions and high during the expansion of 1998-99. During the most recent recession from December 2007-June 2009, however, value stocks did underperform growth stocks and the implied value premium increased. Clearly, the evidence in these plots is not uniformly supportive of the countercyclical risk hypothesis.

To further explore the role of countercyclical risk, we examine whether *IVP* is 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 not able to predict future industrial production growth. The value spread (*VS*), on the other hand, is negatively related to future economic activity. Among the business cycle variables, only the term spread has a statistically significant positive relationship with future growth in industrial production. Overall, we do not find much evidence in support for the countercyclical risk explanation, although we cannot entirely rule it out.

We conduct a variety of robustness checks on our implied value premium measures and confirm

[8] 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.

that the predictive power of IVP for future realized value premium remains strong and significant. For instance, we show that our results are robust to: a) using alternative steady-state earnings growth rates and plowback rates in the construction of the firm-level ICCs, b) using different horizons in the ICC methodology for value and growth firms, and c) using alternative standard errors to evaluate the statistical significance of our regressions. Finally, we also show that time-variations in relative analyst forecast bias between value and growth stocks do not explain our findings.

Our in-sample analysis shows that IVP is an excellent predictor of future realized value premium. We also examine the out-of-sample performance of the implied value premium. Our results show that during the two forecast periods we examine (April 1989-December 2012 and January 1995-December 2012), the implied value premium is a reliable out-of-sample predictor of future realized value premium.[9] 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), Li, Ng, and Swaminathan (2013), Chen, Da, and Zhao (2013), Mo (2014), and Tang, Wu, and Zhang (2014)). 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) value premium is time-varying and the implied value premium (IVP) based on the ICC methodology is the best predictor of the time-varying value premium and (b) this predictability is at least *partially* related to time-varying relative mispricing.

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

Our results are mixed on the countercyclical risk hypothesis although we cannot entirely rule it out. Our results also have implications for style timing since we introduce a new measure of expected value premium that is empirically superior to the widely used value spreads in predicting the ex-post value premium.

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 predictability of future realized value premium by the implied value premium, and investigates the sources behind the strong predictive power of the implied value premium. Section 5 concludes the paper.

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 of 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).[10] 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:[11]

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

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

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

[11] We use the term "dividends" interchangeably with free cash flows to equity (FCFE) to describe all cash flows available to equity.

$t+T$, 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:

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

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 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). (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 $FE_2 = FE_1\left(1+g_2\right)$. 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.[12] 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 the steady-state value 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:

$$g_{t+k} = g_{t+k-1} \times \exp\left[\log\left(g/g_2\right)/T\right] \text{ and} \tag{2}$$

$$FE_{t+k} = FE_{t+k-1} \times \left(1 + g_{t+k}\right). \tag{3}$$

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.

[12] 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 $t+2$.

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.[13] We exclude share repurchases and new equity issues due to the practical problems associated with determining the likelihood of their recurrence in future periods.[14] 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 plowback rate $ROE \times b$ 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 $t+T+1$.[15] 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:

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

[13] 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.

[14] To gauge the impact of share repurchases and new equity issuances, we reestimate the payout ratio by incorporating share repurchases and new equity issuances. We find that our results are robust to including share repurchases and new equity issurances.

[15] 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.

Following Li, Ng, and Swaminathan (2013), we use a 15-year horizon ($T = 15$) to implement the model in (6) and compute r_e as the rate of return that equates the present value of free cash flows to the current stock price. The resulting r_e is the firm-level ICC measure used in our empirical analysis.

2.2 Value and Growth Portfolios

We first construct value and growth portfolios using a two-way sort based on size and book-to-market ratios as in Fama and French (1993). In June of each year from 1976 to 2012, all NYSE stocks on CRSP are ranked on size (market capitalization). The median NYSE size is then used to divide 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). The book equity is stockholder equity plus balance sheet-deferred taxes and investment tax credits 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. 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 size-B/M portfolios (denoted S/L, B/L, S/M, B/M, S/H, and B/H). 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 and HML is (S/H + B/H)/2 -(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 value stocks and low C/P stocks are 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.[16] In June of each year from 1976 to 2012, we construct value/growth portfolios based on a two-way sort involving size and the composite value rank. 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 (ex-ante) implied value premium as follows. Each month, we first compute the ICCs of S/L, B/L, S/H, and B/H by value-weighting the ICCs of their constituent firms using the month-end market capitalization. The ICC for H is a simple average of the ICCs of S/H and B/H, and the ICC for L is a simple average of the ICCs of S/L and B/L. The two measures of implied value premium based on B/M ratio and the composite value rank are:

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

$$IVP(comp)_t = ICCH(comp)_t - ICCL(comp)_t,$$

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. The return of the growth portfolio (L) is computed by averaging the returns of S/L and B/L. The realized value premium, which is the HML constructed from our sample of firms with available analyst forecasts, is defined as

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

$$HML(comp)_t = H(comp)_t - L(comp)_t.$$

[16]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.

If our implied value premium is a good ex-ante measure of the expected value premium, it should predict not only our constructed HML, but also the Fama-French HML factor (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 constructed HML.

An important control variable we examine in our regression analysis is the value spread (VS) which is defined as the difference in the book-to-market ratios of value and growth portfolios. The value spread has been found to be an important predictor of the realized value premium (e.g., Asness, Friedman, Krail, and Liew (2000), Cohen, Polk, and Vuolteenaho (2003)).[17] We compute the book-to-market ratio of 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. We obtain the book-to-market ratio of the growth portfolio in the same manner as the average of the book-to-market ratios of S/L and B/L.[18] The value spread is the difference in the natural logs of the book-to-market ratios of the value and growth portfolios:

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

The value spreads based on B/M and the composite value rank are denoted as *VS(B/M)* and *VS(comp)*, respectively.[19]

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, depreciation and amortization and fiscal year-end date from COMPUSTAT, and analyst earnings forecasts and share price from I/B/E/S. To

[17] Liu and Zhang (2008), on the other hand, argue that the value spread is not a reliable predictor of value premium.

[18] 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 results.

[19] 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.

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 the 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 various business cycle variables: term spread *(Term)*, default spread *(Default)*, and consumption-to-wealth ratio (*Cay*) (Lettau and Ludvigson (2001)). 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.

3.2 Summary Statistics

Table 1 provides summary statistics for the variables used in this paper. Panel A presents the summary statistics for the implied risk premia of the value and growth portfolios and the implied value premium. We subtract the yield on the 1-month T-bill rate (from WRDS) from the ICCs of value and growth portfolios to obtain the corresponding implied risk premia. For value and growth portfolios based on B/M, the average annual risk premia are 11.18% and 7.68%, with standard deviations of 3.28% and 2.23%. For value and growth portfolios based on the composite value rank, the average annual risk premia are 11.05% and 7.60%, with standard deviations of 3.18% and 2.29%. *IVP(B/M)* has a mean of 3.50% and a standard deviation of 2.13%, and *IVP(comp)* has a mean of 3.45% and a standard deviation of 2.05%. Panel B reports the realized risk premia for the constructed value and growth portfolios, the constructed HML and the Fama-French HML. All three HML measures have similar means and standard deviations: the constructed *HML(B/M)* has a mean of 3.57%, and a standard deviation of 9.96%; the constructed *HML(comp)* has a mean of 3.94%, and a standard deviation of 10.34%; and the Fama-French HML factor *HML(FF)* has a mean of 3.73% and a standard deviation of 10.44%. Not surprisingly, they are also highly correlated with one another (correlations ranging from 0.90 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.[20]

Also, the average implied value premium in Panel A is about the same magnitude as the ex-post value premium in Panel B during our sample period. The mean of *IVP(B/M)* and *IVP(comp)* are 3.50% and 3.45% respectively, which is comparable to the means of the three HML factors which are in the range of 3.57% to 3.94%. 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 0.91 and 0.90.[21]

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 might be related to the business cycle. We plot the time-series of the two implied value premium measures *IVP(B/M)* and *IVP(comp)* in Figures 2 and 3. 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. 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 underperformed during 2007-2012 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.

[20]In unreported results, we find that the predictive power of *IVP* for realized value premium remains the same when controlling for the sum of lagged HML (up to 12 lags).

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

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:

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

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.[22]

We estimate the forecasting regression for various horizons: $K = 1$, 12, 24, and 36 months for monthly regressions, and $K = 1$, 2, 3, 4 quarters for quarterly regressions. We use the Generalized Method of Moments (GMM) standard errors with the $K-1$ Newey-West lag correction (Newey and West (1987)) to correct for both autocorrelation and heteroskedasticity in (7). 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 the Monte Carlo simulation methodology. Finally, since the forecasting regressions use the same data at various horizons, the regression slopes will be correlated. Richardson and Stock (1989) propose a joint test based on the average slope coefficient to test the null hypothesis that the slopes at different horizons are jointly zero. Following their paper, we compute the average slope statistic as the arithmetic average of regression slopes at different horizons, and conduct Monte Carlo simulations to assess its statistical significance.

If the implied value premium is a good proxy of the expected value premium, then it should predict HML with a positive sign and, therefore, the slope coefficients associated with *IVP(B/M)* or *IVP(comp)* in (7) should be positive. We also expect a positive sign for the value spread since Asness, Friedman, Krail, and Liew (2000) and Cohen, Polk, and Vuolteenaho (2003) find that the value spread positively predicts ex-post value premium. If the value premium is countercyclical as argued in rational theories, then business cycle variables should also positively predict future

[22] The HMLs are in monthly units. We divide the annual *IVP* by 12 to obtain its monthly values and use them in all regressions throughout the paper.

realized value premium. Therefore, a one-sided test of the null hypothesis is appropriate for all forecasting variables.

Table 2 presents univariate regression results for the implied value premium (*IVP(B/M)* and *IVP(comp)*), the value spread (*VS(B/M)* and *VS(comp)*), and the business cycle variables. Panel A presents the results for predicting *HML(FF)*. Panels B and C present the results for predicting *HML(B/M)* and *HML(comp)*, respectively. 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 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. The slope coefficients of *IVP(B/M)* and *IVP(comp)* are uniformly positive and significant at the 1% or the 5% level (based on the simulated p-values) 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 24% at the 12-month horizon, and 29% at the 36-month horizon. The results in Panels B and C provide adjusted R-squares of the same magnitude. The results are also economically significant. At the 1-month horizon, a one-standard-deviation increase in *IVP(B/M)* (2.13%) translates into an annualized increase of about 4.2% (2.13% $\times$1.96) for *HML(FF)* (Panel A), and an annualized increase of about 4.9% (2.13% $\times$ 2.31) for *HML(B/M)* (Panel B).

The value spread *VS(B/M)* is also a significant predictor of the *HML(FF)* (Panel A) at the 24-month and 36-month horizons with the p-value for the average slope coefficient being 0.05. *VS(comp)* is also a significant predictor of both *HML(FF)* and *HML(comp)* at longer horizons, with p-values of 0.02 and 0.05 for the average slope coefficient (Panels A and C). None of the business cycle variables predict *HML(FF)* reliably and even the signs of their slope coefficients are mixed. Overall, the implied value premium is the strongest predictor of ex-post value premium in univariate regressions.

4.2 Multivariate Regressions

In this section, we examine whether the implied value premium continues to predict ex-post value premium in multivariate regressions that include 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 regression results involving *IVP* and the consumption-to-wealth ratio. 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 the results are similar.

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 always positive. 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. Since HML tends to be higher in January, in unreported results, we also control for the January effect and our results remain unchanged. 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 are interested in exploring the risk versus mispricing debate in the context of predictable time-variation in value premium. As discussed in the introduction, the implication of Lakonishok, Shleifer, and Vishny (1994) and Barberis and Shleifer (2003) is that the time variation in value premium is due to time-varying mispricing caused by investors' extrapolative expectations while that of Zhang (2005) implies that it is due to the countercyclical time-variation in the relative risks of value and growth firms. In the next section, we examine the mispricing implications of the predictive power of *IVP*.

4.3.1 Predicting Price Reactions around Quarterly Earnings Announcements

Earnings announcements are significant news events, which bring new information to the market regarding the fundamental value of firms. Thus, 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 that value stocks earn positive abnormal returns and growth stocks earn negative abnormal returns in the days surrounding their subsequent 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 average CAR of the growth portfolio (*CAR(L)*) from the average 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 CARs are likely to be 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.[23] 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 $t-1$. The sample extends from the first quarter of 1977 to the third quarter of 2012.

The results from univariate regressions are provided in Panels A to D of Table 4. The predictive power of IVP remains strong regardless of whether we use value-weighted *CAR(HML)* or equal-weighted *CAR(HML)*, whether we use *IVP(B/M)* or *IVP(comp)*, or whether we use

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

CAR(HML(FF)) or our own constructed *CAR(HML)*. 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 12% to 28% at the 4-quarter horizon. In untabulated results, we find that only *VS(B/M)* and *VS(comp)* have some predictive power for *CAR(HML)*. None of the business cycle variables *Term*, *Default*, or *Cay* are able to predict *CAR(HML)*: their slope coefficients are not statistically significant, and the adjusted R-squares associated with these regressions are also low.

Table 5 presents multivariate regression results that control for the other forecasting variables. Because the predictive power of *IVP* is stronger for equally-weighted *CAR(HML)*, we report the results only for value-weighted *CAR(HML)* to conserve space. Similarly, we skip results for constructed *CAR(HML)* since they are similar to those based on *CAR(HML(FF))*. 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. Overall, the results in Tables 4 and 5 provide strong support for the 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(HML)* 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). From 1977 to 2012 (see Figure 1), value underperforms growth in 13 calendar years (36%) and outperforms growth in 24 calendar years (64%). 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 four quarters is negative which as explained earlier is rare.

We then estimate the following regression:

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

During normal periods, the predictive power of *IVP* is captured by the coefficient b while during extreme mispricing (value underperformance) it is captured by the sum of b and c. Therefore, we expect a positive sign for c.

Panels A and B of Table 6 provide the regression results. In every panel, the 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. *IVP* still predicts future *CAR* positively in normal 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 plays a major role in the pricing and performance of value and growth stocks over time.

4.3.2 Countercyclical Risk

We now examine the countercyclical risk explanation for the time-variation in value premium. To recap, the countercyclical risk theory predicts expected returns on value stocks should rise and value stocks should underperform during recessions. As explained in the introduction, Figures 1, 2, and 3 provide mixed evidence regarding this prediction: Value underperformed only during the 1980, 1991 and 2008-2009 recessions; it in fact outperformed during the 1981-82 and 2001 recessions and underperformed during the 1998-99 expansion. Clearly there is more at play than just countercyclical risk. The contemporaneous correlation between *IVP(B/M)* (*IVP(comp)*) and a dummy variable for the NBER recession is also only 0.17 (0.33) (p-values 0.00) indicating while there is potentially some countercyclical time variation in the implied value premium, not all of the variation is due to economic cycles.

We now turn to formal tests of the countercyclical theory. If the implied value premium is countercyclical then it should predict proxies of future economic activity with a positive sign. This is because *IVP* should be high in economic downturns which are likely to be followed by economic recovery thus leading to a positive relationship between current *IVP* and future economic activity. In Table 7, we estimate univariate regressions of future cumulative growth rates in industrial production on the implied value premium, value spread, term and default spreads and the consumption-to-wealth ratio.[24] As predicted, the slopes of the implied value premium at the individual regressions are mostly positive although none is statistically significant even at conventional significance levels. The R-squares are also small but the average slope coefficients are statistically significant. Value spread has the wrong sign in predicting growth rates in industrial production and is insignificant. The best predictor of growth rates in industrial production is the term spread which predicts them strongly at every horizon. The R-square is also impressive at 26% at the 36-month horizon. Overall, the evidence in our paper does not unambiguously support the countercyclical risk explanation although we cannot rule it out entirely.

4.4 Robustness

In this section, we conduct a variety of tests to examine the robustness of the predictive power of the implied value premium. To save space, we only report results for predicting *HML(FF)* since the results for predicting *HML(B/M)* and *HML(comp)* are similar.

4.4.1 Alternative Measures of *IVP*

Our primary measure of the implied value premium is constructed by computing the value-weighted average of firm-level ICCs of value and growth firms and taking their difference. As a robustness check, we also compute the equally-weighted average of the firm-level ICCs to obtain the implied value premium, and examine its predictive power for future realized value premium. Panel A of Table 8 shows that the equally-weighted *HML(B/M)* and *HML(comp)* continue to strongly predict the Fama-French HML factor and they generate even higher R-squares than the value-weighted measures.[25]

4.4.2 Alternative Specifications of the ICC Model

Alternative Assumptions on Steady-State Values In our main computation of the ICC, we assume that the earnings growth rates of all stocks mean-revert to the long-run GDP growth

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

[25] As an additional robustness check, we examine whether the low-frequency component of IVP also predicts future realized value premium. To do so, we take the 12-month moving average of the IVP measures and use the smoothed IVP to predict *HML(FF)*. We find that the smoothed IVP also strongly predicts *HML(FF)*.

rate and their plowback rates mean-revert to the long-run plowback rate which also depends on the long-run GDP growth rate. In this subsection, we follow Chen, Da, and Zhao (2013) to allow both parameters to be functions of firm characteristics and show that our results are not sensitive to these assumptions.

More specifically, starting from the end of 1952, we classify all common stocks listed in NYSE/AMEX/Nasdaq in the merged CRSP/Compustat database into 24 portfolios according to the 12 Fama-French industries and size (above or below the median market value in the industry). For each of the 24 portfolios, we compute the median earnings growth rates and plowback rates 15 years later (for the 1952 cohort it would be in 1967).[26] We repeat the calculations for each cohort from 1952 to 1961 (thus the medians are computed for years 1967 through 1976). We then average these long-run growth rates and plowback rates from 1967 to 1976. We use these portfolio averages as our forecasted steady-state earnings growth rates and plowback rates in year 1977 for individual stocks with similar industry and size characteristics. Likewise, we average the long-run rates across portfolios constructed for the 1952-1962 period to obtain forecasts for year 1978. We iterate this process till the end of our sample period where we average the long-run rates across portfolios constructed for the 1967-2011 period to obtain forecasts for year 2012. Therefore, our forecasts are always computed using a backward recursive window which uses all information available at the time for forecasts.

Panel B of Table 8 provides the prediction results using the new *IVP* measures computed based on these forecasted steady-state values. Both *IVP(B/M)* and *IVP(comp)* still strongly predict *HML(FF)*: they are highly significant and their adjusted R-squares are 23% and 18% at the 12-month horizon. These alternate *IVP* measures have correlations of 98% and above with our primary measures.

Different Horizons for Value and Growth Stocks Our main measures of the implied value premium are based on cash flow forecasts up to 15 years, i.e., $T = 15$ in equation (6). A possible concern 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 it takes a longer time for growth stocks to revert to the GDP growth rate than do value stocks, then using the same horizon for both could lead to

[26]For stocks that exit the portfolios over the years for various reasons, we fill in using the median values of earnings growth rates and plowback rates of available stocks in the same industry. The reason to take the median value is to mitigate outliers. Our results are similar if we take the mean values after trimming top 1% and bottom 1% of extreme values.

too low a ICC for growth stocks and too high a ICC for value stocks.[27] 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.

Nevertheless, we reconstruct our *IVP* measures by assuming different horizons for value stocks and growth stocks. We obtain the horizons based on the half-lives of these portfolios. In June of each year from 1965 to 2006, we sort all NYSE/AMEX/Nasdaq stocks into six size-B/M portfolios: B/H, B/L, B/M, S/H, S/L, and S/M. For each firm within each portfolio, we compute its average 5-year earnings growth as $\overline{g}_{i,t+1,t+5} = \frac{g_{i,t+1}+g_{i,t+2}+g_{i,t+3}+g_{i,t+4}+g_{i,t+5}}{5}$, where $g_{i,t+1}$ is the earnings growth for firm i in year $t+1$. Similar to Fama and French (2000), we run the following cross-sectional regressions for each portfolio each year using overlapping observations:

$$\overline{g}_{i,t+1,t+5} - g^*_{t+1} = a + b(\overline{g}_{i,t,t+4} - g^*_t) + \varepsilon_{i,t+1},$$

where g^*_{t+1} is the long-run GDP growth rate in year $t+1$ computed as the historical average of the GDP growth rates using annual data up to year $t+1$. If $b < 1$, then the earning growth reverts to its equilibrium level at the rate $1-b$; different values of b indicate different convergence speed for different portfolios. Based on b, we can obtain the corresponding half-life for $\overline{g}_{i,t+1,t+5}$ as $h = \ln(1/2)/\ln(b)$ (e.g., Abuaf and Jorion (1990), Balvers, Wu, and Gilliland (2000)), and the half-life for $g_{i,t+1}$ is $5h$. To mitigate the impact of outliers, we use ranked values for dependent and independent variables to estimate the above regression.

For each of the six size-B/M portfolios, we average the estimated b's from 1965 to 1971, obtain the corresponding half-life and use its integer part to compute ICCs for firms in the same size-B/M category in year 1977. We average the estimated b's from 1965 to 1972, compute the corresponding half-life and use its integer part to compute ICCs for firms in the same size-B/M category in year 1978. We repeat this analysis till the end of our sample period where we average the estimated b's from 1965 to 2006, compute the corresponding half-life and use its integer part to compute ICCs for firms in the same size-B/M category in year 2012. The average estimated half-lives for B/H, B/L, S/H, and S/L are 10.7, 15.4, 12.8, and 13 years, respectively, suggesting that consistent with Dechow, Sloan, and Soliman (2004), growth rates of growth firms (especially large growth firms)

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

take longer to mean-revert than those of value firms. Using these new horizons, we obtain the mean of *IVP(B/M)* as 3.01% with a standard deviation of 1.86%, and the mean of *IVP(comp)* as 3.31% with a standard deviation of 1.81%. Therefore, the new *IVP* measures have slightly lower mean and standard deviations than our main measures (see Panel A of Table 1).

Panel C of Table 8 provides the regression results when we use the half-life based horizons to obtain the *IVP* measures. The results are quite similar to those in Panel A of Table 2, indicating that the predictive power of *IVP* is robust to using different horizons for value and growth firms.

4.4.3 Analyst Forecast Bias

Our calculation of the 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. If analysts are differentially optimistic about value and growth stocks during recessions and expansions, it could lead to a possible relationship between the implied value premium and future realized value premium. 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.

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 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 growth rates of the individual firms in value and growth portfolios to obtain their portfolio 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, ARO. [28]

Panel D of Table 8 examines the predictive power of *IVP(B/M)* for *HML(FF)* after controlling for ARO. 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 time-variation in analyst forecast optimism.

[28] 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*.

4.4.4 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 alternative standard error to conduct statistical inference and confirm the robustness of our predictability findings.

Panel E of Table 8 shows the results of regressing *HML(FF)* on *IVP(B/M)* and *IVP(comp)*, 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. These results show that the predictive power of the implied value premium is not sensitive to the choice of standard errors.

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 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 and Forecast Evaluation

Consider the following predictive regression:

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

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 (*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 (8) and generate out-of-sample forecasts of the value premium. More 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. We use the first m observations to estimate (8) and obtain the OLS estimators $\hat{\alpha}_{i,m}$ and $\hat{\beta}_{i,m}$, which gives us the first out-of-sample forecast as

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

and we use the first $m+1$ observations to estimate (8) and obtain $\hat{\alpha}_{i,m+1}$ and $\hat{\beta}_{i,m+1}$ which gives us the second out-of-sample forecast as

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

Proceeding in this manner through the end of the forecast period, for each predictive variable x_i, we can obtain a time series of predicted value premium $\{\hat{r}_{i,t+1}\}_{t=m}^{T-1}$. We use the historical average realized value premium returns $\overline{r}_{t+1} = \sum_{j=1}^{t} r_j$ as a benchmark forecasting model (e.g., Campbell and Thompson (2008), Welch and Goyal (2008), and Rapach, Strauss, and Zhou (2010)).

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

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

The R^2_{os} statistic measures the reduction in mean squared prediction error (MSPE) for the predictive regression (8) using a particular forecasting variable relative to the historical average forecast. 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 the null of $R^2_{os} \leq 0$ against the alternative of $R^2_{os} > 0$ by using the adjusted-MSPE statistic of Clark and West (2007).[29]

Finally, we explore the information content of IVP relative to other forecasting variables by conducting a forecast encompassing test due to Harvey, Leybourne, and Newbold (1998) (see also Rapach, Strauss, and Zhou (2010)). 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.[30]

[29] The adjusted-MSPE statistic is defined as:

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

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.

[30] 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

4.5.2 Out-of-sample forecasting results

We consider two forecast periods: (1) from April 1989 to December 2012 and (2) from January 1995 to December 2012. These two forecast periods correspond roughly 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.

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 3.35% in the first forecast period, and 1.82% in the second forecast period. Both R^2_{os} are statistically significant at the 1% level. For *IVP(comp)*, the R^2_{os} is 2.81% in the first forecast period, and 1.75% in the second forecast period, and they are also significant at the 1% level. Campbell and Thompson (2008) argue that for monthly data, 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.

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, value spread contains different information from the term spread and default spread.

conducted as follows:

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

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

5 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 show that the implied value premium is the best predictor of ex-post value premium during 1977 to 2012 and that it vastly outperforms the value spread, default spread, term spread, and the consumption-to-wealth ratio. Additional tests provide strong evidence in support of mispricing. We find 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 hypothesis 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 there are times 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 value spread 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(FF)*. The simulation method is conducted in the same way for other regressions. Define $Z_t = (HML(FF)_t, IVP(B/M)_t)'$, 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 $HML(FF)_t$ 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 $HML(FF)_t$ 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, $(HML(FF)_t, IVP(B/M)_t)$. 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 $HML(FF)_t$ 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 $1,000$ 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 risk premia of the high B/M portfolio (*ICCH(B/M)-tbill*), the low B/M portfolio (*ICCL(B/M)-tbill*), the high composite value portfolio (*ICCH(comp)-tbill*), the low composite value portfolio (*ICCL(comp)-tbill*), the implied value premium based on B/M (*IVP(B/M)*), and the implied value premium based on the composite value rank (*IVP(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 excess returns of the high B/M portfolio (*H(B/M)-tbill*), the low B/M portfolio (*L(B/M)-tbill*), the high composite value portfolio (*H(comp)-tbill*), the low composite value portfolio (*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)*). The autocorrelations in Panel B are calculated as the sum of individual autocorrelations up to that lag. Panel C reports the summary statistics of 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 for different variables (*p*-values in parentheses). *gIP* is the monthly industrial production growth rate. All variables except *Cay* have monthly data spanning from January 1977 to December 2012; *Cay* has quarterly data from 1977.Q1 to 2012.Q3. All variables except the value spread and *Cay* are expressed in annual percentage terms.

Panel A: Expected Returns

					Autocorrelation at Lag					
	Mean	*Std*	*Max*	*Min*	1	12	24	36	48	60
ICCH(B/M)-tbill	11.18	3.28	23.33	4.50	0.93	0.46	-0.04	-0.30	-0.33	-0.16
ICCL(B/M)-tbill	7.68	2.23	13.07	-0.19	0.93	0.49	0.11	-0.13	-0.22	-0.07
ICCH(comp)-tbill	11.05	3.18	22.84	3.79	0.93	0.43	-0.02	-0.25	-0.33	-0.21
ICCL(comp)-tbill	7.60	2.29	13.25	-0.78	0.93	0.50	0.11	-0.16	-0.23	-0.07
IVP(B/M)	3.50	2.13	11.08	-0.21	0.91	0.42	0.06	-0.16	-0.25	-0.24
IVP(comp)	3.45	2.05	10.55	0.02	0.90	0.44	0.05	-0.14	-0.27	-0.32

Panel B: Realized Returns

			Sum of Autocorrelations up to Lag					
	Mean	*Std*	1	12	24	36	48	60
H(B/M)-tbill	11.80	16.75	0.15	-0.05	-0.34	-0.28	-0.36	-0.46
L(B/M)-tbill	8.23	18.89	0.10	-0.20	-0.43	-0.33	-0.44	-0.49
H(comp)-tbill	12.10	17.10	0.17	-0.01	-0.27	-0.22	-0.37	-0.48
L(comp)-tbill	8.16	18.88	0.10	-0.16	-0.43	-0.34	-0.44	-0.50
HML(B/M)	3.57	9.96	0.14	0.34	0.05	-0.26	-0.18	0.04
HML(comp)	3.94	10.34	0.16	0.59	0.33	-0.13	-0.06	0.16
HML(FF)	3.73	10.44	0.16	0.36	-0.09	-0.30	-0.32	-0.13

Panel C: Other Predictors								
			Autocorrelation at Lag					
	Mean	*Std*	1	12	24	36	48	60
VS(B/M)	1.43	0.16	0.97	0.64	0.42	0.33	0.23	0.10
VS(comp)	1.26	0.17	0.97	0.59	0.21	0.08	-0.06	-0.23
Term	3.07	1.57	0.91	0.44	0.09	-0.26	-0.35	-0.16
Default	1.11	0.48	0.96	0.47	0.29	0.21	0.08	0.08
			1 quarter	1 year	2 years	3 years	4 years	5 years
Cay	0.003	0.02	0.93	0.85	0.78	0.69	0.60	0.54

Panel D: Correlations Among Various Variables

	IVP(B/M)	*IVP(comp)*	*VS(B/M)*	*VS(comp)*	*Term*	*Default*	*gIP*
IVP(comp)	0.90						
	(0.00)						
VS(B/M)	0.10	0.21					
	(0.03)	(0.00)					
VS(comp)	0.27	0.39	0.87				
	(0.00)	(0.00)	(0.00)				
Term	0.30	0.22	0.13	0.01			
	(0.00)	(0.00)	(0.01)	(0.78)			
Default	0.36	0.41	-0.19	-0.07	0.15		
	(0.00)	(0.00)	(0.00)	(0.13)	(0.00)		
gIP	0.02	-0.07	-0.01	-0.05	0.01	-0.35	
	(0.61)	(0.16)	(0.79)	(0.31)	(0.82)	(0.00)	
Cay	0.11	0.15	0.05	0.25	-0.02	-0.26	0.10
	(0.18)	(0.07)	(0.54)	(0.00)	(0.82)	(0.00)	(0.24)

	HML(FF)	*HML(B/M)*
HML(B/M)	0.94	
	(0.00)	
HML(comp)	0.90	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 (*HML(FF)* in Panel A, *HML(B/M)* in Panel B, and *HML(comp)* in Panel C). 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 *IVP(B/M)*) or *VS(B/M)*. The independent variable in Panel C is *IVP(comp)* or *VS(comp)*. The regression with *Cay* uses quarterly data from 1977.Q1 to 2012.Q3; all other regressions use monthly data from January 1977 to December 2012. 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 1,000 trials of a Monte Carlo simulation.

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	2.37	0.01	0.01	1.61	1.94	0.04	0.01	0.14	0.83	0.28	0.00
12	2.94	4.95	0.00	0.24	2.67	4.42	0.00	0.18	0.23	1.50	0.19	0.08
24	2.17	4.95	0.00	0.28	2.37	5.05	0.00	0.31	0.23	2.41	0.09	0.17
36	1.60	5.95	0.00	0.29	1.71	5.64	0.00	0.31	0.19	3.00	0.06	0.22
avg.	2.17		0.00		2.09		0.00		0.19		0.05	

	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	0.14	0.74	0.30	0.00	-0.17	-0.16	0.58	0.00	-4.00	-0.88	0.81	0.00
12	0.26	1.76	0.14	0.12	1.00	0.90	0.25	0.02	1.66	0.59	0.33	0.00
24	0.27	4.11	0.02	0.26	0.97	1.14	0.20	0.03	3.67	1.28	0.19	0.04
36	0.22	8.56	0.00	0.33	0.10	0.16	0.44	0.00	2.81	1.02	0.24	0.05
avg.	0.22		0.02		0.47		0.26		1.04		0.38	

	Cay			
Quarter	b	$Z(b)$	*pval*	$adj.R^2$
1	-1.37	-0.55	0.63	0.00
2	-0.64	-0.31	0.52	0.00
3	0.19	0.09	0.40	0.00
4	0.45	0.22	0.36	0.00
avg.	-0.34		0.47	

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	2.31	2.97	0.00	0.02	0.10	0.62	0.34	0.00
12	3.03	6.21	0.00	0.29	0.15	1.15	0.28	0.04
24	2.22	5.43	0.00	0.31	0.14	1.56	0.22	0.07
36	1.70	6.22	0.00	0.33	0.10	1.62	0.25	0.07
avg.	2.32		0.00		0.12		0.15	

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

Month	*IVP(comp)*				*VS(comp)*			
	b	$Z(b)$	*pval*	$adj.R^2$	b	$Z(b)$	*pval*	$adj.R^2$
1	1.77	2.19	0.01	0.01	0.07	0.41	0.44	0.00
12	3.00	5.05	0.00	0.21	0.20	1.36	0.24	0.06
24	2.76	4.97	0.00	0.32	0.25	3.04	0.05	0.17
36	2.21	5.43	0.00	0.36	0.21	5.40	0.00	0.22
avg.	2.44		0.00		0.18		0.05	

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 2012, and regressions in Panels C and D use quarterly data from 1977.Q1 and 2012.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. 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 1,000 trials of a Monte Carlo simulation.

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	2.71	2.70	0.01	0.08	0.46	0.49	-1.06	-0.86	0.78	-7.25	-1.49	0.92	0.02
12	3.02	5.93	0.00	0.17	1.29	0.28	-0.41	-0.41	0.61	-1.83	-1.01	0.76	0.29
24	1.83	4.95	0.00	0.21	2.83	0.08	-0.19	-0.29	0.56	2.27	0.97	0.23	0.40
36	1.42	4.44	0.01	0.18	3.90	0.04	-0.85	-1.93	0.88	2.22	0.84	0.25	0.51
avg.	2.24		0.00	0.16		0.11	-0.63		0.78	-1.15		0.63	

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	2.41	2.24	0.02	0.01	0.06	0.65	-0.48	-0.46	0.68	-7.97	-1.59	0.93	0.01
12	2.35	4.08	0.00	0.14	0.85	0.40	0.42	0.43	0.37	-2.35	-1.19	0.78	0.22
24	1.53	3.29	0.01	0.20	2.25	0.14	0.43	0.71	0.29	1.31	0.55	0.28	0.41
36	1.07	3.26	0.02	0.17	3.98	0.03	-0.37	-0.74	0.70	1.59	0.62	0.28	0.47
avg.	1.84		0.00	0.13		0.18	0.00		0.50	-1.85		0.67	

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	6.89	2.12	0.03	-2.19	-0.88	0.73	0.03
2	8.87	3.35	0.01	-1.62	-0.79	0.66	0.10
3	9.49	4.01	0.00	-0.79	-0.38	0.53	0.18
4	9.79	4.97	0.00	-0.58	-0.27	0.50	0.26
avg.	8.76		0.00	-1.29		0.57	

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	5.11	1.61	0.07	-2.20	-0.88	0.72	0.01
2	6.47	2.41	0.04	-1.67	-0.81	0.67	0.05
3	7.79	3.33	0.01	-1.03	-0.50	0.55	0.11
4	8.85	4.64	0.00	-0.97	-0.46	0.53	0.21
avg.	7.05		0.01	-1.47		0.60	

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

This table reports the regression results of using the implied value premium (*IVP(B/M)* or *IVP(comp)*) to predict the relative earnings surprise between value and growth portfolios (*CAR(HML)*) around future earnings announcements, using quarterly data from 1977.Q1 to 2012.Q3. 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 average *CAR* of the growth portfolio *CAR(L)* from the average *CAR* of the value portfolio *CAR(H)* to compute *CAR(HML)*. *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 reports the regression of future *CAR(HML(B/M))* on *IVP(B/M)*, and Panel D reports the regression of 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 1,000 trials of a Monte Carlo simulation.

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	1.18	2.48	0.01	0.04	1.39	3.45	0.00	0.08
2	1.20	3.02	0.01	0.07	1.43	3.70	0.00	0.14
3	1.21	3.32	0.00	0.11	1.39	4.00	0.00	0.20
4	1.13	3.53	0.01	0.13	1.33	4.68	0.00	0.26
avg.	1.18		0.01		1.39		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	1.11	2.46	0.01	0.03	1.26	3.34	0.00	0.06
2	1.07	2.84	0.01	0.05	1.33	3.80	0.00	0.12
3	1.13	3.10	0.01	0.09	1.35	4.20	0.00	0.19
4	1.08	3.19	0.01	0.12	1.40	4.91	0.00	0.28
avg.	1.10		0.01		1.33		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	1.63	3.34	0.00	0.06	1.52	4.22	0.00	0.08
2	1.60	3.80	0.00	0.10	1.55	4.95	0.00	0.17
3	1.64	4.21	0.00	0.16	1.48	5.21	0.00	0.23
4	1.54	4.33	0.00	0.18	1.39	5.51	0.00	0.28
avg.	1.60		0.00		1.48		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	1.64	3.32	0.00	0.06	1.42	3.22	0.00	0.06
2	1.59	4.62	0.00	0.11	1.44	4.37	0.00	0.12
3	1.73	5.21	0.00	0.19	1.50	5.68	0.00	0.20
4	1.69	5.21	0.00	0.24	1.47	6.44	0.00	0.28
avg.	1.66		0.00		1.46		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 around future earnings announcements, using quarterly data from 1977.Q1 to 2012.Q3. The dependent variable is *CAR(HML(FF))*. 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*), the default spread (*Default*), and the consumption-to-wealth ratio (*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 1,000 trials of a Monte Carlo simulation.

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

	IVP(B/M)			*VS(B/M)*			*Term*		
Quarter	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	d	$Z(d)$	*pval*
1	2.14	3.02	0.00	0.05	0.71	0.36	-1.96	-3.07	1.00
2	1.98	3.27	0.00	0.07	1.03	0.31	-1.57	-2.65	0.98
3	1.87	4.13	0.00	0.06	1.01	0.33	-1.57	-3.18	0.99
4	1.69	4.46	0.00	0.06	1.14	0.31	-1.48	-3.22	0.99
avg.	1.92		0.00	0.06		0.25	-1.64		1.00

	Default			*Cay*			
Quarter	e	$Z(e)$	*pval*	f	$Z(f)$	*pval*	$adj.R^2$
1	-7.41	-1.67	0.92	-0.80	-1.45	0.84	0.12
2	-6.34	-1.69	0.87	-0.63	-1.29	0.75	0.20
3	-5.08	-2.09	0.91	-0.36	-0.84	0.61	0.28
4	-4.19	-2.09	0.90	-0.27	-0.72	0.57	0.32
avg.	-5.76		0.99	-0.51		0.73	

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

	IVP(comp)			*VS(comp)*			*Term*		
Quarter	b	$Z(b)$	*pval*	c	$Z(c)$	*pval*	d	$Z(d)$	*pval*
1	1.90	2.38	0.01	0.07	0.83	0.33	-1.55	-2.58	0.99
2	1.64	2.38	0.03	0.09	1.07	0.30	-1.14	-2.08	0.95
3	1.61	3.33	0.01	0.07	1.00	0.34	-1.18	-2.63	0.98
4	1.45	3.51	0.01	0.08	1.25	0.26	-1.11	-2.65	0.98
avg.	1.65		0.00	0.08		0.23	-1.25		0.99

	Default			*Cay*			
Quarter	e	$Z(e)$	*pval*	f	$Z(f)$	*pval*	$adj.R^2$
1	-8.05	-1.71	0.92	-1.03	-1.77	0.93	0.12
2	-6.82	-1.68	0.85	-0.86	-1.71	0.86	0.19
3	-5.64	-2.13	0.91	-0.59	-1.32	0.77	0.26
4	-4.72	-2.10	0.90	-0.50	-1.28	0.75	0.30
avg.	-6.31		0.99	-0.74		0.82	

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 four quarters is negative. Panel A reports the regression of *CAR(HML(FF))* on *IVP(B/M)* and the interaction of *IVP(B/M)* with the dummy variable D. Panel B reports the regression of *CAR(HML(FF))* on *IVP(comp)* and the interaction of *IVP(comp)* with the dummy variable D. 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. 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 1,000 trials of a Monte Carlo simulation.

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	0.44	0.88	0.20	1.46	2.83	0.00	0.07
12	0.72	2.10	0.04	1.00	2.54	0.02	0.10
24	0.77	2.45	0.03	0.87	2.38	0.03	0.14
36	0.75	2.38	0.04	0.74	2.04	0.05	0.16
avg.	0.67		0.09	1.02		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	0.19	0.39	0.35	1.56	3.00	0.01	0.07
12	0.54	1.58	0.09	0.92	2.27	0.03	0.08
24	0.68	2.01	0.04	0.77	2.06	0.06	0.12
36	0.68	1.93	0.06	0.67	1.83	0.09	0.14
avg.	0.52		0.16	0.98		0.01	

Table 7. Predicting Future Industrial Production Growth Rates

This table provides the univariate regressions on predicting future industrial production growth. The independent variable 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*). All variables (except *Cay*) use monthly data from January 1977 to December 2012, and *Cay* uses quarterly data from 1977.Q1 to 2012.Q3. 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 bootstrapped using data generated under the null of no predictability from 1,000 trials of a Monte Carlo simulation.

	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	0.12	0.63	0.27	0.00	-0.25	-1.14	0.88	0.00	-0.01	-0.40	0.64	0.00
12	0.38	1.24	0.15	0.04	0.26	0.90	0.23	0.02	-0.02	-0.67	0.69	0.01
24	0.36	1.32	0.15	0.06	0.28	0.98	0.23	0.03	-0.01	-0.51	0.65	0.01
36	0.38	1.73	0.10	0.11	0.36	1.66	0.12	0.09	0.01	0.17	0.45	0.00
avg.	0.31		0.01		0.16		0.08		-0.01		0.68	
	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	-0.03	-1.39	0.92	0.00	0.47	1.51	0.09	0.01	-5.83	-5.48	1.00	0.11
12	-0.02	-0.86	0.76	0.01	0.77	3.11	0.01	0.08	-1.47	-1.17	0.84	0.03
24	-0.01	-0.49	0.65	0.01	0.89	4.24	0.00	0.20	-0.18	-0.17	0.58	0.00
36	0.01	0.27	0.44	0.00	0.83	3.83	0.01	0.26	0.18	0.21	0.47	0.00
avg.	-0.01		0.75		0.74		0.00		-1.82		1.00	
	Cay											
Quarter	b	$Z(b)$	*pval*	$adj.R^2$								
1	0.94	1.37	0.10	0.01								
2	1.16	1.48	0.12	0.03								
3	1.16	1.26	0.16	0.03								
4	1.18	1.23	0.17	0.04								
avg.	1.20		0.03									

Table 8. Robustness on the Implied Value Premium

Panel A reports the univariate regressions when the implied value premium (*IVP(B/M)* or *IVP(comp)*) are obtained by equally-weighting the firm-level ICCs. Panel B reports the univariate regressions when *IVP* is computed using industry-size steady-state values for earnings growth and plowback rates. Panel C reports the univariate regressions when *IVP* is computed using half-life based horizons. Panel D reports the bivariate regression result when *HML(FF)* is regressed on *IVP(B/M)* and *ARO*, where *ARO* measures analysts' relative forecast optimism between the value portfolio and the growth portfolio. Panel E reports the univariate regression results when the Z-statistics and their simulated p-values are obtained based on the Hodrick (1992) standard errors. The dependent variable in all regressions is the Fama-French HML factor (*HML(FF)*). All regressions use monthly data from January 1977 to December 2012. 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 all panels except in Panel E. 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 1,000 trials of a Monte Carlo simulation.

Panel A: Equally-weighted *IVP*

	IVP(B/M)				*IVP(comp)*			
Month	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	2.20	2.57	0.01	0.02	1.74	1.91	0.04	0.01
12	2.78	5.27	0.00	0.19	2.77	4.57	0.00	0.17
24	2.27	5.75	0.00	0.27	2.55	5.19	0.00	0.30
36	1.77	8.44	0.00	0.32	1.94	7.13	0.00	0.35
avg.	2.25		0.00		2.25		0.00	

Panel B: *IVP* Using Steady-State Values from Industry-size Portfolios

	IVP(B/M)				*IVP(comp)*			
Month	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	2.17	2.02	0.02	0.01	1.83	1.73	0.05	0.01
12	3.62	4.64	0.00	0.23	3.32	4.38	0.00	0.18
24	2.62	4.25	0.00	0.25	2.90	4.37	0.00	0.29
36	1.90	5.19	0.00	0.26	2.01	4.56	0.00	0.27
avg.	2.58		0.00		2.51		0.00	

Panel C: *IVP* Using Half-life Based Horizons

	IVP(B/M)				*IVP(comp)*			
Month	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	2.21	2.34	0.01	0.01	1.72	1.76	0.05	0.01
12	3.29	4.57	0.00	0.23	3.06	3.93	0.00	0.19
24	2.46	5.00	0.00	0.27	2.73	4.90	0.00	0.31
36	1.82	6.49	0.00	0.29	1.96	6.01	0.00	0.32
avg.	2.45		0.00		2.37		0.00	

Panel D: Bivariate Regression with Analyst Relative Forecast Optimism

	IVP(B/M)			*ARO*			
Month	b	$Z(b)$	$pval$	c	$Z(c)$	$pval$	$adj.R^2$
1	2.18	2.28	0.01	0.00	-0.55	0.73	0.01
12	3.32	4.37	0.00	-0.01	-1.45	0.90	0.26
24	2.50	4.99	0.00	-0.01	-1.61	0.92	0.30
36	1.85	5.99	0.00	0.00	-2.16	0.96	0.32
avg.	2.47		0.00			0.99	

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

	IVP(B/M)				*IVP(comp)*			
Month	b	$Z(b)$	$pval$	$adj.R^2$	b	$Z(b)$	$pval$	$adj.R^2$
1	1.96	2.37	0.01	0.01	1.61	1.94	0.04	0.01
12	2.94	4.19	0.00	0.24	2.67	3.78	0.00	0.18
24	2.17	3.18	0.00	0.28	2.37	3.44	0.00	0.31
36	1.60	2.81	0.01	0.29	1.71	3.19	0.00	0.31
avg.	2.17		0.00		2.09		0.00	

Table 9. Out-of-sample Analysis

This table summarizes the out-of-sample analysis of forecasting models using different forecasting variables. The dependent variable is the Fama-French *HML* (*HML(FF)*). We consider two forecast periods, namely, from April 1989 to December 2012 and from January 1995 to December 2012. In these tests, we perform a 1-year moving average of *IVP(B/M)* and *IVP(comp)*. Panel A reports the R^2_{os} statistic of Campbell and Thompson (2008). 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. Panels B and C report the p-values of the forecasting encompassing test statistic of Harvey, Leybourne, and Newbold (1998) (HLN statistic). 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: 1989.04-2012.12			Forecast Period: 1995.01-2012.12		
	R^2_{os}	*pval*		R^2_{os}	*pval*
IVP(B/M)	3.35	0.00	*IVP(B/M)*	1.82	0.01
IVP(comp)	2.81	0.00	*IVP(comp)*	1.75	0.01
VS(B/M)	-3.13		*VS(B/M)*	-1.56	
VS(comp)	-3.64		*VS(comp)*	-2.25	
Term	-0.28		*Term*	-0.34	
Default	-0.22		*Default*	-0.14	

Panel B: Forecasting Encompassing Test

Forecast Period: 1989.04-2012.12

Row Variables (R)	Column Variables (C)			
	IVP(B/M)	*VS(B/M)*	*Term*	*Default*
IVP(B/M)		0.66	0.57	0.50
VS(B/M)	0.00		0.03	0.02
Term	0.00	0.84		0.38
Default	0.00	0.81	0.45	

Forecast Period: 1995.01-2012.12

Row Variables (R)	Column Variables (C)			
	IVP(B/M)	*VS(B/M)*	*Term*	*Default*
IVP(B/M)		0.45	0.41	0.35
VS(B/M)	0.01		0.20	0.16
Term	0.01	0.62		0.32
Default	0.01	0.62	0.54	

Panel C: Forecasting Encompassing Test

Forecast Period: 1989.04-2012.12

Row Variables (R)	Column Variables (C)			
	IVP(comp)	*VS(comp)*	*Term*	*Default*
IVP(comp)		0.81	0.69	0.59
VS(comp)	0.00		0.04	0.04
Term	0.00	0.78		0.38
Default	0.00	0.76	0.45	

Forecast Period: 1995.01-2012.12

Row Variables	Column Variables (C)			
	IVP(comp)	*VS(comp)*	*Term*	*Default*
IVP(comp)		0.64	0.57	0.46
VS(comp)	0.04		0.17	0.15
Term	0.01	0.62		0.32
Default	0.02	0.63	0.54	

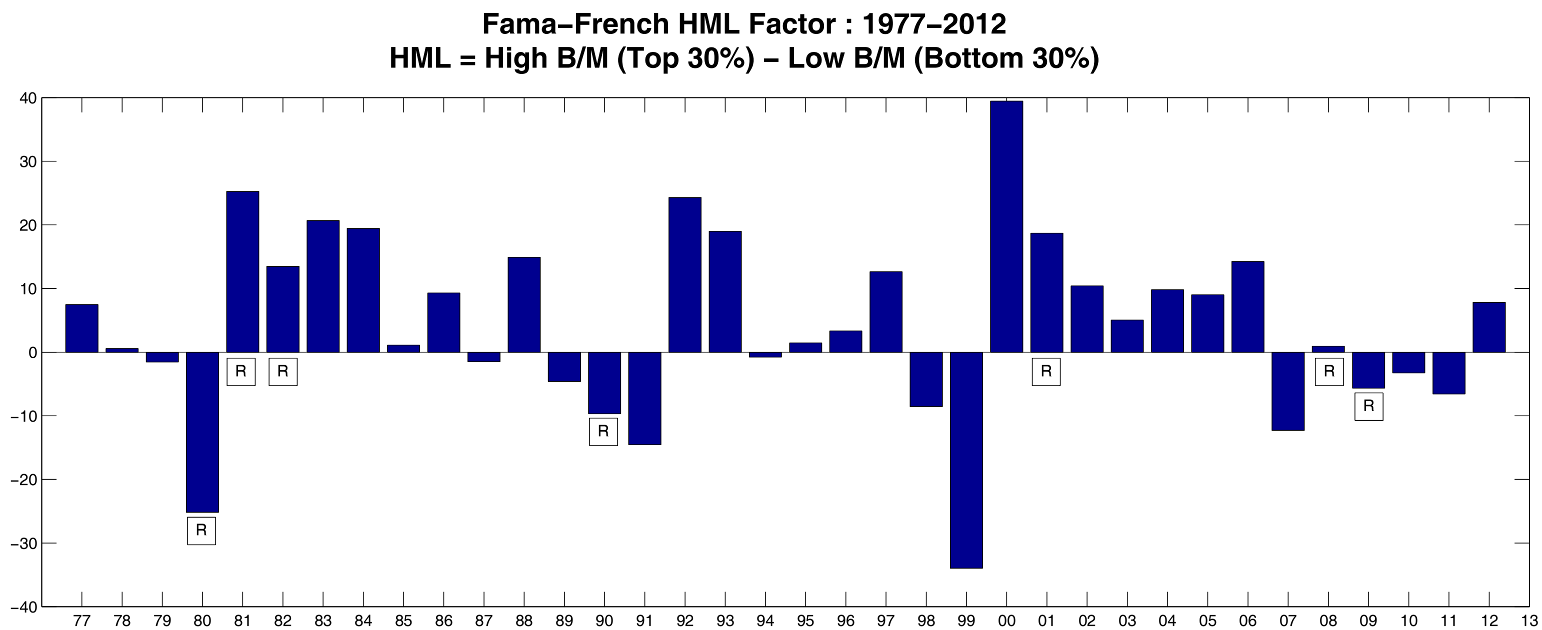

Figure 1: Fama-French HML Factor (1977-2012). The data are taken from Kenneth French's webpage. "R "indicates the NBER recession periods: January 1980-July 1980, July 1981-November 1982, July 1990-March 1991, March 2001-November 2001, and December 2007-June 2009. The average of HML is 4.44% and the percentage of years when HML is positive is 64%.

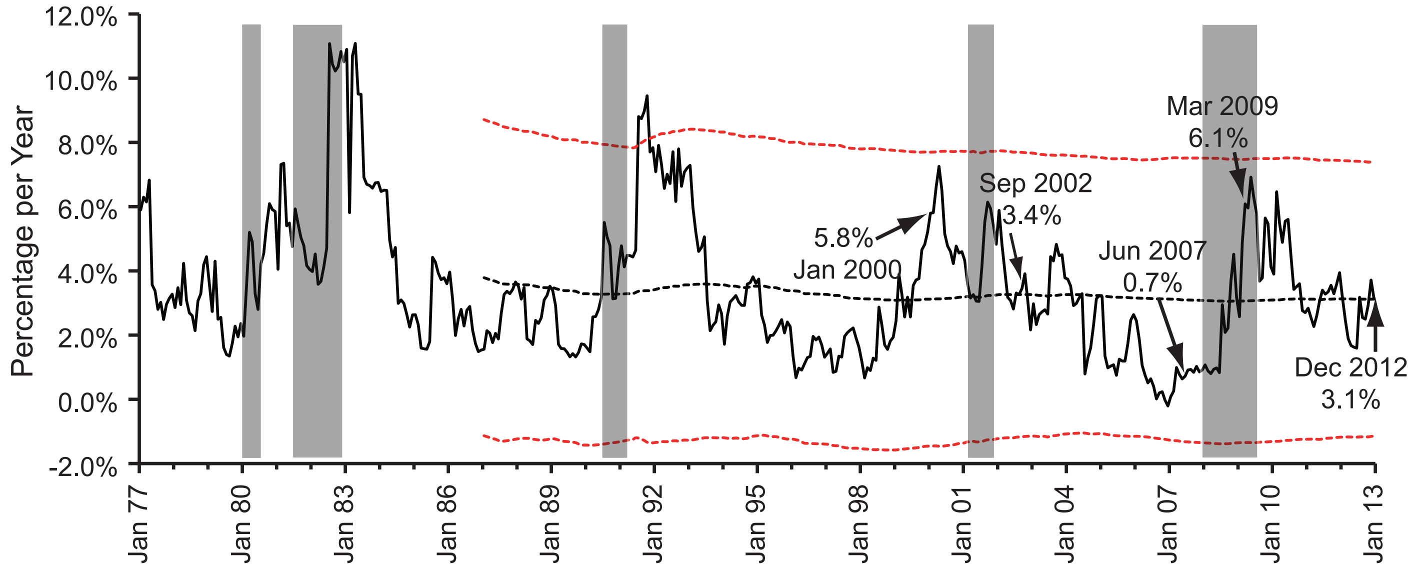

Figure 2: Implied Value Premium *IVP(B/M)* (January 1977-December 2012). This figure plots the time series of the implied value premium constructed from a two-way sort based on size and B/M. *IVP(B/M)* is expressed in annualized percentages. The three horizontal dashed curves correspond to the rolling 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.

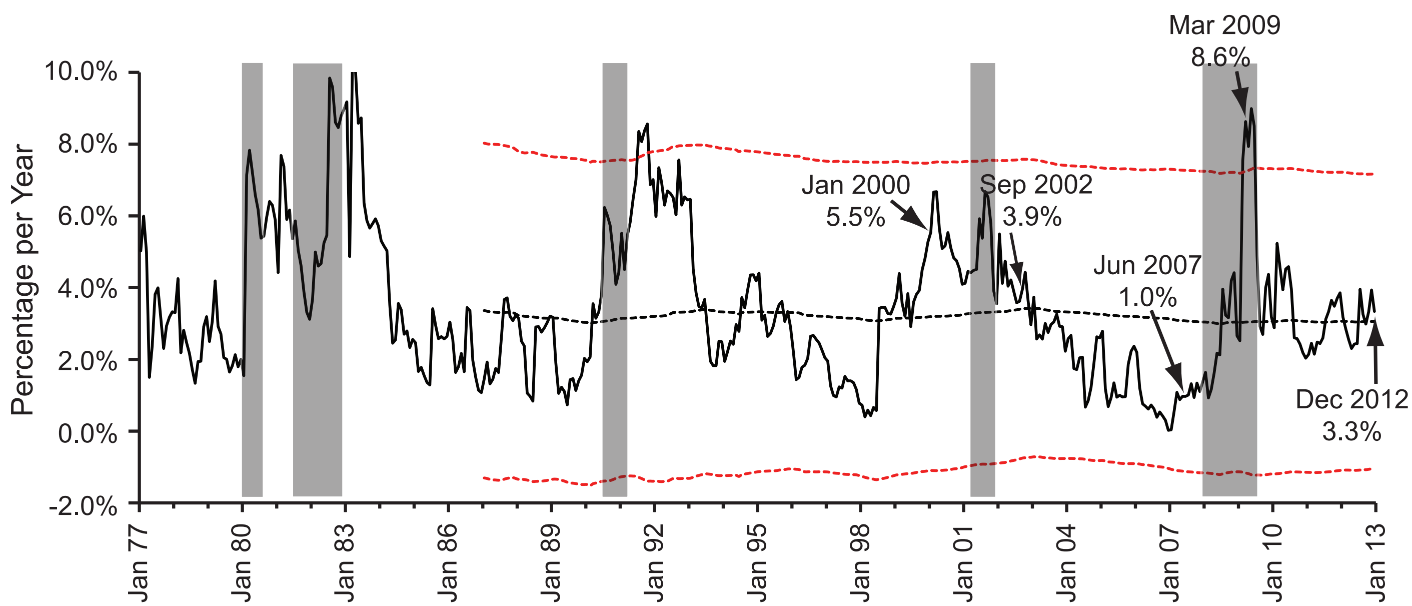

Figure 3: Implied Value Premium *IVP(comp)* (January 1977-December 2012). This figure plots the time series of the implied value premium constructed from a two-way sort on size and a composite measure based on B/M, C/P, FE_1/P and FE_2/P. *IVP(comp)* is expressed in annualized percentages. The three 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.