Value Timing: Risk and Return Across Asset Classes☆

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Abstract

Returns to value strategies in individual equities, commodities, currencies, global government bonds and stock indexes are predictable by the value spread. The value spread captures the strength of the value signal in the long relative to the short portfolio of a value strategy. We show that common and asset-class-specific components of the value spread contribute equally to this predictability. Return variation due to common value is closely associated to standard predictors of risk premia, but is at odds with models that exclusively generate a value premium in equities. Return variation due to specific value presents another challenge for asset pricing models. A number of value timing and rotation strategies shows that investors can benefit from the value spread in real-time.

Keywords: Value Premium, Value Spread Predictability, Stocks, Bonds, Currencies, Commodities.

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 is strongly time-varying. For instance, in the case of individual equities, the value spread is the difference in average book-to-market ratio of value and growth stocks. 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 about 14%, 9%, 11%, 22%, and 10%, for US individual equities, currencies, commodities, global government bonds and stock indexes, respectively. In all asset classes, a standard deviation increase in the value spread predicts an increase in expected value return in 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.[1]

To determine what are the (economic) drivers of this time-variation, we decompose the value spread into a common component and an asset-class-specific component.[2] We find that these two components contribute about equally to return predictability in the pool of value strategies. We show that benchmark predictors popular in the literature to proxy for time-varying risk premia (such as the dividend yield, default spread, illiquidity, real uncertainty, and intermediary leverage) largely explain the time-variation in common value. For instance, the correlation between the first principal component of these benchmark predictors and common value is large at 0.84, and these two series predict value returns similarly in isolation. In a joint test, however, it is our simple, real-time observable measure of common value that dominates. 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

[1]The value premium is one of the main "puzzles" in finance. As argued in Cochrane (2011), the debate between rational explanations (see Fama and French, 1993) and mispricing (see Lakonishok, Shleifer and Vishny, 1994) is still unresolved.

[2]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 results are robust to using the first principal component of value spreads to measure common value, indicating that the variation is truly common.

premia are high.

Nevertheless, a time-varying component of value that is common across asset classes, despite potentially different investors and institutional factors, presents a challenge to existing asset pricing theory. Many behavioral and rational theories for value focus predominantly on the unconditional value premium in equities. In particular, theories that rely on firm investment risk or growth options (see, e.g. Berk, Green and Naik, 1999) seem ill-equipped to explain the comovement in value premia in equities, currencies, and commodities. Our results thus call for a more general framework. Whereas we document comovement in expected value returns, Asness et al. (2013) show that realized value returns comove across asset classes. The large amount of 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.

Asset-class-specific variation in value premia presents another challenge to existing asset pricing models. Although the benchmark predictors also capture some of the time-variation in the specific components of the value spread, we find that the correlation with individual predictors varies dramatically across asset classes in sign and magnitude. A rational explanation for this finding requires some form of market segmentation. For example, the loading on the default spread is positive for equities and negative for government bonds, perhaps consistent with a flight-to-quality story (see, e.g., Connolly et al. (2005) and Baele et al. (2010)). Furthermore, about half of the predictability of value premia due to asset-class-specific value remains once we orthogonalize this component from the benchmark predictors. Absent any further explanation, this residual component can be linked only to mispricing and market inefficiency.

To benchmark the strength of value return predictability in the literature, in particular for the case of US equities, we note that the in-sample relation between value returns and the lagged value spread is slightly stronger than the relation between aggregate stock 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 this in-sample relation is spurious. In contrast, we find that there are large benefits of conditioning on the value spread (across asset classes) in real-time. To this end, we present a number of value timing and rotation strategies. We show that Sharpe ratios of such conditional value strategies are typically about twice the Sharpe ratio 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. We conclude that value-investing is only attractive when the value spread in an asset class is high relative to both its historical average and other asset classes.

Our results contribute to the asset pricing literature in various ways. The literature on the value effect predominantly focuses on its unconditional performance in US individual equities (see Fama and French, 1992). Notable exceptions are Fama and French (1998) and Liew and Vassalou (2000) who investigate international equity markets. Recently, Asness et al. (2013) provide new evidence for value in asset classes not previously studied: international government bonds, currencies and commodities. In contrast to these papers, which characterize unconditional value premia, we characterize the time-variation in value premia within and across asset classes. As argued above, our conditional tests separating common and specific value have important asset pricing implications, consistent with the idea that conditional tests are more powerful than unconditional tests to distinguish between competing models (Campbell and Cochrane (2000), Cochrane (2001, Ch. 8) and Nagel and Singleton (2011)).

There is a large academic and industry literature that attempts to forecast returns using valuation ratios. For instance, Lewellen (1999) asks whether returns of diversified equity portfolios vary with their book-to-market ratio. Cochrane (2011, p. 1099) analyzes 25 size and book-to-market sorted portfolios and argues that "variation over time in a given portfolios book-to-market ratio is a much stronger signal of return variation than the same variation across portfolios in average book-to-market ratio." Kelly et al. (2017) similarly argue that time-variation in a small set of firm characteristics (related to value and recent stock return performance) contains the bulk of information in these characteristics for predicting individual stock returns. 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, Friedman, Krail and Liew (2000). 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, Polk and Vuolteenaho (2003) show that the return of the HML factor (Fama and French (1993)) is predictable by the HML value spread. In contrast to us, these papers do not study the value spread in other asset classes nor do they analyze the potential and robustness of the value spread in an out-of-sample setting.

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? Different from Cohen et al. (2003) (see also Kao and Shumaker, 1999), we find that popular predictors related to aggregate economic and financial conditions not only explain a large fraction of the variation in the value spread, but are also responsible for a large share of its predictive content for value returns. Furthermore, our multi-asset approach provides insight in the common and asset-class-specific components of value premia. In this dimension, our work relates to a recent literature on global asset pricing. Considering both global equities and other asset classes, Frazzini and Pedersen (2014) find consistent returns to "betting against beta," Koijen et al. (2017) document global "carry" returns, and Lettau et al. (2014) find that downside beta is priced in a host of asset classes. These papers mostly characterize unconditional risk premia. An important exception is Moskowitz et al. (2012), who present global evidence for "time-series momentum." 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, Martin-Utrera, Nogales and Uppal, 2017; Freyberger, Neuhierl and Weber, 2017; Kozak, Nagel and Santosh, 2017; Kelly, Pruitt and Su, 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.[3] Our results for value suggest that this transformation shuts down a channel that is important for expected returns: 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, the value measures, and the methodology for constructing value strategies across asset classes. Section 3 asks whether the value spread predicts value returns in individual equities. Section 4 asks whether the value spread predicts returns also in other asset classes and presents some pooled evidence. Section 5 presents a decomposition of the value spread into common and asset-class-specific components, and links these components to aggregate economic and financial conditions. Section 6 presents out-of-sample strategies that attempt to benefit from the information in the value spread in real-time. Section 7 concludes.

2 Data and Methodology

In this section, we describe the method to construct value measures and value returns in different asset classes. We refer the interest reader to Appendix A for additional details on the data sources and data cleaning procedures. 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; all in order to minimize the pernicious effects of data snooping. To this end, we follow closely Asness et al. (2013). Naturally, for individual stocks and global stock indexes, we measure value as a book-to-market ratio. For the remaining asset classes, we measure value using long-term past returns, and consider alternative measures as a check of robustness. This choice is inspired by the long strand of literature that documents a direct link between past returns and book-to-market

[3] These authors use a rank transformation of each characteristic to the unit interval, except for DeMiguel et al. (2017), as they winsorize and standardize each characteristic.

ratios, both empirically (see Bondt and Thaler, 1985; Fama and French, 1996; Gerakos and Linnainmaa, 2017) and theoretically (see Daniel, Hirshleifer and Subrahmanyam, 1998; Hong and Stein, 1999; Vayanos and Woolley, 2013).

We find in unreported results that the benefits of value timing increase when combining different measures of value in a single asset class. For example, our results on US equities can be improved by simultaneously employing alternative proxies for value, such as earnings-to-price and sales-to-price, rather than just using the book-to-market ratio (see Asness, Friedman, Krail and Liew, 2000; Israel and Moskowitz, 2013, for attempts along this line). Similarly, Asness et al. (2013) show that the unconditional value premium in global government bonds is larger for a composite value measure. We leave this avenue for future research.

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. 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. To be precise, we rank stocks based on their end-of-month t market capitalization in descending order. We include in our value strategies only those stocks that account cumulatively for 90% of the total market capitalization.[4]

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 in December to ensure data availability to investors at the time of portfolio formation. The most recent market values are used to compute the ratios following Asness and Frazzini (2013). Consistent

[4]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.

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. (2000) and Cohen and Polk (1998) find that value is a better strategy for choosing stocks within an industry than for choosing industries. 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 also perform a sort across 17 industries, using for each industry the average book-to-market ratio as value signal.

2.2 Commodity Futures

We obtain price data for the following commodities: 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 as the negative of the five-year spot commodity return. As is common in the literature, we proxy for the spot price using the first-nearby futures price, because spot prices are illiquid. The sample period runs from January 1972 to December 2014.

2.3 Currencies

We obtain spot and forward exchange rates covering the following ten currencies: 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 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 the following ten countries: 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 using synthetic prices and yields.[5] The first value 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 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.

2.5 Global Stock Indices

The universe of country equity index futures consists of the following 13 developed markets: Australia, Canada, France, Germany, Hong Kong, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, the United Kingdom, and the United States. To measure value,

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

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 and Value Spreads

Using the value measures described above, we construct a set of value strategy returns from portfolio sorts. In particular, we sort securities within each asset class into P groups based on (the cross-sectional distribution of) the value measures. For individual stocks, we form value-weighted decile portfolios ($P = 10$) each month by sorting on $BM_{i,t,Ex.fin.}$ or $BM_{i,t,Ind.adj.}$. We define the value stock portfolio as decile 10 (high) and the growth stock portfolio as decile 1 (low). For all other class, we pick $P = 2$ and we form an equal-weighted high and low portfolio by splitting the securities at the median of ranked value. Our main interest is in analyzing the time-variation in expected returns to the high-minus-low value portfolio in the month after sorting, R^{H-L}_{t+1}.

We also report results from an alternative rank-weighting procedure, which mitigates the influence of outliers (see, e.g., Asness, Moskowitz and Pedersen, 2013). For any security $i = 1, \dots, N_t$ at time t with value signal $V_{i,t}$, the weight is proportional to its rank in the cross section:

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

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. For the rank-weighted strategy, the return on the value strategy of interest is then: $R^{Rank}_{t+1} = \sum_i w^{Rank}_{i,t} R_{i,t+1}$. 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. Note that these long and short positions are rebalanced every month. To be consistent across asset classes, we compound returns including the T-bill return.[6]

[6] Appendix A presents more details as to the construction of excess returns in different asset classes, and lists the collateral and hedging assumptions for foreign denominated futures.

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 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 results 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 cheaper than normal and the cross section of value measures is wide, whereas a negative value spread indicates the opposite. For other asset classes, the same intuition applies: when the value signal is positive, it means that the value spread is wider than normal. 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, in every asset class a wider value spread today indicates larger value returns in the future.

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 value spread averaged across the asset classes available in month t. The asset-class-specific component is the difference between the value spread in an asset class and the common value. Our 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.[7] 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

[7] We prefer the simple average because 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.

of the IT-bubble and after the recent financial crisis. There is also considerable variation that is asset-class-specific, however. In 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 Individual Equities

In this section, we ask whether value-minus-growth returns in the US equity market are predictable using the value spread. To motivate this analysis, consider the log-linear present value model employed in Vuolteenaho (2002).[8] Vuolteenaho (2002) shows that if the book-to-market ratio is well behaved, then

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

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 Eq. (1) to both portfolios, take conditional expectations, difference, and reorganize, to get:

$$E_t\left[\sum_{j=0}^{\infty} \rho^j r_{t+1+j}^{H-L}\right] = \theta_t^H - \theta_t^L + E_t\left[\sum_{j=0}^{\infty} \rho^j \left(e_{t+1+j}^H - e_{t+1+j}^L\right)\right]. \tag{2}$$

This result provides an economic motivation for running a time-series predictive regression of the high-minus-low value portfolio return (compounded over an horizon h) on the high-minus-low value spread:

$$r_{t+1:t+h}^{H-L} = a_h + b_h\left(\theta_t^H - \theta_t^L\right) + \varepsilon_{t+1:t+h}, \tag{3}$$

where we abstract from the correction for the spread in discounted future expected profitability, and we assume that the percentage variance decomposition for the cross section

[8] Similarly, Asness, Friedman, Krail and Liew (2000) use the static Gordon (1962) model to motivate the use of value spread as a predictor of value versus growth returns.

of book-to-market ratios is approximately constant over time, so that the regression coefficient b_h is constant. In other words, if the variance decomposition implied by the present value model is constant over time with a nontrivial portion of the variance allocated to expected returns, the level of the value spread should predict returns on value-minus-growth strategies. The key role of 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.

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 portfolios and using both signals, $BM_{Ex.fin.}$ and $BM_{Ind.adj.}$. The annualized Sharpe ratios for these strategies are around 0.20 (monthly Sharpe ratio $\times\sqrt{12}$), with the exception of the rank-weighted portfolio based on industry-adjusted book-to-market ratio that obtains a Sharpe ratio of 0.41. These results are consistent with Asness, Friedman, Krail and Liew (2000) and Asness et al. (2013). In fact, the correlation between our first book-to-market strategy (excluding financial firms) and the comparable strategy of Asness et al. (2013) is over 0.98.[9] These Sharpe ratios are a bit lower than what is typically reported for the value premium in the literature, because we focus only on relatively large and liquid stocks that cumulatively account for 90% of the total market capitalization.

[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-West standard errors with h-lags), and R-squares.[10] At all horizons, and for both decile and rank-weighted portfolios, the coefficient on the value spread is economically large and typically statistically significant.

[9] We thank the authors for sharing the returns to value strategies in individual equities as well as in alternative asset classes on their website. 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 five-year return as an alternative measure of value in a robustness check).

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

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% to 22.58% for the high-minus-low decile portfolio. At the 24-month horizon, the coefficient estimates for the decile and the rank-weighted portfolios imply an increase in value premium of 22.58% and 11.25% per standard deviation increase in the value spread, respectively. The R^2 increases also in horizon. For instance, for the high-minus-low decile portfolio, it ranges from 0.85% at the one-month horizon to 30.33% at the 24-month 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 portfolios, respectively, at the 24-month horizon.[11] This result suggests that cleaning valuation ratios from across-industry variation creates a time series of value returns that is more predictable, a fact that we exploit in our out-of-sample tests (see Section 6).

By standardizing the value spread, the ratio of the estimated coefficients, 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 ratio is slightly below one when predicting the aggregate stock market with the dividend yield. Hence 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. The out-of-sample evidence in Section 6 serves to ascertain that this in-sample variation is not spurious. To this end, note also that our results are largely unaffected by a Stambaugh (1999) bias. This bias exists in regressions of returns on valuation ratios, because the left-hand side return is mechanically related to the price-based measure in the right-hand side regressor. Since we regress a difference in returns on a difference in valuation ratios between two portfolios, we break this mechanic relation. The absence of a Stambaugh-bias is important, as this bias is known to exacerbate other problems in long-horizon regressions (see, e.g., Valkanov (2003) and Boudoukh et al. (2006)).

[11] The correlation between the value return series that excludes financials and the industry-adjusted value return series is about 0.75.

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. Bondt 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 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 (see, e.g., Asness et al. (2000) and Cohen and Polk (1998)). 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 strongly time-varying with the value spread: the value premium increases (decreases) as the cross section of valuation ratios expands (compresses). Motivated by this evidence, we ask in the next section whether value premia in other asset class are also predictable by the value spread.

4 Predicting Value Returns in 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.[12]

[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 we standard-

[12] 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.2 of the Internet Appendix.

ize the value signal, this 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.

To gauge the joint strength of the information in the value spread for value returns in different asset classes, 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.[13]

[Insert Table 3 about here]

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

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

for $h = 1, 3, 6, 12, 24, 48$ months, and where c denotes an asset class and $x = \{H - L, Rank\}$. The longer four-year horizon is added, as 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. 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 signalled by the t-statistics, which increase from about 3 at $h = 1$ to over 5 at $h = 48$.

[13]In Table C.3 of the Internet Appendix, we present similar evidence for a pooled regression using alternative value return series for currencies (using as signal the inflation adjusted five year change in spot price) and bonds (using as signal the five year change in yield and using as test assets the synthetic futures returns).

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 of Table 3 shows that this evidence is quantitatively robust when we split the sample in two halves. 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 of Table 3 presents an alternative way of looking at the joint strength of value premium predictability. We regress in the time series the average value returns on the average value spread, where both the returns and value spread are averaged across the six strategies. 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.

Panels E and F present two robustness checks for the pooled and average-on-average regressions. Panel D 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 high-minus-low value returns.

Panel F presents results for an alternative set of rank-weighted value returns used in Asness et al. (2013). The right-hand side value spreads are the same as in Panels A and D and calculated using our own data. 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 our sample of value returns (Panel A), indicating that we match well the unconditional value premia of Asness et al. (2013). 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 tests in Panel F use a pool of five instead of six strategies (as in Panels A to E), because Asness et al. (2013) do not analyze the industry-adjusted book-to-market ratio. 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.

Finally, we ask whether our results are explained by exposure to a market benchmark, which test is inspired by the CAPM (Sharpe (1964), Lintner (1965) and 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, to ascertain that the evidence is not biased by using a market benchmark that consists only of US equities. As before, the benchmark for the value strategies in individual equities is the CRSP portfolio. For commodities, currencies, fixed income, and stock indexes, the benchmark is an equal-weighted basket of the securities in each asset class.

[Insert Table 4 about here]

In short, we see that exposures to neither market benchmark capture the predictability of value returns, as 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, can not explain our results either. In line with this conclusion, Table C.4 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 Eq. (4).[14] Thus, time-variation in the market risk premium is also unlikely to explain the predictability of value premia. In the next section, we analyze whether time-variation in risk premia for additional factors 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.

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 strategies, 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

[14] The insignificance of the value spread in the pooled regression is driven by the fact that stock market returns are weakly predictable by the value spread (in line with Kelly and Pruitt, 2013), whereas market returns in the remaining asset classes are not predictable by the value spread.

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 $\text{VS}_t^{\text{Com}} = \frac{\sum_c^{N_t} VS_{c,t}}{N_t}$, and an asset-class-specific component $\text{VS}_{c,t}^{\text{Spec}} = \text{VS}_{c,t} - \text{VS}_t^{\text{Com}}$ (see Figure 1 for the time series of the value spread and its components). We observe that the coefficient estimates on the common and asset-class-specific components are statistically significant at all horizons, and similar in magnitude to the coefficient 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 aggregate value spread and its two components. We also perform a decomposition of the R^2 to quantify the relative contribution of common and specific value to return predictability. The R^2 decomposition shows that each component contributes about equally to the variability of value strategies at all horizons ranging from one month to four years.[15] 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 by Cochrane (2011): "It is not enough to simply generate temporary price movements in individual securities." The expected returns of value strategies apparently rise and fall globally.

Next, we investigate possible 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.[16] In particular we use: (i) a global recession dummy (see Asness, Moskowitz and Pedersen, 2013); (ii) the dividend yield;[17] (iii)

[15]In Table C.5 of the Internet Appendix, we find similar evidence when we use the first principal component of the value spreads as our measure of common value. None of the remaining principal components contributes to predicting value returns in a joint test. This result suggests that our simpler decomposition better identifies asset-class-specific components of the value spread.

[16]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 risk of overfitting.

[17]As noted in Campbell and Cochrane (1999), the dividend yield is nearly linear in the log surplus consumption ratio, the key state variable in the habit model.

the default spread;[18] (iv) the illiquidity premium of Nagel (2016); (v) real uncertainty of Jurado et al. (2015);[19] and finally, (vi) intermediary leverage.[20] We also control for sentiment (see Baker and Wurgler, 2006).

[Insert Table 6 about here]

Panel A of Table 6 contains simple and multiple regressions of the common component of the value spread on these benchmark predictors. We find that common value loads on the dividend yield, default spread, illiquidity, real uncertainty, and intermediary leverage with positive and statistically significant coefficients. Except for the global recession indicator and sentiment, each risk variable in isolation delivers an R^2 at least as large as 29%. The full model in row 8 explains over 75% of the variation in common value. This evidence confirms that common value is large when the predictors signal high risk premia in bad economic and financial conditions. In row 9, we run the same regression excluding the dividend yield.[21] The result from this specification yields an R^2 of 0.69 and suggests that although the dividend yield is important, it is not single-handedly driving this conclusion. Indeed, we find that the correlation between the first principal component of the benchmark predictors (capturing about half of the total variation in these series) and our measure of common value is large at 0.84.[22] This result suggests that a simple, directly observable (in real-time) measure contains the bulk of information common to popular predictor variables, which is an important advantage of using the value spread. Table 7 presents another advantage: common value performs better in predicting value returns. Although the first principal component of the benchmark predictors is significant in a pooled predictive regression in isolation, common value dominates in predicting value

[18] We measure the default spread as the difference in yields between BAA and AAA long term corporate bonds to capture low frequency movements in business conditions. Replacing this spread with the excess bond premium of Gilchrist and Zakrajsek (2012) yields similar results.

[19] 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).

[20] 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.

[21] Excluding the dividend yield is an important robustness check since the relation between dividend yield and value measures is to some extent mechanical for individual equities. Higher prices (lower dividend yield) will tend to shrink the spread in book-to-market ratio between the long and short portfolios. Having said that, it is not obvious ex ante why the dividend yield would comove with value spreads in the remaining asset classes.

[22] Figure 2 plots these series and shows that the first principal component loads on all benchmark predictors with a positive sign, except sentiment.

returns in a horse race.[23]

[Insert Table 7 about here]

Panel B of Table 6 shows results from a regression of the asset-class-specific components of the value spread on the same predictors. We observe that the full set of predictors explains about half of the variation in the value spread specific to US individual equities, global stock indexes and global government bonds, and less than a third for currencies and commodities. More interestingly, the coefficients on the benchmark predictors vary dramatically across asset classes in magnitude and significance. For example, the loading on the default spread is positive for US individual equities and negative for global stock indexes and government bonds.[24] Also, whereas the sentiment index does not enter significantly in the full model in Panel A, it does so for the component specific to equities with a negative sign (for both individual equities and stock indexes) and for currencies with a positive sign.

Table 8 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.

[Insert Table 8 about here]

Panel A of Table 8 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 $h > 6$ the fraction of value return variation driven by the explained part of common value is about three times the contribution of the unexplained part, e.g., 10.03% vs 3.23% for $h = 24$. Even though the contribution is much smaller from a quantitative perspective, the part orthogonal to the macro and

[23]Table C.6 of the Internet Appendix shows that the dividend yield predicts value returns in isolation, but is driven out by the principal component of the benchmark predictors in a horse race. This result suggests that joint variation in the benchmark predictors is more informative about value returns than the dividend yield alone. Both the dividend yield and the principal component are driven out by our measure of common value, however.

[24]Consistent with this result, Figure 2 shows that the first principal component of the value spreads has a positive loading on all asset classes, except global government bonds.

financial variables continues to be statistically significant. The last two rows of Panel A shows that this conclusion is robust to excluding the dividend yield from the set of benchmark predictors.

Panel B of Table 8 presents the same test for the asset-class-specific component of the value spread. In this case, the predictability is more equally split between the part that is related to the benchmark predictors and the orthogonal part. On one hand, at long horizons ($h \geq 24$), 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 more important at shorter horizons up to one year.

Consistent with the idea that conditional tests are powerful to distinguish between competing models (Campbell and Cochrane (2000), Cochrane (2005, Ch. 8) and Nagel and Singleton (2011)), the results from our relatively simple tests have three important asset pricing implications. First, common variation in the value spread across asset classes is closely associated to common variation in a large set of standard proxies for time-variation in risk premia, including the dividend yield, default spread, illiquidity, intermediary leverage and real uncertainty. These standard proxies also contain the bulk of relevant information in common value for future value returns. It is important to stress that this common time-varying component of value premia is present in asset classes with potentially different investors and institutional factors. Theories that rely on firm investment risk or growth options (see, e.g. Berk, Green and Naik, 1999) can capture value premia in equities, but seem ill-equipped to explain the comovement in value premia between equities, currencies, and commodities. Thus, this result calls for a more general framework.

Second, the benchmark predictors also contain information about asset-class-specific components of the value spread, and can account for part of its predictive power (especially at long horizons). However, the loadings of specific value on these variables differ in sign and magnitude across the asset classes. This result suggests that value strategies in different asset classes relate to aggregate macro and financial conditions (and sentiment) in different ways, such that some form of market segmentation is required to explain the asset-class-specific component of value. This segmentation may derive from the fact that different asset classes have different types of investors, institutional and market structures, and information environments. Alternatively, a flight-to-quality explanation may be at work as hinted by, e.g., the opposite sign of the loading on the default spread for the value spread in equities versus government bonds.

Third, we show that there are components of the value spread that are orthogonal to the large set of benchmark predictors, but that contribute to the predictability of common, and to a larger extent, asset-class-specific value returns. These residual components represent a puzzle as they can be linked only to mispricing and market inefficiencies.

6 Value Timing and Rotation

In this section, we present a number of out-of-sample strategies that 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:

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

Thus, $VS_{t,His}$ tells us 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.[25]

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 capitalization cumulates to either 75%, 90%, or 95% of total market cap-

[25]Our conclusions are similar when we standardize last year's value spread relative to the past ten years. To take care of outliers, which might indicate unrealistic long- and short-positions, we cut off the standardized signal at ±2.

italization 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.[26]

[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 in Panel A and B. 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 into 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.

The fact that our results are robust for 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 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.

[26] 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%, such that 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 large CAPM alphas imply that conditional value strategies are attractive on top of a broader 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:

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

for $h = 1, 3, 6, 12, 24, 48$ months, and 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 lose the first 120 months of returns in each asset class, as we need these to construct 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 $VS_{c,t,His} > 0$ is 68 bps and 66 bps per month, respectively, translating 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 in each sample month t, $1/N_t$ in each of N_t available value strategies (out of the maximum of six). Then we consider a value rotation strategy that overweights (underweights) those asset classes where the value spread is high (low) relative to the remaining 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 relatively low value spread signals that the value strategy will have an excess return that is close to zero. 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 strategy in each asset class (as defined in Table 4). 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 most cases significant. We conclude that the rotation strategies, and especially their long leg, are also attractive next to a portfolio that diversifies unconditionally across these markets.[27]

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 one-third of the sample. We conclude that the benefits from value timing are not only driven by individual equities, but by alternative asset classes just the same.

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 strongly significant and economically large, both in isolation and in the pool of value strategies. Our coefficient

[27]Formally, the 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.

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 already have a hard time to explain the unconditional magnitude of market and value premia in 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 the value spread present another challenge to the literature. Although the specific components of value are partially consistent with some form of (rational) market segmentation, there is a remaining, unexplained part that presents us with a new puzzling aspect of global value premia.

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Figures

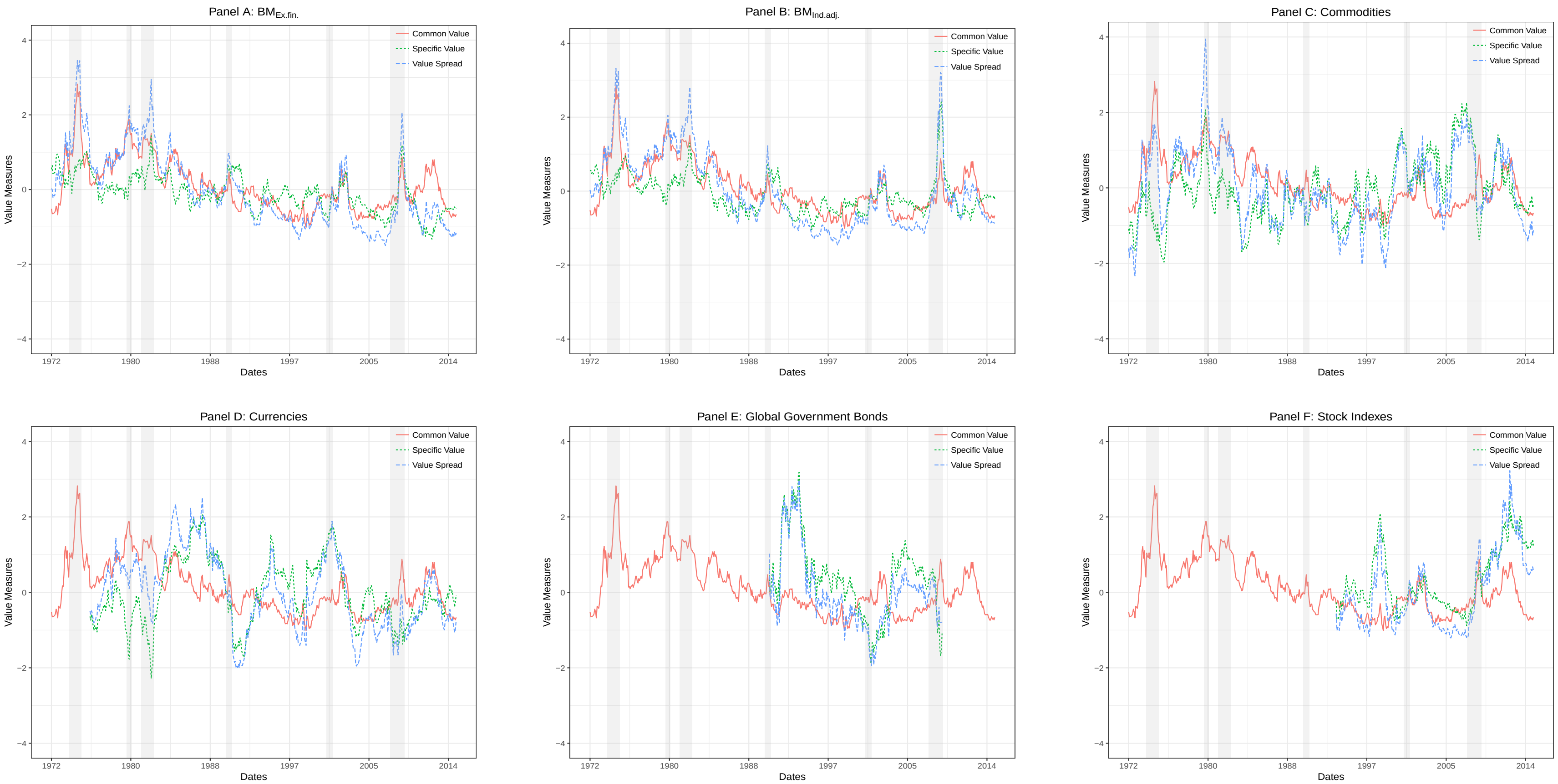

FIGURE 1: **Value Spread Decomposition**
This figure presents the time series of standardized value spreads (in blue) for the following six long-short value strategies: (i) individual equities sorted on book-to-market excluding financials ($BM_{Ex.fin.}$), (ii) individual equities sorted on industry 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 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 and Principal Components of Value Spreads and Benchmark Predictors**

This figure presents the time series of our measure of common value as well as two principal components (PC), with each series standardized to have mean equal to zero and variance equal to one. Our measure of common value is a simple average of the value spreads for six value strategies, $VSAVG$ ((1) individual equities (book-to-market excluding financials), (2) individual equities (industry-adjusted book-to-market), (3) commodities, (4) currencies, (5) global government bonds, and (6) stock indexes) . The first, $VSPC1$, is the first PC of the six value spreads. The second, $MacroPC1$ is the first PC 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). 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: $R^{BM}_{t+h} = a_h + b_h VS_t + \varepsilon_{t+h}$ 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 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, where we take the difference between the long- and short-leg of the value strategy after compounding. 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 $h = 6, 24$. In Panel B and C, the value spread, V_t, is standardized to accommodate interpretation and t-statistics are calculated using Newey-West 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: $R^{BM}_{t+h} = a_h + b_h VS_t + \varepsilon_{t+h}$, in four alternative asset classes. 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, where we take the difference between the long- and short-leg of the value strategy after compounding each portfolio return (including the t-bill return). In Panel B, the value spread, V_t, is standardized to accommodate interpretation and t-statistics are calculated using Newey-West 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	$H-L$ b	$H-L$ t_a	$H-L$ t_b	$H-L$ R^2	$Rank$ a	$Rank$ b	$Rank$ t_a	$Rank$ t_b	$Rank$ 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: Pooling Across Asset Classes** This table reports of joint tests that pool the returns of value strategies across asset classes. We have two value strategies for individual US 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. 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 six holding periods of $h = 1, 3, 6, 12, 24, 48$ months and two portfolio weighting schemes: a high-minus-low spreading portfolio ($H - L$) as well as 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). Panel F reports results for a robustness check that regresses the returns of five rank-weighted value strategies used in Asness et al. (2013) on our rank-weighted measures of the value spread. These tests exclude the industry-adjusted BM strategy, which these authors do not analyze. Throughout, returns for each value strategy are scaled to a standard deviation of 15% annually to make the strategies comparable across asset classes. The t-statistics are Newey-West 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 the alternative asset classes enter the sample only after 1972.

		$H-L$					$Rank$				
	h	a	b	t_a	t_b	$R^2 \times 100$	a	b	t_a	t_b	$R^2 \times 100$
					Panel A: Pooled Predictive Regression						
	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						
First Half	6	0.0232	0.0301	2.45	3.66	6.23	0.0198	0.0280	1.99	3.21	4.94
	24	0.1354	0.1399	3.47	3.66	22.66	0.1112	0.1592	2.27	2.92	22.35
Second Half	6	0.0118	0.0270	1.73	3.47	4.57	0.0222	0.0251	2.54	2.51	3.43
	24	0.0371	0.1228	1.74	3.35	14.25	0.0906	0.1138	4.10	3.70	13.24
					Panel C: Predicting Returns, Volatility, and Sharpe ratio						
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
					Panel D: Average Value Return on Average Value Spread						
	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

Continued

	h	Pooled					Average-on-Average				
		a	b	t_a	t_b	$R^2 \times 100$	a	b	t_a	t_b	$R^2 \times 100$
Panel E: Predicting the Long- and Short-End of Value Returns											
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
Panel F: Returns by Asness et al. (2013) on our Value Spreads											
	6	0.0210	0.0188	3.48	3.14	2.55	0.0268	0.0233	4.67	3.30	12.37
	24	0.0980	0.0897	4.43	4.06	10.47	0.1225	0.0661	5.37	3.36	18.85

Table 4: **Does the CAPM Capture 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 with a 1 in the c'th row (and 0 in all other rows), and $R_{MKT,c,t+1}$ is the market benchmark. The market benchmark is common across asset classes in Panel A, where we use the return of 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, but the alternative asset classes enter the sample only after 1972.

		a	b	β_1	β_2	β_3	β_4	β_5	β_6	$R^2 \times 100$
Panel A: Common Market Benchmark ($R_{MKT,c,t+1}$ = CRSP Value-Weighted Portfolio)										
$H-L$	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										
$H-L$	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: $R_{c,t+1:t+h} = a_h + b_{h,Com} VS_t^{Com} + b_{h,Spec} VS_{c,t}^{Spec} + \varepsilon_{t+h}$. We define common value, $VS_t^{com} = N^{-1} \sum_{i=0}^{N} VS_{c,t}$, 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 full sample period is 1972 to 2014, but the alternative asset classes enter the sample only after 1972.

Panel A

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

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	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. We use: (1) a global recession dummy; (2) the dividend yield; (3) the default spread; (4) the illiquidity premium (measured by the repo-spread); (5) real uncertainty; (6) intermediary leverage; and, (7) 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-West standard errors with 12-lags. The full sample period is 1972 to 2014, but the 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: **Pooled predictive regressions on principal components 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: $R_{c,t+1:t+h} = a_h + b_h Macro_{PC1,t} + \varepsilon_{c,t+1:t+h}$. Panel B controls for common value, which we define as a simple average over the asset classes ($VS_t^{com} = N^{-1} \sum_{i=0}^{N} VS_{c,t}$). 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	$b_{MacroPC1}$	t_a	$t_{b_{MacroPC1}}$	$R^2(\%)$
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 vs. Common Value							
h	a	$b_{MacroPC1}$	b_{Com}	t_a	$t_{b_{MacroPC1}}$	$t_{b_{Com}}$	$R^2(\%)$
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 8: **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 six benchmark predictors that are commonly used to capture time-variation in risk premia, as in specification 8 of Table 6, and saving the predicted value. The orthogonal component of common and specific value is the residual from this time-series regressions. Panel A and B thus reports coefficient estimates from the regression, $R_{c,t+1:t+h} = a_h + b^1_{h,Com}(VS_{c,t}^{Com} - \widehat{VS_{c,t}^{Com}}) + b^2_{h,Com}\widehat{VS_{c,t}^{Com}} + \varepsilon_{c,t+1:t+h}$. Panel B presents results from the same regression for $VS_{c,t}^{Spec}$. Panels C and D report results from the same regression, but exclude 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 the alternative asset classes enter the sample only after 1972.

Panel A: Returns on Components of Common Value										
h	a	b^1_{Com}	b^2_{Com}	t_a	$t_{b^1_{Com}}$	$t_{b^2_{Com}}$	R^2	$R^2_{Com,Orthogonal}$	$R^2_{Com,Explained}$	R^2_{Cov}
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^1_{Spec}	b^2_{Spec}	t_a	$t_{b^1_{Spec}}$	$t_{b^2_{Spec}}$	R^2	$R^2_{Spec,Orthogonal}$	$R^2_{Spec,Explained}$	R^2_{Cov}
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 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 with the historical average value spread and is therefore 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 $2 \times 2 \times 3$ 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 capitalizations cumulate to either 90%, 95%, or 75% of total market capitalization 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-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 for 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, and is observable at time t. 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 the 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

	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 $w^{rot,1}_{c,t} = q_t(VS_{c,t,His} - Mean(VS_{c,t,His}))$, where the scalar q_t ensures that the total weight in the long and short position equal one. The second strategy, with weights denoted $w^{rot,2}_{c,t}$, 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, but the alternative asset classes enter the sample only after 1982. Panel B reports the fraction of the long-leg of the two rotation strategies that is invested in each in each asset class.

Panel A: Performance of Value Rotation Strategies

	Linear Weight ($w^{rot,1}_{c,t}$)						Equal-weight ($w^{rot,2}_{c,t}$)					
	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 Asset Class in $Rotation_{Long}$

	Linear Weight ($w^{rot,1}_{c,t}$)		Equal-weight ($w^{rot,2}_{c,t}$)	
	$H-L$	*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.

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. 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, October, 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,

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

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 Eq. 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).

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

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 decile value 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 graph 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 is not only a natural and simple choice that is particularly suited to real-time exercises, but it is also the most meaningful way to combine the cross section of valuation ratios of book-to-market sorted portfolios from a statistical perspective. It is important to note, however, that this does not imply that the high-minus-low value spread is identical to the best predictive factor for the value premium that can be constructed as a combination of valuation ratios of individual stocks. Determining the shape and comovement of this factor in different asset classes is interesting, and we leave this for future work.

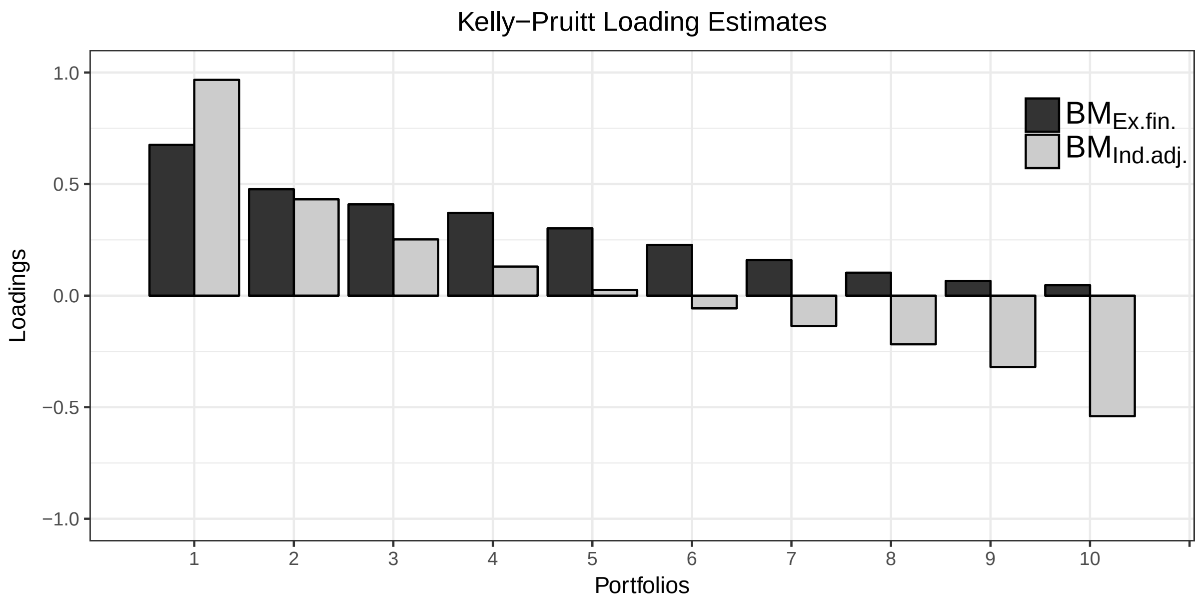

FIGURE B.1: **Kelly-Pruitt Loading Estimates**
This figure shows the Kelly-Pruitt (2013) loading estimates, $\hat{\phi}_i$, for ten decile equity portfolios. BM Ex. Fin. is the liquid US stock sample excluding financial firms and BM Ind. Adj. is the liquid sample of US stocks where book-to-market has been industry adjusted.

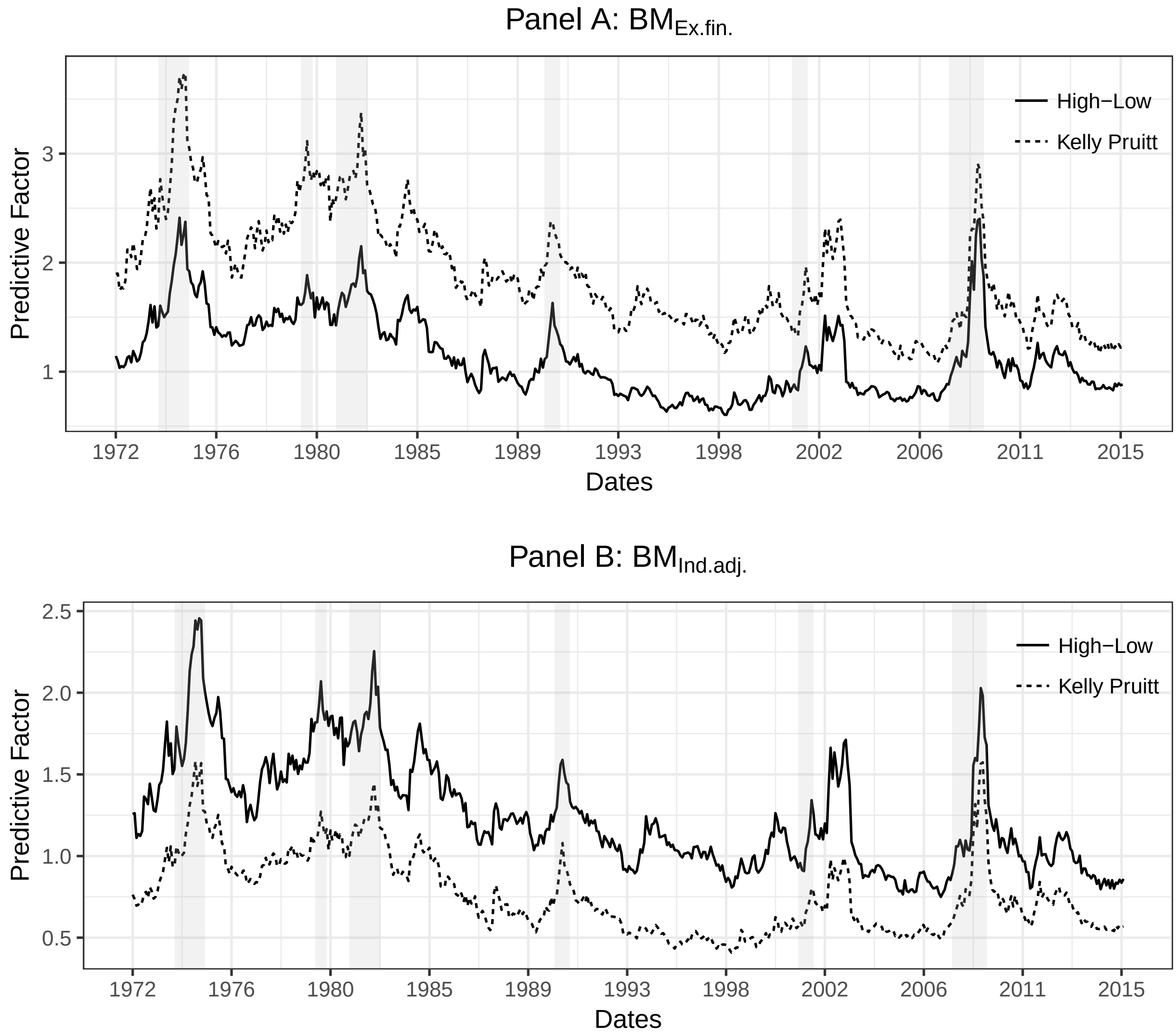

Figure B.2: **Kelly-Pruitt and High-minus-Low Predictive Factor**
This figure compares the Kelly-Pruitt (2013) latent predictive factor, $\hat{F}_t$, to the High minus Low Value Spread (HML) for the periods 1972 to 2015. Panel A contrasts the two predictors for the liquid US stock sample that excludes financial firms. Panel B reports the results for the liquid US stock sample following industry adjusted book-to-market ratios. The shaded areas represent NBER recessions.

C Robustness checks

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: **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.3: **Pooled predictive regressions with alternative value measures**

This table presents the pooled predictive regression of Table 3 in the paper, but now we include 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 by this substitution.

	$H-L$					$Rank$				
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.4: **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.5: **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 across asset classes. 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 individually significant in predicting value returns in a joint test.

Panel A: First Principal Component

h	a	$PC1$	$PC2$	$PC3$	$PC4$	$PC5$	$PC6$	$R^2(\%)$
1	0.0036	0.0018						0.48
	(3.11)	(2.37)						
3	0.0109	0.0060						1.60
	(3.39)	(3.11)						
6	0.0226	0.0123						3.09
	(3.65)	(3.25)						
12	0.0469	0.0241						4.94
	(3.96)	(3.24)						
24	0.1067	0.0573						10.15
	(4.40)	(3.57)						
48	0.2816	0.1487						18.49
	(5.67)	(5.96)						

Panel B: All Principal Components

h	a	$PC1$	$PC2$	$PC3$	$PC4$	$PC5$	$PC6$	$R^2(\%)$
1	0.0038	0.0017	-0.0017	0.0015	-0.0012	0.0031	0.0073	1.07
	3.28	2.36	-1.69	1.12	-1.00	1.68	0.87	
3	0.0114	0.0059	-0.0048	0.0046	-0.0035	0.0087	0.0257	3.15
	3.68	3.30	-1.74	1.31	-1.10	1.71	1.23	
6	0.0237	0.0123	-0.0065	0.0112	-0.0058	0.0137	0.0405	5.19
	4.04	3.65	-1.29	1.74	-0.96	1.42	1.28	
12	0.0489	0.0248	-0.0011	0.0243	-0.0105	0.0270	0.0032	7.57
	4.46	3.77	-0.11	2.18	-0.91	1.73	0.06	
24	0.1066	0.0608	0.0229	0.0337	-0.0453	0.0294	-0.0284	13.49
	4.93	4.66	1.25	2.19	-2.10	1.23	-0.42	
48	0.2791	0.1508	0.0240	0.0368	-0.0246	0.0749	-0.1654	19.94
	6.06	6.65	0.71	1.07	-0.31	1.58	-0.75	

Table C.6: **The role of the dividend yield in pooled predictive regressions**
This table is similar to Table 7 of the paper and presents pooled predictive regressions of value returns on combinations of three predictors: the dividend yield, the first principal component of the seven benchmark predictors, and our measure of common value. We see that the dividend yield predicts value returns in isolation, but is insignificant when controlling for the principal component. Both the dividend yield and the principal component are insignificant controlling for our measure of common value.

h	a	b_{DY}	$b_{MacroPC1}$	b_{Com}	t_a	$t_{b_{DY}}$	$t_{b_{MacroPC1}}$	$t_{b_{Com}}$	$R^2(\%)$
6	0.0220	0.0137			3.47	1.73			1.27
24	0.1082	0.0773			4.01	2.72			6.07
6	0.0218	-0.0073	0.0136		3.53	-0.63	2.06		2.48
24	0.1057	-0.0055	0.0533		4.15	-0.13	2.24		8.83
6	0.0182	-0.0161	0.0058	0.0393	2.86	-1.25	0.72	2.65	3.76
24	0.0866	-0.0453	0.0159	0.1853	3.49	-1.14	1.13	3.42	13.10