Value Return Predictability Across Asset Classes and Commonalities in Risk Premia☆

Fahiz Baba Yara* Martijn Boons† Andrea Tamoni‡

Nova SBE Nova SBE LSE

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Abstract

We show that returns to value strategies in individual equities, currencies, global stock indexes, global government bonds, and commodities are predictable by the value spread. This fact is at odds with models that exclusively generate a value premium in equities. Common and asset-class-specific components of the value spread contribute equally to this predictability. We argue that common variation in value premia is consistent with rationally time-varying expected returns, most importantly because (i) common value is closely associated with standard proxies for risk premia, such as the dividend yield, intermediary leverage and illiquidity, and (ii) value premia are globally high in bad times. In contrast, expected returns to momentum strategies are largely unrelated to standard proxies for risk premia, and, if anything, low in bad times.

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

JEL Classification: E44, G11, G12

*Nova School of Business and Economics, Campus de Campolide, 1099-032 Lisbon, Portugal. E-mail: baba.fahiz@novasbe.pt

†Nova School of Business and Economics and NETSPAR, Campus de Campolide, 1099-032 Lisbon, Portugal. E-mail: martijn.boons@novasbe.pt Web: https://sites.google.com/site/martijnboons/

‡Corresponding author. Department of Finance, London School of Economics and Political Science, Houghton Street, London WC2A 2AE, UK. E-mail: a.g.tamoni@lse.ac.uk Web: http://www.lse.ac.uk/finance/people/profiles/AndreaTamoni.aspx

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1 Introduction

In this paper, we show that expected returns of long-short value strategies in a range of asset classes are increasing in the value spread. The value spread is the difference between the value signal in the long versus short portfolio, and its relation to value premia can be motivated from standard present value logic.[1] The time-variation in value premia we document is both economically and statistically large. Predictive regressions at the one-year horizon attain an R^2 of 14%, 11%, 10%, 20%, and 11%, for US individual equities, currencies, global stock indexes, global government bonds and commodities, respectively. In all these asset classes, a standard deviation increase in the value spread predicts an increase in expected value return of the same order of magnitude (or more) as the unconditional value premium. Thus, expected returns on value strategies vary over time by at least as much as their already puzzling level.

Cochrane (2011) emphasizes that the value premium continues to be one of the main "puzzles" in finance, as the long-standing debate between rational explanations and mispricing is still unresolved. To shed new light on this debate, we set out to determine the economic drivers of the time-variation in expected value returns. To this end, we decompose the value spread into a common component and an asset-class-specific component.[2] Quantifying the relative contribution to predictability of these two components is important, because a large and significant common component is evidence of market integration. Despite this fact, there is little evidence in existing literature of common return predictability across asset classes.

We find that common and specific components contribute about equally to return predictability in the pool of value strategies. Moreover, the common component is strongly countercyclical, thus signaling globally high expected value returns in bad times. We show that two proxies for the risk of financial intermediaries – market leverage and fund-

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

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

ing liquidity – together with a measure of risk aversion are key determinants of common value. Thus our empirical evidence builds support for the recent theoretical literature on intermediary-based asset pricing (see He and Krishnamurthy, 2012, 2013; Brunnermeier and Sannikov, 2014) as well as for asset pricing models featuring time-varying risk aversion (see Campbell and Cochrane, 1999; Menzly et al., 2004; Santos and Veronesi, 2016).

To benchmark these results, we follow Asness et al. (2013) and construct momentum strategies in all the asset classes we study. We find that momentum returns are also significantly and economically predictable by the momentum valuation spread, i.e., the difference in value signal for the assets in the winner versus loser portfolio. Similar to value, a large share of this predictability is common across asset classes. Three important differences between momentum and value stand out, however. First, momentum return predictability is short-lived and peaks at the one-year horizon. In contrast, value return predictability is persistent, strengthens with the horizon, and is significant up to about four years out. Second, the common component of momentum is relatively unrelated to popular proxies for risk premia, and it is, if anything, procyclical. Thus, expected momentum returns are globally low in bad times. Finally, the value spread and the momentum valuation spread are negatively correlated, and so are the expected returns from these two strategies.

We argue that these differences provide key insights into stories of risk and mispricing for the return predictability we document. The fact that expected value returns are high globally in bad times, and remain so for a number years, lends support to an explanation based on rationally time-varying risk premia. This not to say that value returns do not present a challenge for asset pricing theory, however. The common component of value premia is present in asset classes with potentially different investors and institutional factors. Leading theories relying on firm investment risk or growth options can capture value premia in equities, but seem ill-equipped to explain the comovement in value premia across asset classes (see, e.g., Berk et al., 1999; Gomes et al., 2003; Zhang, 2005).[3] Explaining this common dimension of value returns requires a more general framework,

[3]Indeed, we find that the amount of time-variation in the equity value premium we document is about three times larger than what is implied by simulating the investment-based asset pricing model of Zhang (2005).

where in bad times investors shy away from holding different risky assets, such as value stocks and undervalued currencies, so that value spreads widen simultaneously.

Whereas our paper is about comovement in *expected* value returns, Asness et al. (2013) show that *realized* value returns comove across the same asset classes we study. The large amount of common variation in expected returns relative to their unconditional mean suggests that the hurdle for rational, risk-based models is actually much higher than what these authors already discuss. The procyclicality of common momentum returns is even harder to reconcile with rationally, time-varying risk premia. If one is willing to accept that expected returns (and risk) are lower than usual in bad times for winners relative to losers, it is even more puzzling that these winners outperform by a such large margin unconditionally.

Another challenge to existing asset pricing models follows from the asset-class-specific components of the value spread, which point to a mix of risk and mispricing. Although these specific components load on some risk-proxies, such as the default spread and a global recession dummy, we find that the loadings vary dramatically across asset classes. Our findings are consistent with heterogeneity in risk exposures and the idea that investors may rationally move from one asset class to another over time, such as in a flight-to-quality from equities to bonds. However, even after controlling for a broad set of risk-proxies, a large part of asset-class-specific value return predictability still goes unexplained. This conclusion holds equally for the case of momentum and points to mispricing.

Our results contribute to the asset pricing literature in various ways.[4] Unconditional value premia are documented in US individual equities (Fama and French, 1992), international equities (see, e.g., Fama and French, 1998; Liew and Vassalou, 2000), and alternative asset classes (Asness et al., 2013). Unconditional evidence for momentum is similarly abundant (see, e.g., Jegadeesh and Titman (1993), Rouwenhorst (1998), and

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

Asness et al. (2013)). In contrast, we characterize conditional premia. Our conditional tests have important asset pricing implications, consistent with the idea that such tests are relatively powerful to distinguish between competing asset pricing models (Campbell and Cochrane, 2000; Cochrane, 2001; Nagel and Singleton, 2011).

There is a large literature that attempts to forecast returns using valuation ratios. Lewellen (1999) and Cochrane (2011, p. 1099) predict returns of diversified equity portfolios with their book-to-market ratio. Cochrane (2011) concludes that "variation over time in a given portfolio's book-to-market ratio is a much stronger signal of return variation than the same variation across portfolios in average book-to-market ratio." Similarly, Kelly et al. (2017) argue that the relevant information for predicting individual stock returns comes from the time-variation in various value characteristics. Kelly and Pruitt (2013) analyze whether the expansion and compression of the cross section of value characteristics contains information about the aggregate market. In contrast to these papers, we analyze how the returns of the value-minus-growth portfolio vary with the value spread.

Our findings for the value spread in individual equities are consistent with those of Asness et al. (2000a). Using data for large US stocks from 1982 to 1999, they find that industry-adjusted value spreads have predictive power for value-minus-growth returns. Similarly, Cohen et al. (2003) show that the return of the Fama and French (1993) HML factor is predictable by the HML value spread (see also Rytchkov, 2010; Li et al., 2014). In contrast to us, these papers do not study (i) the value spread in other asset classes, (ii) the relation between conditional value and momentum returns, (iii) the relative contribution of common and specific components to predictability as well as their economic drivers, and (iv) the potential and robustness of the value spread in an out-of-sample setting. With regard to the latter, we find that value returns are predictable in real-time, which alleviates concerns that our in-sample evidence is spurious.

Our multi-asset approach is uniquely suited to answer some of the central questions in asset pricing: Do expected returns vary over time and across assets? If so, by how much? And is this time-variation driven by risk or mispricing? In answering these questions, we identify a strongly time-varying, common component in both value and momentum premia. In case of value, our evidence points to a risk-based explanation for the variation in the common component. This component cannot be identified by analyzing a single value premium in isolation, and thus helps to explain recent mixed evidence on the question of whether the equity value premium is driven by risk or mispricing (see Golubov and Konstantinidi, 2016; Gerakos and Linnainmaa, 2017). In this way, our work also contributes to the recent literature on global asset pricing, where "betting against beta" (Frazzini and Pedersen, 2014), "carry" (Koijen et al., 2017b), and downside risk (Lettau et al., 2014) are shown to be factors in US equities as well as a host of other asset classes. In contrast to us, these papers mostly characterize unconditional premia.

A paper close to ours is Haddad et al. (2017), who characterize conditional return variation in stocks, bonds, and currencies. The authors argue just like us that relative (long-short) returns are more predictable than aggregate returns. Whereas Haddad et al. (2017) analyze a different strategy and a different predictor in each asset class, we analyze for both value and momentum a single predictor in all asset classes. This single predictor is the value spread and allows us to identify variation that is common. Moskowitz et al. (2012), Neuhierl and Weber (2017), and Moreira and Muir (2017) also present global evidence for return predictability, respectively, due to time-series momentum, monetary momentum, and volatility timing. In particular, volatility timing strategies are attractive in many 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.

Finally, our paper relates to a recent strand of literature that studies which, potentially non-linear, combinations of a large set of characteristics predict returns in the cross section of individual equities (DeMiguel et al., 2017; Freyberger et al., 2017; Kozak et al., 2017; Kelly et al., 2017). To focus exclusively on the cross-section, these authors transform each characteristic as input to their econometric model so that its cross-sectional standard deviation is (approximately) constant over time.[5] Our results suggest that this transformation shuts down an important driver of expected returns, that is, the expansion and compression of the cross section of a characteristic over time.

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

2 Data and Methodology

In this section, we describe the method to construct value measures and value returns in different asset classes. We refer the interested reader to Appendix A for additional details on the sources and procedures to clean the data. To avoid data snooping, our measures of value are aimed at maintaining simplicity and consistency across asset classes, and, to the extent that a standard exists, being standard. As is common in the literature, we measure value as a book-to-market ratio for individual stocks and global stock indexes. For the remaining asset classes, we follow Asness et al. (2013) and measure value using long-term past returns. This choice is inspired by the long strand of literature that documents a direct link between past returns and book-to-market ratios, both empirically (see DeBondt and Thaler, 1985; Fama and French, 1996; Gerakos and Linnainmaa, 2017) and theoretically (see Daniel et al., 1998; Hong and Stein, 1999; Vayanos and Woolley, 2013).

2.1 Value in Different Asset Classes

2.1.1 US Individual Stocks

The US individual stock data is 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 sizable trading volume. To be precise, we include in our value strategies only those stocks that account cumulatively for 90% of the total market capitalization in CRSP.[6] 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 with strategies in alternative asset classes, where the small set of assets we study is relatively liquid.

To measure value for each firm i, we use the ratio of the book value to the market value of equity, or book-to-market ratio $BM_{i,t}$, as in Fama and French (1992). Book values are observed each June and refer to the previous fiscal year-end. Market values are

[6] The 90% market capitalization cutoff yields an average of 618 stocks for our portfolios. We analyze alternative market capitalization cutoffs of 75% (263 stocks on average) and 95% (934 stocks on average) in Section C.1 of the Internet Appendix, where we discuss a number of out-of-sample tests.

updated monthly as in Asness and Frazzini (2013), but we also consider annually updated market values in a robustness check. Consistent with previous literature, we exclude financial firms: a given book-to-market ratio might indicate distress for a non-financial firm, but not for a financial firm (see Fama and French, 1995). We denote this measure $BM_{i,t,ExFin}$. 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: $BM_{i,t,IndAdj}$. These subtract from each $BM_{i,t}$ the value-weighted average book-to-market ratio of the industry to which stock i belongs. Asness et al. (2000b) and Cohen and Polk (1998) find that industry-adjusted value strategies are relatively attractive. These authors further argue that there is no unconditional value effect across industries. To determine whether there is neither a conditional value effect, we sort 17 industries on their average book-to-market ratio in a robustness check.

2.1.2 Currencies

We obtain spot and forward exchange rates for Australia, Canada, Germany (spliced with the Euro), Japan, New Zealand, Norway, Sweden, Switzerland, UK, and the United States. To measure value, we use the five-year change in relative purchasing power parity, which is calculated as the negative of the five-year spot return adjusted by the five-year foreign−US inflation difference. We use the unadjusted −5-year return in a robustness check. Currency value is 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.

2.1.3 Global Stock Indices

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

2.1.4 Global Government Bonds

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

We define two measures of value for bonds using synthetic prices and yields.[7] The first measure is the negative of the five-year futures return (−5-year return). The second is the five-year change in the ten-year yield (5-year Δy). Using five-year changes in yields avoids potential problems arising from trends and unconditional differences in, e.g., default risk across bond markets. Throughout the paper, our main focus is on strategies that use the first value measure to invest in the traded bond futures, but we present a number of robustness checks for the second value measure and synthetic bond returns. The sample period for global government bonds runs from January 1991 to December 2014.

2.1.5 Commodity Futures

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

2.2 Value Returns

To construct value returns, we sort securities within each asset class into P groups based on (the cross-sectional distribution of) the value measures, $V_{i,t}$. For individual stocks, we

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

form value-weighted decile portfolios ($P = 10$) each month and define the value portfolio as decile 10 (High) and the growth portfolio as decile 1 (Low). For all other classes, we set $P = 2$ and form an equal-weighted High and Low portfolio by splitting the securities at the median of ranked values. We denote with R_{t+1}^{H-L} the return of the High-minus-Low value portfolio in the month after sorting.

We also report results from an alternative rank-weighting procedure that weights each security $i = 1, \dots, N_t$ at time t according to its rank in the cross section:

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

The weights sum to zero, thus representing a dollar-neutral long-short portfolio. The scaling factor q_t ensures that we are one dollar long and one dollar short. The return of this rank-weighted strategy is calculated as $R_{t+1}^{Rank} = \sum_i w_{i,t}^{Rank} R_{i,t+1}$. Throughout the paper, whenever we are predicting returns over horizons longer than one month, we separately compound returns on the long and short position of these value strategies and then take the difference. These long and short positions are rebalanced every month. To be consistent across asset classes, we compound returns including the T-bill return.[8]

2.3 Predicting Value Returns with the Value Spread

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

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

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

[8] Appendix A presents more detail on the construction of excess returns in different asset classes, and lists the collateral and hedging assumptions for foreign currency denominated futures.

well-behaved, then

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

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

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

Empirically, we abstract from the correction for the spread in discounted future expected profitability. Thus, the regression of Eq. (1) provides a lower bound on the predictability of value returns (see Asness et al., 2000a).[9]

As an alternative motivation, consider the investment-based asset pricing model of Zhang (2005). In this model, the value spread predicts value returns in the time series because it signals time-variation in the risk premia of value versus growth stocks. In bad times, the market value of value firms decreases as they are burdened with more unproductive capital and face large adjustment costs, relative to growth firms who want to expand capital in good times. Consequently, value is more risky exactly when risk premia are high. Finally, the value spread can be motivated also relying on a purely statistical approach. In Appendix B, we show that the partial least squares method of Kelly and Pruitt (2015) selects the High-minus-Low value spread as the optimal forecasting factor derived from the cross section of portfolio-level book-to-market ratios.

Similar to Eq. (2), the standard present-value formulation of Engel and West (2005) and Froot and Ramadorai (2005) shows that expected currency returns are a key driver of the real exchange rate. This motivates using real exchange rates as a measure of value for currencies. For bonds, the yield is a natural value metric, where a high yield indicates

[9]For example, one can improve the predictive ability of the value spread in US individual equities by incorporating the restrictions in Eq. (3) within a filtering approach (see Rytchkov, 2010) or by using the implied costs of capital to control for differences in earnings growth rates and payout ratios (see Li et al., 2014).

that the bond is relatively cheap. As for the case of equities, our regressions for currencies and bonds provide a lower bound on the predictability of value returns, since one can likely improve on our results by controlling for expected real interest rate differentials in the case of currencies (see Menkhoff et al., 2016), and differences in expected long-term inflation in the case of bonds (see Asness et al., 2017).[10] Because these adjustments need to be estimated and are different across asset classes, we instead follow Asness et al. (2013) and use a simple, directly observable, measure of value that is common to all asset classes: the negative of five-year returns.

Finally, in the regressions of value returns on the value spread (see Eq. (1)), we consider forecasting horizons h up to four years. Horizons longer than one month help to mitigate the countervailing momentum effect (see Asness and Frazzini, 2013) and better resemble the experience of actual value investors. Moreover, long-horizon regressions of value returns on value spreads are relatively less affected by the inferential problems that are commonly associated to predictability. High first-order autocorrelation of the predictor and Stambaugh (1999) bias have been put forward as leading causes of inaccurate inference when predicting market returns (e.g. Valkanov, 2003; Lewellen, 2004; Boudoukh et al., 2006). The monthly autocorrelation of value spreads in the different asset classes ranges from 0.95 to 0.97, which is small relative to a value of 0.99 for the dividend yield, for instance. In our framework, a Stambaugh-bias is largely absent, because the left-hand side in Eq. (1) is a difference in return between two portfolios, which we regress on the corresponding difference in valuation ratios. This setup in differences breaks the mechanical relation that exists in regressions of a single return on a price-based valuation ratio. Pooled tests of predictability further alleviate concerns about Stambaugh-bias, because the across asset class dimension lowers the pooled correlation between innovations in the value spread and past return shocks.

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

2.4 Time-Variation in Value Spreads

We standardize the value spread in each asset class so that its time-series average equals zero and standard deviation equals one. This standardization makes the coefficients from Eq. (1) comparable across asset classes. The exception are the out-of-sample tests, for which we standardize the value spread in month t using only information available at that point in time. Figure 1 plots the standardized value spreads over time (blue line).[11]

[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 and the cross section of value measures is wider than normal. The same intuition applies to the other asset classes. For currencies, for instance, a large value spread indicates that the deviations from relative purchasing power parity are historically large. The main hypothesis we test in this paper is that, all else equal, a wider value spread today indicates larger value returns in the future in all asset classes.

We also analyze what fraction of the time-variation in value spreads is common across asset classes and what fraction is asset-class-specific (the red and green line, respectively, in Figure 1). Common value is calculated as the average value spread over the asset classes with available data in month t:

$$\mathrm{VS}_t^{\mathrm{Com}} = \frac{\sum_c^{N_t} VS_{c,t}}{N_t} . \tag{4}$$

The asset-class-specific component is the difference between the value spread in an asset class and common value:

$$\mathrm{VS}_{c,t}^{\mathrm{Spec}} = \mathrm{VS}_{c,t} - \mathrm{VS}_t^{\mathrm{Com}} . \tag{5}$$

The panels in Figure 1 present a number of episodes when the value spread was large in more than a few asset classes, such as after the burst of the IT-bubble and the recent financial crisis. Consistent with such common variation, our simple average measure of

[11] We focus on the High-minus-Low strategies, but note that our conclusions are identical for the rank-weighted strategies.

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.[12] There is also considerable variation that is asset-class-specific. 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 Value Return Predictability

In this section, we ask whether the returns to value strategies are predictable in the time series. To this end, we first analyze time-series predictive regressions for value in individual equities and in each of the alternative asset classes. Next, we analyze pooled predictive regressions that assess the joint strength of value return predictability. This pooled evidence is new to the literature and represents a key contribution of our paper.

3.1 Time Series Predictive Regressions

3.1.1 Individual Equities

Asness et al. (2000a) and Cohen et al. (2003) show that the value spread predicts equity value premia over time. We extend their evidence in three directions. First, we consider the sample post-2000 and focus on a relatively small set of large and liquid stocks. Second, we ask whether the investment-based asset pricing model of Zhang (2005), successful in capturing the unconditional value premium, generates the amount of time-variation we document. Third, we test whether the value spread predicts returns out-of-sample.

Panel A of Table 1 shows the unconditional performance of the value-minus-growth strategies. The table reports monthly average return, standard deviation, t-statistic, and Sharpe ratio for both the High-minus-Low and rank-weighted portfolio using the two signals: BM_{ExFin} and BM_{IndAdj}. The annualized Sharpe ratios for these strategies are

[12] We prefer to measure common value as the simple average value spread across asset classes, because the principal component is not observed in real-time and the panel of value spreads is unbalanced. For the principal component analysis, we balance this panel with an algorithm that recursively projects the value spread in an asset class with a shorter sample on the value spreads that are available over the full sample.

around 0.20 (monthly Sharpe ratio $\times\sqrt{12}$). The exception is the rank-weighted portfolio based on the industry-adjusted book-to-market ratio, which obtains a Sharpe ratio of 0.41. These Sharpe ratios are a bit lower than what is typically reported for value in the literature. The reason is that we use only relatively large and liquid stocks that cumulatively account for 90% of the total market capitalization.[13]

[Insert Table 1 about here]

Panel B of Table 1 shows the results from in-sample time-series predictive regressions of value returns on the value spread at forecasting horizons of $h = 1, 3, 6, 12, 24$ months. We present coefficients, t-statistics (based on Newey and West (1987) standard errors with h-lags), and R-squares.[14]

At all horizons, and for both decile and rank-weighted portfolios, the coefficient on the value spread is economically large and typically statistically significant. Let us consider first the book-to-market signal that excludes financials. The coefficient estimate increases with the forecasting horizon, for instance, from 0.57% ($h = 1$) to 22.58% ($h = 24$) for the High-minus-Low decile portfolio. At the two-year horizon, the coefficient estimates for the decile and the rank-weighted portfolio, respectively, imply an increase in the value premium of 22.58% and 11.25% per standard deviation increase in the value spread. The R^2 is also increasing in the horizon. For instance, for the High-minus-Low decile portfolio, the R^2 ranges from 0.85% at the one-month horizon to 30.33% at the two-year horizon. The coefficient estimates are similar in magnitude for the industry-adjusted book-to-market ratio. However, in this case, the R^2's are even larger, reaching 45% and 27% for the High-minus-Low and rank-weighted portfolio, respectively, at the two-year horizon. The correlation between the value return series that excludes financials and the industry-adjusted value return series is about 0.75. This result suggests that cleaning valuation ratios from across-industry variation creates a different time series of value returns that is more predictable.

By standardizing the value spread, the ratio of the estimated coefficients to the in-

[13] Asness et al. (2000a) and Asness et al. (2013) focus on large stocks as well and the correlation between our first book-to-market strategy (excluding financial firms) and the comparable strategy of Asness et al. (2013) is 0.99.

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

tercept, b_h/a_h, measures the implied standard deviation of expected returns relative to the unconditional value premium. At all horizons, this ratio is above two for the High-minus-Low portfolios, and it is above one for the rank-weighted portfolios. We conclude that the value premium in equities strongly increases (decreases) as the cross section of valuation ratios expands (compresses).

To benchmark the strength of this in-sample evidence, consider that Cochrane (2011) reports a ratio slightly below one when predicting the aggregate stock market with the dividend yield. Thus, the variation in expected value returns we document is economically large and it will likely pose a challenge for standard asset pricing models to match. To see this by example, we simulate from the investment-based asset pricing model of Zhang (2005), which contains a time-varying value premium.[15] Table D.2 of the Internet Appendix presents the distribution of unconditional and conditional value premia obtained from 1000 simulations of the model. We see that the median ratio b_h/a_h in a regression of annual High-minus-Low value returns on the lagged value spread is 0.74. This ratio is small relative to our empirical estimates of about 2.5, which falls in the far right tail of the simulated distribution.

Moreover, it is unclear whether the information in the dividend yield can be used profitably in an out-of-sample setting, which has raised concerns that the in-sample relation between stock market returns and the dividend yield is spurious (Lettau and Van Nieuwerburgh (2007) and Goyal and Welch (2008)). In contrast, we find that the value spread predicts returns also out-of-sample. To see this, we present in Table C.1 of the Internet Appendix the performance of linear timing strategies. As described in more detail in Section C.1 of the Internet Appendix, these strategies condition the time-t position in value on an historically standardized value spread. We find that by timing value one attains Sharpe ratios that are twice as large as those of unconditional value strategies.

3.1.2 Alternative Asset Classes

We next ask whether value returns in currencies, stock indexes, global government bonds, and commodities are similarly predictable in the time-series.[16] Panel A of Table 2 reports

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

[16] Throughout, we focus on traded bond futures returns. Results for synthetic bond futures returns are qualitatively similar, but weaker, as reported in Table D.3 of the Internet Appendix.

unconditional performance statistics for both the High-minus-Low and rank-weighted portfolios in these alternative asset classes. We see that most value strategies obtain a positive Sharpe ratio, but there is considerable variation in magnitude. Both value measures for currencies (the negative of the five-year spot exchange rate return with and without inflation adjustment) provide Sharpe ratios greater than 0.29. 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 (−5-year return), the Sharpe ratio of the High-minus-Low and rank-weighted strategy is about zero. This is relative to 0.20 and 0.32 when we measure value by the five-year change in yield (5-year Δy). For stock indexes and commodities, the unconditional Sharpe ratios are about 0.20.

[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 2.37% (currencies, −5-year return) to 13.00% (government bonds, 5-year Δy) for $h = 6$, and from 8.06% (stock indexes) to 36.67% (government bonds, −5-year return) for $h = 24$. In all asset classes, 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 on the value spread relative to the intercept is close to one for currencies and (typically well) above one for stock indexes, bond indexes, and commodities. Since the value spread is standardized, this ratio implies that the standard deviation of expected returns implied by these predictive regressions is in the same order of magnitude (or more) as the unconditional value premium in these asset classes. Thus, we find that value premia consistently vary over time with the value spread. In fact, comparing the evidence in Panel A to Panel B, we must conclude that the conditional variation in value premia is actually more similar across asset classes than are unconditional value premia.

3.2 Pooled Predictive Regressions

We turn to pooled tests for the following six value strategies: individual equities (book-to-market excluding financials and industry-adjusted book-to-market), currencies, global stock indexes, global government bonds, and commodities. These pooled tests shed light on the joint time-variation in expected value premia implied by time-variation in the value spread. Panel A of Table 3 presents results for the pooled predictive regression:

$$R^x_{c,t+1:t+h} = a_h + b_h \ \mathrm{VS}^x_{c,t} + e^x_{c,t+1:t+h}, \tag{6}$$

where c denotes an asset class and $x = H - L, Rank$. We add in these pooled tests a longer four-year horizon, $h = 48$, because pooling should yield more power. We present t-statistics using asymptotic standard errors calculated following Driscoll and Kraay (1998), which are heteroscedasticity-consistent and robust to rather general forms of cross-sectional and temporal dependence when the time dimension becomes large. We find that inference using these standard errors is conservative relative to two-way clustered standard errors.

[Insert Table 3 about here]

In Panel A, we see that the joint predictability is strong for both types of portfolios. For instance, for the High-minus-Low portfolio, the coefficient on the value spread is strongly significant with a t-statistic of 3.52 at $h = 1$ and above 5 for $h \geq 3$. 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 100% (50%) larger than the unconditional value premium in the pool of High-minus-Low (rank-weighted) value strategies. Consistent with these coefficient estimates, the R^2 increases with the horizon, and it reaches over 20% at the 24- and 48-month horizons. The idea that the value spread contains information for value returns at long horizons is further supported by Figure 3. In this figure, we predict future value returns over consecutive semi-annual periods after portfolio formation. We see that the coefficients on the value spread are decreasing as time passes, but are positive and marginally significant up to about four-and-a-half years after portfolio formation.

In Panel B, we present an alternative way of looking at the joint strength of value return predictability. We regress in the time series the average value return on the average value spread, where both cross-sectional averages are taken over the six asset classes. We again see coefficient estimates on the value premium that are statistically significant and economically large. The R^2's are even larger at over 30% for the 24- and 48-month horizons, which is likely due to the fact that averaging smooths out some noise in the individual value strategies. This result not only testifies to the joint strength of value premium predictability, but it also suggests there is common variation in value premia across asset classes. We dig further into this suggestion in the next section.

Inspired by the CAPM (Sharpe, 1964; Lintner, 1965; Mossin, 1966), we ask whether our results are explained by exposure to a market benchmark. To this end, we run the pooled predictive regression of value returns on the value spread, but 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 use as benchmark an equal-weighted portfolio of the securities in each alternative asset class.

[Insert Table 4 about here]

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

[17] Note, US equity market returns are weakly predictable by the equity value spread, as in Kelly and Pruitt (2013). In contrast, market returns in the remaining asset classes are not predictable by the value spread. This latter fact explains the insignificance of the value spread in the pooled regression of Table D.4.

of value premia. In the next section, we analyze whether time-variation in popular proxies for risk premia can explain time-varying value premia.

4 Common Value and Economic Drivers of Value Return Predictability

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 on proxies for risk premia that are popular in the literature. Finally, we investigate how much of the (common and asset-class-specific) predictive power of the value spread can be attributed to these proxies. Throughout this section, we analyze and discuss in detail the results for the High-minus-Low value strategies. By and large identical results for the rank-weighted strategies are reported in Tables D.5, D.6, and D.7 of the Internet Appendix.

4.1 Common versus Asset-Class-Specific Value

We start by investigating how much predictability in value strategies is common across different asset classes. To this end, we present in Table 5 results from a pooled predictive regression, where we decompose the value spread into two components: a component that is common across asset classes, $\mathrm{VS}_t^{\mathrm{Com}} = \frac{\sum_c^{N_t} VS_{c,t}}{N_t}$, and a component that is asset-class-specific, $\mathrm{VS}_{c,t}^{\mathrm{Spec}} = \mathrm{VS}_{c,t} - \mathrm{VS}_t^{\mathrm{Com}}$. See Figure 1 for the time series of each component.

In isolation, the coefficient estimates on the common and asset-class-specific components of the value spread are statistically and economically significant at all horizons. The coefficients are also statistically indistinguishable from the coefficients on the raw (not decomposed) value spread, which are reported in Panel A of Table 3. For instance, at the one-year horizon the coefficients are 7.10%, 8.82% and 6.19%, respectively, for the raw value spread and its common and specific components. The two components explain large and similar amounts of variation in the pool of value returns, with one-year R^2's of

8.26% and 7.69%, respectively. To achieve this R^2, the common component uses only time variation. Because the two components are orthogonal in the pool by construction, the coefficient estimates for the common and asset-class-specific components are unchanged in a joint regression and the total variation explained by these two components is the sum of their individual R^2's, i.e., 15.95% at the annual horizon. The joint R^2's are similar to the R^2's for the raw value spread (e.g., 15.47% at the annual horizon in Panel A of Table 3).[18] The results thus suggest that the common and asset-class-specific components of the value spread about equally split the predictability of value returns at all horizons ranging from one month to four years.

[**Insert Table 5 about here**]

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 that expected returns of value strategies rise and fall globally. As highlighted in Cochrane (2011): "It is not enough to simply generate temporary price movements in individual securities."

4.2 Economic Drivers of the Components of Value

In this section, we analyze the economic sources of variation in the common and asset-class-specific components of the value spread using state variables from recent asset pricing models. In particular, we run time-series regressions of the form:

$$VS_t^{Com} = k_0 + k_1' Z_t + u_t^{Com} \quad \text{and} \tag{7}$$

$$VS_{c,t}^{Spec} = k_0 + k_1' Z_t + u_t^{Spec}, \tag{8}$$

where Z_t is a particular set of state variables (or, more generally, risk-proxies). We report the results from Eq. (7) in Panel A of Table 6 and results from Eq. (8) in Panel B.

Given that intermediaries are the marginal investors in many asset markets, their marginal value of wealth is a plausible pricing kernel for a broad set of securities, which

[18] One can decompose the value spread arbitrarily in two orthogonal components and obtain joint regression results similar to what we present here. However, such arbitrary components will generally not predict value returns well in isolation, especially if one of the components is restricted to not vary across asset classes.

may therefore drive common variation in expected returns. Recent intermediary-based asset pricing models (see He and Krishnamurthy, 2012, 2013; Brunnermeier and Sannikov, 2014) show that the intermediary sector's net worth (or equivalently the reciprocal of leverage, defined as assets over equity) is the key determinant of its marginal value of wealth. We analyze the link between the aggregate leverage of financial intermediaries and the common component of the value spread in row 1 of Panel A. We find a tight relation, with variation in leverage accounting for almost 50% of the overall variation in common value.[19] This *time-series* evidence complements the large and growing body of literature showing that the leverage of financial intermediaries has strong *cross-sectional* predictive power for returns in various asset classes (see Adrian et al., 2014; He et al., 2017).

[Insert Table 6 about here]

Next, guided by theory (see Brunnermeier and Pedersen, 2009) and empirical evidence (see Adrian and Shin, 2010) that implies a close link between funding liquidity and the balance sheet of the financial sector, we investigate the relation between illiquidity and common value. Following Nagel (2016), we proxy for illiquidity with the repo/T-bill spread. In row 2, we see that illiquidity also explains considerable variation in common value with an R^2 of almost 40%. Jointly, leverage and illiquidity explain almost 60% of the variation in common value (row 3). Both variables enter significantly, with economically large coefficients. Common value increases by about 0.3 standard deviations for a standard deviation increase in either variable.

Recent literature acknowledges that financial intermediary leverage is endogenous and its cycles may simply reflect movements in aggregate risk aversion (see Campbell and Cochrane, 1999; Menzly et al., 2004; Santos and Veronesi, 2016).[20] Inspired by Campbell and Cochrane (1999), who argue that the price-to-dividend ratio is nearly linear in the surplus consumption ratio, we next explore the link between common value and the dividend yield. We find in row 4 that the dividend yield explains lots of variation in

[19] To proxy 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.

[20] Our measure of leverage is based on market prices (market leverage) and, in the model of Santos and Veronesi (2016), the debt-to-wealth ratio is monotonically decreasing in the surplus consumption ratio (see their Corollary 13).

common value, with an R^2 of almost 60%. This result is consistent with the idea that the value spread widens when risk aversion is high. We then investigate in row 5 the extent to which leverage and liquidity are just a manifestation of time-varying risk aversion (as proxied by the dividend yield). We see that intermediary leverage, illiquidity, and the dividend yield are all significant and jointly capture about two-thirds of the variation in the common component of the value spread. However, as the intimate link between leverage cycles, liquidity dry-up, and risk aversion would suggest (see Santos and Veronesi, 2016), the magnitude and statistical significance of the individual coefficients fall upon joint inclusion of these variables.

Based on the evidence so far, we conclude that common value is large when, in bad times, intermediaries' balance sheets get shocked and/or aggregate risk aversion is high. Consistent with this result, we see in row 6 that common value is higher by about 0.3 standard deviations in global recessions, which is a rough and general proxy of bad times (see Asness et al., 2013). In row 7, we see that this conclusion is also robust to controlling for additional state variables. Following Koijen et al. (2017a), who link the value spread in equities to business cycle risk, we include the Chicago Fed National Activity Index (CFNAI). We also include the Jurado et al. (2015) real uncertainty index.[21] As pointed out by Nagel (2016), liquidity is likely at least partly driven by the level of uncertainty, since a high level of risk can erode agents' "trust" that bank deposits are a good store of liquidity. Finally, we include the default spread, a popular proxy for cyclical variation in risk premia.[22] In this "kitchen sink" regression, all three additional state variables are insignificant and the R^2 increases only marginally relative to the three-variable model in row 5 (68% vs. 65%). Thus, our evidence suggests that leverage, illiquidity, and the dividend yield are the key drivers of common value.

Panel B of Table 6 presents results from time-series regressions of the asset-class-specific components of the value spread on the same risk-proxies. We focus on the kitchen sink regression to have an upper bound on what risk can explain. Jointly, the risk-proxies explain a considerable fraction of the variation in the specific value spread in some asset

[21]We find that the correlation between common value and uncertainty is slightly stronger for real uncertainty than for macro or financial uncertainty, as defined in Jurado et al. (2015).

[22]The default spread is the difference in yield between BAA and AAA corporate bonds. Replacing this spread with the excess bond premium of Gilchrist and Zakrajsek (2012) yields similar results.

classes, with R^2's ranging from 14% for commodities to about 50% for individual equities and global government bonds. However, the loadings on individual risk-proxies vary dramatically across asset classes, in both magnitude and significance. For instance, the loadings on the default spread and uncertainty are positive for US individual equities and negative for global stock indexes and government bonds. These results are suggestively consistent with a flight-to-quality story, where in bad times investors shy away from more risky value strategies in individual equities towards safer value strategies in global stock indexes and government bonds. Thus, heterogeneity in risk exposure across asset classes may be an important driver of asset-class-specific value.

Table 7 completes our analysis of the economic sources driving the predictability of value returns across asset classes. 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 risk-proxies (the predicted value spread, $k_0 + k_1' Z_t$, in Eqs. (7) and (8)) and how much by the part that is orthogonal (the residual, u_t). We consider two specifications for the set of risk-proxies in Z_t. The first specification is parsimonious and uses only leverage, illiquidity, and the dividend yield. The second specification uses all variables (kitchen sink).

[**Insert Table 7 about here**]

Focusing on the decomposition of R^2, we see in Panel A that most of common value return predictability at longer horizons is explained by the risk-proxies, and this is especially true in the kitchen sink specification. For instance, at the 24-month horizon, the fraction of value return variation attributed to the explained part of common value is over four times what is attributed to the orthogonal part (10.84% versus 2.52%). This ratio is also large at slightly below three in the parsimonious specification (9.59% versus 3.49%). Even though the contribution is smaller quantitatively, the part orthogonal to the risk-proxies continues to be statistically significant at all horizons.

The results for asset-class-specific value return predictability in Panel B paint a different picture. The part of asset-class-specific value that is orthogonal to the risk-proxies is relatively more important for predicting value returns than the explained part. Perhaps unsurprisingly, the orthogonal part is relatively more important in the parsimonious specification.

4.3 Interpretation

The evidence in this section broadly raises two challenges for asset pricing theory. First, our results for common value call for a general framework, where investors shy away in bad times from holding different risky assets, like value stocks and undervalued currencies. Consequently, the value spread widens simultaneously in different asset classes when discount rates (and thus expected value returns) are high. The motivation is that common value return predictability is closely associated to proxies for the risk of financial intermediaries (such as market leverage and funding liquidity) and risk aversion (dividend yield). This common time-varying component of value premia is present in asset classes with potentially different investors and institutional factors. Leading theories relying on firm investment risk or growth options can capture value premia in equities, but seem ill-equipped to explain the comovement in value premia between equities, currencies, and commodities.

Second, our results for asset-class-specific components of the value spread indicate the presence of additional risk and mispricing factors in time-varying value premia. On one hand, we find that correlation between risk-proxies, such as the default spread, and the asset-class-specific components of the value spread contributes to the predictability of value returns. However, the loadings of specific value on these proxies vary across asset classes, consistent with heterogeneity in risk exposures. Moreover, it is the component of the asset-class-specific value spread that is orthogonal to our large set of risk-proxies that contributes relatively more to the predictability of value returns. Albeit small, such an orthogonal component is also present in common value. Absent any further explanation, these orthogonal components represent mispricing.

5 Value Versus Momentum Return Predictability

In this section we benchmark our results to momentum strategies to shed additional light on the relative importance of risk versus mispricing in explaining time-varying value premia. To start, we construct momentum strategies in all asset classes, measuring momentum in month t as an asset's previous twelve month return.[23] Following the approach described in Section 2, we calculate the return of Winner-minus-Loser and rank-weighted momentum strategies. Our interest is in the information content of a signal that we coin the momentum valuation spread, MVS_t, which measures the relative valuation of winners versus losers. For instance, for the Winner-minus-Loser portfolio, we compute MVS_t as the average value signal of the assets in the Winner portfolio minus the average value signal in the Loser portfolio, $MVS_t^{W-L} = V_t^W - V_t^L$.[24]

To set the stage, we first ask whether Winner-minus-Loser momentum returns in different asset classes are predictable in the time series by the momentum valuation spread. We focus on the results from pooled predictive regressions in Table 8 (analogous to Eq. (6)) for the sake of brevity.[25] These pooled tests aggregate consistent evidence from individual time-series regressions, which are reported in Table D.10 of the Internet Appendix.

[Insert Table 8 about here]

In Panel A, we see that momentum returns are also predictable. For horizons up to one year, the coefficient estimates indicate that expected momentum returns increase by about as much as their unconditional mean when the momentum valuation spread increases by one standard deviation. The R^2 is also considerable and increases from 0.92% for $h = 1$ to 6.81% for $h = 12$. At the two- and four-year horizon, we see that the coefficient estimate stabilizes and the R^2 decreases to 2.64% and 0.78%, respectively. The fact that the momentum valuation spread contains no additional information for returns more than one year into the future suggests that momentum return predictability is short-lived.[26] This pattern across horizons marks an important difference between value and momentum. Both strategy's returns are predictable, but value return predictability is relatively more persistent. For value returns, both the coefficient on the value spread and

[23]To be consistent with previous work, we skip a month between portfolio formation and return observation in the case of individual stocks.

[24]We use the following value measures in the different asset classes: book-to-market in equities, negative of the inflation-adjusted five-year return in currencies, MSCI book-to-price in global stock indexes, and the negative of the five-year return in global government bonds and commodities.

[25]We present by and large identical results for the rank-weighted strategies in Tables D.8 and D.9 of the Internet Appendix.

[26]Because we are analyzing the returns to rebalanced momentum strategies, our results are not inconsistent with the long-term reversal effect that exists in buy-and-hold returns to the momentum strategy.

the R^2 increase linearly in horizon up to four years.

Panel B decomposes momentum return predictability in its common and asset-class-specific components. We see that both components contribute individually and significantly to the predictability of momentum returns. The common component contributes more, however. It captures about two-thirds of the joint R^2 at all horizons up to one year. This result is due to coefficient estimates on the common component that are at least twice as large as those on the specific component. Recall that the common and specific component contribute about equally to time-variation in expected value returns. Thus, our results suggest that expected returns to momentum strategies rise and fall globally to an even slightly larger extent than in the case of value.

To understand the economic sources of momentum return predictability, we next investigate the determinants of (components of) the momentum valuation spread. To start, Table 9 shows that the large set of risk-proxies used in Table 6 do not strongly predict the common component of the momentum valuation spread. For instance, in the kitchen sink specification, the R^2 is only 18.27%, which is relative to 67.63% for the common component of the value spread (see Table 6). Moreover, if anything, the results indicate that the momentum valuation spread is low in bad times, not high such as is the case for value. For instance, in global recessions, the momentum valuation spread is significantly lower on average by 0.30 standard deviations, whereas the value spread is higher by 0.33 standard deviations (see row 6 in Table 6). This evidence suggests that in bad times expected momentum returns are globally low, rather than high. Table D.11 of the Internet Appendix presents evidence consistent with this suggestion from pooled predictive regressions of momentum and value returns on the global recession dummy. We find that average momentum returns are significantly lower in recessions (by about -5% annually), whereas value returns are significantly higher (by about 6%).

[**Insert Table 9 about here**]

Panel B of Table 9 presents the loadings on the risk-proxies for the asset-class-specific components of the momentum valuation spread. Different from value (see Table 7), we see that the risk-proxies capture little of the time-variation in any of the asset-class-specific components. However, similar to the case of value, there are some loadings that are significant, but with little consistency in sign or magnitude across asset classes.

The fact that many of our results are opposite for momentum and value is perhaps unsurprising given the evidence in Asness et al. (2013). These authors highlight the negative correlation in realized momentum and value returns. We extend this negative correlation to valuation spreads and thus expected returns, which we argue to contain an economically large, common, time-varying component in different asset classes. Figure 4 plots the valuation spreads for both momentum and value strategies over time. Their negative correlation is immediately clear and ranges from -0.57 for global stock indexes to -0.23 for individual equities. The last panel in the figure shows that these negative correlations aggregate to a correlation of -0.25 between the common component of the value spreads and the common component of the momentum valuation spreads.

This comparison between value and momentum return predictability sheds new light on stories of risk versus mispricing. In particular, the low expected momentum returns in bad times and the short-term nature of momentum return predictability are inconsistent with the idea that variation in the momentum valuation spread captures time-variation in risk premia. In good times, a relatively high momentum valuation spread indicates that winners are cheaper than normal, such that more capital can be allocated to the momentum strategy and return continuation strengthens. Naive extrapolation of winner returns may then lead to abnormally high momentum returns. However, in bad times, momentum underperforms as investors will choose to liquidate first the winners in their portfolio. As conjectured in Asness et al. (2013), the relatively low momentum valuation spread in recessions signals that winners are expensive. Thus, momentum return predictability is more consistent with a story of mispricing. In stark contrast, the evidence for value is consistent with the idea that the value spread captures time-varying risk premia. In bad times, a high common value spread indicates that value assets are cheaper than normal, because an above average risk premium is used to discount their cash flows for a period lasting up to about four years.

6 Robustness Checks

In this section, we discuss additional robustness checks, for which we report results in the Internet Appendix.

6.1 Predicting Value Returns in Individual Equities

We analyze alternative measures of value in equities in Table D.12. We start by sorting stocks on the negative of the past five-year return (see, e.g. DeBondt and Thaler, 1985, who use similar measures for individual stocks to identify "cheap" and "expensive" firms). Next, we consider a sort of 17 industries on the average book-to-market ratio in industry portfolios. Finally, we sort stocks on their 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.

For all three alternative signals, we see positive and (marginally) significant coefficients on the "value spread." The ratio of the estimated coefficient to the intercept indicates that expected returns vary at least as much as the unconditional premium in a sort of stocks on previous five-year returns, a sort of stocks on market cap, and a sort of industries on book-to-market. The coefficient estimate is relatively small 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 of about 6% at the 24-month horizon suggest that the time-variation in across-industry value returns is economically large, which contributes to previous literature that finds no unconditional value effect across industries.

In Panel A of Table D.13, we show evidence similar to Table 1 when we extend the sample for US individual equities back to 1962. In Panel B of Table D.13, we show that value returns based on book-to-market ratios that use annually updated market cap in the denominator are predictable with the value spread. However, consistent with the finding above that market cap contains important information about returns in the time series, the effect is weaker than when using monthly updated market cap.

6.2 Joint Tests of Value Return Predictability

In Table D.14, we show that the value spread predicts value returns in the pool of asset classes in both sample halves split around June 1993. This result suggests that value return predictability is not only driven by the highly popularized value episodes around the tech bubble in the late 1990's and around the 2008 global financial crisis. Moreover, Table D.15 presents the decomposition in common versus specific value return predictability in these subsamples. We see that common value is relatively more important in the recent subsample post-1993. This finding is consistent with our previous result that common value is strongly associated with proxies for the risk of financial intermediaries, because financial intermediation has become progressively more important over time.

Table D.16 presents three robustness checks for the pooled predictive regression of value returns in different asset classes on the value spread. In Panel A, we exclude the value strategies for individual equities and see that our results are not driven by individual equities alone. Value returns in the alternative asset classes (currencies, global stock indexes, global government bonds and commodities) are strongly predictable by the value spread, with a ratio of coefficient to intercept that is slightly above one. Panel B of this table shows that the value spread predicts returns much more strongly than it does 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 (or more) as the unconditional Sharpe ratio of the value strategies. Panel C finally tests whether our results are driven by the long- or short-end of value strategies, or both. Panel A shows that most of the predictability in the pooled regressions comes from the long-end of the value strategy. In contrast, in the average-on-average specification, predictability for the long-end (with a positive sign) and the short-end (with a negative sign) contribute equally to the total predictability of value returns.

Section C.2 of the Internet Appendix shows that return predictability in the pool of value strategies is robust in an out-of-sample test. To this end, we run a pooled predictive regression of value returns on a dummy variable that indicates for each asset class and each month t if the current value spread is historically large. The results, reported in Table C.2, suggest that investing in value is only attractive when the value spread in an asset class is large relative to its own history, which confirms our previous conclusion for individual equities (c.f. Table C.1). Table C.3 shows that this conclusion holds equally for momentum strategies.

7 Conclusion

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

To understand the drivers of this time-variation, we show that common and asset-class-specific components of the value spread contribute about equally to value return predictability. We argue that the main source of common variation in value premia is compensation for risk. The motivation is that the dividend yield, intermediary leverage and an illiquidity premium capture the bulk of variation in common value. Moreover, common value return predictability is persistent and indicates that expected value returns are countercyclical. These findings are new to the literature and are only detected in a joint examination of different asset classes. Our results suggest that mechanisms – such as production- and investment-based theories – that generate value returns exclusively in equities leave unexplained an important time-series dimension of multi-asset value returns. In stark contrast to value, momentum return predictability is short-lived, largely unexplained by a large set of state variables and, if anything, procyclical.

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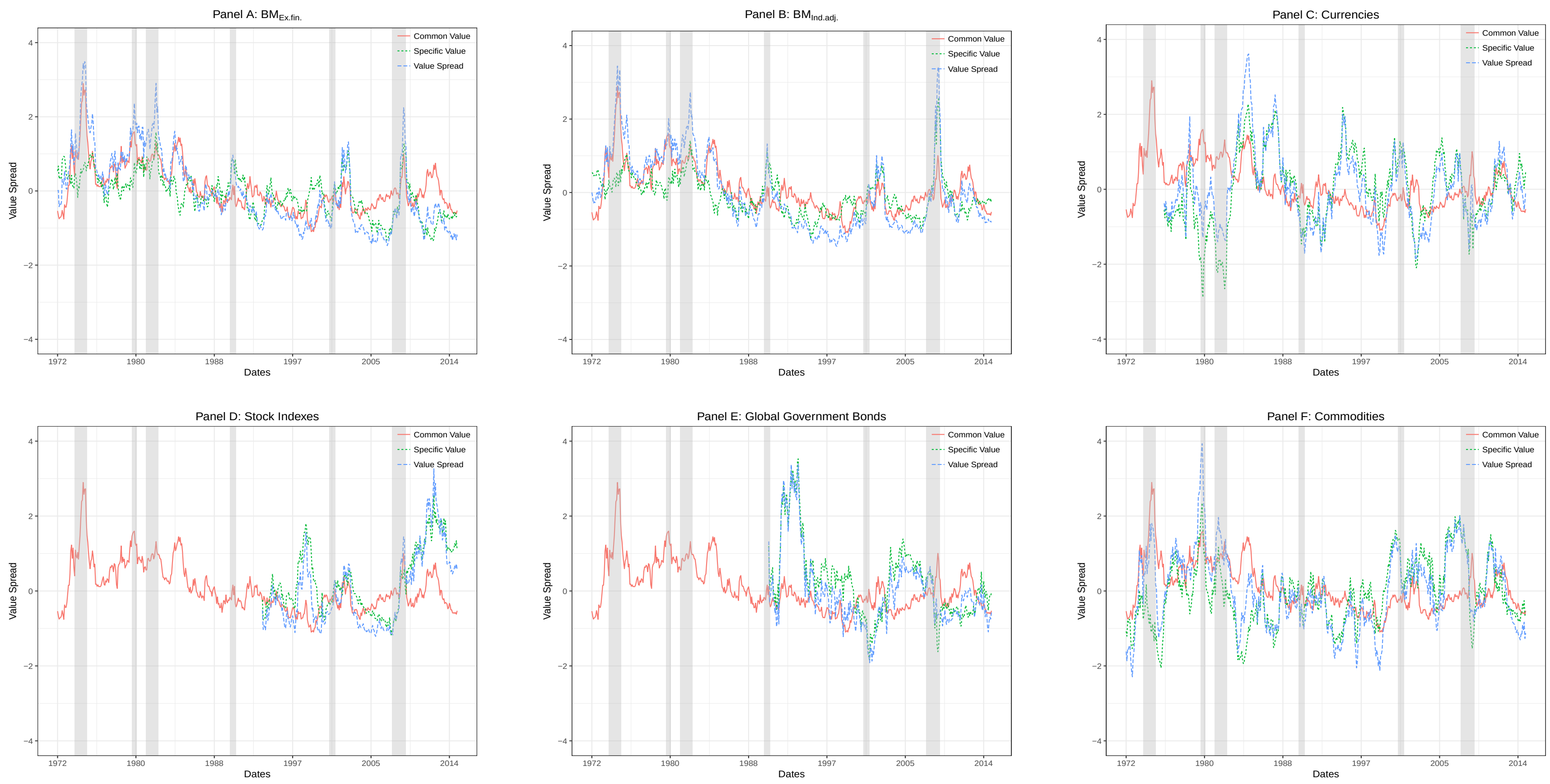

FIGURE 1: **The Value Spread and its Components over Time**

This figure presents the time series of standardized value spreads (in blue) for the following six High-minus-Low value strategies: (i) individual equities (book-to-market excluding financials, $BM_{Ex.fin.}$), (ii) individual equities (industry adjusted book-to-market, $BM_{Ind.Adj.}$), (iii) currencies (inflation-adjusted −5-year return), (iv) global stock indexes (MSCI book-to-price, $MSCI_{BP}$), (v) global government bonds (−5-year return), and (vi) commodities (−5-year return). In each panel, we also present the time series of common value, which is the average value spread across the six value strategies (in red), and the residual asset-class-specific component of the value spread (in green). The shaded areas represent NBER recessions.

FIGURE 2: **Common Value and the First Principal Component of Value Spreads** This figure presents the time series of our measure of common value (the simple average of six value spreads) against the the first principal component (of the six value spreads), with each series standardized to have mean equal to zero and variance equal to one. The loadings of the principal component are given below.

First Principal Component of Value Spreads								
	BM_{ExFin}	$BM_{Ind.Adj.}$	*Commodities*	*Currencies*	*Government Bonds*	*Stock Indexes*	% of Variation	$Corr(\mathrm{VS}^{\mathrm{Com}}, \mathrm{VS}^{\mathrm{PC1}})$
Loadings	0.51	0.51	0.24	0.38	-0.44	0.27	50.80	90.87

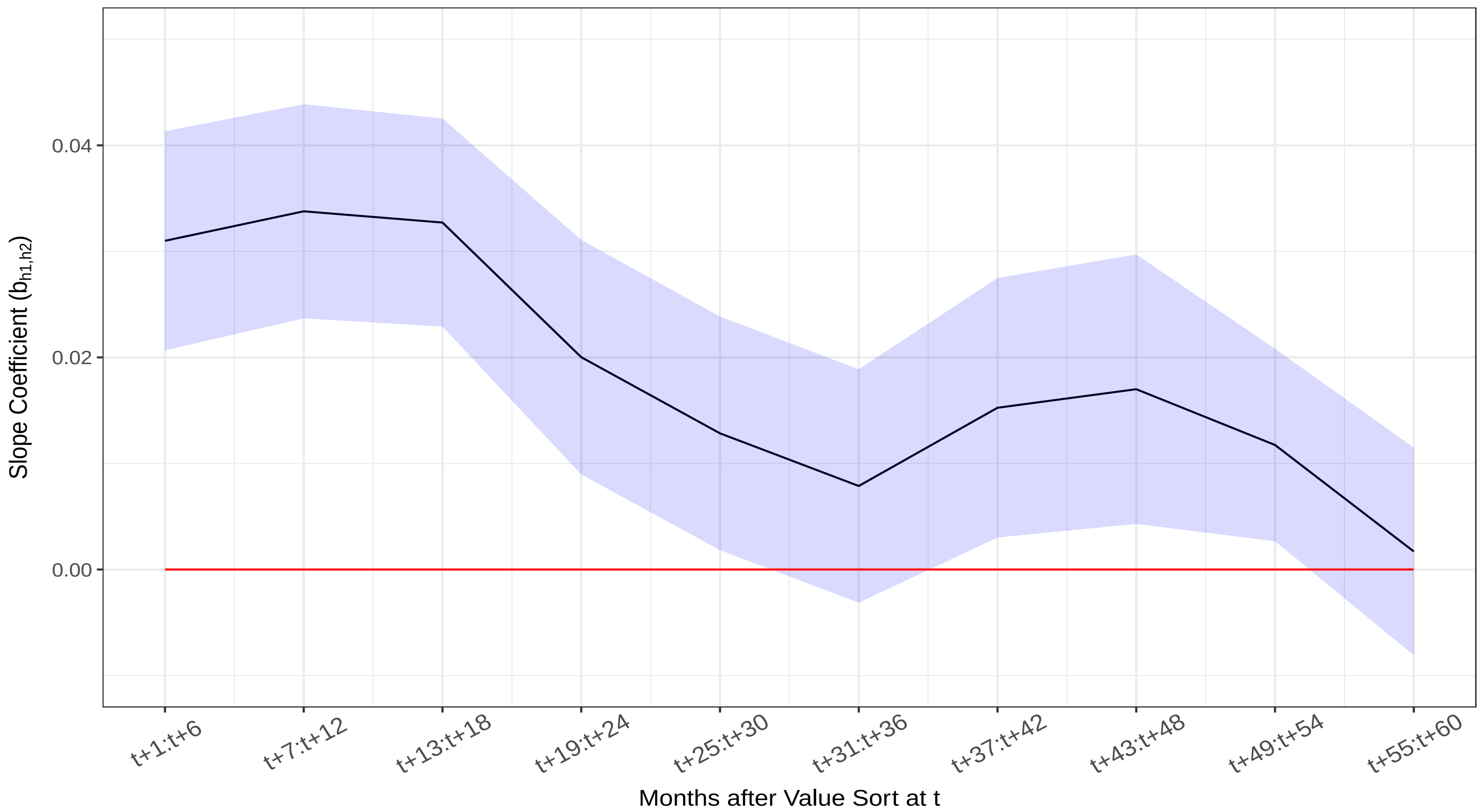

FIGURE 3: **Semi-Annual Future Value Returns on the Value Spread at Time** t

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

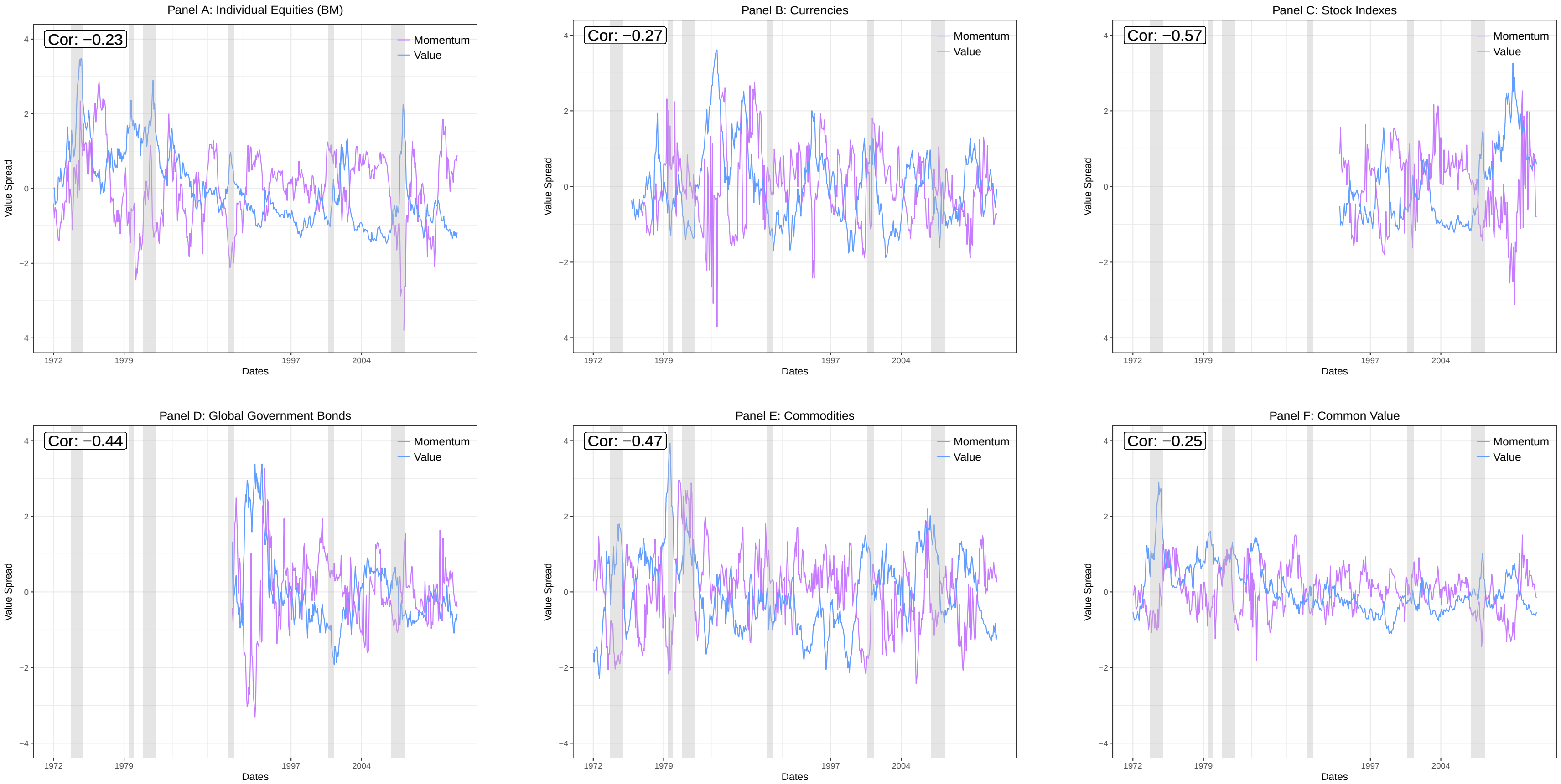

FIGURE 4: **The Momentum Valuation Spread versus the Value Spread**
This figure presents the time series of standardized momentum valuation spreads (in purple) for the following five High-minus-Low momentum strategies: (i) individual equities, (ii) currencies, (iii) global stock indexes, (iv) global government bonds, and (v) commodities. In each panel, we also present the time series of the value spread (the valuation spread for a value strategy as in Figure 1). The sixth panel presents the common components of the momentum valuation spread and the value spread, which are averaged across asset classes. The shaded areas represent NBER recessions.

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

Panel A: Unconditional Performance (Monthly Returns)

	$H - L$				$Rank$			
	Avg. ret.	St. dev.	t	Sharpe	Avg. ret.	St. dev.	t	Sharpe
BM_{ExFin}	0.0028	0.0560	1.1274	0.0493	0.0018	0.0358	1.1650	0.0510
BM_{IndAdj}	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_{ExFin}	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_{IndAdj}	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

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

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

Panel A: Unconditional Performance (Monthly Returns)

		$H-L$				$Rank$			
Asset Class	Value Measure	Avg. ret.	St. dev.	t	Sharpe	Avg. ret.	St. dev.	t	Sharpe
Currencies	Inf. adj. return	0.0015	0.0180	1.8152	0.0840	0.0022	0.0234	2.0615	0.0954
	−5-year return	0.0020	0.0184	2.3737	0.1098	0.0027	0.0237	2.4958	0.1155
Stock Indexes	$MSCI_{BP}$	0.0009	0.0241	0.6079	0.0378	0.0017	0.0284	0.9454	0.0589
Government Bonds	−5-year return	0.0000	0.0098	-0.0118	-0.0007	0.0000	0.0112	-0.0174	-0.0010
	5-year Δy	0.0005	0.0091	0.9991	0.0589	0.0009	0.0099	1.5885	0.0936
Commodities	−5-year return	0.0026	0.0456	1.2846	0.0566	0.0030	0.0592	1.1643	0.0513

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
Currencies	Inf. adj. return	1	0.0015	0.0010	1.77	1.17	0.11	0.0022	0.0015	1.99	1.19	0.17
		3	0.0047	0.0045	2.04	1.93	1.69	0.0069	0.0065	2.25	2.04	2.06
		6	0.0100	0.0099	2.20	2.22	4.38	0.0145	0.0151	2.39	2.45	5.72
		12	0.0220	0.0235	2.31	2.95	10.72	0.0319	0.0331	2.61	3.17	12.29
		24	0.0519	0.0520	2.83	3.84	22.27	0.0757	0.0649	3.45	3.79	22.23

Continued

			$H - L$					$Rank$				
Asset Class	Value Measure	h	a	b	t_a	t_b	R^2	a	b	t_a	t_b	R^2
Currencies	−5-year return	1	0.0020	0.0010	2.27	1.18	0.09	0.0027	0.0017	2.41	1.55	0.30
		3	0.0062	0.0040	2.50	1.60	1.11	0.0084	0.0060	2.65	1.95	1.65
		6	0.0130	0.0079	2.78	1.60	2.37	0.0175	0.0119	2.85	2.05	3.30
		12	0.0280	0.0127	2.96	1.41	3.07	0.0375	0.0206	3.02	2.00	4.78
		24	0.0650	0.0338	3.49	2.29	9.64	0.0863	0.0500	3.63	3.00	12.63
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
Government Bonds	−5-year return	1	0.0000	0.0014	-0.01	1.69	1.56	0.0000	0.0016	-0.02	1.90	1.66
		3	-0.0002	0.0038	-0.16	2.31	5.15	-0.0002	0.0044	-0.11	2.39	5.59
		6	-0.0004	0.0076	-0.15	3.98	11.39	-0.0001	0.0081	-0.05	2.91	10.73
		12	-0.0003	0.0144	-0.06	4.39	20.24	0.0008	0.0149	0.16	4.04	18.60
		24	0.0003	0.0309	0.03	5.08	36.67	0.0030	0.0290	0.30	7.00	30.93
	5-year Δy	1	0.0005	0.0010	1.02	1.22	0.82	0.0009	0.0016	1.62	2.04	2.14
		3	0.0017	0.0033	1.35	1.83	4.42	0.0028	0.0050	1.95	3.02	8.41
		6	0.0035	0.0074	1.56	3.84	13.00	0.0057	0.0103	2.11	4.16	17.34
		12	0.0077	0.0115	1.70	3.63	15.20	0.0129	0.0170	2.38	3.93	22.09
		24	0.0193	0.0213	1.93	3.77	22.83	0.0294	0.0339	2.34	3.94	32.84
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

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

This table reports results from joint tests that pool the returns of value strategies across asset classes. We have two value strategies for US individual equities using book-to-market ($BM_{Ex.fin.}$ and $BM_{Ind.adj.}$) and four value strategies from alternative asset classes. For commodities 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 ($MSCI_{BP}$) and for currencies we use the inflation adjusted five year return (Inf. adj. return). Panel A reports regression results for the pooled predictive regression, $R_{c,t+1:t+h} = a_h + b_h VS_{c,t} + \varepsilon_{c,t+1:t+h}$. We standardize the value spread, $VS_{c,t}$, in each asset class to make them comparable. To this end, we also scale the returns for each value strategy to a standard deviation of 15% annually. Panel B reports results of a simple time-series regression of the cross-sectional average value return (over the six strategies) on the cross-sectional average (standardized) value spread: $\overline{R_{t+1:t+h}} = a_h + b_h \overline{VS_t} + \varepsilon_{t+1:t+h}$. We consider $h = 1, 3, 6, 12, 24, 48$ months and two portfolio weighting schemes: a High-minus-Low spreading portfolio ($H - L$) and a rank-weighted portfolio (*Rank*). The t-statistics are Newey and West (1987) with h-lags for the average-on-average time-series regression and Driscoll and Kraay (1998) with h-lags for the pooled regression. The sample period is 1972 to 2014, but some alternative asset classes enter the sample only after 1972.

Panel A: Pooled Predictive Regression

	$H - L$					*Rank*				
h	a	b	t_a	t_b	$R^2 \times 100$	a	b	t_a	t_b	$R^2 \times 100$
1	0.0024	0.0042	2.33	3.52	0.95	0.0030	0.0034	2.79	2.69	0.63
3	0.0071	0.0140	2.61	5.01	3.24	0.0090	0.0116	2.99	3.64	2.11
6	0.0148	0.0310	2.90	6.00	7.31	0.0192	0.0266	3.16	4.24	4.89
12	0.0312	0.0710	3.16	6.27	15.47	0.0417	0.0636	3.48	4.76	11.37
24	0.0720	0.1532	3.16	5.91	25.16	0.0980	0.1420	4.02	4.55	21.34
48	0.1814	0.3257	2.69	5.67	27.88	0.2535	0.2834	4.32	6.57	26.55

Panel B: Average Value Return on Average Value Spread

	$H - L$					*Rank*				
h	a	b	t_a	t_b	$R^2 \times 100$	a	b	t_a	t_b	$R^2 \times 100$
1	0.0030	0.0039	2.72	2.26	2.42	0.0035	0.0032	3.07	1.93	1.54
3	0.0090	0.0128	3.17	3.68	8.03	0.0105	0.0104	3.33	2.84	4.76
6	0.0190	0.0271	3.57	4.64	17.85	0.0223	0.0223	3.50	3.21	9.65
12	0.0406	0.0565	3.98	5.62	32.42	0.0485	0.0492	3.80	3.47	19.25
24	0.0979	0.1177	4.13	6.00	43.57	0.1176	0.1171	4.31	3.53	36.47
48	0.2514	0.2474	3.86	6.58	41.57	0.3097	0.2429	5.31	6.60	47.83

TABLE 4: **Does the CAPM Explain Time-Variation in Value Returns?**
This table reports the results of a pooled predictive regression of returns on six value strategies (across different asset classes as in Table 3) on the value spread, controlling for exposure to a market benchmark, $R_{MKT,c,t+1}$: $R_{c,t+1} = a + bVS_{c,t} + \sum_{z=1}^{6} \beta_z R_{MKT,z,t+1} I_{z=c} + \varepsilon_{c,t+1}$, where $VS_{c,t}$ is the value spread in asset class c. The market benchmark is common across asset classes in Panel A: the CRSP value-weighted stock market portfolio. The market benchmark is asset-class-specific in Panel B. For the value strategies using individual equities we use the CRSP value-weighted stock market portfolio, whereas for all remaining asset classes we use an equal-weighted portfolio of returns in that asset class as market benchmark. β_1 through β_6 represent the unconditional market exposure of the following value strategies: (1) individual equities ($BM_{Ex.fin.}$), (2) individual equities ($BM_{Ind.Adj.}$), (3) currencies (Inf. adj. return), (4) stock indexes ($MSCI_{BP}$), (5) global government bonds (−5-year return), and (6) commodities (−5-year return). t-statistics are Driscoll and Kraay (1998) with h-lags. The full sample period is 1972 to 2014.

Panel A: Common Market Benchmark: CRSP

		a	b	β_1	β_2	β_3	β_4	β_5	β_6	$R^2 \times 100$
$H-L$	$Coef$	0.0024	0.0042	-0.2019	-0.0224	0.0186	0.0303	0.1227	0.1739	2.41
	(t)	2.36	3.48	-3.22	-0.35	0.40	0.45	2.05	2.49	
$Rank$	$Coef$	0.0031	0.0034	-0.2651	-0.0447	0.0391	0.0083	0.0858	0.2131	2.88
	(t)	2.89	2.71	-4.18	-0.67	0.83	0.12	1.37	3.31	

Panel B: Asset-Class-Specific Market Benchmark

		a	b	β_1	β_2	β_3	β_4	β_5	β_6	$R^2 \times 100$
$H-L$	$Coef$	0.0030	0.0040	-0.2034	-0.0239	-0.2133	-0.2694	-0.3284	0.2888	4.26
	(t)	3.00	3.34	-3.24	-0.37	-3.48	-2.01	-0.93	3.89	
$Rank$	$Coef$	0.0037	0.0031	-0.2664	-0.0461	-0.2608	-0.3522	0.3102	0.3612	5.96
	(t)	3.55	2.52	-4.19	-0.69	-3.99	-2.71	1.02	5.33	

Table 5: **Common and Specific Components of the Value Spread**
This table reports results for pooled predictive regressions of High-minus-Low value returns on components of the value spread for six strategies: (1) individual equities ($BM_{Ex.fin.}$), (2) individual equities ($BM_{Ind.Adj.}$), (3) currencies (Inf. adj. return), (4) stock indexes ($MSCI_{BP}$), (5) global government bonds (−5-year return), and (6) commodities (−5-year return). Panel A reports the results of a pooled predictive regression on the common value spread: $R_{c,t+1:t+h} = a_h + b_{h,Com} VS_t^{Com} + \varepsilon_{t+h}$. Panel B reports results for the asset-class-specific component: $R_{c,t+1:t+h} = a_h + b_{h,Spec} VS_{c,t}^{Spec} + \varepsilon_{t+h}$. Panel C reports the results of a pooled regression on both 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, $VS_t^{com} = N_t^{-1} \sum_{i=0}^{N_t} VS_{c,t}$, and specific value, $VS_{c,t}^{Spec} = VS_{c,t} - VS_t^{Com}$. t-statistics are calculated using Driscoll and Kraay (1998) standard errors with h-lags. The sample is 1972 to 2014, but some alternative asset classes enter the sample only after 1972.

Panel A: Common Value

h	a	b_{Com}	b_{Spec}	t_a	$t_{b_{Com}}$	$t_{b_{Spec}}$	$R^2 \times 100$
1	0.0024	0.0062		2.34	2.65		0.72
3	0.0071	0.0202		2.62	3.71		2.35
6	0.0148	0.0423		2.91	4.40		4.73
12	0.0312	0.0882		3.18	5.51		8.26
24	0.0720	0.1825		3.22	6.15		12.39
48	0.1814	0.4065		2.88	6.88		14.94

Panel B: Specific Value

h	a	b_{Com}	b_{Spec}	t_a	$t_{b_{Com}}$	$t_{b_{Spec}}$	$R^2 \times 100$
1	0.0024		0.0032	2.30		2.65	0.35
3	0.0071		0.0107	2.50		3.77	1.24
6	0.0148		0.0250	2.63		4.70	3.10
12	0.0312		0.0619	2.60		4.98	7.69
24	0.0720		0.1376	2.34		5.00	13.26
48	0.1814		0.2833	1.86		4.58	13.84

Panel C: Common and Specific Value

h	a	b_{Com}	b_{Spec}	t_a	$t_{b_{Com}}$	$t_{b_{Spec}}$	$R^2 \times 100$
1	0.0024	0.0062	0.0032	2.34	2.65	2.65	1.07
3	0.0071	0.0202	0.0107	2.62	3.71	3.77	3.58
6	0.0148	0.0423	0.0250	2.91	4.40	4.70	7.83
12	0.0312	0.0882	0.0619	3.18	5.51	4.98	15.95
24	0.0720	0.1825	0.1376	3.22	6.15	5.00	25.65
48	0.1814	0.4065	0.2833	2.88	6.88	4.58	28.78

Table 6: **Comovement Between Risk-Proxies and the Value Spread**
This table regresses components of the High-minus-Low value spread on state variables, collected in the vector Z_t, that are popular in the literature to proxy for time-variation in risk premia (intermediary leverage; the illiquidity premium (measured by the repo-spread); the dividend yield; a global recession dummy; the default spread; real uncertainty; and, Chicago Fed National Activity Index). Panel A reports results from time-series regressions of the common component of the value spread (across six value strategies in different asset classes) on the risk-proxies, $VS_t^{Com} = k_0 + k_1' Z_t + u_t$. We consider both simple regressions on individual risk-proxies (Specifications 1, 2, 4 and 6) and multiple regressions on sets of risk-proxies (Specifications 3, 5 and 7). Panel B regresses the specific component of the value spread in each asset class on the full set of risk-proxies (as in Specification 7), $VS_{c,t}^{Spec} = k_0 + k_1' Z_t + u_t$, where $VS_{c,t}^{Spec} = VS_{c,t} - VS_t^{Com}$. t-statistics are calculated using Newey and West (1987) standard errors with 12-lags. The full sample period is 1972 to 2014, but some alternative asset classes enter the sample only after 1972.

	Intermediary Leverage	Illiquidity Premium	Dividend Yield	Global Recession	Default Spread	Real Uncertainty	Chicago Fed National Activity Index	$R^2 \times 100$
Panel A: Common Value								
1	0.44							47.48
	(6.14)							
2		0.40						38.05
		(8.70)						
3	0.33	0.25						59.36
	(5.57)	(3.30)						
4			0.49					58.34
			(8.29)					
5	0.16	0.17	0.27					65.34
	(2.44)	(2.18)	(3.60)					
6				0.33				6.32
				(1.97)				
7	0.10	0.13	0.30	0.13	-0.01	0.07	-0.04	67.63
	(1.06)	(2.03)	(3.28)	(1.40)	(-0.12)	(0.91)	(-0.66)	
Panel B: Asset-Class-Specific Value								
Ind. Equities ($BM_{Ex.fin.}$)	-0.20	0.05	0.27	0.20	0.21	0.12	0.06	47.23
	(-1.85)	(1.13)	(2.85)	(1.81)	(4.06)	(2.20)	(1.42)	
Ind. Equities ($BM_{Ind.Adj.}$)	0.04	-0.06	0.08	0.06	0.24	0.17	0.03	58.78
	(0.43)	(-1.27)	(1.14)	(0.63)	(4.52)	(3.22)	(0.87)	
Currencies	-0.03	0.09	-0.15	-0.48	0.01	-0.33	0.09	30.41
	(-0.21)	(0.71)	(-0.87)	(-2.03)	(0.04)	(-2.53)	(1.09)	
Stock Indexes	0.93	-0.14	-0.28	0.50	-0.33	-0.14	0.21	32.41
	(2.72)	(-1.20)	(-1.52)	(2.01)	(-1.81)	(-1.07)	(1.86)	
Government Bonds	-0.63	0.09	0.79	-0.29	-0.03	-0.06	0.14	48.46
	(-2.81)	(1.02)	(3.68)	(-1.37)	(-0.19)	(-0.60)	(2.01)	
Commodities	0.15	0.01	-0.36	-0.03	-0.18	0.18	-0.14	13.59
	(0.71)	(0.06)	(-1.93)	(-0.18)	(-1.32)	(1.39)	(-1.70)	

Table 7: **Common Versus Specific Value Return Predictability Net of Risk-Proxies** This table presents the results from pooled predictive regressions of High-minus-Low value returns on the explained and orthogonal components of common value (Panel A) and asset-class-specific value (Panel B). The explained components of common and specific value (denoted $\widehat{VS}^{Com}_{c,t}$ and $\widehat{VS}^{Spec}_{c,t}$) are pre-estimated by regressing each series on the risk-proxies used in Table 6, and saving the predicted value. The orthogonal component of common and specific value is the residual from this time-series regression. Panel A thus reports coefficient estimates from the regression, $R_{c,t+1:t+h} = a_h + b_{Com,Orth}(VS^{Com}_{c,t} - \widehat{VS}^{Com}_{c,t}) + b_{Com,Expl}\widehat{VS}^{Com}_{c,t} + \varepsilon_{c,t+1:t+h}$ and Panel B for the analogous regression for the components of $VS^{Spec}_{c,t}$. For each value spread component, we consider a parsimonious specification of the pre-estimation step that includes intermediary leverage, the illiquidity premium (measured by the repo-spread) and the dividend yield. We also present results for a kitchen sink specification of the pre-estimation step that uses all the risk-proxies. t-statistics in the pooled regressions are calculated using Driscoll and Kraay (1998) standard errors with h-lags. We also present the relative contribution to R^2 from the explained and orthogonal components. The full sample period is 1972 to 2014, but some alternative asset classes enter the sample only after 1972.

Panel A: Common Value

Specification	h	a	$b_{Com,Orth}$	$b_{Com,Expl}$	t_a	$t_{Com,Orth}$	$t_{Com,Expl}$	R^2	$R^2_{Com,Orth}$	$R^2_{Com,Expl}$
Parsimonious	1	0.0024	0.0090	0.0049	2.35	2.53	1.82	0.79	0.52	0.31
	3	0.0071	0.0281	0.0164	2.63	3.47	2.35	2.54	1.58	1.08
	6	0.0148	0.0525	0.0374	2.92	3.83	2.82	4.88	2.56	2.58
	12	0.0313	0.1049	0.0800	3.18	4.32	3.76	8.42	4.13	4.75
	24	0.0719	0.1615	0.1930	3.24	3.48	5.71	12.48	3.49	9.59
	48	0.1812	0.2626	0.4740	3.07	2.46	7.84	15.94	2.17	14.42
Kitchen	1	0.0024	0.0078	0.0055	2.34	2.25	2.06	0.74	0.37	0.41
Sink	3	0.0071	0.0248	0.0182	2.62	3.02	2.66	2.40	1.17	1.38
	6	0.0148	0.0465	0.0405	2.91	3.38	3.07	4.75	1.91	3.12
	12	0.0312	0.0922	0.0864	3.18	3.82	4.01	8.27	3.05	5.71
	24	0.0719	0.1403	0.2018	3.27	3.10	5.88	12.74	2.52	10.84
	48	0.1815	0.2390	0.4723	3.08	1.77	7.73	16.08	1.60	15.06

Panel B: Asset-Class-Specific Value

	h	a	$b_{Spec,Orth}$	$b_{Spec,Expl}$	t_a	$t_{Spec,Orth}$	$t_{Spec,Expl}$	R^2	$R^2_{Spec,Orth}$	$R^2_{Spec,Expl}$
Parsimonious	1	0.0024	0.0030	0.0038	2.30	2.17	1.42	0.35	0.23	0.13
	3	0.0071	0.0108	0.0106	2.50	3.36	1.68	1.24	0.93	0.31
	6	0.0148	0.0252	0.0243	2.63	4.32	2.00	3.10	2.35	0.75
	12	0.0312	0.0645	0.0543	2.60	5.05	2.01	7.73	6.21	1.52
	24	0.0720	0.1401	0.1304	2.34	5.45	2.32	13.27	10.16	3.11
	48	0.1814	0.2556	0.3659	1.85	4.27	2.35	14.23	8.43	5.81
Kitchen	1	0.0024	0.0030	0.0034	2.30	1.95	1.64	0.35	0.20	0.15
Sink	3	0.0071	0.0101	0.0117	2.50	2.71	2.53	1.24	0.69	0.55
	6	0.0148	0.0250	0.0249	2.63	3.78	2.68	3.10	1.95	1.15
	12	0.0312	0.0587	0.0672	2.60	4.52	3.11	7.72	4.30	3.42
	24	0.0720	0.1160	0.1716	2.34	4.86	3.35	13.77	5.76	8.01
	48	0.1814	0.2039	0.4204	1.83	3.74	3.54	15.72	4.54	11.18

TABLE 8: **Momentum Return Predictability**

This table reports results for pooled predictive regressions of Winner-minus-Loser momentum returns on (components of) the momentum valuation spread, $MVS_{c,t}$. We consider five asset classes: individual equities, currencies, global stock indexes, global government bonds, and commodities. Panel A reports results for the pooled predictive regression, $R^{mom}_{c,t+1:t+h} = a_h + b_h MVS_{c,t} + \varepsilon^{mom}_{c,t+1:t+h}$. We standardize $MVS_{c,t}$ in each asset class to make them comparable. To this end, we also scale the returns for each momentum strategy to a standard deviation of 15% annually. Panel B reports results for pooled predictive regressions that decompose $MVS_{c,t}$ into a common and asset-class-specific component, as in Table 5. The common component, $MVS^{com}_t = N_t^{-1} \sum_{i=0}^{N_t} MVS_{c,t}$, and the specific component, $MVS^{Spec}_{c,t} = MVS_{c,t} - MVS^{Com}_t$. t-statistics are calculated using Driscoll and Kraay (1998) standard errors with h-lags. The sample is 1972 to 2014, but some alternative asset classes enter the sample only after 1972.

Panel A: Pooled Predictive Regression

h	a	b	t_a	t_b	$R^2 \times 100$
1	0.0037	0.0042	3.13	3.54	0.92
3	0.0113	0.0120	3.57	3.88	2.33
6	0.0234	0.0266	4.03	4.76	5.30
12	0.0500	0.0435	4.88	4.83	6.81
24	0.1103	0.0448	4.55	2.89	2.64
48	0.2901	0.0446	4.59	1.49	0.78

Panel B: Common and Specific Components of the Momentum Valuation Spread

h	a	b_{Com}	b_{Spec}	t_a	$t_{b_{Com}}$	$t_{b_{Spec}}$	$R^2 \times 100$
1	0.0037	0.0075		3.13	3.54		0.85
3	0.0113	0.0193		3.60	3.19		1.71
6	0.0234	0.0424		4.10	4.18		3.87
12	0.0500	0.0774		5.16	5.11		6.13
24	0.1103	0.0950		4.79	3.54		3.30
48	0.2901	0.1599		4.80	2.22		2.50
1	0.0037		0.0029	3.09		2.36	0.31
3	0.0113		0.0091	3.47		2.99	0.96
6	0.0234		0.0202	3.75		3.37	2.19
12	0.0500		0.0300	4.34		2.85	2.32
24	0.1103		0.0255	4.30		1.46	0.62
48	0.2901		0.0065	4.50		0.23	0.01
1	0.0037	0.0075	0.0029	3.13	3.54	2.36	1.16
3	0.0113	0.0193	0.0091	3.60	3.19	2.99	2.67
6	0.0234	0.0424	0.0202	4.10	4.18	3.37	6.06
12	0.0500	0.0774	0.0300	5.16	5.11	2.85	8.45
24	0.1103	0.0950	0.0255	4.79	3.54	1.46	3.92
48	0.2901	0.1599	0.0065	4.80	2.22	0.23	2.52

Table 9: **Comovement Between Risk-Proxies and the Momentum Valuation Spread** This table regresses components of the momentum valuation spread on risk-proxies that capture time-variation in risk premia (intermediary leverage; the illiquidity premium (measured by the repo-spread); the dividend yield; a global recession dummy; the default spread; real uncertainty; and, Chicago Fed National Activity Index). Panel A reports results from time-series regressions of the common component of the momentum valuation spread (across five momentum strategies in different asset classes) on the risk-proxies collected in the vector Z_t, $MVS_t^{Com} = k_0 + k_1' Z_t + u_t$. We consider both simple regressions on individual risk-proxies (Specifications 1, 2, 4 and 6) and multiple regressions on sets of risk-proxies (Specifications 3, 5 and 7). Panel B regresses the asset-class-specific component of the momentum valuation spread on the full set of risk-proxies (as in Specification 7), $MVS_{c,t}^{Spec} = k_0 + k_1 Z_t + u_t$, where $MVS_{c,t}^{Spec} = MVS_{c,t} - MVS_t^{Com}$. t-statistics are calculated using Newey and West (1987) standard errors with 12-lags. The full sample period is 1972 to 2014, but some alternative asset classes enter the sample only after 1972.

	Intermediary Leverage	Illiquidity Premium	Dividend Yield	Global Recession	Default Spread	Real Uncertainty	Chicago Fed National Activity Index	$R^2 \times 100$
Panel A: Common Component of the Momentum Valuation Spread								
1	-0.11							3.76
	(-2.16)							
2		-0.04						0.36
		(-0.68)						
3	-0.12	0.01						3.60
	(-1.75)	(0.12)						
4			0.01					-0.16
			(0.17)					
5	-0.28	-0.07	0.27					11.35
	(-3.65)	(-0.97)	(2.71)					
6				-0.30				6.81
				(-2.81)				
7	-0.34	-0.02	0.27	-0.30	0.12	-0.08	-0.07	18.27
	(-2.89)	(-0.32)	(2.73)	(-3.10)	(1.23)	(-1.49)	(-1.65)	
Panel B: Asset-Class-Specific Components								
Ind. Equities	-0.36	-0.08	0.28	-0.15	-0.30	0.11	-0.08	21.86
	(-3.16)	(-0.65)	(1.83)	(-0.90)	(-2.78)	(1.04)	(-0.90)	
Commodities	0.07	0.06	-0.02	0.32	-0.05	-0.04	-0.12	7.58
	(0.56)	(0.71)	(-0.20)	(2.10)	(-0.44)	(-0.41)	(-1.61)	
Stock Indexes	-0.13	-0.01	-0.19	-0.79	0.16	-0.04	-0.14	20.64
	(-0.65)	(-0.13)	(-1.35)	(-4.02)	(1.32)	(-0.40)	(-1.57)	
Government Bonds	0.33	0.18	-0.28	0.13	0.08	0.08	0.10	13.37
	(2.25)	(2.34)	(-1.32)	(0.61)	(0.59)	(0.63)	(1.40)	
Currencies	0.23	-0.05	0.02	0.23	0.17	-0.18	0.16	10.73
	(2.00)	(-0.46)	(0.16)	(1.53)	(1.56)	(-1.71)	(2.18)	

Internet Appendix for
"Value Return Predictability Across Asset Classes and Commonalities in Risk Premia"

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_{ExFin}. 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_{IndAdj}. We compute this measure as:

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

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 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.

To measure value, we follow Asness et al. (2013) and Menkhoff et al. (2016) and use the five-year change in relative purchasing power parity, which is a natural choice to measure value in currencies. This value measure consists of two parts: (i) 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; and, (ii) an inflation adjustment, by subtracting from −5-year return 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. We end up with a sample period from February 1976 (four currencies) to December 2014 (all currencies available).

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

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

A.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 up to May 2009. From June 2009 to December 2014, zero coupon bond yields are from Bloomberg. 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. (2017b), we calculate the monthly dollar excess return on a fully-collateralized, currency-hedged position in the foreign currency-denominated futures contracts (see their Appendix A). To be precise, for each bond index futures i the monthly return of the first-nearby futures strategy (that rolls at the end of the month prior to expiration) equals:

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

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

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

At expiration, the price of the one-month futures contract equals the spot price of a bond that matures in nine years and eleven months: $Price^{0,syn}_{i,t+1} = S^{119}_{i,t+1} = exp(-y^{119}_{i,t+1} \times$

119), where $y^{119}_{i,t+1}$ is found by linear interpolation. As for the traded bond returns, we calculate synthetic futures returns from these prices assuming that the investor is fully-collateralized and hedges out the currency risk (denoted $R^{Syn.fut.}_{i,t+1}$).

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

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

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

A.5 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: $R^{fut}_{i,t} = Price^{T_1}_{i,t}/Price^{T_1}_{i,t-1} - 1$, where $Price^{T_1}_{i,t}$ 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= $ln(\overline{Price^{T_1}_{i,t-60}}/Price^{T_1}_{i,t})$, where $\overline{Price^{T_1}_{i,t-60}}$ 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).

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

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

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

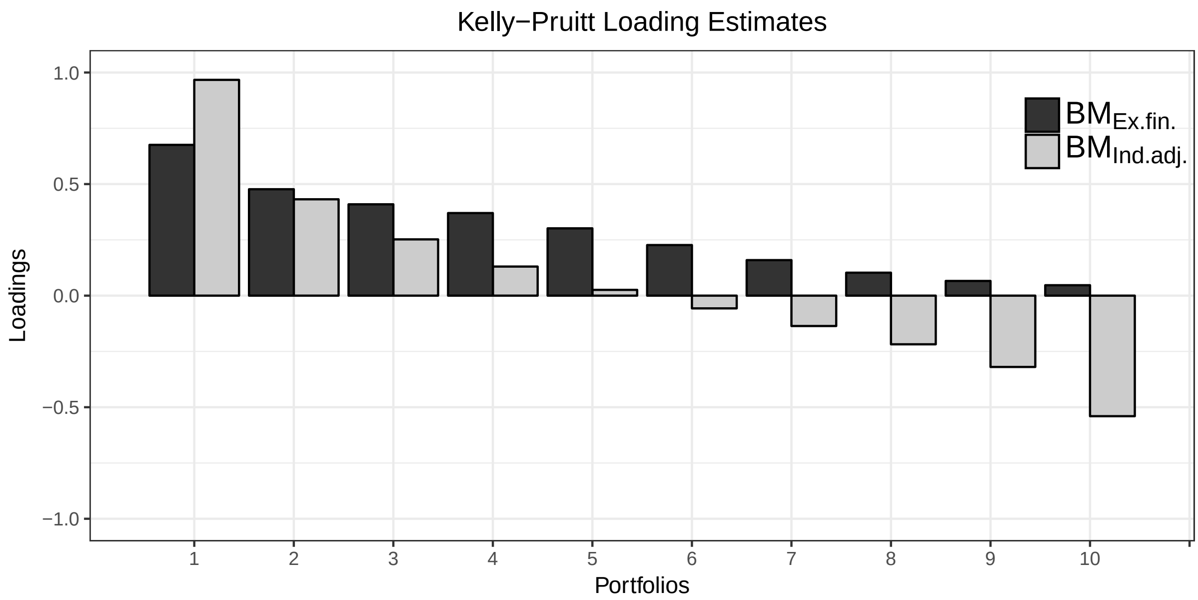

FIGURE B.1: **Kelly-Pruitt Loading Estimates**
This figure shows the loadings in the first stage of the 3PRF procedure of Kelly and Pruitt (2013). We apply their procedure to predict the High-minus-Low book-to-market decile spreading return using the valuation ratios of ten book-to-market deciles. We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

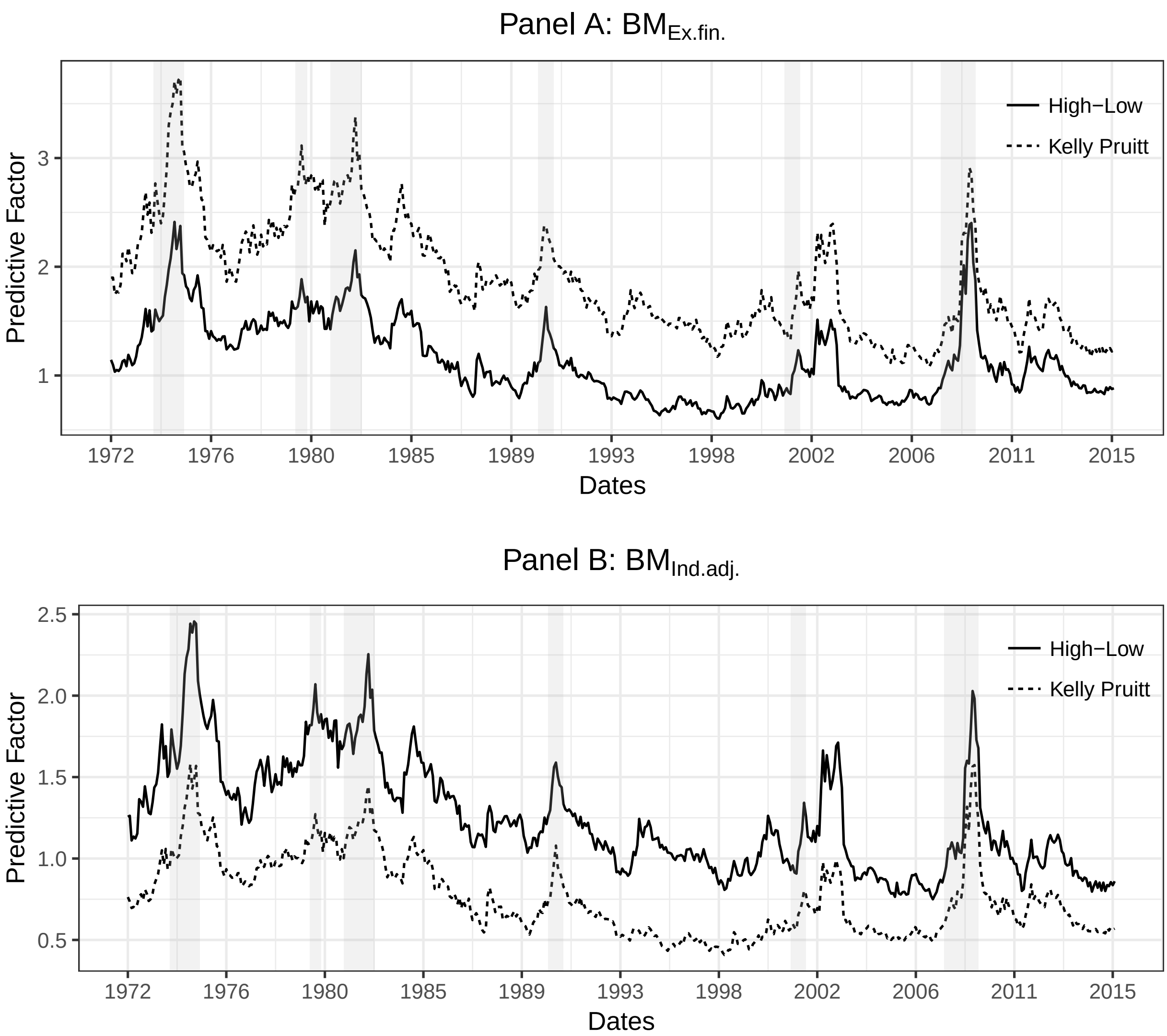

Figure B.2: **Kelly-Pruitt and High-minus-Low Predictive Factor**
This figure compares the latent predictive factor of Kelly and Pruitt (2013) extracted from the valuation ratios of ten book-to-market portfolios (either using all stocks except for financials (Panel A) or using industry-adjusted book-to-market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

C Out-of-Sample Predictability

In this section, we show that the value spread predicts returns out-of-sample.

C.1 Value-Timing in Individual Equities

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

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

Thus, $VS_{t,His}$ indicates whether the average value spread over the last twelve months is historically large. We take an annual average to accommodate that return predictability using the value spread strengthens in horizon.[27]

Table C.1 presents summary performance statistics for three strategies: a unit weight strategy that captures the unconditional value premium, a linear timing strategy that invests $VS_{t,His}$ dollars, and, finally, a combined strategy that invests $1 + VS_{t,His}$ dollars. We consider $2 \times 2 \times 3$ variations of these strategies: using (i) either the book-to-market signal excluding financials or the industry-adjusted book-to-market ratio, (ii) either the High-minus-Low decile portfolio or the rank-weighted portfolio, and (iii) the largest stocks whose market caps cumulate to either 75%, 90%, or 95% of total market cap in the CRSP file. To make the results comparable across strategies, we standardize each return series to have an annualized standard deviation of 15%. We perform this standardization relative to the last ten years of returns so that we do not use any forward looking information.[28]

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

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

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

highly correlated, the combined strategy comes out as most attractive in all cases. The average monthly return and CAPM alpha of the combined strategy range from 50 to 105 bps and 61 to 107 bps, respectively, over the twelve strategies. These returns translate to an annualized Sharpe ratio of 0.42 (0.12 on average $\times\sqrt{12}$), which is relative to 0.18 (0.05 on average $\times\sqrt{12}$) for the unit weight strategy.

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

C.2 Value-Timing Across Asset Classes

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, see Equation (C.1)) is above the historical average:

$$R^{x}_{c,t+1:t+h,15\%} = a_h + b_h I_{VS^{x}_{c,t,His}>0} + e_{c,t+1:t+h}, \tag{C.2}$$

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

Table C.2 presents the results. For the one-month horizon, we see that the coefficient estimate b is large and significant at 64 bps ($t = 2.76$) and 50 bps ($t = 1.97$) for the High-minus-Low and rank-weighted portfolios, respectively. Combined with the estimated intercept, these numbers imply that the average return of a value strategy that invests only in an asset class when $VS_{c,t,His} > 0$ equals 57 bps and 56 bps per month, respectively. These returns translate to annualized Sharpe ratios over 0.41 ($0.1184\times\sqrt{12}$). In comparison, the Sharpe ratio of investing when $VS_{c,t,His} \leq 0$ is -0.05 and 0.05, 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.

Finally, in Table C.3 we show similar out-of-sample results for predictive regressions of momentum returns across asset classes on the momentum valuation spread. The key difference with our results for value is again that momentum return predictability is short-lived and significant only for horizons smaller than or equal to one year.

Table C.1: **Value Timing in Individual Equities**

This table reports unconditional performance statistics for the monthly returns of a strategy that times value using the signal: $VS_{t,His} = \sigma(VS_{1:t-12})^{-1}((12)^{-1}\sum_{s=0}^{11} VS_{t-s} - (t-12)^{-1}\sum_{s=12}^{t-1} VS_{t-s})$. $VS_{t,His}$ captures deviations of last year's value spread from the historical average value spread and is observable at time t. We present results for a unit weight strategy that passively captures the unconditional value premium, a linear timing strategy that invests $VS_{t,His}$ dollars, and, finally, a combined strategy that invests $1 + VS_{t,His}$. We consider $2\times 2\times 3$ 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 caps cumulate to either 90%, 95%, or 75% of total market cap in the CRSP file. To make these different value strategies comparable, we scale each value return series to have an annualized standard deviation of 15%. We perform this standardization in each month relative to the last ten years of returns so that we do not use forward looking information. The sample period is 1972 to 2014.

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

Table C.2: **Value Timing in the Pool of Value Strategies**

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

Panel A: Pooled Regression on Dummy indicating High Value Spread

	$H-L$					$Rank$				
h	a	b	t_a	t_b	R^2	a	b	t_a	t_b	R^2
1	-0.0007	0.0064	-0.47	2.76	0.49	0.0006	0.0050	0.38	1.97	0.29
3	-0.0017	0.0187	-0.41	3.12	1.28	0.0024	0.0144	0.53	2.04	0.70
6	-0.0032	0.0378	-0.39	3.12	2.42	0.0056	0.0298	0.58	2.06	1.37
12	-0.0068	0.0782	-0.38	2.90	4.47	0.0111	0.0683	0.54	2.19	3.03
24	-0.0203	0.1802	-0.44	2.55	7.52	0.0284	0.1511	0.63	1.97	4.89
48	-0.0905	0.4737	-0.68	2.42	10.81	0.0569	0.3822	0.49	2.41	8.99

Panel B: Implied Performance of Timing Value across Asset Classes

	$H-L$			$Rank$		
	Avg. ret.	St. dev.	Sharpe	Avg. ret.	St. dev.	Sharpe
Invest when $VS_{c,t,His} > 0$	0.0057	0.0452	0.1271	0.0056	0.0471	0.1184
Invest when $VS_{c,t,His} \leq 0$	-0.0007	0.0436	-0.0158	0.0006	0.0436	0.0135

TABLE C.3: **Timing Momentum using the Momentum Valuation Spread**

This table is similar to Table C.2, but reports results for pooled predictive regressions of momentum returns on a dummy variable indicating whether the current momentum valuation spread in an asset class is historically high or low. To be precise, we run $R^{mom}_{c,t+1:t+h,15\%} = a + bI_{MVS_{c,t,His}>0} + e^{mom}_{c,t+1:t+h}$, where $I_{MVS_{c,t,His}>0}$ is an indicator function that is one when the timing signal, $MVS_{c,t,His} = \sigma(MVS_{c,1:t-12})^{-1}((12)^{-1}\sum_{s=0}^{11} MVS_{c,t-s} - (t-12)^{-1}\sum_{s=12}^{t-1} MVS_{c,t-s})$ is positive, and zero otherwise. We consider returns of both Winner-minus-Loser and rank-weighted momentum strategies and 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 momentum strategy that invests only in asset class, c when $MVS_{c,t,His} > 0$, 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 $MVS_{c,t,His} \leq 0$ is equal to the estimated intercept a. The full sample period is 1972 to 2014, but some alternative asset classes enter the sample only after 1972.

Panel A: Pooled Regression on Dummy indicating High Momentum Valuation Spread

	$H-L$					$Rank$				
h	a	b	t_a	t_b	R^2	a	b	t_a	t_b	R^2
1	-0.0008	0.0090	-0.41	3.79	1.05	-0.0001	0.0079	-0.06	3.55	0.80
3	-0.0009	0.0242	-0.18	3.79	2.41	-0.0001	0.0229	-0.01	4.15	2.21
6	-0.0005	0.0466	-0.05	3.67	4.09	0.0007	0.0459	0.08	4.20	4.38
12	0.0096	0.0800	0.62	3.17	5.73	0.0120	0.0806	0.76	3.53	6.39
24	0.0579	0.1096	1.61	2.02	3.91	0.0665	0.1088	1.87	2.32	4.47
48	0.2217	0.1599	2.14	1.18	2.08	0.2232	0.2003	2.24	1.49	3.02

Panel B: Implied Performance of Timing Momentum across Asset Classes

	$H-L$			$Rank$		
	Avg. ret.	St. dev.	Sharpe	Avg. ret.	St. dev.	Sharpe
Invest when $MVS_{c,t,His} > 0$	0.0082	0.0387	0.2111	0.0078	0.0392	0.1981
Invest when $MVS_{c,t,His} \leq 0$	-0.0008	0.0457	-0.0173	-0.0001	0.0451	-0.0023

D Robustness Checks

TABLE D.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_{ExFin}	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_{IndAdj}	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
Currencies (Inf. adj. return)	6	0.0100	0.0099	2.01	2.20	4.38	0.0145	0.0151	2.24	2.38	5.72
	24	0.0519	0.0520	2.65	3.44	22.27	0.0757	0.0649	2.97	3.35	22.23
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
Government bonds (−5-year return)	6	-0.0004	0.0076	-0.10	1.97	11.39	-0.0001	0.0081	-0.03	1.82	10.73
	24	0.0003	0.0309	0.03	2.34	36.67	0.0030	0.0290	0.21	1.91	30.93
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

TABLE D.2: **Simulating from Zhang (2005)**
This table reports results from 1000 simulations of the Zhang (2005) investment-based asset pricing model. This model endogenously generates a time-varying value spread that predicts value returns in the time series. We ask whether this model can match the variation in expected value returns observed in the data, while matching other moments of interest. Panel A reports the unconditional moments of value decile portfolios (focusing on deciles 1 (Low), 4, 7, and 10 (High) for brevity) and the High-minus-Low decile value premium. We see that our distribution is close to what is reported in Zhang (2005, Table III). Panel B reports the *Ratio* of the predictive regression coefficient to the intercept and the R^2 at the annual horizon ($h = 12$). We compare the level of these estimates from the data (as reported in Table 1) to the distribution of their counterparts estimated from simulating the model. We rank all simulations on the *Ratio* and report both the *Ratio* and R^2 at the 50, 90, 95, and 99th percentile of that distribution. The final column presents the mean across simulations as reported in Zhang (2005), where we have backed out the *Ratio* of 0.76 from results reported in his Table III and V.

Panel A: Unconditional Moments for Value Decile Portfolios

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

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

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

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

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	0.0008	0.72	0.62	0.04	0.0010	0.0010	1.15	0.73	0.09
	3	0.0013	0.0020	0.74	0.80	0.52	0.0028	0.0025	1.37	0.85	0.70
	6	0.0025	0.0058	0.86	2.19	3.91	0.0056	0.0060	1.59	1.21	2.99
	12	0.0044	0.0092	0.96	1.91	7.24	0.0115	0.0080	1.99	1.06	3.71
	24	0.0087	0.0234	1.25	3.96	28.16	0.0264	0.0232	2.65	4.19	17.72

Table D.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					*Rank*				
h	a	b	t_a	t_b	$R^2(\%)$	a	b	t_a	t_b	$R^2(\%)$
1	0.0052	0.0004	4.08	0.32	0.01	0.0052	0.0003	4.08	0.23	0.00
3	0.0159	0.0024	4.58	0.71	0.09	0.0159	0.0019	4.58	0.58	0.06
6	0.0330	0.0060	4.62	0.94	0.24	0.0330	0.0049	4.63	0.75	0.16
12	0.0692	0.0082	4.70	0.59	0.18	0.0692	0.0061	4.71	0.42	0.10
24	0.1459	0.0168	4.73	0.54	0.29	0.1459	0.0122	4.74	0.39	0.16
48	0.3214	0.0810	5.14	1.49	2.62	0.3214	0.0740	5.14	1.37	2.19

TABLE D.5: **Common and Specific Components of the Value Spread (Rank-Weighted)**

This table is identical to Table 5 of the paper, but uses rank-weighted value strategies instead of High-minus-Low value strategies. We report results for pooled predictive regressions of value returns on components of the value spread.

Panel A: Common Value

h	a	b_{Com}	b_{Spec}	t_a	$t_{b_{Com}}$	$t_{b_{Spec}}$	$R^2 \times 100$
1	0.0030	0.0051		2.79	2.17		0.49
3	0.0090	0.0165		2.99	2.76		1.48
6	0.0192	0.0349		3.15	3.01		2.92
12	0.0417	0.0753		3.47	3.46		5.50
24	0.0980	0.1714		3.98	3.67		10.73
48	0.2535	0.3891		4.50	6.37		16.86

Panel B: Specific Value

h	a	b_{Com}	b_{Spec}	t_a	$t_{b_{Com}}$	$t_{b_{Spec}}$	$R^2 \times 100$
1	0.0030		0.0025	2.77		2.02	0.23
3	0.0090		0.0090	2.92		2.86	0.83
6	0.0192		0.0222	3.02		3.55	2.23
12	0.0417		0.0574	3.20		4.32	6.08
24	0.0980		0.1265	3.36		4.52	11.09
48	0.2535		0.2297	3.13		6.02	11.56

Panel C: Common and Specific Value

h	a	b_{Com}	b_{Spec}	t_a	$t_{b_{Com}}$	$t_{b_{Spec}}$	$R^2 \times 100$
1	0.0030	0.0051	0.0025	2.79	2.17	2.02	0.71
3	0.0090	0.0165	0.0090	2.99	2.76	2.86	2.31
6	0.0192	0.0349	0.0222	3.15	3.01	3.55	5.15
12	0.0417	0.0753	0.0574	3.47	3.46	4.32	11.58
24	0.0980	0.1714	0.1265	3.98	3.67	4.52	21.82
48	0.2535	0.3891	0.2297	4.50	6.37	6.02	28.42

Table D.6: **Comovement Between Risk-Proxies and the Value Spread (Rank-Weighted)**
This table is identical to Table 6 of the paper, but uses rank-weighted value strategies instead of High-minus-Low value strategies. This table regresses components of the value spread on popular proxies of risk premia.

	Intermediary Leverage	Illiquidity Premium	Dividend Yield	Global Recession	Default Spread	Real Uncertainty	Chicago Fed National Activity Index	$R^2 \times 100$
Panel A: Common Value								
1	0.45							49.77
	(5.73)							
2		0.40						40.14
		(10.77)						
3	0.33	0.25						62.39
	(5.04)	(3.80)						
4			0.51					64.23
			(9.91)					
5	0.14	0.16	0.31					70.39
	(1.95)	(2.46)	(4.14)					
6				0.32				5.89
				(1.88)				
7	0.10	0.12	0.32	0.14	-0.01	0.07	-0.00	72.24
	(1.02)	(2.39)	(3.63)	(1.74)	(-0.14)	(1.08)	(-0.07)	
Panel B: Asset-Class-Specific Value								
Ind. Equities ($BM_{Ex.fin.}$)	-0.22	0.03	0.34	0.15	0.20	0.12	0.05	54.90
	(-2.23)	(0.75)	(3.89)	(1.56)	(3.84)	(2.34)	(1.18)	
Ind. Equities ($BM_{Ind.Adj.}$)	0.04	-0.03	0.09	0.02	0.22	0.20	0.05	64.74
	(0.53)	(-0.93)	(1.33)	(0.30)	(4.33)	(3.82)	(1.18)	
Currencies	-0.06	0.13	-0.22	-0.51	-0.01	-0.30	0.10	33.54
	(-0.38)	(1.06)	(-1.24)	(-2.14)	(-0.08)	(-2.33)	(1.12)	
Stock Indexes	0.83	-0.16	-0.30	0.57	-0.25	-0.11	0.19	29.79
	(2.68)	(-1.36)	(-1.63)	(2.18)	(-1.39)	(-0.87)	(1.62)	
Government Bonds	-0.55	0.08	0.79	-0.21	-0.11	-0.08	0.12	53.90
	(-2.83)	(1.02)	(4.03)	(-1.07)	(-0.89)	(-0.94)	(1.96)	
Commodities	0.19	-0.01	-0.38	-0.02	-0.13	0.12	-0.14	13.24
	(0.89)	(-0.13)	(-2.03)	(-0.10)	(-0.94)	(1.02)	(-1.59)	

Table D.7: **Common Versus Specific Value: Net of Risk-Proxies (Rank-Weighted)** This table is identical to Table 7 of the paper, but uses rank-weighted value strategies instead of High-minus-Low value strategies. We present results from pooled predictive regressions of value returns on the components of common value (Panel A) and specific value (Panel B) that are explained by or orthogonal to a set of benchmark risk-proxies.

Panel A: Common Value

Specification	h	a	$b_{Com,Orth}$	$b_{Com,Expl}$	t_a	$t_{Com,Orth}$	$t_{Com,Expl}$	R^2	$R^2_{Com,Orth}$	$R^2_{Com,Expl}$
Parsimonious	1	0.0030	0.0092	0.0036	2.80	2.57	1.31	0.62	0.47	0.18
	3	0.0091	0.0303	0.0112	3.01	3.31	1.45	1.92	1.49	0.51
	6	0.0193	0.0604	0.0251	3.19	3.46	1.63	3.58	2.61	1.12
	12	0.0419	0.1277	0.0550	3.50	3.68	2.09	6.64	4.76	2.18
	24	0.0982	0.2174	0.1530	4.02	3.29	3.06	11.07	5.31	6.30
	48	0.2534	0.3761	0.3935	4.52	3.06	5.59	16.87	4.42	13.30
Kitchen Sink	1	0.0030	0.0076	0.0043	2.79	2.16	1.57	0.53	0.30	0.26
	3	0.0091	0.0253	0.0134	2.98	2.82	1.75	1.65	0.99	0.74
	6	0.0193	0.0504	0.0294	3.15	2.89	1.89	3.15	1.75	1.57
	12	0.0418	0.1047	0.0648	3.45	3.13	2.36	5.84	3.08	3.09
	24	0.0981	0.1867	0.1657	3.99	2.96	3.21	10.77	3.77	7.57
	48	0.2535	0.3231	0.4079	4.56	2.35	5.96	17.02	2.88	14.88

Panel B: Asset-Class-Specific Value

	h	a	$b_{Spec,Orth}$	$b_{Spec,Expl}$	t_a	$t_{Spec,Orth}$	$t_{Spec,Expl}$	R^2	$R^2_{Spec,Orth}$	$R^2_{Spec,Expl}$
Parsimonious	1	0.0030	0.0031	0.0011	2.76	2.20	0.41	0.26	0.24	0.01
	3	0.0090	0.0115	0.0030	2.91	3.34	0.45	0.98	0.96	0.03
	6	0.0192	0.0281	0.0079	3.01	4.32	0.58	2.62	2.54	0.08
	12	0.0417	0.0720	0.0227	3.17	5.38	0.78	7.01	6.73	0.28
	24	0.0980	0.1493	0.0735	3.35	5.45	1.44	11.93	10.81	1.13
	48	0.2535	0.2360	0.2138	3.13	5.25	2.46	11.59	8.72	2.86
Kitchen Sink	1	0.0030	0.0037	0.0008	2.76	2.32	0.38	0.29	0.28	0.01
	3	0.0090	0.0123	0.0041	2.92	3.17	0.81	1.00	0.93	0.07
	6	0.0192	0.0304	0.0099	3.02	4.26	0.95	2.69	2.51	0.18
	12	0.0417	0.0688	0.0407	3.18	5.15	1.74	6.43	5.19	1.23
	24	0.0980	0.1248	0.1288	3.36	4.53	2.78	11.10	6.28	4.82
	48	0.2535	0.1932	0.2847	3.11	4.81	4.11	12.00	4.92	7.09

TABLE D.8: **Momentum Return Predictability (Rank-Weighted)**
This table is identical to Table 8 of the paper, but uses rank-weighted momentum strategies instead of Winner-minus-Loser momentum strategies. We report results for pooled predictive regressions of momentum returns on (components of) the momentum valuation spread, $MVS_{c,t}$.

Panel A: Pooled Predictive Regression							
h	a	b		t_a	t_b		$R^2 \times 100$
1	0.0038	0.0042		3.11	3.85		0.94
3	0.0115	0.0120		3.54	4.30		2.28
6	0.0239	0.0236		3.91	4.53		4.26
12	0.0519	0.0399		4.45	4.08		5.60
24	0.1127	0.0332		4.12	1.92		1.41
48	0.2928	0.0376		4.09	1.12		0.52

Panel B: Common and Specific Components of the Momentum Valuation Spread							
h	a	b_{Com}	b_{Spec}	t_a	$t_{b_{Com}}$	$t_{b_{Spec}}$	$R^2 \times 100$
1	0.0038	0.0076		3.11	4.08		0.86
3	0.0115	0.0225		3.56	4.90		2.29
6	0.0239	0.0427		3.96	5.67		3.96
12	0.0519	0.0772		4.61	6.58		5.95
24	0.1127	0.0999		4.33	3.30		3.60
48	0.2928	0.2158		4.52	2.74		4.43
1	0.0038		0.0029	3.08		2.45	0.31
3	0.0115		0.0078	3.45		2.54	0.69
6	0.0239		0.0160	3.71		2.65	1.41
12	0.0519		0.0251	4.11		2.09	1.59
24	0.1127		0.0071	3.97		0.37	0.05
48	0.2928		-0.0251	4.00		-0.67	0.17
1	0.0038	0.0076	0.0029	3.11	4.08	2.45	1.18
3	0.0115	0.0225	0.0078	3.56	4.90	2.54	2.98
6	0.0239	0.0427	0.0160	3.96	5.67	2.65	5.37
12	0.0519	0.0772	0.0251	4.61	6.58	2.09	7.54
24	0.1127	0.0999	0.0071	4.33	3.30	0.37	3.65
48	0.2928	0.2158	-0.0251	4.52	2.74	-0.67	4.60

TABLE D.9: **Comovement Between Risk-Proxies and the Momentum Valuation Spread (Rank-Weighted)**

This table is identical to Table 9 of the paper, but uses the momentum valuation spreads estimated from rank-weighted momentum strategies instead of Winner-minus-Loser strategies. We report results from regressions of the common and asset-class-specific components of the momentum valuation spread on risk-proxies.

	Intermediary Leverage	Illiquidity Premium	Dividend Yield	Global Recession	Default Spread	Real Uncertainty	Chicago Fed National Activity Index	$R^2 \times 100$
Panel A: Common Value								
1	-0.12							4.25
	(-2.05)							
2		-0.02						0.00
		(-0.41)						
3	-0.13	0.03						4.38
	(-2.16)	(0.51)						
4			-0.01					-0.13
			(-0.22)					
5	-0.25	-0.02	0.19					8.36
	(-2.94)	(-0.38)	(1.92)					
6				-0.23				4.06
				(-2.05)				
7	-0.32	0.02	0.24	-0.28	0.10	-0.14	-0.14	17.67
	(-2.84)	(0.47)	(2.32)	(-2.98)	(1.10)	(-2.33)	(-3.06)	
Panel B: Asset-Class-Specific Value								
Ind. Equities	-0.26	-0.16	0.23	-0.13	-0.29	0.01	-0.13	20.43
	(-1.88)	(-1.14)	(1.31)	(-0.74)	(-2.67)	(0.06)	(-1.29)	
Commodities	0.12	0.10	-0.05	0.47	-0.15	0.06	-0.05	11.99
	(0.86)	(1.24)	(-0.43)	(2.82)	(-1.16)	(0.48)	(-0.68)	
Stock Indexes	-0.35	-0.06	-0.11	-0.93	0.23	0.00	-0.22	29.78
	(-1.29)	(-0.62)	(-0.76)	(-4.34)	(1.59)	(-0.01)	(-2.42)	
Government Bonds	0.36	0.16	-0.31	0.12	-0.01	0.08	0.08	10.76
	(2.33)	(2.30)	(-1.42)	(0.58)	(-0.03)	(0.61)	(1.33)	
Currencies	0.16	0.03	0.03	0.17	0.25	-0.16	0.18	12.63
	(1.38)	(0.23)	(0.18)	(1.15)	(2.15)	(-1.58)	(2.25)	

Table D.10: **Predicting Momentum Returns with the Momentum Valuation Spread**

This table presents the results from time-series predictive regressions of momentum returns in five different asset classes on the momentum valuation spread: $R^{mom}_{c,t+1:t+h} = a_h + b_h MVS_{c,t} + \varepsilon^{mom}_{t+1:t+h}$. In each class, we present in *italic* the value measured that is used to calculate the momentum valuation spread. Momentum returns are calculated from two strategies: Winner-minus-Loser (split at the deciles of ranked values and value-weighting for individual equities; split at the median of ranked values and equal-weighting for the other asset classes) or rank-weighted. The regression results are for holding periods of $h = 1, 3, 6, 12, 24$ months. The momentum valuation spread, $MVS_{c,t}$, is standardized to accommodate interpretation and t-statistics are calculated using Newey and West (1987) standard errors with h-lags.

		$H-L$					$Rank$				
	h	a	b	t_a	t_b	R^2	a	b	t_a	t_b	R^2
Equities	1	0.0089	0.0050	2.84	1.02	0.31	0.0045	0.0034	2.35	1.21	0.46
BM	3	0.0270	0.0257	3.22	2.03	3.84	0.0131	0.0125	2.56	1.64	2.40
	6	0.0547	0.0565	3.30	2.66	8.68	0.0268	0.0285	2.67	2.04	6.24
	12	0.1181	0.0706	3.61	2.53	6.45	0.0585	0.0459	3.03	2.29	7.71
	24	0.2643	0.0994	3.62	2.67	4.82	0.1345	0.0404	3.59	1.18	2.95
Currencies	1	0.0008	0.0031	0.92	3.31	2.24	0.0021	0.0038	1.85	3.45	2.24
Inf. adj. return	3	0.0022	0.0072	0.94	3.80	4.16	0.0060	0.0107	2.06	4.63	6.06
	6	0.0043	0.0142	1.05	4.71	8.76	0.0119	0.0198	2.37	5.07	10.99
	12	0.0091	0.0215	1.28	4.75	12.37	0.0253	0.0289	2.92	4.79	14.74
	24	0.0176	0.0205	1.11	2.74	5.37	0.0520	0.0194	2.76	1.73	3.16
Stock Indexes	1	0.0003	0.0037	0.17	1.87	1.26	0.0003	0.0053	0.12	1.80	1.67
$MSCI_{BP}$	3	0.0019	0.0097	0.39	2.06	2.89	0.0020	0.0131	0.31	1.85	3.24
	6	0.0048	0.0160	0.51	2.51	4.10	0.0059	0.0181	0.48	1.86	3.13
	12	0.0132	0.0280	0.67	2.18	5.73	0.0183	0.0346	0.73	2.34	5.62
	24	0.0434	0.0230	0.94	1.08	1.08	0.0541	0.0446	0.93	2.12	3.3
Government Bonds	1	-0.0001	0.0009	-0.19	1.38	0.59	-0.0007	0.0016	-1.16	2.15	1.94
−5-*year return*	3	-0.0004	0.0028	-0.25	2.00	2.41	-0.0022	0.0047	-1.29	2.80	5.95
	6	-0.0008	0.0085	-0.25	3.65	9.67	-0.0043	0.0117	-1.34	4.18	16.51
	12	-0.0021	0.0159	-0.35	3.45	16.43	-0.0092	0.0209	-1.38	4.08	22.44
	24	-0.0052	0.0216	-0.42	3.20	14.63	-0.0203	0.0227	-1.23	3.07	9.96
Commodities	1	0.0074	0.0025	3.85	1.22	0.15	0.0112	0.0050	4.31	1.71	0.56
−5-*year return*	3	0.0227	0.0055	4.55	1.11	0.32	0.0347	0.0137	5.18	2.05	1.54
	6	0.0472	0.0102	5.07	1.16	0.71	0.0721	0.0216	5.88	1.98	2.08
	12	0.1005	0.0191	5.43	1.59	1.40	0.1546	0.0285	6.16	1.79	1.72
	24	0.2251	-0.003	5.44	-0.10	-0.19	0.3420	0.0074	5.83	0.18	-0.16

Table D.11: **Pooled Regressions of Value and Momentum Returns on a Global Recession Dummy**

This table presents the results from pooled regressions of value and momentum returns in different asset classes on the global recession dummy.

		$H-L$					$Rank$				
	h	a	b	t_a	t_b	R^2	a	b	t_a	t_b	R^2
Value	1	0.0009	0.0036	0.79	1.63	0.17	0.0011	0.0046	0.93	1.99	0.28
	3	0.0013	0.0140	0.40	2.46	0.79	0.0018	0.0178	0.51	2.86	1.20
	6	0.0016	0.0319	0.23	2.99	1.88	0.0027	0.0400	0.36	3.47	2.69
	12	0.0050	0.0626	0.35	3.41	2.94	0.0075	0.0816	0.52	4.48	4.56
	24	0.0267	0.1050	0.96	2.55	2.91	0.0333	0.1499	1.27	3.35	5.85
	48	0.1215	0.1393	1.26	1.74	1.25	0.1545	0.2300	1.89	3.02	4.30
Momentum	1	0.0044	-0.0018	3.56	-0.69	0.04	0.0049	-0.0029	4.04	-1.08	0.11
	3	0.0157	-0.0107	4.72	-1.58	0.45	0.0170	-0.0134	5.37	-1.92	0.70
	6	0.0347	-0.0272	5.17	-2.14	1.35	0.0373	-0.0322	5.80	-2.43	1.93
	12	0.0734	-0.0555	6.07	-2.82	2.71	0.0790	-0.0643	6.51	-2.86	3.56
	24	0.1449	-0.0796	5.18	-2.19	2.06	0.1553	-0.0978	5.23	-2.32	3.02
	48	0.3567	-0.1537	4.76	-2.50	2.30	0.3617	-0.1590	4.02	-2.03	2.28

Table D.12: **Alternative Strategies in Individual Equities and Industries**
This table presents the results from overlapping predictive regressions of monthly High-minus-Low value returns on the value spread: $R_{t+1:t+h} = a_h + b_h VS_t + \varepsilon_{t+1:t+h}$ from 1972 to 2014. We consider two alternative value strategies. One sorts stocks on the negative of the past five-year return. The other sorts 17 industries on their book-to-market ratio, which is calculated as the value-weighted average BM within each industry. Finally, we sort individual stocks on market capitalization and use the difference in total market cap between the Big and Small portfolio to predict Small-minus-Big returns.

		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 D.13: **Evidence from Alternative Book-to-Market Measures**
Panel A of this table presents time-series regressions of high-minus-low and rank-weighted book-to-market returns on the value spread, where we extend the sample back to 1962. Panel B presents the same regression, but uses an alternative measure of book-to-market that updates market cap in the denominator only once per year. In both panels, we focus on the sample excluding financial firms.

	H − L					*Rank*				
h	a	b	t_a	t_b	R^2	a	b	t_a	t_b	R^2
	Panel A: Extended sample period: 1962-2014									
1	0.0022	0.0056	0.99	2.39	0.94	0.0018	0.0025	1.32	1.45	0.39
3	0.0062	0.0176	1.04	3.26	3.08	0.0055	0.0076	1.40	1.89	1.27
6	0.0124	0.0368	1.04	3.39	6.17	0.0115	0.0158	1.45	1.89	2.60
12	0.0246	0.0838	1.03	4.10	14.01	0.0247	0.0364	1.50	2.12	5.96
24	0.0464	0.2073	0.94	4.43	29.04	0.0554	0.0980	1.68	2.57	16.79
	Panel B: Annually updated market cap in book-to-market ratio									
1	0.0026	0.0051	1.21	2.47	0.88	0.0016	0.0031	1.19	2.27	0.81
3	0.0080	0.0143	1.36	2.86	2.50	0.0051	0.0089	1.34	2.40	2.30
6	0.0166	0.0282	1.38	2.91	4.36	0.0111	0.0174	1.44	2.28	3.99
12	0.0355	0.0608	1.43	3.13	8.82	0.0251	0.0365	1.57	2.29	7.73
24	0.0760	0.1245	1.30	3.04	12.48	0.0580	0.0744	1.65	2.61	11.32

Table D.14: **Pooled Predictive Regression of Value Returns in Subsamples**
This table is similar to Table 3 of the paper, but runs the pooled predictive regression, $R_{c,t+1:t+h} = a_h + b_h VS_{c,t} + \varepsilon_{c,t+1:t+h}$ over the first and second half of the sample.

	$H-L$					$Rank$				
h	a	b	t_a	t_b	$R^2 \times 100$	a	b	t_a	t_b	$R^2 \times 100$
Panel A: First half (January 1972 to June 1993)										
1	0.0055	0.0033	3.25	1.50	0.58	0.0055	0.0027	3.16	1.20	0.39
3	0.0167	0.0122	3.72	2.56	2.28	0.0163	0.0097	3.25	1.98	1.40
6	0.0351	0.0307	4.02	3.64	6.53	0.0337	0.0259	3.27	2.84	4.09
12	0.0744	0.0762	4.28	4.16	16.63	0.0717	0.0701	3.31	3.08	12.09
24	0.1762	0.1760	4.78	4.82	31.44	0.1706	0.1902	3.49	3.42	26.99
Panel B: Second half (July 1993 to December 2014)										
1	0.0003	0.0040	0.28	2.70	0.84	0.0014	0.0035	1.01	1.99	0.66
3	0.0007	0.0127	0.20	4.38	2.80	0.0040	0.0120	1.06	3.11	2.34
6	0.0007	0.0247	0.12	4.88	5.02	0.0084	0.0251	1.13	3.52	4.77
12	-0.0009	0.0550	-0.08	5.27	10.07	0.0168	0.0571	1.21	4.99	10.13
24	-0.0147	0.1100	-0.72	4.64	15.20	0.0300	0.1149	1.26	5.87	18.69

Table D.15: **Common Versus Specific Components of the Value Spread in Subsamples**

This table presents the decomposition into common and specific value predictability (reported in Table 5 of the paper) over two subsamples split in June 1993 and for both High-minus-Low and rank-weighted value strategies.

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}
					Panel A: High-minus-Low					
					First Half					
1	0.0055	0.0026	0.0037	3.26	0.78	1.61	0.55	0.18	0.37	0.00
3	0.0168	0.0097	0.0141	3.84	1.41	2.36	2.27	0.70	1.57	-0.00
6	0.0357	0.0221	0.0377	4.33	1.79	3.64	6.87	1.67	5.20	0.00
12	0.0782	0.0457	0.0948	4.94	1.93	4.52	17.15	3.07	14.08	-0.00
24	0.1936	0.0956	0.2029	5.93	2.15	5.66	29.64	5.11	24.53	0.00
					Second Half					
1	0.0003	0.0087	0.0028	0.27	2.34	1.95	1.14	0.80	0.34	0.00
3	0.0006	0.0280	0.0090	0.19	2.67	3.36	3.79	2.66	1.13	0.00
6	0.0007	0.0531	0.0179	0.12	3.13	3.91	6.65	4.51	2.14	-0.00
12	-0.0010	0.1008	0.0440	-0.09	5.52	4.27	11.79	6.56	5.23	-0.00
24	-0.0157	0.1346	0.1029	-0.72	4.52	3.84	15.11	4.48	10.63	0.00
					Panel B: Rank-Weighted					
					First Half					
1	0.0054	0.0018	0.0035	3.20	0.54	1.54	0.42	0.08	0.34	-0.00
3	0.0165	0.0061	0.0128	3.43	0.85	2.28	1.58	0.27	1.32	0.00
6	0.0348	0.0147	0.0352	3.57	1.03	3.65	4.89	0.65	4.23	0.00
12	0.0769	0.0365	0.0888	3.86	1.14	4.29	12.95	1.69	11.26	0.00
24	0.1908	0.1152	0.1839	4.31	1.61	4.47	22.01	5.68	16.33	-0.00
					Second Half					
1	0.0014	0.0084	0.0023	1.02	2.06	1.38	1.00	0.77	0.23	0.00
3	0.0041	0.0270	0.0084	1.08	2.29	2.46	3.28	2.37	0.91	-0.00
6	0.0088	0.0538	0.0187	1.17	2.60	2.83	6.37	4.30	2.07	-0.00
12	0.0175	0.0988	0.0482	1.23	3.75	4.38	11.51	5.91	5.60	-0.00
24	0.0311	0.1255	0.1142	1.26	5.35	4.73	18.60	4.45	14.16	0.00

Table D.16: **Robustness Checks for Pooled Tests of Value Return Predictability**
This table reports robustness checks for the joint tests that pool the returns of value strategies across asset classes (see Table 3 of the paper). In Panel A, we exclude the value strategies that use US individual equities. This leaves us with four value strategies, using currencies, stock indexes, global government bonds and commodities. Panel B 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 C 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 A: Excluding Individual Equities											
		$H-L$					*Rank*				
	h	a	b	t_a	t_b	$R^2 \times 100$	a	b	t_a	t_b	$R^2 \times 100$
	1	0.0021	0.0034	1.88	2.67	0.62	0.0023	0.0030	1.98	2.40	0.49
	3	0.0061	0.0113	2.08	3.50	2.20	0.0068	0.0105	2.10	3.37	1.87
	6	0.0127	0.0258	2.11	4.47	5.44	0.0140	0.0253	2.10	4.30	5.00
	12	0.0278	0.0613	2.16	5.48	12.13	0.0309	0.0617	2.24	5.39	12.26
	24	0.0689	0.1169	2.44	5.88	17.26	0.0735	0.1169	2.59	5.61	19.07
	48	0.1902	0.2399	2.00	3.76	17.53	0.1955	0.2135	2.41	5.25	19.21
Panel B: Predicting Returns, Volatility, and Sharpe Ratio											
Avg. ret.		0.0024	0.0050	3.12	6.21	13.43	0.0031	0.0044	3.47	4.87	9.99
St. dev.		0.0396	0.0028	24.92	1.95	2.87	0.0389	0.0036	21.90	2.38	3.90
Sharpe		0.0676	0.1174	3.32	5.08	10.57	0.0946	0.0996	3.79	3.85	7.15
Panel C: Predicting the long- and short-end of value returns											
		Pooled					Average-on-average				
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