Value Timing: Risk and Return Across Asset Classes☆

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Abstract

Returns to value strategies in individual equities, commodities, currencies, global bonds and stock indexes are predictable by the value spread. Common and asset-class-specific components of the value spread contribute equally to this predictability. Return variation due to common value is closely associated with standard proxies for risk premia, such as dividend yield, intermediary leverage and illiquidity, but it is at odds with models that exclusively generate a value premium in equities. Return variation due to asset-class-specific value presents another challenge for asset pricing models. The outperformance of value timing and rotation strategies indicates that investors can benefit from the value spread in real-time.

Keywords: Value Premia, Global Asset Pricing, Return Predictability, Alternative Assets, Common and Asset-Class-Specific Value.

JEL Classification: E31, E43, E44, E52, E63, G12

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1 Introduction

Expected returns of long-short value strategies in a range of asset classes are increasing in the value spread. The value spread is the difference between the value signal in the long versus short portfolio, and its relation to value premia can be motivated from standard present value logic.[1] The time-variation in value premia we document is both economically and statistically large: Predictive regressions at the one-year horizon obtain an R^2 of 14%, 9%, 11%, 22%, and 10%, for US individual equities, currencies, commodities, global government bonds and stock indexes, respectively. In all these asset classes, a standard deviation increase in the value spread predicts an increase in expected value return of the same order of magnitude (or more) as the unconditional value premium. Thus, expected returns on value strategies vary over time by at least as much as their already puzzling level.[2]

To determine the economic drivers of this time-variation, we start by decomposing the value spread into a common component and an asset-class-specific component.[3] We find that these two components contribute about equally to return predictability in the pool of value strategies. Quantifying the relative contribution of these two components is important, as the existing literature provides little guidance despite a large and significant common component being evidence of market integration.

The common value component is largely determined by benchmark predictors that are popular in the literature to proxy for time-varying risk premia. For instance, the correlation between the first principal component of a large set of benchmark predictors and common value is large, at 0.84, and the two series predict value returns similarly in isolation. However, it is our simple, real-time observable measure of common value that dominates in a joint test. Among the predictors we study, two proxies for risk aversion in

[1]For instance, in the case of individual equities, the present value model of Vuolteenaho (2002) indicates that the value spread in average book-to-market of value versus growth stocks predicts equity value returns. Similarly, for currencies, the present-value formulation of Engel and West (2005) and Froot and Ramadorai (2005) indicates that the value spread in average real exchange rate between cheap and expensive currencies predicts currency value returns.

[2] Cochrane (2011) emphasizes that the value premium is one of the main "puzzles" in finance, because the long-standing debate between rational explanations and mispricing is still unresolved.

[3]Common value is defined as the equal-weighted average value spread across value strategies in different asset classes. Asset-class-specific value is the difference between the value spread and common value. Our conclusions are robust to using the first principal component of value spreads to measure common value, which confirms that the variation we measure is truly common.

habit models: the dividend yield and intermediary leverage (see Campbell and Cochrane, 1999; Menzly et al., 2004; Santos and Veronesi, 2016), and an illiquidity premium (Nagel, 2016) turn out to be the key determinants of common value.

The fact that there is variation in value returns that is common across asset classes and highly correlated with popular proxies of risk lends support to an explanation based on rationally time-varying expected returns. As conjectured in Cochrane (2011), value premia globally increase when aggregate risk premia are high. Nevertheless, a time-varying component of value that is common across asset classes, despite the presence of potentially different investors and institutional factors, presents a challenge to existing asset pricing theory. Many behavioral and rational theories for value are designed exclusively to explain the unconditional value premium in equities. In particular, theories that rely on firm investment risk or growth options (see, e.g., Berk et al., 1999; Gomes et al., 2003; Zhang, 2005) seem ill-equipped to explain the comovement in value premia across asset classes. Our results thus call for a more general framework, where investors shy away from holding different risky assets – like value stocks and undervalued currencies – in bad times, such that value spreads widen simultaneously.

Whereas we document comovement in expected value returns, Asness et al. (2013) show that realized value returns comove across the same asset classes we study. The large amount of common variation in expected value returns relative to their unconditional mean suggests that the quantitative hurdle for rational, risk-based models is actually much higher than what these authors already discuss. To quantify this hurdle, we focus on the case of individual equities and simulate from the investment-based asset pricing model of Zhang (2005). We show that the amount of time-variation in the value premium we document is about three times as large than in the standard calibration of this model.

Another challenge to existing asset pricing models follows from the asset-class-specific components of the value spread, which point to a mix of risky and behavioral factors, as well as to mispricing, as determinants of value return predictability. The benchmark risk-proxies capture a considerable fraction of the variation in the specific components of the value spread. However, the loadings of specific value on individual proxies, like the default spread, vary dramatically across asset classes. This finding is consistent with heterogeneity in risk exposures, and the idea that investors rationally move from one asset class to another over time, such as in a flight-to-quality from equities to bonds (see, e.g., Connolly et al., 2005; Baele et al., 2010). Behavioral factors are likely to play a role too, since we find loadings of specific value on the sentiment measure of Baker and Wurgler (2006) that are statistically significant, and yet different across asset classes. In contrast, common value is largely unrelated to this equity-based measure of sentiment. Finally, about half of the predictability of value premia due to the specific components of the value spread remains once we orthogonalize these components from the risk-proxies and sentiment. This finding is suggestive of mispricing.

To benchmark the strength of value return predictability, we observe that for the case of US equities the *in-sample* relation between value returns and the lagged value spread is slightly stronger than the relation between stock market returns and the dividend yield (see, e.g., Cochrane, 2011). As argued in Lettau and Van Nieuwerburgh (2007) and Goyal and Welch (2008), it is unclear whether the information in the dividend yield can be used profitably in an out-of-sample setting, which has raised concerns that the in-sample relation between stock market returns and the dividend yield is spurious. In contrast, we find that there are large benefits of conditioning on the value spread in *out-of-sample* tests. To this end, we present a number of value timing and rotation strategies. We show that the Sharpe ratios of such conditional value strategies are typically about twice the Sharpe ratios of unconditional value strategies. This improvement is driven by variation in the value spread over time as well as across asset classes, and cannot be captured by simply investing in the market portfolio of the different asset classes.

Our results contribute to the asset pricing literature in various ways.[4] Unconditional value premia are documented in US individual equities (Fama and French, 1992), international equities (see, e.g., Fama and French, 1998; Liew and Vassalou, 2000), and alternative asset classes (Asness et al., 2013). In contrast, we characterize conditional value premia. Our conditional tests have important asset pricing implications, consistent

[4] A contemporaneous paper, Asness et al. (2017), independently reaches the same conclusion that value returns are predictable in different asset classes. The key difference from their paper is that we use the value spread as a simple measure of the expected return to a value strategy and analyze its variation over time in a pool of asset classes. This setup allows us to decompose value into common and asset-class-specific components, thus enabling us to highlight the close association between common value and aggregate risk premia. Asness et al. (2017) focus on "deep" value events. They also have more extensive data for equities in particular, which enables them to highlight the fundamentals of low and high value stocks and to test alternative behavioral theories for the value effect.

with the idea that such tests are relatively powerful to distinguish between competing asset pricing models (Campbell and Cochrane, 2000; Cochrane, 2001; Nagel and Singleton, 2011).

There is a large literature that attempts to forecast returns using valuation ratios. Lewellen (1999) and Cochrane (2011, p. 1099) predict returns of diversified equity portfolios with their book-to-market ratio. Cochrane (2011) concludes that "variation over time in a given portfolio's book-to-market ratio is a much stronger signal of return variation than the same variation across portfolios in average book-to-market ratio." Similarly, Kelly et al. (2017) argue that the relevant information for predicting individual stock returns comes from the time-variation in various value characteristics. Kelly and Pruitt (2013) analyze whether the expansion and compression of the cross section of value characteristics contains information about the aggregate market. In contrast to these papers, we analyze how the returns of the value-minus-growth portfolio vary with the value spread. Our findings for the value spread in individual equities are consistent with those of Asness et al. (2000a). Using data for large US stocks from 1982 to 1999, they find that industry-adjusted value spreads (as well as spreads in projected earnings growth) have predictive power for value-minus-growth returns. Similarly, Cohen et al. (2003) show that the return of the Fama and French (1993) HML factor is predictable by the HML value spread. In contrast to us, these papers do not (i) ask whether the predictability of value returns in equities is consistent with an investment-based asset pricing model, (ii) analyze the potential and robustness of the value spread in an out-of-sample setting, nor (iii) study the value spread in other asset classes.

Our multi-asset approach is uniquely suited to answer some central questions in asset pricing: Do expected value returns vary over time and across assets? If so, by how much? And is this time-variation in value premia driven by risk or mispricing? In answering these questions, we identify a strongly time-varying, common component of value premia that is risky. This component cannot be identified by analyzing a single value premium in isolation, and thus helps to explain recent mixed evidence on the question of whether the equity value premium is driven by risk or mispricing (see Golubov and Konstantinidi, 2016; Gerakos and Linnainmaa, 2017). In this way, our work also contributes to the recent literature on global asset pricing, where "betting against beta" (Frazzini and Pedersen, 2014), "carry" (Koijen et al., 2017), and downside risk (Lettau et al., 2014) are shown to be factors in US equities as well as a host of other asset classes. These papers mostly characterize unconditional premia. Important exceptions are Moskowitz et al. (2012) and Neuhierl and Weber (2017), who present global evidence for "time-series momentum" and "monetary momentum," respectively. Moreira and Muir (2017) show that volatility timing strategies are attractive in a range of asset classes, because low current volatility indicates lower future volatility, but not lower future returns. In contrast, we find that the value spread predicts returns, but not volatility, thus explaining the improvement in Sharpe ratio in out-of-sample tests.

Finally, our paper relates to a recent strand of literature that studies which, potentially non-linear, combinations of a large set of characteristics predict returns in the cross section of individual equities (DeMiguel et al., 2017; Freyberger et al., 2017; Kozak et al., 2017; Kelly et al., 2017). To focus exclusively on the cross-section, these authors transform each characteristic as input to their econometric model so that its cross-sectional standard deviation is (approximately) constant over time.[5] Our results for value suggest that this transformation shuts down an important driver of the width of the cross section of expected returns, that is, the expansion and compression of the cross section of a characteristic over time. Indeed, our results are not limited to value, as we present a similar result for size. As the difference in market capitalization between big and small stocks increases, returns to a small-minus-big strategy also increase.

The remainder of the paper is organized as follows. Section 2 describes the data and method used to construct value strategies. Section 3 asks whether the value spread predicts value returns in the time series in different asset classes, whereas Section 4 presents evidence from pooled regressions to gauge the joint strength of value return predictability. Section 5 decomposes the value spread into common and asset-class-specific components to shed light on the (economic) drivers of value return predictability. Section 6 presents out-of-sample strategies that condition on the value spread. Section 7 concludes.

[5] Except for DeMiguel et al. (2017), who winsorize and standardize each characteristic, these authors use a rank transformation (to the unit interval) for each characteristic.

2 Data and Methodology

In this section, we briefly describe the method to construct value measures and value returns in different asset classes, which closely follows Asness et al. (2013). We refer the interested reader to Appendix A for additional details on the sources of and procedures to clean the data. In this appendix, we also validate our key empirical result using directly the value returns of Asness et al. (2013).[6] To start, we note that our measures of value are aimed at maintaining simplicity and consistency across asset classes, and, to the extent that a standard exists, being standard. We do so to minimize the pernicious effects of data snooping. As is common in the literature, we measure value as a book-to-market ratio for individual stocks and global stock indexes. For the remaining asset classes, we measure value using long-term past returns. This choice is inspired by the long strand of literature that documents a direct link between past returns and book-to-market ratios, both empirically (see DeBondt and Thaler, 1985; Fama and French, 1996; Gerakos and Linnainmaa, 2017) and theoretically (see Daniel et al., 1998; Hong and Stein, 1999; Vayanos and Woolley, 2013). In the following, we do consider alternative measures of value and show that our results are robust.

2.1 US Individual Stocks

The US stock data is standard from CRSP and Compustat. Following Asness et al. (2013), we limit the analysis to a sample from January 1972 to December 2014 and a universe of stocks that is liquid and that can be traded at reasonably low cost in sizeable trading volume. To be precise, we include in our value strategies only those stocks that account cumulatively for 90% of the total market capitalization in CRSP.[7] The idea is twofold. First, by doing so we provide conservative estimates for an implementable set of trading strategies. Second, this allows for a better comparison of individual stock strategies with the set of strategies we employ in commodities, currencies, government bonds, and stock indexes. These assets tend to be liquid relative to an individual stock.

[6]We thank these authors for sharing value returns in different asset classes on their website.

[7]The 90% market capitalization cutoff yields an average of 618 stocks for our portfolios. For the out-of-sample analysis of Section 6, we analyze alternative market capitalization cutoffs of 75% (263 stocks on average) and 95% (934 stocks on average), respectively.

To measure value for each firm i, we use the ratio of the book value to the market value of equity, or book-to-market ratio $BM_{i,t}$, as in Fama and French (1992). Book values are observed each June and refer to the previous fiscal year-end; market values are updated monthly as in Asness and Frazzini (2013). Consistent with previous literature, we exclude financial firms: a given book-to-market ratio might indicate distress for a non-financial firm, but not for a financial firm (see Fama and French, 1995). We denote this measure $BM_{i,t,Ex.fin.}$. However, because many financial firms are large and in the investment opportunity set of most investors, we also consider a second set of industry-adjusted book-to-market ratios: $BM_{i,t,Ind.adj.}$, which subtract from each $BM_{i,t}$ the value-weighted average book-to-market ratio of the industry to which stock i belongs. Asness et al. (2000b) and Cohen and Polk (1998) find that industry-adjusted value strategies are relatively attractive. In fact, these authors argue that there is no unconditional value effect across industries. To determine whether there is neither a conditional value effect, we sort 17 industries on their average book-to-market ratio in a robustness check.

2.2 Commodity Futures

We obtain futures price data for Crude Oil, Gasoline, Heating Oil, Natural Gas, Gas-Oil Petroleum, Coffee, Rough Rice, Orange Juice, Cocoa, Soybean Oil, Soybean Meal, Soybeans, Corn, Oats, Wheat, Cotton, Gold, Silver, Platinum, Feeder Cattle, Live Cattle, Lean Hogs (from the Commodity Research Bureau) and Aluminium, Nickel, Tin, Lead, Zinc, and Copper (from Datastream). We define value for commodities as the negative of the five-year spot return. As is common in the literature, we use the more liquid first-nearby futures price to proxy for the spot price. The sample period runs from January 1972 to December 2014.

2.3 Currencies

We obtain spot and forward exchange rates for Australia, Canada, Germany (spliced with the Euro), Japan, New Zealand, Norway, Sweden, Switzerland, UK, and the United States. We consider two measures of value for currencies, for which results are similar. The first is the negative of the five-year spot return (−5-year return). The second adjusts this return by the five-year foreign–US inflation difference, and thus represents the five-year change in relative purchasing power parity. These value measures are large when the foreign currency has weakened relative to the dollar. As noted in Menkhoff et al. (2016), using five-year changes avoids potential problems arising from nonstationarity and base-year effects. The sample period for currencies runs from February 1976 to December 2014.

2.4 Global Government Bonds

We obtain government bond data for Australia, Canada, New Zealand, Germany, Japan, Norway, Sweden, Switzerland, the United Kingdom, and the United States. We consider two sets of returns. Synthetic prices and returns for a one-month futures contract on a ten-year bond are derived for all countries from the constant maturity, zero coupon, government bond yield data from Wright (2011). Traded bond index futures returns are available for six countries only (Australia, Canada, Germany, Japan, the UK and the US).

We define two measures of value for bonds using synthetic prices and yields.[8] The first measure is the negative of the five-year log futures return (−5-year return). The second is the five-year change in the ten-year yield (5-year Δy). Using five-year changes in yields avoids potential problems arising from trends and unconditional differences in, e.g., default risk, across bond markets. Throughout the paper, our main focus is on strategies that use the first value measure to invest in the traded bond futures. We report results for the second value measure and synthetic bond returns in the Internet Appendix. As noted in Asness et al. (2013), the results are qualitatively similar across these alternatives, but there is considerable variation in magnitude. Dictated by data availability, the sample period for global government bonds runs from January 1991 to May 2009.

[8] The cheapest-to-deliver feature of traded bond futures makes it hard to compare returns and yields over time and across countries.

2.5 Global Stock Indices

The universe of developed country stock index futures consists of Australia, Canada, France, Germany, Hong Kong, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, the United Kingdom, and the United States. To measure value for stock indexes, we use the inverse of the MSCI price-to-book ratio (denoted $MSCI_{BP}$). Dictated by data availability, the sample period for these stock indexes runs from January 1994 to December 2014.

2.6 Value Returns

To construct value returns, we sort securities within each asset class into P groups based on (the cross-sectional distribution of) the value measures, $V_{i,t}$. For individual stocks, we form value-weighted decile portfolios ($P = 10$) each month and define the value stock portfolio as decile 10 (High) and the growth stock portfolio as decile 1 (Low). For all other classes, we set $P = 2$ and form an equal-weighted High and Low portfolio by splitting the securities at the median of ranked values. Our main interest is in analyzing the time-variation in the expected return to the High-minus-Low value portfolio (denoted R_{t+1}^{H-L} for the month after sorting).

We also report results from an alternative rank-weighting procedure, which mitigates the influence of outliers. For any security $i = 1, \ldots, N_t$ at time t, the weight is proportional to its rank in the cross section:

$$w_{i,t}^{Rank} = q_t \left(\text{Rank}(V_{i,t}) - \frac{\sum_i^{N_t} \text{Rank}(V_{i,t})}{N_t} \right).$$

The weights sum to zero, thus representing a dollar-neutral long-short portfolio. The scaling factor q_t ensures that we are one dollar long and one dollar short. The return of this rank-weighted strategy is calculated as $R_{t+1}^{Rank} = \sum_i w_{i,t}^{Rank} R_{i,t+1}$. Throughout the paper, whenever we are predicting returns over horizons longer than one month, we separately compound returns on the long and short position of these value strategies and then take the difference. These long and short positions are rebalanced every month. To be consistent across asset classes, we compound returns including the T-bill return.[9]

[9] Appendix A presents more details as to the construction of excess returns in different asset classes,

2.7 Predicting Value Returns with the Value Spread

The signal of interest is the value spread, which is defined as the difference between the average value signal in the High and Low portfolio, $VS_t^{H-L} = V_t^H - V_t^L$, or the rank-weighted average value signal, $VS_t^{Rank} = \sum_i w_{i,t}^{Rank} V_{i,t}$. We conduct predictive regressions of value portfolio returns (compounded over an horizon h) on the lagged value spread:

$$R_{t+1,t+h}^x = a_h + b_h VS_t^x + \varepsilon_{t+1:t+h} \text{ for } x = H-L, Rank\ . \tag{1}$$

This regression is easily motivated economically. For equities, consider the log-linear present value model employed in Vuolteenaho (2002): If the book-to-market ratio is well-behaved, then

$$\theta_t = \sum_{j=0}^{\infty} \rho^j r_{t+1+j} + \sum_{j=0}^{\infty} \rho^j (-e_{t+1+j}) + \sum_{j=0}^{\infty} \rho^j k_{t+1+j}, \tag{2}$$

where θ_t is the log book-to-market ratio, $r_{t+1} \equiv \log\left(1 + \frac{\Delta ME_{t+1} + D_{t+1}}{ME_t}\right)$ denotes the log stock return, and $e_{t+1} \equiv \log\left(1 + \frac{\Delta BE_{t+1} + D_{t+1}}{BE_t}\right)$ is the log clean-surplus accounting return on equity. Now, consider a portfolio that is long high book-to-market stocks and short low book-to-market stocks. We apply Equation (2) to both portfolios, take conditional expectations, difference, and reorganize, to get:

$$E_t\left[\sum_{j=0}^{\infty} \rho^j r_{t+1+j}^{H-L}\right] = \theta_t^H - \theta_t^L + E_t\left[\sum_{j=0}^{\infty} \rho^j (e_{t+1+j}^H - e_{t+1+j}^L)\right]. \tag{3}$$

Empirically, we abstract from the correction for the spread in discounted future expected profitability. Thus, the regression of Eq. (1) provides a lower bound on the predictability of value returns (see also Asness et al., 2000a). As an alternative motivation, consider the model of Zhang (2005). In this model, the value spread predicts value returns in the time series because it signals time-variation in the risk premia of value versus growth stocks. In bad times, the market value of value firms decreases as they are burdened with more unproductive capital and face large adjustment costs (relative to growth firms who want to expand capital in good times), such that value is more risky exactly when risk premia

and lists the collateral and hedging assumptions for foreign denominated futures.

are high. Finally, the value spread can be motivated also relying on a purely statistical approach. In Appendix B, we show that the partial least squares method of Kelly and Pruitt (2015) selects the High-minus-Low value spread as the optimal forecasting factor derived from the cross section of portfolio-level book-to-market ratios.

Similar to Eq. (2), the standard present-value formulation of Engel and West (2005) and Froot and Ramadorai (2005) shows that expected currency returns are a key driver of the real exchange rate. This motivates using real exchange rates as a measure of value for currencies. For bonds, the yield is a natural value metric, where a high yield indicates that the bond is relatively cheap. As for the case of equities, our regressions for currencies and bonds provide a lower bound on the predictability of value returns, since one can likely improve on our results by controlling for expected real interest rate differentials in the case of currencies (Menkhoff et al., 2016) and differences in expected long-term inflation in the case of bonds (Asness et al., 2017).[10] Because these adjustments need to be estimated and are different across asset classes, we instead follow Asness et al. (2013) and use simple and directly observable measures of value. One of these measures is common to all asset classes: the negative of five-year returns.

Finally, in the regressions of value returns on the value spread (see Eq. (1)), we consider forecasting horizons h up to four years. Horizons longer than one month help to mitigate the countervailing momentum effect (see Asness and Frazzini, 2013) and better resemble the experience of actual value investors. Moreover, long-horizon regressions of value returns on value spreads are less affected by the inferential issues that one typically associates with predictability problems. High first-order autocorrelation of the predictor and Stambaugh (1999) bias, in particular, has been put forward as a leading cause of inaccurate inference in predictability (e.g. Valkanov, 2003; Lewellen, 2004; Boudoukh et al., 2006). In our framework, however, the Stambaugh-bias is absent, because the left-hand side in Eq. (1) is a difference in return between two portfolios, which we regress on the corresponding difference in valuation ratio. This setup in differences breaks the mechanical relation that exists in regressions of a single return on a price-based valuation ratio. Furthermore, the monthly autocorrelation of value spreads in the different asset

[10] Similarly, one can likely strengthen the results by combining different measures of value in a single asset class. For instance, larger unconditional value effects are found for equities in Asness et al. (2000a) and Israel and Moskowitz (2013) by combining earnings-to-price, sales-to-price, and book-to-price.

classes ranges from 0.95 to 0.97, a much lower value than 0.99 which is typical for the dividend yield.

2.8 Time-Variation in Value Spreads

We standardize the value spread in each asset class so that its time-series average is zero and standard deviation is one. This standardization makes the coefficients from Equation (1) comparable across asset classes. The exception are the out-of-sample tests, for which we standardize the value spread in month t using only information available at that point in time. Figure 1 plots the standardized value spreads over time (blue line).

[Insert Figure 1 about here]

To interpret the time-variation in the value spread, let us consider the case of US individual stocks. When the value spread is zero, value stocks are cheaper than growth stocks by their historical average amount. A positive value spread indicates that value stocks are historically cheap and the cross section of value measures is wide. The same intuition applies to the other asset classes. For currencies, for instance, a large value spread indicates that the deviations from relative purchasing power parity are historically large. The main hypothesis we test in this paper is that, all else equal, a wider value spread today indicates larger value returns in the future in all asset classes.

We also analyze what fraction of the time-variation in value spreads is common across asset classes and what fraction is asset-class-specific (the red and green line, respectively, in Figure 1). Common value is calculated as the average value spread over the asset classes with available data in month t. The asset-class-specific component is the difference between the value spread in an asset class and common value. The panels in Figure 1 present a number of episodes when the value spread was large in more than a few asset classes, such as after the burst of the IT-bubble and the recent financial crisis. Consistent with such common variation, our simple measure of common value is closely related to the first principal component of the value spreads with a correlation of 0.91. This first principal component is presented in Figure 2 and explains 50% of the total variation in value spreads.[11] There is also considerable variation that is asset-class-specific. In

[11] We prefer to measure common value as the simple average value spread across asset classes, because

particular, the value spread in global government bonds often moves in the opposite direction to the remaining asset classes.

[Insert Figure 2 about here]

3 Predicting Value Returns in the Time Series

In this section, we ask whether value-minus-growth returns in different asset classes are predictable using the value spread.

3.1 Individual Equities

Asness et al. (2000a) and Cohen et al. (2003) show that the value spread predicts equity value premia over time. We extend their in-sample evidence in a number of directions: we extend the sample post 2000, we consider alternative measures of value (e.g., across industries), and focus on a relatively small set of large and liquid stocks. Moreover, we ask whether the investment-based asset pricing model of Zhang (2005), successful in capturing the unconditional value premium, generates the amount of time-variation we document. A test of whether the value spread predicts returns out-of-sample is also new to the literature, but we postpone this analysis to Section 6.1.

Panel A of Table 1 shows the unconditional performance of our value-minus-growth strategies. The table reports monthly average return, standard deviation, t-statistic, and Sharpe ratio for both the High-minus-Low and rank-weighted portfolio using the two signals: $BM_{Ex.fin.}$ and $BM_{Ind.adj.}$. The annualized Sharpe ratios for these strategies are around 0.20 (monthly Sharpe ratio $\times\sqrt{12}$). The exception is the rank-weighted portfolio based on the industry-adjusted book-to-market ratio, which obtains a Sharpe ratio of 0.41. These Sharpe ratios are a bit lower than what is typically reported for the value premium in the literature. The reason is that we focus only on relatively large and liquid stocks that cumulatively account for 90% of the total market capitalization, which is similar to Asness et al. (2000a) and Asness et al. (2013). In fact, the correlation between

the principal component is not observed in real-time and the panel of value spreads is unbalanced. For the principal component analysis, we balance this panel with an algorithm that recursively projects the value spread in an asset class with a shorter sample on the value spreads that are available over the full sample.

our first book-to-market strategy (excluding financial firms) and the comparable strategy of Asness et al. (2013) is over 0.98.[12]

[Insert Table 1 about here]

Panel B of Table 1 shows the results from in-sample time-series predictive regressions of value returns on the value spread at forecasting horizons of $h = 1, 3, 6, 12, 24$ months. We present coefficients, t-statistics (based on Newey and West (1987) standard errors with h-lags), and R-squares.[13] At all horizons, and for both decile and rank-weighted portfolios, the coefficient on the value spread is economically large and typically statistically significant. Let us consider first the book-to-market signal that excludes financials. The coefficient estimate increases with the forecasting horizon, for instance, from 0.57% ($h = 1$) to 22.58% ($h = 24$) for the High-minus-Low decile portfolio. At the two-year horizon, the coefficient estimates for the decile and the rank-weighted portfolio, respectively, imply an increase in value premium of 22.58% and 11.25% per standard deviation increase in the value spread. The R^2 is also increasing in the horizon. For instance, for the High-minus-Low decile portfolio, the R^2 ranges from 0.85% at the one-month horizon to 30.33% at the two-year horizon.

The coefficient estimates are similar in magnitude for the industry-adjusted book-to-market ratio, but in this case the R^2's are even larger at 45% and 27% for the High-minus-Low and rank-weighted portfolio, respectively, at the two-year horizon. The correlation between the value return series that excludes financials and the industry-adjusted value return series is about 0.75. This result suggests that cleaning valuation ratios from across-industry variation creates a different time series of value returns that is more predictable.

By standardizing the value spread, the ratio of the estimated coefficients to the intercept, b_h/a_h, measures the standard deviation of expected returns (due to variation in the value spread) relative to the unconditional value premium. For the High-minus-Low portfolio this ratio is over two at all horizons, whereas for the rank-weighted portfolios this ratio is over one at all horizons. For comparison, Cochrane (2011) shows that this

[12]The correlation increases to 0.99 when we drop the requirement that a stock needs to have the last five years of returns available. We use the negative of the five-year return as an alternative measure of value in a robustness check.

[13]Table C.1 of the Internet Appendix presents t-statistics calculated using Hodrick (1992) standard errors, which are slightly more conservative.

ratio is slightly below one when predicting the aggregate stock market with the dividend yield. Thus, the variation in expected value returns we document is economically large and it will pose an enormous challenge for standard asset pricing models to match. To see an example of this challenge, we simulate from the investment-based asset pricing model of Zhang (2005), which contains a time-varying value premium.[14] Table C.2 of the Internet Appendix presents the simulated distribution of unconditional and conditional value premia from 1000 simulations. We see that the median ratio b_h/a_h in a regression of annual High-minus-Low decile value returns on the lagged value spread is 0.74. This ratio is small relative to our empirical estimates of about 2.5, which fall in the far right tail of the simulated distribution.

Panel C extends these results in three dimensions. We start by sorting stocks on the negative of the past five-year return (see, e.g. DeBondt and Thaler, 1985, who use similar measures for individual stocks to identify "cheap" and "expensive" firms.). Next, we consider a sort of 17 industries on the average book-to-market ratio in each industry portfolio. Finally, we sort stocks based on market cap, which is a factor in itself but also the denominator of the book-to-market ratio. Here, we predict returns of the Small-minus-Big portfolio with the difference in total market cap between the Big and Small portfolio.

In short, we see positive and (marginally) significant coefficients on the value spread in all three cases, which translate to sizeable R^2's ranging from 9.16% to 25.58% at the 24-month horizon. The effects are similar in magnitude for −5-year return and market cap. For instance, for the rank-weighted portfolios, the coefficient estimates at the 24-month horizon are 7.31% and 7.87%, respectively. Again, these estimates indicate that expected returns vary at least as much as the unconditional premium for the −5-year return and market cap signals. The t-statistics are relatively large for market cap, suggesting that these coefficients are estimated most precisely. The effects are slightly smaller in magnitude for across-industry value, which is perhaps unsurprising given that cross-sectional return variation is considerably smaller across industries than across individual stocks. Indeed, the significant coefficient estimates (for the High-minus-Low and rank-weighted portfolio) of about 6% at the 24-month horizon suggest that the time-variation

[14]We thank Lu Zhang for sharing the code on his website.

in across-industry value returns is economically large. The small and insignificant intercepts indicate that the unconditional value premium across industries is small, consistent with previous literature. Our contribution is in showing that there is evidence in support of a conditional value premium across industries.

We conclude that the returns to value strategies in equities are robustly time-varying: the value premium increases (decreases) as the cross section of valuation ratios expands (compresses). Next, we ask whether value premia in other asset classes are also predictable by the value spread.

3.2 Alternative Asset Classes

This section presents time-series evidence for the predictability of value returns in commodities, currencies, global government bonds, and stock indexes. Panel A of Table 2 reports unconditional performance statistics for both the High-minus-Low and rank-weighted portfolios in these alternative asset classes. We see that all value strategies obtain a positive Sharpe ratio, but there is considerable variation. Annualized Sharpe ratios range from 0.13 ($= 0.0378 \times \sqrt{12}$) for the High-minus-Low portfolio in stock indexes to 0.65 for the rank-weighted portfolio of government bonds (using as value measure the five-year change in yield of the ten-year government bond, denoted 5-year Δy). Interestingly, both value measures for currencies (the negative of the five-year spot exchange rate return with and without inflation adjustment, denoted −5-year return and Inf. adj. return) provide Sharpe ratios greater than 0.30. Consistent with Asness et al. (2013), we instead observe a large difference for the case of government bonds depending on the value signal that is used: when we measure value by the negative of the five-year return (denoted −5-year return), the Sharpe ratio is 0.14 for the High-minus-Low portfolio and 0.20 for the rank-weighted portfolio, which is relative to 0.39 and 0.65 for 5-year Δy.

[Insert Table 2 about here]

Panel B of Table 2 presents predictive regressions of overlapping value returns over horizons of $h = 1, 3, 6, 12, 24$ months on the lagged value spread. As for the case of individual equities, we see positive coefficients throughout and an R^2 that strongly increases in horizon. For instance, for the High-minus-Low portfolios, the R^2 ranges from 3.03%

(commodities) to 11.79% (government bonds, −5-year return) for $h = 6$, and from 8.06% (stock indexes) to 40.36% (government bonds, −5-year return) for $h = 24$. In each asset class, the coefficient on the value spread is typically significant for all horizons $h \geq 3$ months. The magnitudes cannot be directly compared across asset classes, due to differences in return volatility. However, the effects are economically large. To see this, note that the ratio of the coefficient estimate on the value spread relative to the estimated intercept is close to one for currencies and above one for commodities and stock indexes. Since the value signal is standardized, this ratio implies that the standard deviation of expected returns implied by these predictive regressions is in the same order of magnitude as the unconditional value premium in these asset classes. For global government bonds, the two alternative measures of value provide a somewhat mixed picture. On one hand, the ratio is far above one when the value signal is −5-year return. This finding is partly driven by a relatively small unconditional value premium. The unconditional value premium is larger when the value signal is 5-year Δy. Because in this case the predictability induced by the value spread is relatively weak, the ratio of expected value return variation to unconditional value is only about 0.5.[15]

4 Joint Tests of Value Return Predictability

In this section, we analyze the joint strength of value return predictability in different asset classes, which is our primary interest. We present pooled tests for the following six value strategies: individual equities (book-to-market excluding financials and industry-adjusted book-to-market), commodities, currencies, global government bonds, and global stock indexes. For both currencies and government bonds we use the negative of the five-year return as value signal.

[Insert Table 3 about here]

Panel A of Table 3 presents results for the pooled predictive regression:

$$R^x_{c,t+1:t+h} = a_h + b_h \ \mathrm{VS}^x_{c,t} + e^x_{c,t+1:t+h}, \tag{4}$$

[15] These results for bonds are calculated using traded bond futures returns. Results for synthetic bond futures returns are qualitatively similar, but weaker, as reported in Table C.3 of the Internet Appendix.

where c denotes an asset class and $x = H - L, Rank$. We add in these pooled tests a longer four-year horizon, $h = 48$, because pooling should yield more power. We present t-statistics using asymptotic standard errors calculated following Driscoll and Kraay (1998), which are heteroscedasticity-consistent and robust to rather general forms of cross-sectional and temporal dependence when the time dimension becomes large. We find that inference using these standard errors is conservative relative to two-way clustered standard errors. Panel A shows that, for both types of portfolios, the joint predictability is strong as signaled by the t-statistics, which increase from about 3 at $h = 1$ to over 5 at $h = 48$. Consistent with this pattern, the R^2 increases with the horizon, and it reaches over 20% at the 24- and 48-month horizons. The coefficient estimates are economically large, too. Looking at the ratio of the estimated coefficient to the intercept, we see that the standard deviation of expected returns implied by the value spread is about 50% larger than the unconditional value premium in the pool of value strategies.

Panel B shows that this evidence is quantitatively robust when we split the sample in two halves. This result suggests that value return predictability is not only driven by the highly popularized value episodes around the tech bubble in the late 1990s and around the 2008 global financial crisis. Panel C shows that the value spread predicts returns, but not volatility (at the annual horizon). Consequently, a standard deviation increase in the value spread implies an increase in Sharpe ratio in the same order of magnitude as the unconditional Sharpe ratio of the value strategies. Panel D presents an alternative way of looking at the joint strength of value premium predictability. We regress in the time series the average value return on the average value spread, where both cross-sectional averages are taken over the six asset classes. We again see coefficient estimates on the value premium that are statistically significant and economically large. The R^2's are even larger at over 30% for the 24- and 48-month horizons, which is likely due to the fact that averaging smooths out some noise in the individual value strategies. This result not only testifies to the joint strength of value premium predictability, but it also suggests there is common variation in value premia across asset classes. We dig further into this suggestion in the next section. Panel E shows that most of the predictability in the pooled regressions of Panel A comes from the long-end of the value strategy. In the average-on-average specification of Panel D, however, both predictability for the long-end (with a positive sign) and the short-end (with a negative sign) contribute to the total predictability of value returns. In Figure C.1 of the Internet Appendix, we predict future value returns over separate semi-annual periods. We see that the coefficients on the value spread are decreasing as time passes, but are positive and marginally significant up to about four-and-a-half years after portfolio formation.[16]

Next, we ask whether our results are explained by exposure to a market benchmark, which test is inspired by the CAPM (Sharpe, 1964; Lintner, 1965; Mossin, 1966). To this end, we run the pooled predictive regression of value returns on the value spread, but we control for market exposure in each asset class. The results are reported in Table 4. In Panel A, we use the CRSP value-weighted stock market portfolio as the benchmark in all asset classes. This portfolio is the most common proxy for the CAPM market portfolio in the literature. In Panel B, we vary the benchmark across asset classes, such that the benchmark is an equal-weighted basket of the securities in each asset class (for commodities, currencies, fixed income, and stock indexes).

[Insert Table 4 about here]

In short, we see that exposures to neither market benchmark capture the predictability of value returns. The estimated coefficients on the value spread are similarly large in economic magnitude and significance to those in Panel A of Table 3. Thus, our evidence is robust to controlling for the correlation between the value spread and market returns, and we conclude that an unconditional CAPM cannot explain our results. In unreported tests, we find that a conditional CAPM where market betas vary over time with the value spread, cannot explain our results either. In line with this conclusion, Table C.6 of the Internet Appendix shows that the value spread is insignificant at all horizons when we predict market returns (instead of value returns) in the pooled regression of Equation (4).[17] Thus, time-variation in the market risk premium is also unlikely to explain the

[16]Table C.4 of the Internet Appendix confirms the evidence in Section 3.2 and shows that the pooled regression is not driven by individual equities alone: value returns in the alternative asset classes are strongly predictable by the value spread, with a ratio of coefficient to intercept that is slightly above one. Table C.5 of the Internet Appendix presents similar evidence for pooled regressions that use alternative value return series for currencies (the signal is the inflation-adjusted five year change in spot price) and bonds (the signal is the five year change in yield and the test assets are the synthetic futures returns).

[17]The insignificance of the value spread in the pooled regression is driven by the fact that stock market returns are weakly predictable by the equity value spread, as shown in Kelly and Pruitt (2013). In contrast, market returns in the remaining asset classes are not predictable by the value spread.

predictability of value premia. In the next section, we analyze whether time-variation in various proxies of risk premia does play a key role.

5 Risk and Return of Value Strategies: A Decomposition

In this section, we investigate (i) the strength of comovement between expected returns on value strategies in different asset classes, and (ii) whether this comovement is driven by economic fundamentals. To this end, we decompose the value spread into two components, one that is common across asset classes and one that is asset-class-specific instead. We then regress each of these components in turn on several variables that are likely to be related to aggregate economic and financial conditions. Finally, we investigate how much of the (common and asset-class-specific) predictive power can be attributed to these variables.

5.1 Common versus Asset-Class-Specific Value

We start by investigating how much predictability in value strategies is common across different asset classes. To smooth out noise, our decomposition of value predictability focuses on the average return of the High-minus-Low and rank-weighted value strategy, i.e., $R_{c,t+1} = \frac{R^{H-L}_{c,t+1} + R^{\text{Rank}}_{c,t+1}}{2}$. Analogously, the value spread is defined as the average value signal between the two weighting schemes. Panel A of Table 5 presents the results from a pooled predictive regression of these smoothed versions of the value return on the value spread. The results are almost identical to what we report in Table 3, and we only report them as a benchmark for what follows.

[Insert Table 5 about here]

Panel B of Table 5 presents results from a pooled predictive regression, where we decompose the value spread into two components, a component that is common across asset classes $\text{VS}^{\text{Com}}_t = \frac{\sum_c^{N_t} VS_{c,t}}{N_t}$, and an asset-class-specific component $\text{VS}^{\text{Spec}}_{c,t} = \text{VS}_{c,t} - \text{VS}^{\text{Com}}_t$ (see Figure 1 for the time series of the value spread and its components).

In isolation, the coefficient estimates on the common and asset-class-specific components of the value spread are statistically and economically significant at all horizons. The coefficients are also statistically indistinguishable from the coefficients on the raw (not decomposed) value spread in Panel A. For instance, at the one-year horizon the coefficients are close to 7% for both the raw value spread and its two components. The two components explain large and similar amounts of variation in the pool of value returns, with one-year R^2's of 6.24% and 7.33%, respectively. Note, to achieve this R^2, the common component uses only time variation.[18] Given that the two components are (close to) orthogonal by construction, the coefficient estimates for the common and asset-class-specific components are largely unchanged in a joint regression. Consequently, the joint variation explained by these two components is virtually identical to what is explained by the raw value spread in Panel A. To conclude, a decomposition of the joint R^2 confirms that common and asset-class-specific components of the value spread contribute about equally to the variability of value strategies at all horizons ranging from one month to four years. A component of the value spread that is common across asset classes and determines half of the variance of expected returns in value strategies is interesting from a theoretical perspective. Asset pricing models now must also explain the global comovement of value premia. As highlighted in Cochrane (2011): "It is not enough to simply generate temporary price movements in individual securities." The expected returns of value strategies rise and fall globally.

Consistent with the intuition that (institutional) investors are increasingly active in different asset classes over time, Table C.8 shows that common value is relatively more important in the second half of our sample period, whereas specific value is more important in the first half.

Next, we ask whether the value spread in one asset class is informative about value returns in another asset class. To this end, we create two groups of value strategies: individual equities ($BM_{Ex.fin.}$ and $BM_{Ind.adj.}$) and other asset classes (commodities, cur-

[18] In Table C.7 of the Internet Appendix, we find that the first principal component of the value spreads predicts returns similar to our simple measure of common value. One can decompose the value spread arbitrarily in two orthogonal components and obtain joint regression results similar to what we present here. However, such arbitrary components will generally not predict value returns well in isolation, especially if the component does not vary across asset classes. To see this by example, Table C.7 also presents results for the second to sixth principal component, which do not contain much information about value returns in isolation.

rencies, global government bonds and stock indexes). We then conduct time-series regressions of the average value return from one group on the average value spread from the other group. Table C.9 of the Internet Appendix presents the results. Consistent with the evidence in favor of a "common" value component, there is evidence of across-asset-class value return predictability. The coefficient estimates on the value spread are positive throughout and in many cases economically large (with a ratio of coefficient to intercept of about one). The evidence suggests that individual equities are leading, because the value spread from individual equities significantly predicts average value returns in the other asset classes for horizons up to one year, with an R^2 that peaks at 10% for the six month horizon. In contrast, the value spread in the other asset classes only weakly predicts individual equity value returns. The leading role of value in individual equities is even more pronounced when commodities are excluded from the other asset classes.

5.2 Economic Drivers of the Components of Value

We investigate possible economic sources driving common and specific value. Table 6 reports results from time-series regressions of the common and asset-class-specific components of the value spread on several benchmark predictor variables. These variables are related to aggregate economic and financial conditions and are popular in the literature to proxy for time-variation in risk premia.[19] In particular we use: (i) a global recession dummy (see Asness et al., 2013); (ii) the dividend yield; (iii) the default spread; (iv) the illiquidity premium of Nagel (2016); (v) real uncertainty of Jurado et al. (2015); and, (vi) intermediary leverage.[20] We also control for sentiment of Baker and Wurgler (2006), a behavioral factor.

[Insert Table 6 about here]

[19]In unreported results we find that our conclusions are qualitatively robust to expanding the set of benchmark predictors. Quantitatively, the results do vary. Following Occam's razor, our choice of seven variables trades off information with the danger of overfitting.

[20]Our measure of the default spread is the difference in yield between BAA and AAA corporate bonds. Replacing this spread with the excess bond premium of Gilchrist and Zakrajsek (2012) yields similar results, thus validating our measure as a proxy of low frequency movements in business conditions. Although our results are strongest for real uncertainty, we find similar evidence when we use macro or financial uncertainty, as defined in Jurado et al. (2015). For intermediary leverage, we follow He et al. (2017) and use the inverse of the squared intermediary capital ratio, which predicts future returns in many asset classes with a positive sign.

Panel A of Table 6 contains simple and multiple regressions of the common component of the value spread on these benchmark predictors. Except for the global recession dummy and sentiment, all variables deliver a considerable R^2 of at least 29% in a simple regression. The estimated loading of common value on the dividend yield, default spread, illiquidity, real uncertainty, and intermediary leverage is significantly positive and economically large. These results suggest that common value is large when each of these risk-proxies signals high risk premia in bad times.

The multiple regression in row 8 shows that these variables together explain over 75% of the variation in common value. When we exclude the dividend yield in row 9, the explanatory power remains large ($R^2 = 69\%$), which is mostly due to an increase in the coefficient on intermediary leverage.[21] Since both the dividend-price and leverage ratios are proxies for risk aversion in habit models (see, Campbell and Cochrane, 1999; Menzly et al., 2004; Santos and Veronesi, 2016), we interpret these multiple regressions as assigning a key role to time-varying risk aversion in determining common value.[22] The multiple regressions also assign a key role to the illiquidity premium, which Nagel (2016) argues is mostly driven by time-variation in the price of liquidity. After controlling for prices of risk, the quantity of risk – as proxied by real uncertainty – turns insignificant.

Panel B of Table 6 shows that the benchmark predictors jointly also explain a considerable fraction of the variation in the value spread that is asset-class-specific (with an R^2 ranging from 15% for commodities to about 60% for individual equities and global government bonds). However, the coefficients on the benchmark predictors vary dramatically across asset classes, in both magnitude and significance. The loading on the default spread is positive for US individual equities and negative for global stock indexes and government bonds. The loading on the global recession indicator is positive for global

[21] Excluding the dividend yield is an important robustness check for individual equities, because a lower dividend yield driven by an increase in prices tends to coincide with a shrinking spread in book-to-market ratio. Having said that, it is not obvious ex ante why the dividend yield would comove with value spreads in the remaining asset classes.

[22] Campbell and Cochrane (1999) note that the price-dividend ratio is nearly linear in the surplus consumption ratio (see their Figure 3), the key state variable in the habit model. Our measure of leverage is based on market prices (market leverage) and, in the model of Santos and Veronesi (2016), the debt-to-wealth ratio is monotonically decreasing in the surplus consumption ratio (see their Corollary 13). Finally, note that the global recession indicator shows up significantly with a positive sign in row 8, and marginally so in row 9. This finding further supports the time-varying risk aversion channel, because a "recession indicator" is also akin to the (inverse of the) surplus consumption ratio (see Proposition 3 in Santos and Veronesi (2016)).

stock indexes and negative for government bonds. These results are broadly consistent with a flight-to-quality story, where in bad times (as proxied by a global recession and/or a high default spread) investors shy away from more risky value strategies in individual equities towards safer value strategies in global stock indexes and especially government bonds. Thus, heterogeneity in risk exposure across asset classes is likely an important driver of asset-class-specific value. The significant loadings on sentiment (negative for individual equities and stock indexes; positive for currencies) suggest that behavioral factors are likely to play a role in explaining specific value as well. In contrast, we saw in Panel A that common value is largely unrelated to sentiment.

5.3 Decomposing Common and Specific Value Return Predictability

Table 7 completes our analysis of the decomposition of the value spread. In particular, we ask how much of the predictive ability of the common and asset-class-specific components of the value spread is captured by the part that is correlated with the benchmark predictors, and how much is driven by the part that is left unexplained by these variables.

Panel A of Table 7 shows the results for common value. Focusing on the decomposition of R^2, we see that most of the predictability coming from the common component of the value spread is due to the part explained by the benchmark predictors, especially at longer horizons. To be precise, for horizons $h > 3$ the fraction of value return variation driven by the explained part of common value is about three times the contribution of the orthogonal part. Even though the contribution is much smaller from a quantitative perspective, the part orthogonal to the benchmark predictors continues to be statistically significant. The last two rows of Panel A show similar results when we exclude the dividend yield.

[Insert Table 7 about here]

To see the strong association between common value return predictability and the benchmark predictors in another way, we show in Table 8 that the first principal component of the benchmark predictors significantly predicts value returns in a pooled predictive regression.[23] However, it is common value that dominates in predicting value returns in a joint test. Hence, we have two advantages of looking at the data from the vantage point of the value spread. First, our simple, and available in real time, measure of common value contains the bulk of information common to popular risk-proxies. Indeed, the correlation between the first principal component of the benchmark predictors and common value is large at 0.84. Second, common value outperforms in predicting value returns in a horse race.

[**Insert Table 8 about here**]

Panel B of Table 7 decomposes asset-class-specific value return predictability into the part coming from the explained (by the benchmark predictors) and orthogonal components of the asset-class-specific value spread. We see that specific value return predictability is more equally split between these two parts, relative to common value. On one hand, at horizons above one year, more than half of the predictive ability of the asset-class-specific value spread is driven by the benchmark predictors. On the other hand, the orthogonal part of specific value is relatively important at shorter horizons up to one year.

5.4 Interpretation

The evidence in this section broadly raises two challenges for asset pricing theory. First, our results for common value call for a general framework, where investors shy away from holding different risky assets – like value stocks and undervalued currencies – in bad times. Consequently, the value spread widens simultaneously in different asset classes when prices of risk (and thus expected value returns) are high. The motivation is that common value return predictability is closely associated with common variation in a large set of benchmark predictors, among which proxies for risk aversion (dividend yield and intermediary leverage) and an illiquidity premium are most relevant. This common time-varying component of value premia is present in asset classes with potentially different investors and institutional factors. Leading theories relying on firm investment risk or

[23] Figure 2 shows that the first principal component explains about half of the total variation in the benchmark predictors and loads on all predictors with a positive sign, except sentiment.

growth options can capture value premia in equities, but seem ill-equipped to explain the comovement in value premia between equities, currencies, and commodities.

Second, our results for asset-class-specific components of the value spread indicate the presence of additional risky, behavioral, and mispricing factors in time-varying value premia. On one hand, we find that the correlation between risky variables, such as the default spread, and asset-class-specific components of the value spread contributes to the predictability of value returns (especially at long horizons). However, the loadings of specific value on these variables vary across asset classes, consistent with heterogeneity in risk and the idea that investors rationally move from one asset class to another over time, like in a flight-to-quality. On the other hand, loadings on sentiment also vary across asset classes. In addition, the component of the asset-class-specific value spread that is orthogonal to the large set of benchmark predictors (including sentiment), contributes to the predictability of value returns (especially at short horizons). Albeit small, such an orthogonal component is also present in common value. Absent any further explanation, these orthogonal components represent a puzzling mispricing.

6 Value Timing and Rotation

In this section, we present a number of out-of-sample strategies that intend to take advantage of the information in the value spread in real-time.

6.1 Value Timing in Individual Equities

We construct a linear timing strategy for value in individual equities by constructing a value spread that is standardized in month t using only historical information:

$$VS_{t,His} = \frac{\left(\sum_{s=0}^{11} VS_{t-s}/12 - \sum_{s=12}^{t-1} VS_{t-s}/(t-12)\right)}{\sigma(VS_{1:t-12})}. \tag{5}$$

Thus, $VS_{t,His}$ indicates whether the average value spread over the last twelve months is historically large. We take an annual average to accommodate that return predictability using the value spread strengthens in horizon.[24]

Table 9 presents summary performance statistics for three strategies: a unit weight strategy that captures the unconditional value premium, a linear timing strategy that invests $VS_{t,His}$ dollars, and, finally, a combined strategy that invests $1 + VS_{t,His}$ dollars. We consider $2 \times 2 \times 3$ variations of these strategies: using (i) either the book-to-market signal excluding financials or the industry-adjusted book-to-market ratio, (ii) either the High-minus-Low decile portfolio or the rank-weighted portfolio, and (iii) the largest stocks whose market caps cumulate to either 75%, 90%, or 95% of total market cap in the CRSP file. To make the results comparable across strategies, we standardize each return series to have an annualized standard deviation of 15%. We perform this standardization relative to the last ten years of returns so that we do not use any forward looking information.[25]

[Insert Table 9 about here]

Over the strategies we consider, the linear timing strategy obtains a return that is typically much larger than the unit weight strategy both on average and in CAPM alpha. For instance, for the High-minus-Low decile book-to-market strategy that excludes financials and uses only the 90% largest stocks, we find an average return for the linear timing strategy of 67 bps ($t = 2.70$) per month, which is relative to 9 bps ($t = 0.45$) for the unconditional strategy. The Sharpe ratio of the linear timing strategies is relatively large in these cases as well, because the large increase in average returns is not accompanied by a proportional increase in standard deviation. The exception is the set of rank-weighted, industry-adjusted book-to-market strategies, where the linear timing and unit weight strategy perform similarly. Since the unit weight and linear timing strategies are not highly correlated, the combined strategy comes out as most attractive in all cases. The average monthly return and CAPM alpha of the combined strategy range from 50 to 105 bps and 61 to 107 bps, respectively, over the twelve strategies. These returns translate to an annualized Sharpe ratio of 0.42 (0.12 on average $\times\sqrt{12}$), which is relative to 0.18 (0.05 on average $\times\sqrt{12}$) for the unit weight strategy.

[24] Our conclusions are similar when we standardize last year's value spread relative to the past ten years. To ensure the dynamic strategies are not extreme, we cut off the standardized signal at ±2.

[25] To be precise, the month t position in the High-minus-Low or rank-weighted value strategy for each signal ($BM_{Ex.fin.}$ and $BM_{Ind.adj.}$) is rescaled to an ex ante annualized volatility of 15%. Thus, the ex post return on the position equals: $R^x_{t+1,15\%} = \frac{R^x_{t+1} \times 15\%}{\sigma(R^x_{t-120:t}) \times \sqrt{12}}$.

The fact that our results are robust to alternative market cap cutoffs is interesting. With the 95% cutoff, we use an additional 300 relatively small stocks every month, which increases transaction costs. Including these smaller stocks does increase the unconditional value premium, consistent with previous literature. With the 75% cutoff, we use on average only 263 stocks per month, which should lower transaction costs considerably. Indeed, recall that we only need 2×10% of these stocks to construct the high and low decile portfolios. We conclude that information in the value spread can be used by investors in real-time to improve the performance of their value strategies in the stock market. The large CAPM alphas suggest that conditional value strategies are attractive on top of an indexed market strategy.

6.2 Value Timing in the Pool of Value Strategies

Having shown that value timing is attractive in individual equities, we move to value timing in the pool of asset classes. To start, we run a pooled regression on a dummy variable that indicates for each asset class whether the current value spread (averaged over the last twelve months) is above the historical average:

$$R^x_{c,t+1:t+h,15\%} = a_h + b_h I_{VS^x_{c,t,His}>0} + e_{c,t+1:t+h}, \tag{6}$$

where c denotes an asset class and $x = H - L, Rank$. The subscript indicates that we standardize each return series to have an annualized standard deviation of 15% to ensure comparability across asset classes. We use the first 120 months in each asset class as burn-in period for the historically demeaned value spread.

Table 10 presents the results. For the one-month horizon, we see that the coefficient estimate b is large and significant at 72 bps (t = 2.97) and 54 bps (t = 2.02) for the High-minus-Low and rank-weighted portfolios, respectively. Combined with the estimated intercept, these numbers imply that the average return of a value strategy that invests only in an asset class when $VS_{c,t,His} > 0$ equals 68 bps and 66 bps per month, respectively. These returns translate to annualized Sharpe ratios over 0.49 ($0.1414 \times \sqrt{12}$). In comparison, the Sharpe ratio of investing when $VS_{c,t,His} \leq 0$ is -0.04 and 0.10, respectively. The regressions for longer horizons present coefficient estimates that are larger statistically, but consistent in economic magnitude as they increase almost linearly in the horizon. This result suggests that strategies that rebalance less frequently than monthly are likely more attractive. From this simple test, we conclude that investing across asset classes in value strategies is only attractive when the value spread is historically large, which echoes our previous conclusion for individual equities.

[Insert Table 10 about here]

Finally, we turn to strategies that rotate across asset classes. To start, we consider an unconditional value strategy that invests $1/N_t$ in each of N_t available value strategies (out of the maximum of six) in each sample month t. Next, we consider a value rotation strategy that overweights (underweights) those asset classes where the value spread is high (low) relative to the other asset classes. We consider two alternatives. The first rotation strategy takes a position in each asset class c in month t equal to:

$$w_{c,t}^{rot,1} = q_t \left(VS_{c,t,His} - \sum_{c=1}^{N_t} VS_{c,t,His}/N_t \right), \tag{7}$$

where the scalar q_t ensures that the total weight in the long and short position equal one. The second strategy, with weights denoted $w_{c,t}^{rot,2}$, invests an equal weight in each asset class with $VS_{c,t,His}$ above (below) the mean value spread across asset classes. As before, the value strategy returns are scaled to a standard deviation of 15% using only backward looking information.

We calculate performance measures for these two long-short rotation strategies as well as for a combination with the unconditional strategy. We also present results for the long-only position of the rotation strategies. The motivation is that the evidence above implies that a historically high value spread signals outperformance, whereas a historically low value spread does not signal underperformance. Rather, a low value spread signals an expected excess return that is close to zero for the value strategy. Table 11 presents the results.

[Insert Table 11 about here]

The first block of results in Panel A uses the High-minus-Low portfolios. We see that the two rotation strategies outperform the unconditional strategy. For instance, the average return and (annualized) Sharpe ratio of the first rotation strategy equal 56 bps ($t = 2.13$) and 0.37, respectively, which is large relative to 15 bps ($t = 1.21$) and 0.21 for the unconditional strategy. Combining the two rotation strategies with the unconditional strategy leads to a small further improvement in Sharpe ratio to about 0.43. We note that similar improvements in Sharpe ratio are obtained when we invest only in the long leg of the value rotation strategies, which will reduce transaction costs. This finding extends our previous conclusion in the time series (that value investing is only attractive when the value spread is historically high) to the cross section: Asset classes with value spreads that are large relative to other asset classes tend to outperform, but asset classes with value spreads that are small relative to other asset classes do not tend to underperform. Moving to the second block of results for the rank-weighted value strategies, we see that the long-short value rotation strategies do not perform as well, as the Sharpe ratio is slightly below the unconditional strategy. However, investing only in the long leg of the rotation strategies does create value over the unconditional strategy. For both rotation strategies, combining the long leg with the unconditional value strategy yields an average return of 85 bps per month ($t \approx 3$) and an annualized Sharpe ratio over 0.50.

The table also reports the abnormal return, or α, of the rotation strategies relative to an equal-weighted portfolio of the market strategies in each asset class (as defined in Panel B of Table 4). Note, this aggregate market benchmark is well-diversified and presents a tough benchmark for the dynamic strategy to beat. The value rotation strategies have lower α's than average returns, suggesting that there is some market exposure. However, the reduction is generally small (about 10 bps), such that the remaining abnormal return is economically large and in many cases significant. We conclude that rotation strategies, and especially their long leg, are attractive investments next to a portfolio that diversifies unconditionally across these markets.[26]

Panel B of Table 11 presents the fraction of months in which the long leg of the two rotation strategies invests in each asset class. We see that the strategy diversifies across different asset classes over time: no asset class is present in the long leg for more than

[26] Formally, positive α's indicate that a more efficient portfolio is obtained (with higher Sharpe ratio) by complementing investment in the market strategy with a position in one of the rotation strategies. Given that the alternative asset classes require an investment in futures that need to be rolled frequently, the rotation strategies will not necessarily face significantly larger transaction costs than the long-only market benchmark in these asset classes.

one-third of the sample. We conclude that all asset classes, not just individual equities, contribute to the benefits of value timing.

7 Conclusion

The returns to value strategies are strongly time-varying and comove across asset classes. In particular, we show that returns to value strategies in individual equities, commodities, currencies, global government bonds and stock indexes are predictable in the time series using the value spread. The predictability we document is statistically significant and economically large, both in isolation and in the pool of value strategies. Our coefficient estimates suggest that expected value returns vary by at least as much as their unconditional level. This finding presents a challenge for current asset pricing models that are specifically designed to match the unconditional magnitude of the value premium in a single asset class: US individual equities.

We show that common and asset-class-specific components of the value spread contribute about equally to this predictability. We argue that the source of the common variation in value returns is compensation for risk. Indeed, a small set of predictors that proxy for aggregate economic and financial conditions explains the bulk of the variation in common value. This finding is new to the literature and is only detected in a joint examination of different asset classes. Our results from this multi-asset perspective suggest to revisit those mechanisms – such as production- and investment-based theories – that generate value returns exclusively in equities and cannot be easily applied to other asset classes. The asset-class-specific components of value return predictability point to additional risky, behavioral, and mispricing factors that move different investors to invest in value in different asset classes at different times.

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Figures

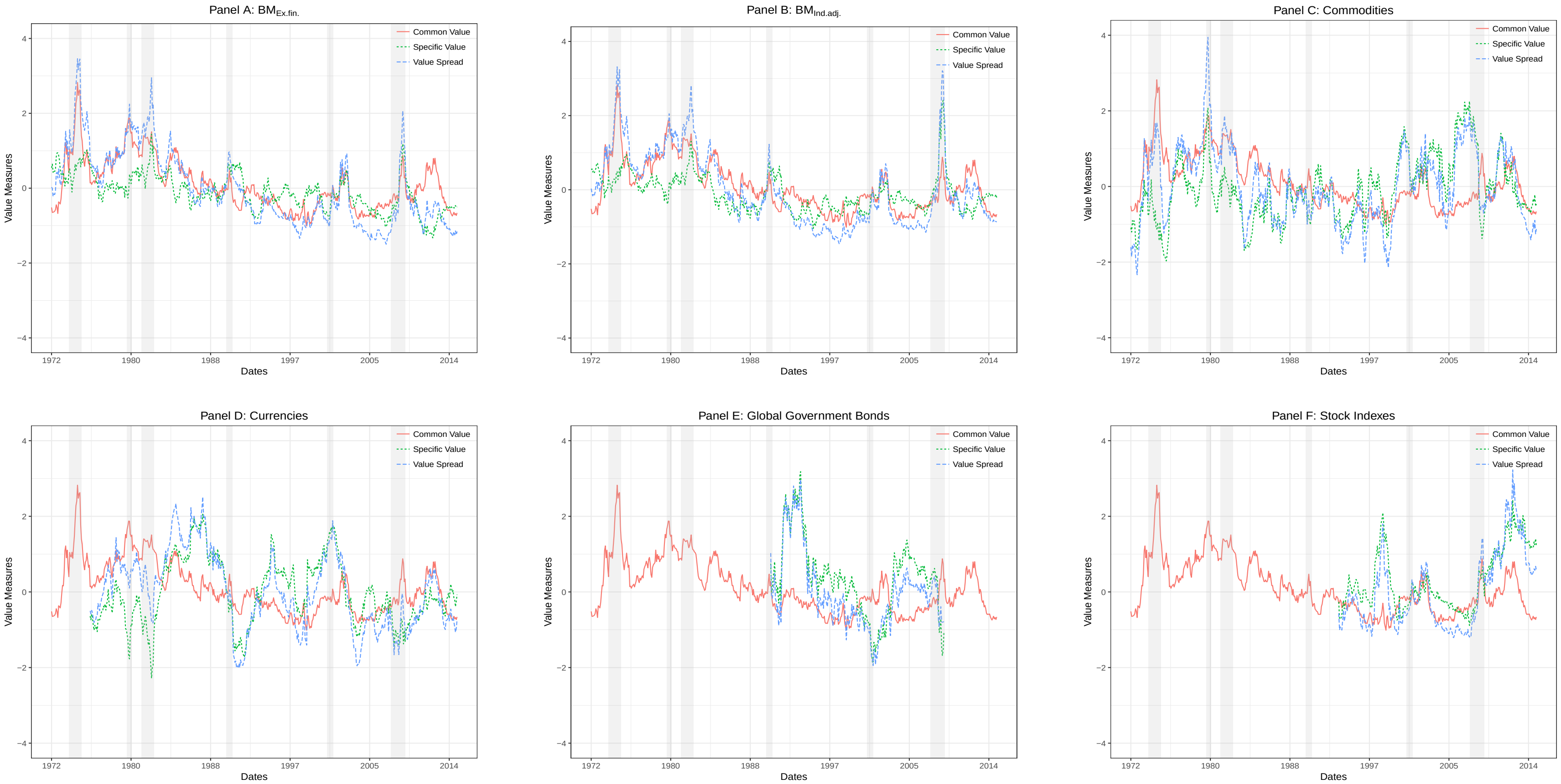

FIGURE 1: **The Value Spread and its Components over Time**
This figure presents the time series of standardized value spreads (in blue) for the following six long-short value strategies: (i) individual equities sorted on book-to-market excluding financials ($BM_{Ex.fin.}$), (ii) individual equities sorted on industry adjusted book-to-market ($BM_{Ind.Adj.}$), (iii) commodities sorted on the negative of the five-year return (−5-year return), (iv) currencies sorted on −5-year return, (v) global government bonds sorted on −5-year return, and (vi) stock indexes sorted on MSCI book-to-price ($MSCI_{BP}$). In each panel, we also present the time series of common value, which is the average value spread across the six value strategies (in red), and the residual asset-class-specific component of the value spread (in green). The shaded areas represent NBER recessions. Each value spread is the average of the value spread from a high-minus-low portfolio strategy and a rank-weighted portfolio strategy to smooth out noise introduced by a particular weighting scheme.

FIGURE 2: **Common Value versus Principal Components of Value Spreads and Benchmark Predictors**
This figure presents the time series of our measure of common value (the simple average of six value spreads) as well as two principal components (PC), with each series standardized to have mean equal to zero and variance equal to one. The first PC of six value spreads is denoted VS^{PC1}. The first PC of seven benchmark predictors (a global recession dummy; the dividend yield; the default spread; the illiquidity premium; real uncertainty; intermediary leverage; and, sentiment) is denoted $Macro^{PC1}$. The loadings of the two PC's and their correlation with common value are presented below.

First Principal Component of Value Spreads									
	$BM_{Ex.fin.}$	$BM_{Ind.Adj.}$	*Commodities*	*Currencies*	*Government Bonds*	*Stock Indexes*		% of Variation	$Corr(\text{VS}^{\text{Com}}, \text{VS}^{\text{PC1}})$
Loadings	0.50	0.51	0.24	0.38	-0.43	0.33		50.11	90.81
First Principal Component of Benchmark Predictors									
	Global Recession	*Dividend Yield*	*Default Spread*	*Illiquidity*	*Macro Uncertainty*	*Leverage*	*Sentiment*	% of Variation	$Corr(\text{VS}^{\text{Com}}, \text{Macro}^{\text{PC1}})$
Loadings	0.17	0.46	0.40	0.36	0.44	0.48	-0.22	48.28	84.27

Tables

Table 1: **Predicting Value Returns with the Value Spread: Individual Equities**
This table presents the results from overlapping predictive regressions of monthly value returns on the value spread: $R_{t+1:t+h} = a_h + b_h VS_t + \varepsilon_{t+1:t+h}$ from 1972 to 2014. We consider two measures of value for individual equities. The first is book-to-market, BM, excluding financial firms ($BM_{Ex.fin.}$) and the second is industry-adjusted BM ($BM_{Ind.adj.}$). In both cases, market capitalization is updated monthly and we use only the largest stocks that cumulatively account for 90 percent of the total market capitalization in the cross section. Value returns are calculated from two strategies, a High-minus-Low value-weighted decile spreading portfolio ($H - L$) or a rank-weighted portfolio ($Rank$). Panel A reports unconditional performance statistics for monthly returns. Panel B presents the regression results for holding periods of $h = 1, 3, 6, 12, 24$ months. Panel C presents results for two alternative measures of value (sorting stocks on the negative of the past five-year return and sorting 17 industries on their book-to-market ratio, which is calculated as the value-weighted average BM within each industry) as well as market capitalization. To conserve space, we focus on the H-L portfolio strategy and present results only for $h = 6, 24$. The value spread, VS_t, is standardized to accommodate interpretation and t-statistics are calculated using Newey and West (1987) standard errors with h-lags.

Panel A: Unconditional Performance (Monthly Returns)

	$H-L$				$Rank$			
	Avg. ret.	St. dev.	t	Sharpe	Avg. ret.	St. dev.	t	Sharpe
$BM_{Ex.fin.}$	0.0028	0.0560	1.1274	0.0493	0.0018	0.0358	1.1650	0.0510
$BM_{Ind.adj.}$	0.0025	0.0393	1.4763	0.0646	0.0028	0.0241	2.6847	0.1175

Panel B: Predictive Regressions of Value Returns on the Value Spread

		$H-L$					$Rank$				
	h	a	b	t_a	t_b	$R^2 \times 100$	a	b	t_a	t_b	$R^2 \times 100$
$BM_{Ex.fin.}$	1	0.0028	0.0057	1.09	2.18	0.85	0.0018	0.0027	1.12	1.39	0.38
	3	0.0083	0.0183	1.19	3.00	2.95	0.0058	0.0081	1.26	1.77	1.25
	6	0.0174	0.0379	1.25	3.08	5.88	0.0126	0.0170	1.35	1.78	2.62
	12	0.0371	0.0872	1.33	3.78	13.73	0.0281	0.0405	1.45	2.08	6.55
	24	0.0788	0.2258	1.35	4.44	30.33	0.0658	0.1125	1.69	2.66	19.35
$BM_{Ind.adj.}$	1	0.0025	0.0063	1.44	2.79	2.41	0.0028	0.0030	2.55	1.94	1.32
	3	0.0082	0.0209	1.73	4.40	7.88	0.0090	0.0099	2.77	2.62	4.20
	6	0.0176	0.0450	1.90	5.05	16.60	0.0188	0.0212	2.86	2.79	8.29
	12	0.0367	0.0946	1.92	5.02	29.73	0.0404	0.0433	2.92	2.89	14.22
	24	0.0778	0.2184	1.97	5.02	45.24	0.0915	0.0978	3.31	3.19	26.83

Panel C: Alternative Value Measures and Market Cap

		$H-L$					$Rank$				
	h	a	b	t_a	t_b	$R^2 \times 100$	a	b	t_a	t_b	$R^2 \times 100$
−5-year return	6	0.0016	0.0376	0.11	1.96	5.34	0.0085	0.0173	0.86	1.22	2.54
	24	-0.0050	0.1483	-0.09	2.42	16.18	0.0364	0.0731	0.96	1.64	9.16
Industry BM	6	0.0033	0.0094	0.61	2.05	2.13	0.0051	0.0107	0.71	1.75	1.60
	24	0.0198	0.0585	0.78	2.73	14.36	0.0293	0.0623	0.88	2.15	10.15
Market cap	6	0.0178	0.0207	2.06	2.50	4.73	0.0136	0.0129	2.67	1.97	5.40
	24	0.0822	0.0927	1.94	3.63	13.88	0.0638	0.0787	2.54	3.29	25.58

TABLE 2: **Predicting Value Returns with the Value Spread: Alternative Asset Classes**

This table presents the results from overlapping predictive regressions of monthly value returns on the value spread: $R_{c,t+1:t+h} = a_h + b_h VS_{c,t} + \varepsilon_{t+1:t+h}$, in four alternative asset classes c. For commodities, the sample ranges from 1972 to 2014 and we measure value as the negative of the five-year spot return (−5-year return). For currencies, the sample ranges from 1976 to 2014 and we measure value as the negative of the five-year spot return (−5-year return), but also consider an inflation-adjusted version of this measure (Inf. adj. return). For government bonds, the sample ranges from 1991 to 2009 (dictated by the yield data of Wright (2011)) and we measure value as the negative of the five-year return of a one-month futures on a 10-year government bond (−5-year return), but also consider the five-year change in 10-year bond yield (5-year Δy). For stock indexes, the sample ranges from 1994 to 2014 and we measure value using the MSCI Book-to-Price ratio ($MSCI_{BP}$). Value returns are calculated from two strategies, a High-minus-Low equal-weighted spreading portfolio split at the median of ranked values ($H - L$) or a rank-weighted portfolio ($Rank$). Panel A reports unconditional performance statistics for monthly value returns in each asset class. Panel B presents the regression results for holding periods of $h = 1, 3, 6, 12, 24$ months. The value spread, $VS_{c,t}$, is standardized to accommodate interpretation and t-statistics are calculated using Newey and West (1987) standard errors with h-lags.

Panel A: Unconditional Performance (Monthly Returns)

		$H - L$				$Rank$			
Asset Class	Value Measure	Avg. ret.	St. dev.	t	Sharpe	Avg. ret.	St. dev.	t	Sharpe
Commodities	−5-year return	0.0026	0.0456	1.2846	0.0566	0.0030	0.0592	1.1643	0.0513
Currencies	−5-year return	0.0021	0.0186	2.4407	0.1129	0.0027	0.0233	2.4860	0.1150
	Inf. adj. return	0.0016	0.0178	1.9885	0.0920	0.0023	0.0231	2.1090	0.0976
Government Bonds	−5-year return	0.0004	0.0102	0.5932	0.0399	0.0007	0.0114	0.8646	0.0582
	5-year Δy	0.0010	0.0094	1.6534	0.1112	0.0018	0.0097	2.8047	0.1887
Stock Indexes	$MSCI_{BP}$	0.0009	0.0241	0.6079	0.0378	0.0017	0.0284	0.9454	0.0589

Panel B: Predictive Regressions of Value Returns on the Value Spread

			$H - L$					$Rank$				
		h	a	b	t_a	t_b	R^2	a	b	t_a	t_b	R^2
Commodities	−5-year return	1	0.0026	0.0021	1.29	0.94	0.03	0.0030	0.0018	1.15	0.61	-0.10
		3	0.0075	0.0074	1.38	1.18	0.67	0.0082	0.0071	1.13	0.91	0.26
		6	0.0146	0.0213	1.31	1.81	3.03	0.0153	0.0266	1.00	1.79	2.48
		12	0.0275	0.0597	1.27	2.94	10.68	0.0269	0.0854	0.88	2.81	11.32
		24	0.0716	0.0820	1.79	3.09	11.27	0.0693	0.1569	1.20	2.83	19.18

Continued

Asset Class	Value Measure	h	$H-L$ a	b	t_a	t_b	R^2	$Rank$ a	b	t_a	t_b	R^2
Currencies	−5-year return	1	0.0021	0.0015	2.35	1.77	0.44	0.0027	0.0024	2.41	2.22	0.85
		3	0.0064	0.0053	2.58	2.23	2.07	0.0082	0.0078	2.66	2.63	3.03
		6	0.0134	0.0099	2.86	2.10	3.76	0.0171	0.0147	2.87	2.57	5.33
		12	0.0290	0.0160	3.06	1.78	4.92	0.0367	0.0249	3.06	2.23	7.30
		24	0.0668	0.0426	3.77	2.73	15.30	0.0845	0.0589	3.88	3.11	18.44
	Inf. adj. return	1	0.0016	0.0012	1.94	1.35	0.22	0.0023	0.0016	2.04	1.38	0.24
		3	0.0051	0.0045	2.23	2.00	1.74	0.0070	0.0061	2.29	2.15	1.91
		6	0.0108	0.0096	2.38	2.20	4.11	0.0146	0.0138	2.42	2.38	4.82
		12	0.0236	0.0210	2.45	2.43	8.57	0.0320	0.0281	2.60	2.52	8.87
		24	0.0551	0.0430	2.87	2.56	15.17	0.0757	0.0501	3.29	2.45	13.35
Government Bonds	−5-year return	1	0.0004	0.0012	0.59	1.31	0.94	0.0007	0.0013	0.89	1.37	0.84
		3	0.0007	0.0038	0.47	2.01	4.53	0.0016	0.0040	1.00	1.94	4.43
		6	0.0013	0.0079	0.48	3.72	11.79	0.0031	0.0077	1.13	2.48	10.38
		12	0.0036	0.0152	0.65	3.97	21.74	0.0068	0.0141	1.28	3.42	18.68
		24	0.0099	0.0338	0.94	5.17	40.36	0.0170	0.0270	1.68	5.87	29.91
	5-year Δy	1	0.0010	0.0006	1.68	0.69	0.01	0.0018	0.0010	2.85	1.15	0.58
		3	0.0032	0.0025	2.17	1.23	2.16	0.0054	0.0037	3.52	2.07	4.72
		6	0.0067	0.0059	2.61	2.85	8.01	0.0110	0.0076	3.97	3.34	11.62
		12	0.0138	0.0086	2.73	2.86	8.74	0.0232	0.0120	4.60	3.51	14.89
		24	0.0336	0.0129	3.44	3.04	10.95	0.0519	0.0220	5.30	5.45	25.69
Stock Indexes	$MSCI_{BP}$	1	0.0009	0.0030	0.63	1.92	1.11	0.0017	0.0025	0.93	1.36	0.42
		3	0.0020	0.0079	0.56	2.10	3.49	0.0044	0.0076	0.91	1.58	1.92
		6	0.0031	0.0150	0.41	2.00	6.52	0.0077	0.0157	0.78	1.66	4.26
		12	0.0039	0.0305	0.23	1.88	10.09	0.0149	0.0387	0.71	1.77	10.09
		24	0.0030	0.0431	0.09	1.75	8.06	0.0263	0.0630	0.65	1.75	12.40

TABLE 3: **Predicting Value Returns with the Value Spread: Pooled Tests**

This table reports results from joint tests that pool the returns of value strategies across asset classes. We have two value strategies for US individual equities using book-to-market ($BM_{Ex.fin.}$ and $BM_{Ind.adj.}$) and four value strategies from alternative asset classes. For commodities, currencies, and bond indexes, we use as value measure the negative of the five year return (−5-year return); for stock indexes we use price-to-book ($MSCI_{BP}$). Panel A reports regression results for the pooled predictive regression, $R_{c,t+1:t+h} = a_h + b_h VS_{c,t} + \varepsilon_{c,t+1:t+h}$. We standardize the value spread, $VS_{c,t}$, in each asset class to make them comparable (to this end, we also scale the returns for each value strategy to a standard deviation of 15% annually). Panel B reports results for two sample halves split at June 1993. Panel C asks whether the value spread predicts returns, volatility, or Sharpe ratio at the annual horizon. The left-hand side variables are the average and standard deviation of returns from $t+1$ to $t+12$ as well as their ratio. Panel D reports results of a simple time-series regression of the cross-sectional average value return (over the six strategies) on the cross-sectional average (standardized) value spread: $\overline{R_{t+1:t+h}} = a_h + b_h \overline{VS_t} + \varepsilon_{t+1:t+h}$. We consider $h = 1, 3, 6, 12, 24, 48$ months and two portfolio weighting schemes: a High-minus-Low spreading portfolio ($H - L$) and a rank-weighted portfolio ($Rank$). Panel E reports results from the pooled and average-on-average regression when we use as left-hand side returns either the long- or short-end of the value strategy (focusing on the High-minus-Low portfolio). The t-statistics are Newey and West (1987) with h-lags for the average-on-average time-series regression and Driscoll and Kraay (1998) with h-lags for the pooled regression. The sample period is 1972 to 2014, but some alternative asset classes enter the sample only after 1972.

Panel A: Pooled Predictive Regression

	h	$H-L$					$Rank$				
		a	b	t_a	t_b	$R^2 \times 100$	a	b	t_a	t_b	$R^2 \times 100$
	1	0.0028	0.0043	2.66	3.59	0.98	0.0034	0.0036	3.14	2.83	0.69
	3	0.0083	0.0141	2.87	4.96	3.24	0.0104	0.0118	3.31	3.69	2.15
	6	0.0171	0.0306	3.15	5.55	7.02	0.0218	0.0261	3.48	4.08	4.68
	12	0.0359	0.0672	3.47	5.65	13.96	0.0464	0.0606	3.85	4.52	10.41
	24	0.0825	0.1489	3.67	5.54	23.82	0.1082	0.1404	4.74	4.60	21.03
	48	0.2174	0.3332	3.39	5.54	29.11	0.2820	0.2860	5.72	6.39	27.99

Panel B: Pooled Regression in Subsamples

	h	$H-L$					$Rank$				
		a	b	t_a	t_b	$R^2 \times 100$	a	b	t_a	t_b	$R^2 \times 100$
First half	6	0.0369	0.0298	3.91	3.55	6.26	0.0332	0.0260	3.21	3.02	4.38
	24	0.1946	0.1416	5.29	3.80	24.08	0.1825	0.1573	3.81	3.05	22.53
Second half	6	0.0033	0.0253	0.51	4.61	5.18	0.0137	0.0268	1.80	3.48	5.23
	24	-0.0020	0.1138	-0.09	4.08	15.36	0.0523	0.1152	2.61	5.06	17.73

Panel C: Predicting Returns, Volatility, and Sharpe Ratio

	h	$H-L$					$Rank$				
		a	b	t_a	t_b	$R^2 \times 100$	a	b	t_a	t_b	$R^2 \times 100$
Avg. ret.		0.0028	0.0047	3.65	4.96	12.03	0.0035	0.0041	4.05	4.38	8.80
St. dev.		0.0395	0.0028	19.56	1.54	2.72	0.0388	0.0033	17.61	1.73	3.20
Sharpe		0.0830	0.1065	3.70	3.76	8.84	0.1080	0.0893	4.13	3.09	5.82

Continued

Panel D: Average Value Return on Average Value Spread

h	$H-L$					$Rank$				
	a	b	t_a	t_b	$R^2 \times 100$	a	b	t_a	t_b	$R^2 \times 100$
1	0.0033	0.0034	2.95	2.00	1.68	0.0038	0.0028	3.27	1.72	1.10
3	0.0100	0.0114	3.30	3.13	5.77	0.0114	0.0090	3.50	2.38	3.33
6	0.0211	0.0248	3.65	3.76	13.20	0.0242	0.0189	3.68	2.54	6.52
12	0.0447	0.0517	4.03	4.29	25.21	0.0521	0.0423	3.96	2.69	13.90
24	0.1064	0.1130	4.42	5.06	39.68	0.1249	0.1126	4.67	3.34	34.35
48	0.2782	0.2507	4.41	6.28	44.35	0.3277	0.2386	6.23	6.10	49.70

Panel E: Predicting the Long- and Short-End of Value Returns

	h	$H-L$					$Rank$				
		a	b	t_a	t_b	$R^2 \times 100$	a	b	t_a	t_b	$R^2 \times 100$
Long	6	0.0478	0.0290	4.92	3.38	3.32	0.0503	0.0128	5.45	1.35	1.44
	24	0.2199	0.1227	5.37	3.14	8.98	0.2295	0.0557	5.87	1.28	5.40
Short	6	0.0307	-0.0016	3.28	-0.20	0.01	0.0292	-0.0120	3.19	-1.39	1.30
	24	0.1373	-0.0262	3.20	-0.62	0.39	0.1231	-0.0573	3.18	-1.49	5.22

TABLE 4: **Does the CAPM Explain Time-Variation in Value Returns?**
This table reports the results of a pooled predictive regression of returns on six value strategies (across different asset classes as in Table 3) on the value spread, controlling for exposure to a market benchmark: $R_{c,t+1} = a + bVS_{c,t} + \sum_{c=1}^{6} \beta_c(\imath_c \otimes R_{MKT,c,t+1}) + \varepsilon_{c,t+1}$, where $VS_{c,t}$ is the value spread of strategy c, $\imath_c$ denotes the c'th unit vector, and $R_{MKT,c,t+1}$ is the market benchmark. The market benchmark is common across asset classes in Panel A: the CRSP value-weighted stock market portfolio. The market benchmark is asset-class-specific in Panel B. For the value strategies using individual equities we use the CRSP value-weighted stock market portfolio, whereas for all remaining asset classes we use an equal-weighted portfolio of returns in that asset class as market benchmark. β_1 through β_6 represent the unconditional market exposure of the following value strategies: (1) individual equities ($BM_{Ex.fin.}$), (2) individual equities ($BM_{Ind.Adj.}$), (3) commodities (−5-year return), (4) currencies (−5-year return), (5) global government bonds (−5-year return), and (6) stock indexes ($MSCI_{BP}$). t-statistics are Driscoll and Kraay (1998) with h-lags. The full sample period is 1972 to 2014.

Panel A: Common Market Benchmark ($R_{MKT,c,t+1}$ = CRSP Value-Weighted Portfolio)

		a	b	β_1	β_2	β_3	β_4	β_5	β_6	$R^2 \times 100$
$H-L$	$Coef$	0.0028	0.0043	-0.2031	-0.0235	0.0177	0.1216	0.0913	0.1724	2.67
	(t)	2.67	3.57	-3.24	-0.36	0.38	1.90	1.42	2.48	
$Rank$	$Coef$	0.0035	0.0036	-0.2663	-0.0459	0.0384	0.1161	0.0481	0.2114	3.21
	(t)	3.21	2.89	-4.20	-0.68	0.82	1.84	0.72	3.29	

Panel B: Asset-Class-Specific Market Benchmark

		a	b	β_1	β_2	β_3	β_4	β_5	β_6	$R^2 \times 100$
$H-L$	$Coef$	0.0033	0.0042	-0.2043	-0.0248	-0.2137	-0.2865	-0.3137	0.2878	4.42
	(t)	3.16	3.56	-3.26	-0.38	-3.48	-2.21	-0.92	3.88	
$Rank$	$Coef$	0.0039	0.0035	-0.2673	-0.0469	-0.2609	-0.3686	0.3066	0.3601	6.17
	(t)	3.63	2.89	-4.21	-0.70	-3.99	-3.03	1.03	5.33	

Table 5: **Common and Specific Components of the Value Spread**

This table reports results for pooled predictive regressions of value returns on components of the value spread for six strategies: (1) individual equities ($BM_{Ex.fin.}$), (2) individual equities ($BM_{Ind.Adj.}$), (3) commodities (−5-year return), (4) currencies (−5-year return), (5) global government bonds (−5-year return), and (6) stock indexes ($MSCI_{BP}$). For these component-wise regressions, we average over the returns and value spreads of the two weighting schemes ($H-L$ and $Rank$) to smooth out noise introduced by each specific weighing scheme. Panel A reports the results of a pooled predictive regression on the value spread: $R_{c,t+1:t+h} = a_h + b_h VS_{c,t} + \varepsilon_{c,t+1:t+h}$. Panel B reports the results of a pooled regression on components of the value spread: $R_{c,t+1:t+h} = a_h + b_{h,Com} VS_t^{Com} + b_{h,Spec} VS_{c,t}^{Spec} + \varepsilon_{t+h}$, where we also report the pooled regression on each individual component. We define common value, $VS_t^{com} = N_t^{-1} \sum_{i=0}^{N_t} VS_{c,t}$, and specific value, $VS_{c,t}^{Spec} = VS_{c,t} - VS_t^{Com}$. R^2_{Com} is the proportion of variation in returns explained by the common component of the value spread, while R^2_{Spec} is the proportion of variation in returns explained by the specific component. R^2_{Cov} is the proportion of variation in returns explained by the covariance between common and specific value. t-statistics are calculated using Driscoll and Kraay (1998) standard errors with h-lags. The sample is 1972 to 2014, but some alternative asset classes enter the sample only after 1972.

Panel A: Averaged Value Return on Averaged Value Spread

h	a	b	t_a	t_b	$R^2 \times 100$
1	0.0032	0.0041	2.93	3.31	0.91
3	0.0094	0.0137	3.11	4.51	2.92
6	0.0194	0.0300	3.34	5.04	6.38
12	0.0404	0.0678	3.65	5.36	13.50
24	0.0912	0.1552	4.13	5.38	25.40
48	0.2448	0.3465	4.41	6.82	33.82

Panel B: Common and Specific Component of the Value Spread

h	a	b_{Com}	b_{Spec}	t_a	$t_{b_{Com}}$	$t_{b_{Spec}}$	$R^2 \times 100$	R^2_{Com}	R^2_{Spec}	R^2_{Cov}
1	0.0032	0.0048		2.92	2.22		0.52			
3	0.0094	0.0158		3.11	2.90		1.64			
6	0.0195	0.0334		3.34	3.18		3.31			
12	0.0405	0.0712		3.67	3.62		6.24			
24	0.0912	0.1676		4.17	4.58		12.56			
48	0.2420	0.3942		4.51	6.86		19.03			
1	0.0032		0.0036	2.89		2.81	0.41			
3	0.0094		0.0122	3.03		3.73	1.33			
6	0.0196		0.0278	3.17		4.26	3.15			
12	0.0413		0.0658	3.28		4.65	7.33			
24	0.0950		0.1474	3.15		4.88	13.07			
48	0.2486		0.3183	2.69		5.51	15.70			
1	0.0032	0.0048	0.0036	2.92	2.22	2.81	0.93	0.52	0.41	0.00
3	0.0094	0.0158	0.0121	3.11	2.90	3.73	2.97	1.64	1.33	0.00
6	0.0194	0.0333	0.0277	3.33	3.18	4.26	6.43	3.29	3.12	0.02
12	0.0403	0.0709	0.0656	3.66	3.62	4.65	13.52	6.19	7.28	0.05
24	0.0910	0.1667	0.1466	4.15	4.57	4.86	25.51	12.43	12.94	0.13
48	0.2441	0.3887	0.3130	4.53	6.78	5.24	34.20	18.50	15.18	0.52

Table 6: **Comovement Between Benchmark Predictors and the Value Spread**
This table regresses components of the value spread on benchmark predictors that previous literature argues capture time-variation in risk premia (a global recession dummy; the dividend yield; the default spread; the illiquidity premium (measured by the repo-spread); real uncertainty; and, intermediary leverage) as well as sentiment. Panel A reports results from time-series regressions of the the common component of the value spread (across six value strategies in different asset classes) on the benchmark predictors, $VS_t^{Com} = k_0 + k_1' Z_t + u_t$, where Z_t is the vector containing the time t realization of each benchmark predictor. We consider both simple regressions (Specifications 1 to 7) on each individual predictor as well as a multiple regression on all predictors jointly (Specification 8). To ensure our results are not driven only by the dividend yield, Specification 9 excludes this variable from the joint regression. Panel B regresses the specific component of the value spread in each asset class on the full set of predictors (as in Specification 8), $VS_{c,t}^{Spec} = k_0 + k_1 Z_t + u_t$, where $VS_{c,t}^{Spec}$ is the asset-class-specific value spread; $VS_{c,t} - VS_t^{Com}$. t-statistics are calculated using Newey and West (1987) standard errors with 12-lags. The full sample period is 1972 to 2014, but some alternative asset classes enter the sample only after 1972.

	Global Recession	Dividend Yield	Default Spread	Illiquidity Premium	Real Uncertainty	Intermediary Leverage	Sentiment	$R^2 \times 100$
Panel A: Common Value								
1	0.42							8.74
	(2.28)							
2		0.55						64.44
		(9.43)						
3			0.37					28.56
			(4.39)					
4				0.44				41.28
				(10.62)				
5					0.42			37.33
					(5.61)			
6						0.50		52.57
						(5.81)		
7							-0.21	8.91
							(-2.13)	
8	0.22	0.32	0.03	0.14	0.07	0.11	-0.04	75.64
	(2.24)	(3.65)	(0.56)	(2.77)	(1.11)	(1.15)	(-0.73)	
9	0.16		0.04	0.24	0.07	0.29	-0.08	68.93
	(1.50)		(0.70)	(4.22)	(1.09)	(3.89)	(-1.55)	
Panel B: Asset-Class-Specific Value								
Ind. Equities ($BM_{Ex.fin.}$)	0.12	0.28	0.20	0.04	0.05	-0.23	-0.10	49.51
	(1.13)	(3.08)	(4.92)	(1.00)	(0.95)	(-2.06)	(-2.33)	
Ind. Equities ($BM_{Ind.Adj.}$)	0.00	0.04	0.23	-0.04	0.11	0.03	-0.13	60.41
	(0.00)	(0.59)	(5.38)	(-1.22)	(1.93)	(0.32)	(-3.03)	
Commodities	-0.03	-0.44	-0.16	0.00	0.20	0.21	0.06	15.10
	(-0.17)	(-2.50)	(-1.20)	(-0.04)	(1.93)	(1.15)	(0.47)	
Currencies	-0.32	0.17	-0.01	0.06	-0.17	-0.20	0.34	29.44
	(-1.28)	(1.13)	(-0.06)	(0.50)	(-1.58)	(-1.41)	(4.28)	
Government Bonds	-0.57	0.72	-0.57	-0.03	0.03	-0.13	-0.08	57.63
	(-2.59)	(3.42)	(-3.52)	(-0.37)	(0.35)	(-0.70)	(-0.75)	
Stock Indexes	0.55	-0.27	-0.60	-0.08	-0.11	0.84	-0.34	41.53
	(2.37)	(-1.70)	(-3.34)	(-0.78)	(-1.22)	(2.85)	(-3.38)	

Table 7: **Common Versus Specific Value: Net of Benchmark Predictors**
This table presents the results from pooled predictive regressions of value returns on the explained and orthogonal components of common value (Panel A) and specific value (Panel B). The explained components of common and specific value (denoted $\widehat{VS_{c,t}^{Com}}$ and $\widehat{VS_{c,t}^{Spec}}$) are pre-estimated by regressing each series on the benchmark predictors used in Table 6, and saving the predicted value. The orthogonal component of common and specific value is the residual from this time-series regression. Panel A and B thus reports coefficient estimates from the regression, $R_{c,t+1:t+h} = a_h + b_{h,Com}^1(VS_{c,t}^{Com} - \widehat{VS_{c,t}^{Com}}) + b_{h,Com}^2\widehat{VS_{c,t}^{Com}} + \varepsilon_{c,t+1:t+h}$. Panel B presents results from the same regression for $VS_{c,t}^{Spec}$. We also consider a specification of the pre-estimation step that excludes the Dividend Yield from the set of benchmark predictors. t-statistics in the pooled regressions are calculated using Driscoll and Kraay (1998) standard errors with h-lags. We decompose the R^2 in each regression into the proportion of variation in returns explained by the explained and orthogonal components, of either common or specific value, as well as their covariance. The full sample period is 1972 to 2014, but some alternative asset classes enter the sample only after 1972.

Panel A: Returns on Components of Common Value

h	a	b_{Com}^1	b_{Com}^2	t_a	$t_{b_{Com}^1}$	$t_{b_{Com}^2}$	R^2	$R_{Com,Orthogonal}^2$	$R_{Com,Explained}^2$	R_{Cov}^2
1	0.0032	0.0075	0.0040	2.95	2.08	1.58	0.58	0.33	0.28	-0.03
3	0.0095	0.0224	0.0138	3.13	2.52	1.98	1.74	0.86	0.99	-0.10
6	0.0195	0.0365	0.0324	3.35	2.29	2.35	3.32	1.04	2.46	-0.18
12	0.0405	0.0688	0.0720	3.68	2.26	3.06	6.24	1.53	5.05	-0.34
24	0.0912	0.1658	0.1682	4.18	2.78	4.33	12.57	3.23	10.03	-0.69
48	0.2436	0.4327	0.3839	4.60	3.40	6.88	19.08	5.23	14.53	-0.67
Dividend Yield Excluded from Benchmark Predictors										
6	0.0195	0.0326	0.0337	3.41	2.02	2.21	3.31	1.05	2.41	-0.14
24	0.0911	0.1658	0.1684	4.18	3.49	4.55	12.57	4.04	9.11	-0.58

Panel B: Returns on Components of Specific Value

h	a	b_{Spec}^1	b_{Spec}^2	t_a	$t_{b_{Spec}^1}$	$t_{b_{Spec}^2}$	R^2	$R_{Spec,Orthogonal}^2$	$R_{Spec,Explained}^2$	R_{Cov}^2
1	0.0032	0.0043	0.0027	2.89	2.58	1.22	0.42	0.33	0.09	0.00
3	0.0094	0.0142	0.0092	3.03	3.50	1.75	1.39	1.07	0.31	0.00
6	0.0196	0.0328	0.0204	3.17	4.47	1.81	3.30	2.61	0.68	0.01
12	0.0413	0.0677	0.0629	3.28	5.14	2.41	7.34	4.63	2.68	0.03
24	0.0948	0.1264	0.1782	3.14	4.55	3.23	13.46	5.72	7.77	-0.02
48	0.2495	0.2455	0.4330	2.66	4.53	4.55	17.10	5.89	11.84	-0.63
Dividend Yield Excluded from Benchmark Predictors										
6	0.0196	0.0273	0.0287	3.17	3.84	2.44	3.15	1.98	1.13	0.03
24	0.0948	0.1145	0.2117	3.11	4.58	3.63	14.32	5.19	9.00	0.13

Table 8: **Common Value versus Principal Component of Benchmark Predictors**
This table runs a horse race between a principal component of seven benchmark predictors ((1) a global recession dummy; (2) the dividend yield; (3) the default spread; (4) the illiquidity premium; (5) real uncertainty; (6) intermediary leverage; and, (7) sentiment) and our measure of common value. Panel A presents results from pooled predictive regressions of value returns (from six value strategies: (1) individual equities ($BM_{Ex.fin.}$), (2) individual equities ($BM_{Ind.Adj.}$), (3) commodities (−5-year return), (4) currencies (−5-year return), (5) global government bonds (−5-year return), and (6) stock indexes ($MSCI_{BP}$)) on the first principal component of the benchmark predictors: $R_{c,t+1:t+h} = a_h + b_h Macro_t^{PC1} + \varepsilon_{c,t+1:t+h}$. Panel B controls for common value, which we define as the simple average value spread over the asset classes. t-statistics are calculated using Driscoll and Kraay (1998) standard errors with h-lags. The full sample period is 1972 to 2014, but the alternative asset classes enter the sample only after 1972.

Panel A: Value Returns on Principal Component of Benchmark Predictors

h	a	$b_{Macro^{PC1}}$	t_a	$t_{b_{Macro^{PC1}}}$	$R^2(\%)$
1	0.0035	0.0013	2.99	1.46	0.27
3	0.0105	0.0043	3.23	1.83	0.94
6	0.0222	0.0102	3.55	2.27	2.38
12	0.0470	0.0229	4.00	3.14	4.92
24	0.1061	0.0508	4.18	3.81	8.82
48	0.2681	0.1126	4.16	4.34	12.17

Panel B: Principal Component of Benchmark Predictors versus Common Value

h	a	$b_{Macro^{PC1}}$	b_{Com}	t_a	$t_{b_{Macro^{PC1}}}$	$t_{b_{Com}}$	$R^2(\%)$
1	0.0030	-0.0006	0.0062	2.55	-0.42	1.74	0.54
3	0.0091	-0.0013	0.0188	2.64	-0.32	2.13	1.67
6	0.0197	0.0007	0.0318	3.00	0.09	2.04	3.31
12	0.0418	0.0047	0.0605	3.62	0.44	2.18	6.30
24	0.0915	0.0012	0.1649	4.10	0.10	3.34	12.57
48	0.2376	-0.0203	0.4421	4.56	-0.58	4.33	19.14

Table 9: **Value Timing in Individual Equities**

This table reports unconditional performance statistics for the monthly returns of a strategy that times value using the signal: $VS_{t,His} = \sigma(VS_{1:t-12})^{-1}((12)^{-1}\sum_{s=0}^{11} VS_{t-s} - (t-12)^{-1}\sum_{s=12}^{t-1} VS_{t-s})$. $VS_{t,His}$ captures deviations of last year's value spread from the historical average value spread and is observable at time t. We present results for a unit weight strategy that passively captures the unconditional value premium, a linear timing strategy that invests $VS_{t,His}$ dollars, and, finally, a combined strategy that invests $1+VS_{t,His}$. We consider $2\times2\times3$ variations of each value strategy: using (i) either the book-to-market signal excluding financials or the industry-adjusted book-to-market ratio, (ii) either the High-minus-Low decile portfolio or the rank-weighted portfolio, and (iii) the largest stocks whose market caps cumulate to either 90%, 95%, or 75% of total market cap in the CRSP file. To make these different value strategies comparable, we scale each value return series to have an annualized standard deviation of 15%. We perform this standardization in each month relative to the last ten years of returns so that we do not use forward looking information. The sample period is 1972 to 2014.

Market Cap Cutoff		90%					95%					75%				
		Avg. ret.	t	Sharpe	α_{CAPM}	t_α	Avg. ret.	t	Sharpe	α_{CAPM}	t_α	Avg. ret.	t	Sharpe	α_{CAPM}	t_α
Panel A: High-minus-Low Portfolios																
Ind. Equities ($BM_{Ex.fin.}$)	Unit weight	0.0009	0.45	0.0196	0.0022	1.05	0.0021	1.04	0.0454	0.0033	1.59	0.0003	0.15	0.0064	0.0015	0.73
	Linear Timing	0.0067	2.70	0.1183	0.0061	2.44	0.0052	2.26	0.0990	0.0044	1.90	0.0065	2.22	0.0971	0.0058	1.97
	Combined	0.0076	2.71	0.1185	0.0082	3.00	0.0073	2.80	0.1224	0.0077	3.02	0.0068	2.31	0.1012	0.0072	2.49
Ind. Equities ($BM_{Ind.adj.}$)	Unit Weight	0.0023	1.15	0.0503	0.0025	1.23	0.0026	1.30	0.0569	0.0028	1.37	0.0025	1.29	0.0567	0.0031	1.59
	Linear Timing	0.0076	3.04	0.1330	0.0070	2.99	0.0072	2.96	0.1296	0.0066	2.90	0.0058	2.30	0.1005	0.0053	2.15
	Combined	0.0098	3.38	0.1480	0.0095	3.51	0.0098	3.38	0.1479	0.0094	3.49	0.0084	2.95	0.1293	0.0084	3.00
Panel B: Rank-Weighted Portfolios																
Ind. Equities ($BM_{Ex.fin.}$)	Unit weight	0.0012	0.59	0.0259	0.0029	1.39	0.0025	1.20	0.0526	0.0041	1.99	0.0007	0.35	0.0155	0.0023	1.17
	Linear Timing	0.0057	2.17	0.0948	0.0054	2.02	0.0049	1.94	0.0848	0.0046	1.80	0.0043	1.42	0.0622	0.0038	1.19
	Combined	0.0069	2.19	0.0960	0.0083	2.65	0.0074	2.46	0.1075	0.0087	2.93	0.0050	1.58	0.0690	0.0061	1.87
Ind. Equities ($BM_{Ind.adj.}$)	Unit Weight	0.0046	2.25	0.0986	0.0050	2.36	0.0061	2.97	0.1299	0.0063	2.93	0.0036	1.78	0.0781	0.0046	2.23
	Linear Timing	0.0059	2.16	0.0944	0.0057	2.04	0.0043	1.70	0.0743	0.0042	1.62	0.0050	1.67	0.0732	0.0044	1.42
	Combined	0.0105	3.21	0.1406	0.0107	3.34	0.0104	3.41	0.1492	0.0105	3.53	0.0086	2.65	0.1159	0.0089	2.70

TABLE 10: **Value Timing in the Pool of Value Strategies**

This table reports results for pooled predictive regressions of returns on six value strategies ((1) individual equities ($BM_{Ex.fin.}$), (2) individual equities ($BM_{Ind.Adj.}$), (3) commodities (−5-year return), (4) currencies (−5-year return), (5) global government bonds (−5-year return), and (6) stock indexes ($MSCI_{BP}$)) on a dummy variable indicating whether the current value spread in an asset class is historically high or low. To be precise, we run $R_{c,t+1:t+h,15\%} = a + bI_{VS_{c,t,His}>0} + e_{c,t+1:t+h}$, where $I_{VS_{c,t,His}>0}$ is an indicator function that is one when the timing signal, $VS_{c,t,His} = \sigma(VS_{c,1:t-12})^{-1}((12)^{-1}\sum_{s=0}^{11} VS_{c,t-s} - (t-12)^{-1}\sum_{s=12}^{t-1} VS_{c,t-s})$ is positive, and zero otherwise. $Value_{c,t,His}$ captures deviations of the last year average value spread from the historical average value spread of asset class c. We consider returns of both High-minus-Low and rank-weighted value strategies. To make the value strategies comparable across asset classes, we scale each return series to have an annualized standard deviation of 15%. We perform this standardization in each month relative to the last ten years of returns so that we do not use forward looking information. t-statistics in the pooled regressions are calculated using Driscoll and Kraay (1998) standard errors with h-lags. Panel B reports unconditional performance statistics for a value strategy that invests only in asset class, c when $Value_{c,t,His} > 0$, which average return is equal to the sum of the estimated coefficients $a + b$ from the pooled regression at horizon $h = 1$. Conversely, the average return of a strategy that only invests in the value strategy of asset class c when $Value_{c,t,His} \leq 0$ is equal to the estimated intercept a. The full sample period is 1972 to 2014, but some alternative asset classes enter the sample only after 1972.

Panel A: Pooled Regression on Dummy indicating High Value Spread

	$H-L$					$Rank$				
h	a	b	t_a	t_b	R^2	a	b	t_a	t_b	R^2
1	-0.0005	0.0072	-0.30	2.97	0.62	0.0012	0.0054	0.77	2.02	0.33
3	-0.0012	0.0213	-0.29	3.39	1.63	0.0042	0.0156	0.91	2.16	0.82
6	-0.0009	0.0397	-0.11	3.18	2.58	0.0099	0.0304	1.06	2.08	1.42
12	-0.0022	0.0851	-0.13	3.16	5.16	0.0211	0.0665	1.09	2.16	2.86
24	-0.0106	0.2015	-0.25	2.86	8.82	0.0505	0.1458	1.27	1.87	4.51
48	-0.0803	0.6010	-0.64	3.27	16.14	0.101489	0.4015	1.04	2.49	10.03

Panel B: Implied Performance of Timing Value across Asset Classes

	$H-L$			$Rank$		
	Avg. ret.	St. dev.	Sharpe	Avg. ret.	St. dev.	Sharpe
Invest when $VS_{c,t,His} > 0$	0.0068	0.0450	0.1508	0.0066	0.0466	0.1414
Invest when $VS_{c,t,His} \leq 0$	-0.0005	0.0436	-0.0104	0.0012	0.0435	0.0281

Table 11: **Rotating Value Across Asset Classes**

This table reports unconditional performance statistics for monthly returns of strategies that rotate value across asset classes and overweight (underweight) those asset classes where the value spread is high (low) relative to the other asset classes. As a benchmark, we consider an unconditional value strategy that invests, in each sample month t, $1/N_t$ in each of the N_t available value strategies (out of the maximum of six). The first rotation strategy takes a position in each asset class i in month t equal to $w_{c,t}^{rot,1} = q_t(VS_{c,t,His} - Mean(VS_{c,t,His})$, where the scalar q_t ensures that the total weight in the long and short position equal one. The second strategy, with weights denoted $w_{c,t}^{rot,2}$, invests an equal weight in each asset class with $VS_{c,t,His}$ above (below) the mean value spread across asset classes. We calculate performance measures for these two long-short rotation strategies (denoted $Rotation_{Long-Short}$) as well as for a combination with the unconditional strategy (denoted $Combined_{Long-Short}$). We also present results for the long-only position of the rotation strategies. The reported α is relative to an unconditional market strategy, which equally-weights the market portfolio in each asset class (defined as in Table 4). As before, the value strategy returns are scaled in each asset class to have a standard deviation of 15% using only backward looking information. We lose the first 120 months of returns in each asset class, as we need these to construct a backward-looking value signal. Therefore the full out-of-sample period is 1982 to 2014. Panel B reports the fraction of the long-leg of the two rotation strategies that is invested in each asset class.

Panel A: Performance of Value Rotation Strategies

	Linear Weight ($w_{c,t}^{rot,1}$)						Equal-weight ($w_{c,t}^{rot,2}$)					
	Avg. ret.	St. dev.	t	Sharpe	α	t	Avg. ret.	Std. dev.	t	Sharpe	α	t
	High-minus-Low Value Strategies ($H-L$)											
Unconditional	0.0015	0.0252	1.21	0.0608	0.0018	1.32	0.0015	0.0252	1.21	0.0608	0.0018	1.32
$Rotation_{Long-Short}$	0.0056	0.0525	2.13	0.1070	0.0036	1.43	0.0049	0.0486	2.02	0.1017	0.0030	1.25
$Rotation_{Long}$	0.0050	0.0399	2.50	0.1257	0.0039	1.97	0.0046	0.0358	2.57	0.1293	0.0036	2.00
$Combined_{Long-Short}$	0.0072	0.0573	2.48	0.1248	0.0054	1.96	0.0065	0.0529	2.43	0.1223	0.0048	1.83
$Combined_{Long}$	0.0065	0.0580	2.25	0.1129	0.0057	1.92	0.0062	0.0549	2.23	0.1123	0.0054	1.88
	Rank-Weighted Value Strategies ($Rank$)											
Unconditional	0.0028	0.0265	2.09	0.1049	0.0030	2.12	0.0028	0.0265	2.09	0.1049	0.0030	2.12
$Rotation_{Long-Short}$	0.0041	0.0533	1.54	0.0775	0.0022	0.82	0.0045	0.0490	1.82	0.0916	0.0029	1.15
$Rotation_{Long}$	0.0057	0.0392	2.92	0.1466	0.0048	2.42	0.0057	0.0363	3.13	0.1571	0.0050	2.71
$Combined_{Long-Short}$	0.0069	0.0564	2.44	0.1225	0.0052	1.87	0.0073	0.0522	2.77	0.1393	0.0059	2.23
$Combined_{Long}$	0.0085	0.0582	2.91	0.1464	0.0078	2.60	0.0085	0.0558	3.02	0.1519	0.0080	2.76

Panel B: % Allocation to each Assset Class in $Rotation_{Long}$

	Linear Weight ($w_{c,t}^{rot,1}$)		Equal-weight ($w_{c,t}^{rot,2}$)	
	$H-L$	$Rank$	$H-L$	$Rank$
Ind. Equities ($BM_{Ex.fin.}$)	0.07	0.08	0.10	0.10
Ind. Equities ($BM_{Ind.adj.}$)	0.09	0.07	0.10	0.08
Commodities	0.31	0.30	0.31	0.30
Currencies	0.27	0.30	0.24	0.29
Government bonds	0.08	0.07	0.09	0.09
Stock indexes	0.18	0.17	0.15	0.15

A Variable Construction

In this section, we describe our data sources and methodology for constructing value strategies in different asset classes. We also validate our data through a direct comparison with Asness et al. (2013).

A.1 US Individual Stocks

The US stock universe consists of all common equity in CRSP that trade on the NYSE, AMEX, and NASDAQ (sharecodes 10 and 11; exchange codes 1 to 3), which we match to book values from Compustat. Following Davis et al. (2000), we compute book equity as shareholder's book equity, plus balance sheet deferred taxes and investment tax credit (item TXDITC) minus the book value of preferred stock. Shareholders' equity is the Compustat item SEQ if available. Otherwise, we compute shareholders' equity as common equity (item CEQ) plus the par value of preferred stock (item PSTK), or total assets (AT) minus total liabilities (LT). When TXDITC is absent, we compute deferred taxes and investment tax credit as deferred taxes (item TXDB) plus investment tax credit (item ITCB). We define the book value of preferred stock as redemption (item PSTKRV), liquidating (item PSTKL) or par value (item PSTK), depending on availability. Delisting returns realised after the last trading day of month t are considered to have accrued in month *t+1*.

Following Asness et al. (2013), we limit the analysis to a sample from January 1972 to December 2014 and a universe of stocks that is liquid and that can be traded at reasonably low cost in sizeable trading volume. Specifically, we rank stocks, in the cross section, based on their end-of-month t market capitalization in descending order. We then sample the stocks that account cumulatively for 90% of the total market capitalization of the entire stock market in month t.

We measure value for firm i as the ratio of book value of equity to market value of equity: $BM_{i,t} = \frac{BE_{i,t}}{ME_{i,t}}$. Book equity is updated every June using data from the previous fiscal year to ensure that the data was available to investors at the time of portfolio formation. Market values are updated monthly following Asness and Frazzini (2013). We consider two alternative value strategies. In the first strategy, we construct our value portfolios excluding all financial firms, which we denote: $BM_{Ex.fin.}$. The motivation is that the same book-to-market ratio may signal distress for a non-financial firm, but not for a financial firm (Fama and French, 1995). The second strategy uses industry-adjusted book-to-market ratios, which we denote as $BM_{Ind.adj.}$. We compute this measure as:

$$BM_{i,t,Ind.adj.} = BM_{i,t} - J_K^{-1} \sum_j BM_{j,t} I_K(i) \tag{A.1}$$

where $J_K^{-1} \sum_i BM_{i,t} I_K(i)$ is the value-weighted average book-to-market ratio of the industry K (which contains a total of J_K firms) to which stock i belongs (as determined by the indicator function $I_K(i)$). We use the 17 industry classification available on Kenneth French's webpage. To be consistent with our analysis of individual stocks, we construct these industry portfolios using only the restricted set of relatively large stocks.

A.2 Commodity Futures

We obtain futures price data on Crude Oil, Gasoline, Heating Oil, Natural Gas, Gas-Oil Petroleum, Coffee, Rough Rice, Orange Juice, Cocoa, Soybean Oil, Soybean Meal, Soybeans, Corn, Oats, Wheat, Cotton, Gold, Silver, Platinum, Feeder Cattle, Live Cattle, Lean Hogs from the Commodity Research Bureau and Aluminium, Nickel, Tin, Lead, Zinc, and Copper from Datastream. We calculate monthly returns as the return on the nearest-to-maturity futures contract: $R_{i,t}^{fut} = Price_{i,t}^{T_1} / Price_{i,t-1}^{T_1} - 1$, where $Price_{i,t}^{T_1}$ is the time t price of the nearest-to-maturity futures contract of commodity i. We exclude contracts that mature in month *t+1*.

For commodities, we measure value as the negative of the five year log spot return (−5-year return) as in Asness et al. (2013). As spot prices of commodities are illiquid, we use the nearest-to-maturity futures prices to calculate the signal: −5-year return= $ln(\overline{Price_{i,t-60}^{T_1}} / Price_{i,t}^{T_1})$, where $\overline{Price_{i,t-60}^{T_1}}$ is the average price from 4.5 to 5.5 years ago to smooth out some noise. The sample period runs from January 1972 (when we have data for eleven commodities) to December 2014 (when we have data for all 28 commodities).

A.3 Currencies

We obtain exchange rate data (spot and one-month forward rates) from Datastream for 9 countries: Australia, Canada, Germany (replaced with the Euro from January 1999), Japan, New Zealand, Norway, Sweden, Switzerland and the UK. We compute currency returns as:

$$R_{i,t+1}^{Cur} = (e_{i,t+1} / f_{i,t}) - 1 \tag{A.2}$$

where $e_{i,t}$ is the time t spot exchange rate and $f_{i,t}$ is the previous month's closing price of a one-month forward.

We consider two measures of value, which closely follow Asness et al. (2013). Our first measure of value for currencies is the negative of the five year log spot return: −5-year return= $ln(\overline{e_{i,t-60}} / e_{i,t})$, where $\overline{e_{i,t-60}}$ is the average spot exchange rate from 4.5 to 5.5 years ago to smooth out some noise. Our second measure of value adjusts this five-year return with inflation, by subtracting the five-year foreign-US inflation difference. Consumer Price Indexes are from Global Financial Data, and we interpolate the quarterly Australian and New Zealand CPI estimates to get a monthly series. This second measure represents the 5-year change in purchasing power parity, which is a natural choice to measure value in currencies. Requiring both measures of value to be available, we end up with a sample period from February 1976 (four currencies) to December 2014 (all currencies available).

A.4 Global Government Bonds

The universe of government bond securities we analyze consists of Australia, Canada, Germany, Japan, Norway, New Zealand, Sweden, Switzerland, the UK and the US. We use constant maturity, zero coupon bond yields from Jonathan Wright's webpage to calculate synthetic bond futures prices and returns and to define our value measures. We also construct traded bond index futures returns using first and second generic nearest-to-maturity futures prices from Bloomberg. These are available for six of the ten countries only (Australia, Canada, Germany, Japan, the UK and the US). Table A.1 provides Bloomberg tickers for the futures contracts we use.

[Insert Table A.1 about here]

Following Koijen et al. (2017), we calculate the monthly dollar excess return on a fully-collateralized, currency-hedged position in the foreign currency-denominated futures contracts (see their Appendix A). To be precise, for each bond index futures i the monthly return of the first-nearby futures strategy (that rolls at the end of the month prior to expiration) equals:

$$R^{fut}_{i,t+1} = \frac{Price^{T_n}_{i,t+1} - Price^{T_n}_{i,t}}{Price^{T_n}_{i,t}} + \frac{e_{i,t+1} - e_{i,t}}{e_{i,t}} \frac{Price^{T_n}_{i,t+1} - Price^{T_n}_{i,t}}{Price^{T_n}_{i,t}} \tag{A.3}$$

where $Price^{T_n}_{i,t}$ is the foreign currency price of the second-nearby generic futures contract, $(Price^{T_2}_{i,t})$, in roll-over months (which are the same for all bond indexes: March, June, September, and December) and the first-nearby generic futures contract, $(Price^{T_1}_{i,t})$, in all other months. $e_{i,t}$ is the time t exchange rate (in USD per unit of foreign currency i). Each month, we calculate the price of a synthetic one-month futures on the ten year zero coupon bond (with spot price $S^{120}_{i,t} = exp(-y^{120}_{i,t} \times 120)$) from the no-arbitrage relation:

$$Price^{1,syn}_{i,t} = S^{120}_{i,t} \times exp(y^{1}_{i,t}). \tag{A.4}$$

At expiration, the price of the one-month futures contract equals the spot price of a bond that matures in nine years and eleven months: $Price^{0,syn}_{i,t+1} = S^{119}_{i,t+1} = exp(-y^{119}_{i,t+1} \times 119)$, where $y^{119}_{i,t+1}$ is found by linear interpolation. As for the traded bond returns, we calculate synthetic futures returns from these prices assuming that the investor is fully-collateralized and hedges out the currency risk (denoted $R^{Syn.fut.}_{i,t+1}$).

For these global government bonds, we define two measures of value. Given that traded bond futures data is relatively scarce, we define the value measures using the yield data of Jonathan Wright. The first value measure is the negative of the five-year log return of the one-month future on the ten-year zero coupon bond,

$$\text{5-year return} = -ln(\prod_{j=1}^{60} 1 + R^{Syn.fut.}_{i,t-j+1}). \tag{A.5}$$

The second value measure we consider is the five-year change in the ten-year yield (5-year Δy).

A.5 Global Stock Indexes

The global stock index futures data cover thirteen markets: Australia (S&P ASX 200), Canada (S&P TSE 60), France (CAC), Germany (DAX), Hong Kong (Hang Seng), Italy (FTSE MIB), Japan (Nikkei), the Netherlands (EOE AEX), Sweden (OMX), Spain (IBEX), Switzerland (SMI), the UK (FTSE 100) and the US (S&P 500). We collect spot and (first and second generic nearest-to-maturity) futures prices from Bloomberg.

[Insert Table A.1 about here]

Following Koijen et al. (2017), we calculate the monthly dollar excess return on a fully-collateralized, currency-hedged position in the foreign currency-denominated stock index futures contracts using Equation A.3.

As in Asness et al. (2013), we use the inverse of the MSCI country-level price-to-book ratio as our measure of value for stock indexes (available from Datastream (ticker: MSBP) and denoted $MSCI_{BP}$). Requiring both past five-year returns and book-to-price to be available, we end up with a sample period from January 1994 (four markets) to December 2014 (all markets available).

A.6 Data Validation

Table A.2 serves to validate our data and presents results for the pooled and average-on-average predictive regression for the rank-weighted value returns used in Asness et al. (2013). The right-hand side value spreads are calculated using our own data (as used in Table 3). In short, we see that our value spreads predict these alternative returns in a statistically and economically significant way. The estimated intercepts are similar to what we find, indicating that we match well the unconditional value premia of Asness et al.

(2013) over the sample period over which we observe value returns in the different asset classes. The conditional variation in value premia due to the value spread is somewhat weaker than for our returns, however. This result is clear from the lower ratio of the coefficient estimate to the intercept (slightly below 1) and the R^2 (at 10% and 19% for $h = 24$ for the pooled and average-on-average specifications).

This difference is only partly due to the fact that the set of value strategies used in these tests excludes the individual equity strategy based on industry-adjusted book-to-market, which Asness et al. (2013) do not analyze. Indeed, there are additional differences in the two samples mostly driven by data availability. First, they have returns for more assets in some markets. For instance, we do not have available for five additional countries (in either Bloomberg or Datastream) the returns to a synthetic MSCI index swap instrument. Second, they have a longer history in some markets. For currencies, for instance, they have data for all ten countries available from 1980, whereas we have complete data only from 1990 onwards. To the extent that these differences introduce a disconnect between the two datasets, one would indeed expect the results to become weaker. The fact that our conclusions extend even in the presence of this disconnect is a testament to the strength of the information in the value spread.

Table A.1: **Bloomberg Index Tickers**

The table reports the tickers for the first and second generic futures prices series for global stock indexes and global government bonds from Bloomberg. To retrieve the first or second generic futures series, replace "**x**" in the futures ticker with 1 and 2. For example, SP1 Index and SP2 Index are the first and second generic futures contracts for the S&P 500 and XM1 Comdty and XM2 Comdty are the first and second generic futures contracts for the Australian 10-year bond.

Country	Spot Ticker	Futures Ticker	Bond Ticker	Futures Ticker
	Stock Index Tickers		Zero Coupon Bond Tickers	
Australia	AS51 Index	XPx Index	F12710y Index	XMx Comdty
Canada	SPTSX60 Index	PTx Index	F10110y Index	CNx Comdty
France	CAC Index	CFx Index		
Germany	DAX Index	GXx Index	F91010y Index	RXx Comdty
Hong Kong	HSI Index	HIx Index		
Italy	FTSEMIB Index	STx Index		
Japan	NKY Index	NKx Index	F10510y Index	JBx Comdty
Neatherlands	AEX Index	EOx Index		
New Zealand	-	-	F25010y Index	-
Norway	-	-	F26610y Index	-
Sweden	OMX Index	QCx Index	F25910y Index	-
Spain	IBEX Index	IBx Index		
Switzerland	SMI Index	SMx Index	F25610y Index	-
UK	UKX Index	Zx Index	F11010y Index	Gx Comdty
US	SPX Index	SPx Index	F08210y Index	TYx Comdty

TABLE A.2: **Pooled Tests for Asness et al. (2013) Value Returns on our Value Spreads**
This table reports the results from the validation exercise. We regress rank-weighted value returns of Asness et al. (2013) (as available from `http://www.lhpedersen.com/data`) on our rank-weighted average value spreads. We consider the pooled and average-on-average specification (see Table 3). The number of value strategies included in each test is five: individual equities ($BM_{Ex.fin.}$); commodities, currencies, and bond indexes (the negative of the five year return, −5-year return); and, stock indexes ($MSCI_{BP}$). To make the asset classes comparable, we standardize the value spread and scale the value return to a standard deviation of 15% annually. The t-statistics are Newey and West (1987) with h-lags for the average-on-average time-series regression and Driscoll and Kraay (1998) with h-lags for the pooled regression. The full sample period is 1972 to 2014, but some alternative asset classes enter the sample only after 1972.

	Pooled					Average-on-Average				
h	a	b	t_a	t_b	$R^2 \times 100$	a	b	t_a	t_b	$R^2 \times 100$
1	0.0032	0.0024	3.01	2.21	0.33	0.0040	0.0031	3.73	1.80	1.55
3	0.0101	0.0083	3.36	2.91	1.12	0.0127	0.0102	4.34	2.33	5.06
6	0.0210	0.0188	3.48	3.14	2.55	0.0268	0.0233	4.67	3.30	12.37
12	0.0458	0.0412	4.03	3.57	5.01	0.0576	0.0444	5.34	4.86	19.74
24	0.0980	0.0897	4.43	4.06	10.47	0.1225	0.0661	5.37	3.36	18.85

B Three-Pass Regression Filter and the Value Spread

Kelly and Pruitt (2015) propose a three-pass regression filter (3PRF) that exploits the wealth of information in a cross section of predictor variables with a relatively short time series. Given a forecast target, the 3PRF constructs a single forecasting factor that is a linear combination of the predictor variables that are driving the forecast target itself. Importantly, the 3PRF estimator requires specifying only the number of relevant factors, regardless of the total number of common factors driving the cross section of predictors. Practically, they use a cross section of valuation ratios to construct a single forecasting factor for the market risk premium. We adopt the 3PRF to forecast the returns of a value-minus-growth strategy using a cross section of portfolio-level book-to-market ratios.

In the first step of the 3PRF, we estimate time-series regressions of the book-to-market ratio in month t of each decile portfolio on the forecast target, the High-minus-Low book-to-market decile spreading return in month $t+1$. Figure B.1 plots the coefficients. We observe that the coefficients are monotonically decreasing from High to Low for both value measures, i.e., book-to-market excluding financials and industry-adjusted book-to-market. This finding suggests that the High-minus-Low value spread is likely to be close to the single, optimal 3PRF forecasting factor. We confirm this intuition in Figure B.2, which plots the time series of the extracted factor versus the High-minus-Low value spread. To be precise, in the second step of the 3PRF, we estimate cross-sectional regressions in each month t of ten book-to-market ratios on the ten estimated coefficients from step 1. The estimated loading in this second step represents the single, optimal 3PRF forecasting factor. We see that the two series are almost identical, with correlations exceeding 0.995, suggesting that the two measures contain virtually identical information.

[**Insert Figures B.1 and B.2 about here**]

We conclude that using the High-minus-Low value spread to predict value-minus-growth returns is not only a natural and simple choice that is particularly suited to real-time exercises, but it is also the statistically optimal way to combine the cross section of valuation ratios of book-to-market sorted portfolios.

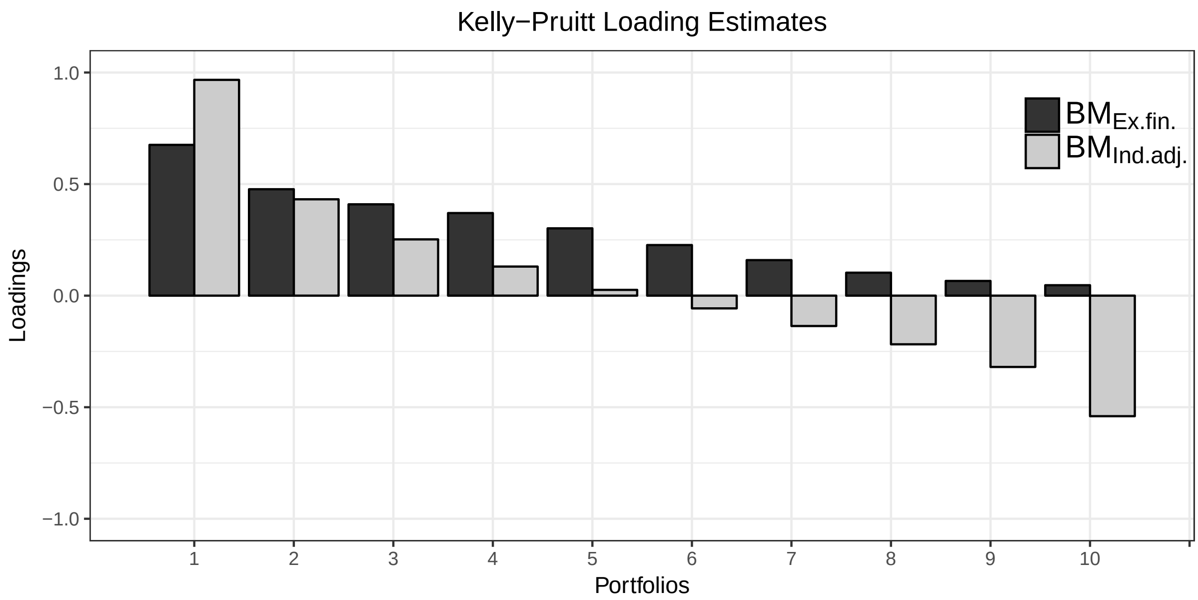

Figure B.1: **Kelly-Pruitt Loading Estimates**
This figure shows the loadings in the first stage of the 3PRF procedure of Kelly and Pruitt (2013). We apply their procedure to predict the High-minus-Low book-to-market decile spreading return using the valuation ratios of ten book-to-market deciles. We consider two measures of book-to-market: BM Ex. Fin. is the liquid US stock sample excluding financial firms, BM Ind. Adj. uses industry-adjusted book-to-market ratios.

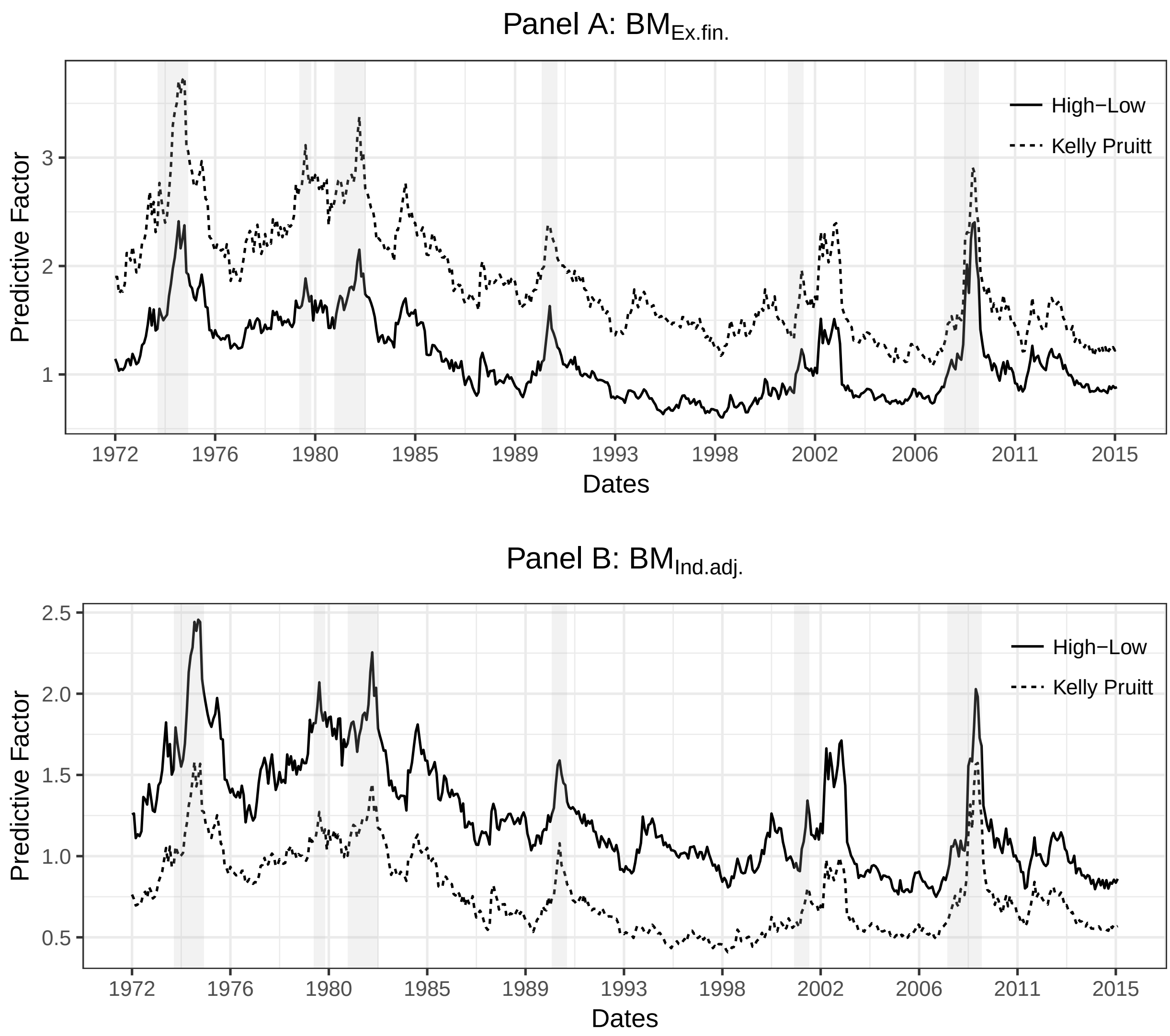

FIGURE B.2: **Kelly-Pruitt and High-minus-Low Predictive Factor**
This figure compares the latent predictive factor of Kelly and Pruitt (2013) extracted from the valuation ratios of ten book-to-market portfolios (either using all stocks except for financials (Panel A) or using industry-adjusted book-to-market ratios (Panel B)) to the High-minus-Low value spread for the sample period from 1972 to 2015. The shaded areas represent NBER recessions.

C Robustness Checks

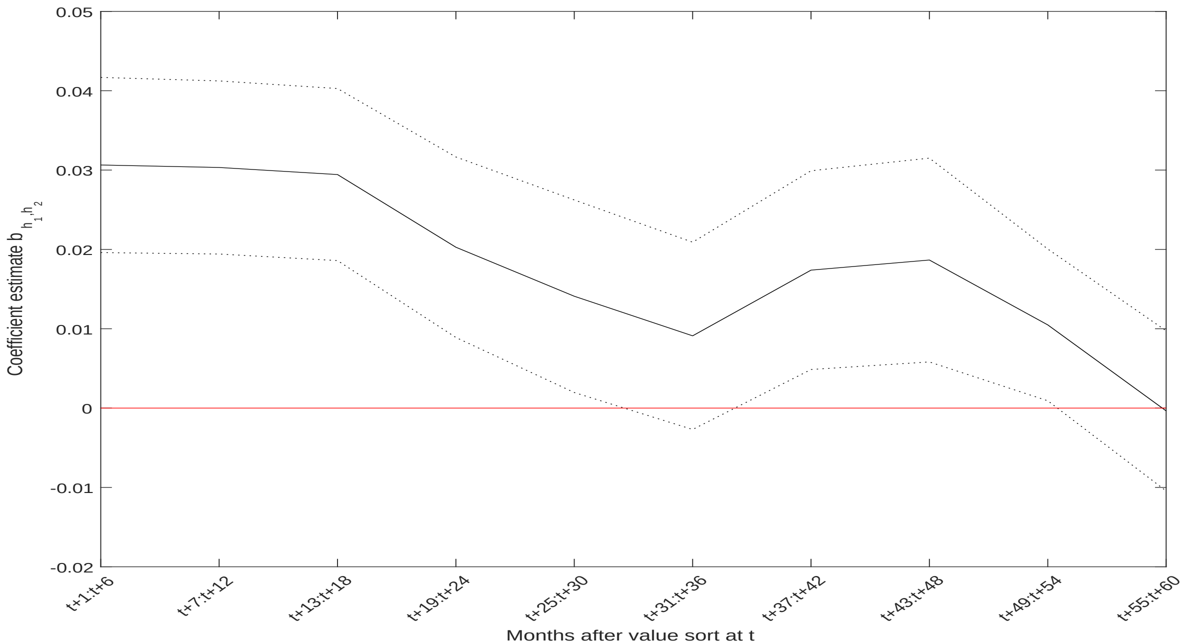

FIGURE C.1: **Semi-Annual Future Value Returns on the Value Spread at Time** t

This figure presents the coefficient estimates (± two standard errors) from a pooled predictive regression of semi-annual value returns on the value spread: $R_{c,t+h_1:t+h_2} = a_{h_1,h_2} + b_{h_1,h_2}\ \mathrm{VS}^x_{c,t} + e_{c,t+h_1:t+h_2}$. The semi-annual value returns range from six months ($h_1 = 1, h_2 = 6$) to five years ($h_1 = 55, h_2 = 60$) after the value spread is observed in month t. We include in the pool of value strategies the High-minus-Low value return in (i) individual equities sorted on book-to-market excluding financials ($BM_{Ex.fin.}$), (ii) individual equities sorted on industry adjusted book-to-market ($BM_{Ind.Adj.}$), (iii) commodities sorted on the negative of the five-year return (−5-year return), (iv) currencies sorted on −5-year return, (v) global government bonds sorted on −5-year return, and (vi) stock indexes sorted on MSCI book-to-price ($MSCI_{BP}$). The value spread is standardized.

TABLE C.1: **Hodrick (1992) Standard Errors**

This table presents time-series regressions of value returns on the value spread as in Tables 1 and 2 of the paper, but presents t-statistics calculated using Hodrick (1992) standard errors. We see that these standard errors are slightly more conservative, but the value spread remains marginally significant in all asset classes.

Value Measure		*H – L*					*Rank*				
	h	a	b	t_a	t_b	R^2	a	b	t_a	t_b	R^2
$BM_{Ex.fin.}$	6	0.0174	0.0379	1.19	2.46	5.88	0.0126	0.0170	1.35	1.63	2.62
	24	0.0788	0.2258	1.37	4.25	30.33	0.0658	0.1125	1.78	3.10	19.35
$BM_{Ind.adj.}$	6	0.0176	0.0450	1.71	3.62	16.60	0.0188	0.0212	2.99	2.70	8.29
	24	0.0778	0.2184	1.92	5.56	45.24	0.0915	0.0978	3.66	3.80	26.83
Commodities	6	0.0146	0.0213	1.21	1.65	3.03	0.0153	0.0266	0.98	1.63	2.48
	24	0.0716	0.0820	1.58	2.19	11.27	0.0693	0.1569	1.19	3.34	19.18
Currencies (−5-year return)	6	0.0134	0.0099	2.61	2.04	3.76	0.0171	0.0147	2.66	2.33	5.33
	24	0.0668	0.0426	3.29	2.34	15.30	0.0845	0.0589	3.34	2.48	18.44
Government bonds (−5-year return)	6	0.0013	0.0079	0.33	1.81	11.79	0.0031	0.0077	0.67	1.52	10.38
	24	0.0099	0.0338	0.69	2.29	40.36	0.0170	0.0270	1.04	1.57	29.91
Stock indexes	6	0.0031	0.0150	0.35	1.66	6.52	0.0077	0.0157	0.74	1.38	4.26
	24	0.0030	0.0431	0.09	1.50	8.06	0.0263	0.0630	0.66	1.82	12.40

Table C.2: **Simulating from Zhang (2005)**

This table reports results from 1000 simulations from the investment-based asset pricing model of Zhang (2005). This model endogenously generates a time-varying value spread that predicts value returns in the time series. The relevant question our study poses to the model is whether or not it can match the variation in expected value returns we see in the data, while matching other moments of interest. Panel A reports the unconditional moments of value decile portfolios (focusing on deciles 1 (Low), 4, 7, and 10 (High) for brevity) and the High-minus-Low decile value premium. We see that our distribution is close to what is reported in Zhang (2005, Table III). Panel B reports the *Ratio* of the predictive regression coefficient to the intercept and the R^2 at the annual horizon (h = 12). We compare the level of these estimates from the data (as reported in Table 1) to the distribution of their counterparts estimated from simulating the model. We rank all simulations on the *Ratio* and report both the *Ratio* and R^2 at the 50, 90, 95, and 99th percentile of that distribution. The final column presents the mean across simulations as reported in Zhang (2005), where we have backed out the *Ratio* of 0.76 from results reported in his Table III and V.

Panel A: Unconditional Moments for Value Decile Portfolios

	Simulated Distribution					Zhang (2005)
	1 (Low)	4	7	10 (High)	H-L	HML
Mean of avg. ret.	0.0073	0.0085	0.0094	0.0114	0.0041	0.0039
Mean of st. dev.	0.0677	0.0770	0.0842	0.1039	0.0384	0.0346

Panel B: Simulated Distribution of Annual H-L Value Premium on H-L Value Spread

	Data		Simulated Distribution				Zhang (2005)
	$BM_{Ex.fin.}$	$BM_{Ind.adj.}$	50	90	95	99	Mean
Ratio	2.35	2.57	0.7409	1.3916	1.6399	2.4963	0.76
R^2	13.73	29.73	0.2002	3.3226	6.8879	27.2623	8.84

TABLE C.3: **Synthetic Bond Futures Returns**
This table presents time-series regressions of value returns on the value spread using synthetic (global government) bond futures returns constructed as in Koijen et al. (2017), similar to Table 2 of the paper. Although the evidence is weaker than for traded bond futures returns, we find positive coefficients on the value spread in almost all cases and these coefficients are non-negligible economically at longer horizons.

Value Measure		*H − L*					*Rank*				
	h	a	b	t_a	t_b	R^2	a	b	t_a	t_b	R^2
−5-year return	1	0.0006	0.0009	0.57	0.59	-0.06	0.0011	0.0010	1.00	0.62	-0.11
	3	0.0012	0.0022	0.51	0.78	0.43	0.0030	0.0025	1.14	0.74	0.40
	6	0.0019	0.0073	0.54	2.45	5.08	0.0056	0.0068	1.26	1.21	3.14
	12	0.0023	0.0129	0.42	2.40	12.10	0.0098	0.0105	1.43	1.23	5.46
	24	0.0050	0.0318	0.76	5.27	42.51	0.0205	0.0311	1.92	3.95	27.81
5-year Δy	1	0.0016	-0.0004	1.53	-0.25	-0.38	0.0033	-0.0001	2.78	-0.05	-0.45
	3	0.0047	0.0004	1.64	0.09	-0.44	0.0096	0.0012	3.13	0.28	-0.30
	6	0.0087	0.0044	1.64	0.72	0.81	0.0185	0.0039	3.37	0.57	0.45
	12	0.0157	0.0104	1.61	1.04	3.42	0.0365	0.0078	3.61	0.64	1.53
	24	0.0385	0.0267	2.09	3.13	11.51	0.0817	0.0315	4.19	3.30	14.41

TABLE C.4: **Pooled Predictive Regression Excluding Individual Equities**
This table presents the pooled predictive regression of Table 3 in the paper, but now we exclude the value strategies that use US individual equities. This leaves us with four value strategies, using global government bonds, commodities, currencies, and stock indexes. We see that value returns in these alternative asset classes are predictable using the value spread.

	H − L				
h	a	b	t_a	t_b	$R^2(\%)$
1	0.0029	0.0035	2.46	2.85	0.65
3	0.0082	0.0114	2.60	3.56	2.17
6	0.0167	0.0250	2.66	4.10	4.94
12	0.0358	0.0544	2.78	4.38	9.69
24	0.0870	0.1083	3.41	4.73	14.97
48	0.2529	0.2511	2.99	3.55	19.33

Table C.5: **Pooled Predictive Regressions with Alternative Value Measures**
This table presents the pooled predictive regression of Table 3 in the paper, but now we use the alternative value return series for currencies (using as signal the inflation-adjusted five-year change in spot price) and global government bonds (using as signal the five-year change in yield and using as test assets the synthetic bond futures returns). Our conclusions are unaffected when we use these alternative value return series.

	$H-L$					*Rank*				
h	a	b	t_a	t_b	$R^2(\%)$	a	b	t_a	t_b	$R^2(\%)$
1	0.0029	0.0036	2.85	2.93	0.70	0.0038	0.0029	3.56	2.17	0.43
3	0.0087	0.0124	3.16	4.37	2.51	0.0115	0.0100	3.75	3.13	1.56
6	0.0179	0.0284	3.47	5.25	6.04	0.0238	0.0238	3.90	3.74	3.86
12	0.0364	0.0661	3.94	5.43	13.34	0.0502	0.0582	4.43	4.13	9.42
24	0.0838	0.1435	4.18	5.26	21.91	0.1169	0.1358	5.45	4.20	19.31
48	0.2169	0.3021	3.49	4.67	25.26	0.3064	0.2683	6.05	5.15	23.97

Table C.6: **Pooled Predictive Regression of Market Returns on Value Spread**
This table presents the pooled predictive regression of Table 3 in the paper, but now we substitute market returns on the left-hand side. We find no evidence that the (High-minus-Low) value spread predicts market returns in the pool of asset classes.

	$H-L$				
h	a	b	t_a	t_b	$R^2(\%)$
1	0.0049	0.0006	3.72	0.49	0.02
3	0.0152	0.0030	4.19	0.89	0.14
6	0.0317	0.0073	4.27	1.12	0.36
12	0.0663	0.0100	4.39	0.71	0.28
24	0.1391	0.0193	4.41	0.60	0.39
48	0.3053	0.0709	4.68	1.23	2.09

TABLE C.7: **Pooled Predictive Regressions on Principal Components of Value Spreads**

This table presents results from pooled predictive regressions of returns on six principal components that can be extracted from the six value spreads we have for different asset classes. In Panel A, we see that $PC1$ predicts value returns similar to our measure of common value in Table 5 of the paper (in both economic and statistical magnitude). None of the remaining principal components is a strong predictor of value returns in isolation. Joint tests, including each principal component as well as a complementary variable capturing the remaining variation in the value spread (e.g., $|PC1_{c,t} = \text{VS}_{c,t} - PC1_t$), provide a fit that is similar to the joint regression in Table 5 of the paper. This result is due to the fact that the fit in a joint regression will always be at least as good as in the original simple regression of value returns on the not decomposed value spread. Economically, these results imply that it is only the first principal component of the value spreads, close to our simple measure of common value, that explains a large amount of time-variation in value returns.

Panel A: First Principal Component

h	a	b_{PC1}	$b_{\|PC1}$	t_a	$t_{b_{PC1}}$	$t_{b_{\|PC1}}$	$R^2(\%)$
1	0.0036	0.0018		3.11	2.37		0.48
3	0.0109	0.0060		3.39	3.11		1.60
6	0.0226	0.0123		3.65	3.25		3.09
12	0.0469	0.0241		3.96	3.24		4.94
24	0.1067	0.0573		4.40	3.57		10.15
48	0.2816	0.1487		5.67	5.96		18.49
1	0.0033	0.0039	0.0032	2.88	3.32	2.82	0.93
3	0.0099	0.0128	0.0103	3.08	4.47	3.74	2.97
6	0.0204	0.0279	0.0234	3.27	4.98	4.49	6.29
12	0.0419	0.0621	0.0569	3.56	5.10	4.62	12.83
24	0.0973	0.1419	0.1267	4.22	5.00	4.62	24.02
48	0.2669	0.3230	0.2637	5.22	6.25	5.29	33.70

Panel B: Remaining Principal Components

h	a	b_{PC2}	$b_{\|PC2}$	t_a	$t_{b_{PC2}}$	$t_{b_{\|PC2}}$	$R^2(\%)$
12	0.0417	-0.0039		3.29	-0.36		0.05
12	0.0411	0.0532	0.0619	3.76	3.48	5.00	12.93
h	a	b_{PC3}	$b_{\|PC3}$	t_a	$t_{b_{PC3}}$	$t_{b_{\|PC3}}$	$R^2(\%)$
12	0.0432	0.0238		3.60	1.89		1.47
12	0.0417	0.0746	0.0595	3.96	4.56	5.05	13.25
h	a	b_{PC4}	$b_{\|PC4}$	t_a	$t_{b_{PC4}}$	$t_{b_{\|PC4}}$	$R^2(\%)$
12	0.0416	-0.0068		3.30	-0.54		0.09
12	0.0407	0.0528	0.0614	3.74	2.95	5.10	12.81
h	a	b_{PC5}	$b_{\|PC5}$	t_a	$t_{b_{PC5}}$	$t_{b_{\|PC5}}$	$R^2(\%)$
12	0.0417	0.0296		3.37	1.55		0.93
12	0.0407	0.0688	0.0603	3.72	3.50	5.04	12.74
h	a	b_{PC6}	$b_{\|PC6}$	t_a	$t_{b_{PC6}}$	$t_{b_{\|PC6}}$	$R^2(\%)$
12	0.0416	0.0109		3.29	0.16		0.01
12	0.0407	0.0766	0.0613	3.71	1.37	5.07	12.69

Table C.8: **Common vs Specific Components of the Value Spread in Subsamples** This table presents the decomposition into common and specific value predictability (reported in Table 5 of the paper) over two subsamples split in June 1993. We drop the longest four-year horizon, because we find that these long-term coefficients are hard-to-estimate in the smaller subsamples. We see that the common component of value has become more important relative to the specific component over time.

Panel A: First Half

h	a	b_{Com}	b_{Spec}	t_a	$t_{b_{Com}}$	$t_{b_{Spec}}$	$R^2 \times 100$	R^2_{Com}	R^2_{Spec}	R^2_{Cov}
1	0.0057	0.0017	0.0055	3.17	0.51	2.35	0.84	0.08	0.76	0.00
3	0.0173	0.0068	0.0186	3.44	0.90	3.08	2.81	0.35	2.46	0.00
6	0.0364	0.0160	0.0444	3.74	1.14	4.31	7.09	0.88	6.22	0.00
12	0.0793	0.0355	0.1017	4.15	1.23	4.55	16.38	1.91	14.47	0.00
24	0.1943	0.1059	0.2168	5.00	1.91	4.78	29.18	5.99	23.20	0.00

Panel B: Second Half

h	a	b_{Com}	b_{Spec}	t_a	$t_{b_{Com}}$	$t_{b_{Spec}}$	$R^2 \times 100$	R^2_{Com}	R^2_{Spec}	R^2_{Cov}
1	0.0015	0.0076	0.0026	1.10	2.24	1.64	1.07	0.82	0.26	0.00
3	0.0041	0.0239	0.0089	1.11	2.59	2.90	3.41	2.44	0.94	0.03
6	0.0080	0.0472	0.0190	1.17	2.89	3.34	6.45	4.33	1.98	0.14
12	0.0145	0.0898	0.0467	1.21	4.17	4.11	11.47	6.29	4.87	0.31
24	0.0201	0.1385	0.1109	0.93	5.08	3.94	17.38	6.05	10.87	0.46

TABLE C.9: **Across Asset Class Predictability**

This table presents a test of whether value returns in one asset class are predictable using the value spread from other asset classes. We create two groups of value strategies: individual equities ($BM_{Ex.fin.}$ and $BM_{Ind.adj.}$), denoted *Equities*, versus other asset classes (*Others* includes commodities, currencies, global government bonds and stock indexes; *Others* (*Excl. Commodities*) excludes commodities). We run the time-series regressions of average value returns from one group on the average value spread from the other group, that is for instance, $R_{Equities,t+1} = a + bVS_{Other,t} + \varepsilon_{t+1}$ with $R_{Equities,t+1:t+h} = (R_{BM_{Ex.fin.},t+1} + R_{BM_{Ind.adj.},t+1})/2$ and $VS_{Other,t} = (VS_{Com,t+1} + VS_{Cur,t+1} + VS_{Bonds,t+1} + VS_{Stock,t+1})/4$. The sample period is January 1991 to December 2014, which sample start coincides with the earliest availability of global government bond data.

h	a	b	t_a	t_b	$R^2(\%)$	a	b	t_a	t_b	$R^2(\%)$
Avg. Value Return			*Equities*					*Others*		
Avg. Value Spread			*Others*					*Equities*		
1	0.0023	0.0031	0.84	1.49	0.17	0.0030	0.0038	2.26	2.69	2.34
3	0.0077	0.0113	0.98	1.85	1.43	0.0086	0.0104	2.52	2.56	6.32
6	0.0178	0.0185	1.10	1.57	1.72	0.0171	0.0194	2.45	3.16	10.34
12	0.0361	0.0405	1.11	1.77	3.71	0.0360	0.0264	2.45	2.55	7.84
24	0.0698	0.0589	1.22	1.87	3.73	0.0722	0.0277	2.91	1.17	4.40
Avg. Value Return			*Equities*					*Others* (*Excl. Commodities*)		
Avg. Value Spread			*Others* (*Excl. Commodities*)					*Equities*		
1	0.0023	0.0022	0.84	1.30	-0.10	0.0039	0.0045	2.39	2.36	2.18
3	0.0077	0.0066	0.97	1.48	0.25	0.0114	0.0141	2.77	2.58	7.73
6	0.0178	0.0076	1.09	0.90	-0.01	0.0234	0.0285	2.94	3.53	15.03
12	0.0361	0.0146	1.08	0.97	0.17	0.0489	0.0357	2.96	2.81	10.86
24	0.0698	0.0263	1.17	0.75	0.43	0.0977	0.0357	3.35	1.41	5.20