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Value Return Predictability across Asset Classes and Commonalities in Risk Premia*

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Abstract

We show that returns to value strategies in individual equities, industries, commodities, currencies, global government bonds, and global stock indexes are predictable in the time series by their respective value spreads. In all these asset classes, expected value returns vary by at least as much as their unconditional level. A single common component of the value spreads captures about two-thirds of value return predictability and the remainder is asset class specific. We argue that common variation in value premia is consistent with rationally time-varying expected returns, 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.

JEL classification: E44, G11, G12

Keywords: Value spread, Global asset pricing, Return predictability, Alternative assets, Common and asset class-specific value

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1. Introduction

In this article, we show that the expected returns of long-short value strategies in a range of asset classes increase in the value spread. The value spread is the difference between the value signal in the long versus the short portfolio, and its relation to value premia can be motivated from standard present value logic (e.g., Vuolteenaho, 2002; Froot and Ramadorai, 2005). The time variation in value premia we document is both economically and statistically large. At the 1-year horizon, the R^2 in a time series predictive regression equals 14% and 6% for US individual equities and industries, respectively, as well as 9, 11, 19, and 8% for commodities, currencies, global government bonds, and global stock indexes, respectively, and 13% in a pooled regression. In all these asset classes, a standard deviation increase in the value spread predicts an increase in the 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 provide new insight, we analyze the economic drivers of the time variation in expected value returns. We first decompose the value spread into a common component, defined as the first principal component of value spreads, and asset class-specific components. While the common component captures about half of the variation in value spreads, it captures more—about two-thirds—of the variation in expected value returns in the pool of asset classes. The remaining one-third is asset class specific. Quantifying the relative contribution of these two components to predictability is important, because a large and significant common component is evidence of market integration. Despite this fact, there is little evidence in the literature for common return predictability across asset classes (e.g., Cochrane, 2011).

We argue that time-varying risk premia drive the common component of value. Indeed, we find that expected value returns are globally high in bad times and remain so for number years. Moreover, two proxies for the risk of financial intermediaries—market leverage and funding liquidity—together with a measure of risk aversion explain the bulk of time variation in the common component. Thus, our evidence builds support for the recent theoretical literature on intermediary-based asset pricing (He and Krishnamurthy, 2012, 2013; Brunnermeier and Sannikov, 2014), as well as for asset pricing models featuring time-varying risk aversion (Campbell and Cochrane, 1999; Menzly et al., 2004; Santos and Veronesi, 2016). Thus, the quantitatively large amount of value return predictability we find in asset classes with potentially different investors and institutional settings presents a challenge for asset pricing theory. Our results suggest that a full explanation of the value premium requires a general framework, where in bad times investors shy away from holding different risky assets, so that value spreads widen simultaneously.

Another challenge to 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 components load on risk proxies, such as leverage and uncertainty, we find that the loadings vary considerably across asset classes. In addition, the risk proxies leave a large share of asset class-specific value return predictability unexplained, which points to mispricing. Consistent with these findings, we show that the common component of the value spread contributes relatively more than the asset class-specific components to value return predictability in the recent subsample. We find that common value is strongly associated with proxies for the risk of financial intermediaries, and financial intermediation has become more important over time. Moreover, if limits to arbitrage partially drive the asset class-specific components of value return predictability, one would expect these components to become less important over time.

Our results contribute to the asset pricing literature in various ways.[1] Unconditional value premia are documented for US individual equities (Fama and French, 1992),

1 A contemporaneous paper, Asness et al. (2018), independently reaches the same conclusion that value returns are predictable in different asset classes. The key different 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. (2018) focus on "deep" value events. They have more extensive data for equities, which enables them to highlight the

international equities (e.g., Fama and French, 1998; Liew and Vassalou, 2000), and alternative asset classes (Asness et al., 2013). Whereas our article is about comovement in expected value returns, Asness et al. (2013) show that realized value returns comove across asset classes. Conditional tests are relatively powerful in distinguishing between competing asset pricing models (Campbell and Cochrane, 2000; Cochrane, 2001; Nagel and Singleton, 2011). Therefore, the large amount of common variation in expected value returns that we document sets a higher hurdle for rational, risk-based models than what Asness et al. (2013) discuss.

We analyze the ability of the value spread to predict a value-minus-growth portfolio return over time, whereas many studies attempt to forecast (long-only) returns using valuation ratios. Lewellen (1999) and Cochrane (2011) predict the returns of diversified equity portfolios with their book-to-market ratio. Cochrane (2011, p. 1099) 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." Kelly and Pruitt (2013) conclude that the expansion and compression of the cross-section of value characteristics contain information about expected stock market returns. We show that this conclusion applies equally to expected value returns in all the asset classes we study.

Our findings for the value spread in individual equities are consistent with those of Asness et al. (2000a). Using data for large US individual equities from 1982 to 1999, they find that industry-adjusted value spreads have predictive power for value-minus-growth returns.[2] We contribute to this literature by studying (i) the value spread in other asset classes; (ii) the relative contribution of common and specific components of the value spread to predictability, as well as their economic drivers; and (iii) the potential for timing and rotation using the value spread in an out-of-sample setting. In particular, we find that value returns are predictable in real time, which alleviates concerns that our in-sample evidence is spurious.

Our multiasset 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? Our risky common component of expected value returns cannot be identified by analyzing a single value strategy in isolation. This fact helps to explain recent mixed evidence on the question of whether the equity value premium is driven by risk or mispricing (Golubov and Konstantinidi, 2016; Gerakos and Linnainmaa, 2018). Our work also contributes to the literature on global asset pricing, where "betting against beta" (Frazzini and Pedersen, 2014), "carry" (Koijen et al., 2018), and downside risk (Lettau et al., 2014) are shown to be factors in US individual equities, as well as a host of other asset classes. In contrast to us, these papers mostly characterize unconditional premia. Haddad et al. (2017) characterize conditional return variation in stocks, currencies, and bonds and argue, just like us, that long-short returns are more predictable than long-only

fundamentals of low and high value stocks and to test more rigorously alternative behavioral theories for the value effect.

2 Similarly, Cohen, Polk, and Vuolteenaho (2003) show that the return of the Fama and French (1993) HML factor is predictable by the HML value spread. Asness et al. (2017) study strategies that time and rotate value, momentum, and betting-against-beta in equities using their respective value spreads.

market returns.[3] Haddad et al. (2017) analyze a different strategy and a different predictor in each asset class. We analyze a single strategy (value) and a single predictor (the value spread) in all asset classes, and we extract a single common component.

2. Data and Methodology

In this section, we describe the construction of our value measures and value returns in different asset classes. The sources and procedures to clean the data are in Online Appendix A. There, we also validate our key result using the value returns of Asness et al. (2013). As is common in the literature, we use the book-to-market ratio as our measure of value for individual equities, industries, 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 literature documenting a direct link between past returns and book-to-market ratios, both empirically (DeBondt and Thaler, 1985; Fama and French, 1996; Gerakos and Linnainmaa, 2018) and theoretically (Daniel et al., 1998; Hong and Stein, 1999; Vayanos and Woolley, 2013).

2.1 Value in Different Asset Classes

2.1.a. ***US individual equities and industries***

The US individual equities data are from the Center for Research in Security Prices (CRSP) and Compustat. Following Asness et al. (2013), we limit the analysis to a sample from January 1972 to December 2017 and a universe of stocks that is liquid and can be traded at reasonably low cost in sizable trading volume. To be precise, we include in our value strategies only those stocks that cumulatively account for 90% of the total market capitalization in CRSP, which cutoff yields an average of 495 stocks for our portfolios. The idea is twofold. This allows us to provide conservative estimates for an implementable set of trading strategies. The cutoff also allows for a better comparison with the value strategies in alternative asset classes, where the securities are relatively liquid.

To measure value for each firm i, we use the ratio of the book value to the market value of equity, or the book-to-market ratio, $BM_{i,t}$, as in Fama and French (1992). Book values are observed each June and refer to the previous fiscal year-end. Market values are updated monthly as in Asness and Frazzini (2013), but we also consider annually updated market values in a robustness check. Consistent with the literature, we exclude financial firms: a given book-to-market ratio might indicate distress for a nonfinancial firm, but not for a financial firm (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 the second set of industry-adjusted book-to-market ratios. To find the industry-adjusted book-to-market ratio for stock i, $BM_{i,t,IndAdj}$, we subtract from its book-to-market ratio 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. They argue that there is no unconditional value effect across industries. To determine whether there is a conditional value effect, we sort seventeen industry portfolios on the value-weighted average book-to-market ratio within each

3 Moskowitz, Ooi, and Pedersen (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.

industry. To be consistent with our analysis of individual stocks, we construct the seventeen industry portfolios using only the restricted set of relatively large stocks.

2.1.b. Commodity futures. We obtain commodity 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 aluminum, nickel, tin, lead, zinc, and copper (from Datastream). We define value for commodities as the negative of the 5-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 for commodities runs from January 1972 to December 2017.

2.1.c. Currencies. We obtain spot and forward currency exchange rates for Australia, Canada, Germany (spliced with the euro), Japan, New Zealand, Norway, Sweden, Switzerland, the UK, and the USA. To measure value, we use the 5-year change in relative purchasing power parity, which is calculated as the negative of the 5-year spot return adjusted by the 5-year foreign–US inflation difference. Currency value is large when the foreign currency has weakened relative to the dollar. As noted in Menkhoff et al. (2016), using 5-year changes avoids potential problems that may arise from nonstationarity and base-year effects. The sample period for currencies runs from February 1976 to December 2017.

2.1.d. Global government bonds. We obtain global government bond data for Australia, Canada, New Zealand, Germany, Japan, Norway, Sweden, Switzerland, the UK, and the USA. We consider two sets of returns. Synthetic prices and returns for a 1-month futures contract on a 10-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 USA). We define two measures of value for bonds using synthetic prices and yields, because the cheapest-to-deliver feature of traded bond futures makes it hard to compare yields over time and across countries. The first measure is the negative of the 5-year futures return (–5-year return). The second is the 5-year change in the 10-year yield (5-year Δy). Using 5-year changes in yields avoids potential problems that may arise from trends and unconditional differences across bond markets in default risk, for instance. Throughout the article, 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 2017.

2.1.e. Global stock indexes. The universe of developed country stock index futures consists of Australia, Canada, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Spain, Sweden, Switzerland, the UK, and the USA. To measure value for global stock indexes, we use the inverse of the MSCI price-to-book ratio ($MSCI_{BP}$). Dictated by data availability, the sample period for these stock indexes runs from January 1994 to December 2017.

2.2 Value Returns and Value Spreads

To construct value returns, we sort securities within each asset class into P groups based on the cross-section of value measures, $V_{i,t}$. For individual stocks, we form market 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 $i = 1, \ldots, N_t$ 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 article, whenever we are predicting returns over horizons longer than 1 month, we separately compound total returns on the long and short position of these value strategies and then take the difference. These long and short positions are rebalanced for every month.

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 returns (compounded over horizon h) on the lagged value spread:

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

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

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

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. Next, 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:

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

Empirically, we abstract from the correction for the spread in discounted future expected profitability. Thus, the specification in Equation (1) provides a lower bound on the predictability of value returns (Asness et al., 2000a).[4]

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 (relative to growth firms) as they are burdened with more unproductive capital and face large adjustment costs. Consequently, value is riskier exactly when risk premia are high. Finally, the value spread can be motivated on purely statistical grounds. In Section B of Online Appendix, 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 Equation (2), the present value formulation of Froot and Ramadorai (2005) shows that expected currency returns are a key driver of real exchange rates. This motivates using real exchange rates as a measure of value for currencies. For bonds, the yield is a natural value metric, where a high yield indicates that the bond is relatively cheap. As for the case of equities, our regressions for currencies and bonds provide a lower bound on the predictability of value returns, since one can likely improve on our results by controlling for expected real interest rate differentials, in the case of currencies (Menkhoff et al., 2016), and differences in expected long-term inflation, in the case of bonds (Asness et al., 2018).[5] Because these adjustments need to be estimated and are different across asset classes, we prefer the simpler, directly observable, measures of value that are used in Asness et al. (2013).

In the regressions of value returns on the value spread, we consider forecasting horizon h up to 4 years. Horizons longer than 1 month help to mitigate the countervailing momentum effect (Asness and Frazzini, 2013) and better resemble the experience of actual value investors. It is important to note that long-horizon regressions of value returns on the value spread are relatively less affected by the inferential problems that are commonly associated with predictability. High first-order autocorrelation of the predictor and Stambaugh (1999) bias have been put forward as leading causes of inaccurate inference when predicting aggregate stock market returns (e.g., Valkanov, 2003; Lewellen, 2004; Boudoukh et al., 2006). However, the monthly autocorrelation of value spreads in the different asset classes ranges from 0.95 to 0.98 (see Panel A of Table I), which is small relative to an autocorrelation of 0.993 for the dividend yield over our sample period from 1972 to 2017. Moreover, as we show in Table C.1 in Online Appendix, the Stambaugh bias is small when predicting value returns with the value spread in individual equities. The intuition for this result is that the

4 Indeed, the predictive ability of the value spread in US individual equities improves when incorporating the restrictions in Equation (3) in a filtering approach (Rytchkov, 2010) or by using the implied costs of capital to control for differences in earnings growth rates and payout ratios (Li, Ng, and Swaminathan, 2014).

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

Table I. Correlations and factor structure of value spreads

Panel A of this table presents the correlation matrix of the high-minus-low value spread in different asset classes (*P*-value in parentheses), with first-order autocorrelations on the diagonal. We consider two measures of value for individual equities: book-to-market excluding financial firms (BM_{ExFin}) and industry-adjusted book-to-market (BM_{IndAdj}). For seventeen industries, the value measure is the market-cap-weighted book-to-market ratio. In all three cases, the data cover the period from 1972 to 2017. Market cap in the denominator of the book-to-market ratio is updated monthly and we use only the largest stocks that cumulatively account for 90% of the total market cap in CRSP. For commodities, the sample ranges from 1972 to 2017 and we measure value as the negative of the 5-year spot return (–5-year return). For currencies, the sample ranges from 1976 to 2017 and we measure value as the inflation-adjusted negative 5-year spot return (Inf. adj. return). For global government bonds, the sample ranges from 1991 to 2017 and we measure value as the negative of the 5-year return of a 1-month futures on a 10-year global government bond (–5-year return). For global stock indexes, the sample ranges from 1994 to 2017 and we measure value using the MSCI book-to-price ratio ($MSCI_{BP}$). Panel B presents the loadings of the first three principal components of the seven value spreads and the fraction of total variance explained by each component, which are extracted using the approach of Stock and Watson (2002).

	Panel A: (Auto-) Correlations						
Asset class	BM_{ExFin}	BM_{IndAdj}	US industries	Commodities	Currencies	Bonds	Equity indexes
BM_{ExFin}	0.97	0.95	0.86	0.34	0.04	−0.13	0.20
	(0.00)	(0.00)	(0.00)	(0.00)	(0.38)	(0.02)	(0.00)
BM_{IndAdj}		0.97	0.80	0.39	0.00	−0.17	0.40
		(0.00)	(0.00)	(0.00)	(0.96)	(0.00)	(0.00)
US industries			0.98	0.18	−0.01	−0.08	0.59
			(0.00)	(0.00)	(0.86)	(0.13)	(0.00)
Commodities				0.95	−0.12	−0.08	−0.09
				(0.00)	(0.01)	(0.17)	(0.11)
Currencies					0.95	0.01	−0.10
					(0.00)	(0.83)	(0.10)
Bonds						0.95	−0.33
						(0.00)	(0.00)
Equity indexes							0.97
							(0.00)

	Panel B: Principal Components							
Loadings	BM_{ExFin}	BM_{IndAdj}	Industries	Commodities	Currencies	Bonds	Equity indexes	Var. exp. (%)
PC1	1.34	1.34	1.29	0.59	0.07	0.16	1.17	51
PC2	−0.22	−0.09	−0.29	0.78	−1.66	−1.77	0.60	26
PC3	0.03	0.14	−0.64	2.28	0.94	−0.01	−0.70	12

left-hand side in Equation (1) is a difference in returns between two portfolios, which we regress on the corresponding difference in valuation ratios. This setup in differences largely breaks the mechanical relation that exists in regressions of a single return on a price-based valuation ratio.[6]

6 Pooling also helps to alleviate concerns about Stambaugh bias, because the across asset class dimension lowers the correlation between innovations in the value spread and past return shocks.

Thus, our setting is different from the usual setting in the predictability literature. Figure C.1 in Online Appendix presents the coefficient estimates, t-statistics, and R^2s from predictive regressions of nonoverlapping value returns on the value spread, as well as market returns on the dividend yield. The figure shows that the value spread predicts value returns more strongly and farther into the future than the dividend yield predicts aggregate stock market returns.

2.4 Time Variation in Value Spreads

To accommodate comparison across asset classes, we standardize each value spread so that its time series average equals 0 and standard deviation equals 1. We present the time series of (high-minus-low) value spreads in all seven asset classes in Figure 1.

To interpret the time variation in the value spread, let us consider the case of US individual equities in the top-left panel. When the value spread is 0, 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 current value spread indicates that deviations from relative purchasing power parity are historically large.

The seven panels in Figure 1 present a number of episodes when the value spread is large in more than a few asset classes, such as after the collapse of the dot-com bubble and the recent financial crisis. Thus, the value spread is correlated across asset classes. This conclusion is confirmed in Panel A of Table I, which presents the correlation matrix of value spreads. We find that the value spreads in US individual equities, industries, commodities, and global equity indexes correlate strongly and positively with each other.

These results suggest that the time variation of value spreads in different asset classes may be well captured by a small number of factors. Because the panel of value spreads is unbalanced due to limited data availability early in the sample period, we follow the procedure described in Stock and Watson (2002) to estimate the principal component factors using an iterative method based on the Expectation–maximization (EM) algorithm. Panel B of Table I shows that the first principal component of value spreads explains about 51% of the total variation. This first principal component is also presented in each panel of Figure 1. All value spreads load positively on the first principal component, and consistent with the correlations in Panel A, the loadings decrease from US individual equities to industries, equity indexes, commodities, bonds, and currencies. Consistent with these positive loadings, the correlation between a simple across-asset class average of the value spreads and the first principal component is large at 0.95.[7]

In what follows, we refer to this first principal component as the common component of the value spreads, VS_t^{Com}. The common component explains about half of the variation in value spreads, but it is an empirical question as to what fraction of value return predictability it captures. The answer to this question is important because it determines to what extent expected returns comove across asset classes. In theory, one would expect strong comovement, but empirical evidence of this effect is scarce in the literature. For instance, following up on the evidence in Cochrane and Piazzesi (2005), who show that a single common factor extracted from forward rates describes the majority of the variance of expected

7 The second principal component explains another 26% of the variation and loads heavily on currencies and bonds.

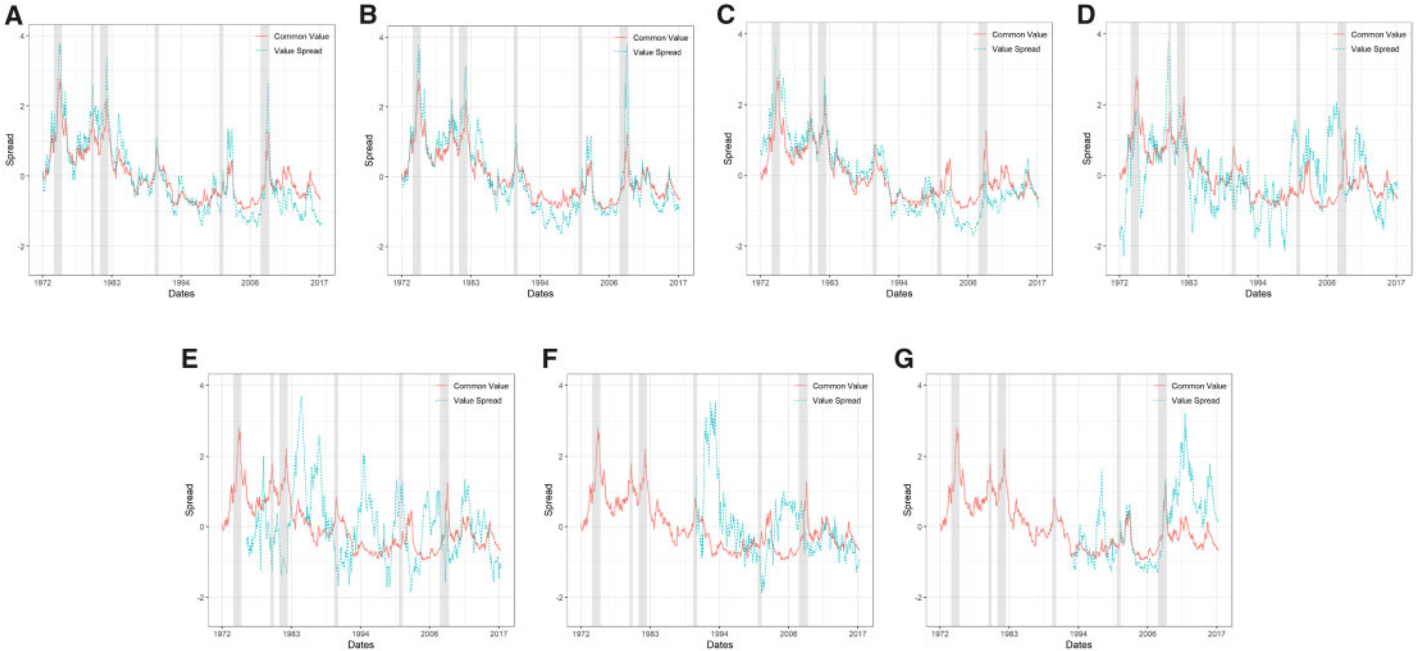

Figure 1. The value spread in different asset classes. This figure presents the time series of standardized value spreads (in blue) for the following seven value strategies: (**A**) individual equities: book-to-market excluding financials, (**B**) individual equities: industry adjusted book-to-market, (**C**) US industries, (**D**) commodities, (**E**) currencies, (**F**) global government bonds, and (**G**) global stock indexes. In each panel, we also present the time series of common value (defined as the first principal component of value spreads). The shaded areas represent NBER recessions.

bond returns, Cochrane (2011, p. 1054) asks: "[W]hat similar patterns hold across broad asset classes?"

Figure 1 also provides evidence of asset class-specific variation in the value spreads. For instance, the value spread in global government bonds often moves in the opposite direction to the remaining asset classes. To analyze the fraction of value return predictability that is asset class specific, we define the asset class-specific component of the value spread, VS_t^{Spec}, as the residual from a regression of the value spread in an asset class on the common component.

3. In-Sample Value Return Predictability

In this section, we ask whether returns to value strategies are predictable in the time series. To this end, we first analyze time series predictive regressions for each asset class. There is ample evidence for US equities in the literature; however, our evidence for the other asset classes is new. Next, we analyze pooled predictive regressions to assess the joint strength of value return predictability. This pooled evidence represents a key contribution of our article.

Panel A of Table II presents the unconditional performance of the high-minus-low and rank-weighted value strategies. All returns are scaled to have an annual standard deviation of 15% to accommodate comparison. Consider first the evidence for individual equities, for which we have two signals: BM_{ExFin} and BM_{IndAdj}. Consistent with the literature, we find that the industry-adjusted value strategy performs well, with annualized Sharpe ratios (monthly Sharpe ratio $\times\sqrt{12}$) of 0.24 and 0.38 for the high-minus-low and rank-weighted strategy, respectively. These numbers are relative to 0.14 and 0.17 for the strategy excluding financials. Overall, these Sharpe ratios are slightly lower than what is typically reported for value in the literature, because we focus on the set of relatively large and liquid stocks that cumulatively account for 90% of the total market capitalization (and value returns have generally been poor in recent years).[8]

For industries, commodities, currencies, global government bonds, and global stock indexes, we see that most value strategies generate a positive Sharpe ratio, but there is considerable variation in magnitude. Annualized Sharpe ratios range between 0.20 and 0.30 for the value strategies in commodities, currencies, and global stock indexes. Consistent with the literature, a value strategy using industries does not perform well unconditionally and produces a Sharpe ratio of 0.03. The Sharpe ratio of the value strategy using global government bonds is similarly small at −0.03.[9]

3.1 Time Series Predictive Regressions

Panel B of Table II shows the results from time series predictive regressions of value returns on the value spread at forecasting horizons of $h = 1$, 12, and 24 months for all seven asset

8 Our focus on large stocks is similar to Asness et al. (2013), and the correlation between their book-to-market strategy and our strategy excluding financial firms is 0.99.

9 This strategy uses traded bond futures returns and −5-year return as the value signal. Alternative strategies, using synthetic bond futures returns or the 5-year change in yield as value signal, perform slightly better unconditionally (see Table C.II of Online Appendix). Asness, Moskowitz, and Pedersen (2013) also find that value strategies using global government bonds vary considerably across specifications.

Table II. Time series predictive regressions of value returns on the value spread

This table presents the results from 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 all asset classes c. Value is measured in each asset class as explained in Table I. Value returns are calculated from two portfolio strategies: high-minus-low ($H-L$) or rank-weighted (*Rank*). For individual equities, we sort stocks in ten value-weighted deciles. For the remaining asset classes, we sort securities in two equal-weighted portfolios, split at the median of value measures in that asset class. Panel A reports unconditional performance statistics for monthly value returns in each asset class. Panel B presents the regression results for overlapping holding period returns of $h = 1, 12, 24$ months. For the sake of comparison across asset classes, value spreads, $VS_{c,t}$, are standardized to have mean equal to 0 and variance equal to 1; and, value returns are scaled to have an annual standard deviation of 15%. t^{nw} and t^{hd} indicate t-statistics calculated using Newey and West (1987) and Hodrick (1992) standard errors, respectively.

Panel A: Unconditional performance (monthly returns)

		$H-L$			*Rank*		
Asset class	Value measure	Avg. ret.	t	Sharpe	Avg. ret.	t	Sharpe
Ind. equities	BM_{ExFin}	0.15	0.83	0.04	0.21	1.11	0.05
	BM_{IndAdj}	0.32	1.73	0.07	0.49	2.65	0.11
Industries	BM	0.04	0.19	0.01	0.05	0.25	0.01
Commodities	–5-year return	0.30	1.60	0.07	0.27	1.48	0.06
Currencies	Inf. adj. return	0.41	2.13	0.09	0.46	2.38	0.11
Gov't bonds	–5-year return	−0.04	−0.16	−0.01	−0.05	−0.20	−0.01
Stock indexes	$MSCI_{BP}$	0.22	0.87	0.05	0.32	1.27	0.08

Panel B: Predictive regressions of value returns on the value spread

			$H-L$							*Rank*						
		h	a	b	t_a^{nw}	t_b^{nw}	t_a^{hd}	t_b^{hd}	R^2	a	b	t_a^{nw}	t_b^{nw}	t_a^{hd}	t_b^{hd}	R^2
Ind. equities	BM_{ExFin}	1	0.15	0.48	0.80	2.35	0.84	2.20	1.03	0.21	0.35	1.06	1.53	1.11	1.52	0.47
		12	2.01	6.97	0.96	3.89	0.92	3.24	13.94	3.01	5.54	1.30	2.30	1.38	2.45	7.96
		24	4.49	16.96	1.09	4.88	1.04	4.24	30.86	7.19	15.62	1.53	2.99	1.65	3.66	22.81

(continued)

Table II. Continued

Panel B: Predictive regressions of value returns on the value spread

			H – L							*Rank*						
		h	a	b	t_a^{nw}	t_b^{nw}	t_a^{hd}	t_b^{hd}	R^2	a	b	t_a^{nw}	t_b^{nw}	t_a^{hd}	t_b^{hd}	R^2
Ind. equities	BM_{IndAdj}	1	0.32	0.65	1.65	2.76	1.73	2.75	2.09	0.49	0.54	2.52	2.02	2.65	2.04	1.40
		12	4.59	9.72	2.22	4.62	2.10	4.17	26.24	7.28	8.79	2.87	2.91	3.33	3.59	15.56
		24	9.98	22.46	2.24	4.21	2.31	5.31	39.95	16.94	22.35	3.22	3.36	3.89	4.93	31.86
US industries	BM	1	0.04	0.20	0.19	1.07	0.19	1.00	0.03	0.05	0.18	0.24	0.87	0.25	0.83	−0.02
		12	0.29	4.34	0.15	2.58	0.13	2.09	6.44	0.41	3.67	0.18	1.78	0.19	1.65	3.63
		24	−0.10	13.17	−0.02	3.08	−0.02	3.39	16.86	0.02	11.73	0.00	2.06	0.00	2.86	11.09
Commodities	–5-year return	1	0.30	0.17	1.60	0.83	1.61	0.85	−0.02	0.27	0.11	1.47	0.52	1.49	0.54	−0.11
		12	3.10	5.08	1.55	2.62	1.42	2.28	8.65	2.72	5.35	1.27	2.56	1.24	2.47	8.78
		24	7.56	6.86	2.07	2.67	1.81	1.94	8.91	6.34	9.78	1.59	2.64	1.54	2.85	15.26
Currencies	Inf. adj. return	1	0.41	0.22	2.08	1.10	2.13	1.15	0.07	0.46	0.25	2.31	1.15	2.39	1.19	0.14
		12	6.15	6.07	2.70	2.99	2.67	3.11	11.40	6.37	6.12	2.88	3.13	2.77	3.01	11.94
		24	14.80	15.28	3.36	4.35	3.25	4.36	27.32	15.02	12.99	3.69	3.94	3.31	3.74	23.40
Gov't bonds	–5-year return	1	−0.04	0.57	−0.16	1.70	−0.16	1.80	1.42	−0.05	0.60	−0.21	1.97	−0.20	1.96	1.59
		12	−0.96	7.00	−0.44	4.42	−0.34	2.36	18.76	−0.55	6.37	−0.28	3.99	−0.19	2.14	18.29
		24	−1.74	15.60	−0.39	5.51	−0.33	2.80	33.92	−0.75	12.32	−0.18	6.44	−0.14	2.22	26.81
Stock indexes	$MSCI_{BP}$	1	0.22	0.44	0.90	1.68	0.88	1.57	0.67	0.32	0.36	1.25	1.28	1.29	1.22	0.33
		12	1.54	5.39	0.47	1.76	0.53	1.91	7.68	3.58	5.76	1.16	1.79	1.22	1.92	9.12
		24	1.13	7.79	0.16	1.50	0.20	1.63	5.21	6.11	8.70	1.02	1.69	1.06	1.75	9.10

classes. We present regression coefficients, t-statistics (using Newey and West (1987) t^{nw} and Hodrick (1992) t^{hd} standard errors with h lags), and R^2s.

We see that the coefficient on the value spread is positive for all asset classes and for all horizons. The evidence is strong at the annual horizon, where the coefficient estimate is significant and positive at the 10% level in all asset classes using both Newey-West and Hodrick standard errors. Similarly, strong evidence is found at the 2-year horizon, with global equity indexes significant at the 10% level and all other asset classes significant at the 5% level. At the 1-month horizon, the coefficient estimate is significant in half (one-third) of the asset classes for the high-minus-low (rank-weighted) portfolios. So, statistically, there is considerable evidence that the value spread predicts value returns. The information in the value spread takes longer than a month to fully materialize, however. Indeed, both the coefficient estimates and R^2s are, in most cases, increasing with the horizon.

The economic magnitudes of the coefficients on the value spread are also large. To see this, consider first the evidence for individual equities. For the high-minus-low value strategy excluding financials, the coefficient estimates translate to an increase in monthly, annual, and bi-annual future return equal to 0.48, 6.97, and 16.96% (with Hodrick t-statistics of 2.20, 3.24, and 4.24, respectively) for a standard deviation increase in the value spread. The R^2 in these same regressions are 1.03, 13.94, and 30.86% respectively. Thus, time variation in the value spread explains almost one-third of the variation in the 2-year returns of this strategy. For the industry-adjusted book-to-market strategy, the coefficient estimates and R^2 are even larger. The correlation between the value return series that excludes financials and the industry-adjusted value return series is about 0.69. This result suggests that cleaning valuation ratios from across-industry variation creates a different time series of value returns that is more predictable. For the rank-weighted portfolios, we also see economically large coefficients and R^2s, although the evidence is a bit weaker than for the decile portfolio strategy.[10]

Recall that by standardizing the value spread, the ratio of the estimated coefficient to the intercept, b_h/a_h, measures the implied standard deviation of expected returns relative to the unconditional value premium. At all horizons, this ratio is over 2 (2.8 on average) for the high-minus-low portfolios and over 1.1 (1.6 on average) for the rank-weighted portfolios. We conclude that the value premium in US individual 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 return with the dividend yield.

Although the fact that value returns in US individual equities are predictable using the value spread is not new (e.g., Asness et al., 2000a; Cohen et al., 2003), our evidence contributes to the literature along the following dimensions. First, we focus on a relatively small set of large and liquid stocks and extend the sample period post-2000, thus including two major recessions and the recent period of low-value returns. Second, we show in the next section that the value spread predicts value returns out-of-sample. This finding is

10 In Table C.III of Online Appendix, we show that the value spread remains a significant predictor when we (i) extend the sample back to 1962, (ii) calculate the book-to-market ratio with annually updated market cap (as in Fama and French, 1992), and (iii) sort stocks on the negative of the past 5-year return (e.g., DeBondt and Thaler, 1985, who use a similar measure to identify undervalued firms).

important because even after a long history of research on the predictive relation between market returns and the dividend yield, it is unclear whether the information in the dividend yield can be used profitably in an out-of-sample setting. This lack of out-of-sample evidence has raised concerns that the in-sample predictability is spurious (Lettau and Van Nieuwerburgh, 2007; Goyal and Welch, 2008). Third, the variation in expected value returns we document is economically large and 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. Table C.IV of Online Appendix presents the distribution of unconditional and conditional value premia obtained from 1,000 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 estimates of 3.47 (in case we exclude financials) and 2.12 (in case we use industry-adjusted book-to-market), which both fall in the far right tail of the simulated distribution.

In the remainder of Table II, we see that the value spread predicts value returns similarly in the other asset classes, although the evidence is slightly weaker statistically. This is partly due to a lack of power in asset classes with shorter sample periods (e.g., global government bonds and global stock indexes). Let us focus on the high-minus-low strategies for interpretation. At the annual horizon, the coefficient estimate on the value spread ranges from 4.34% ($t^{hd} = 2.09$) for industries to 7.00% ($t^{hd} = 2.36$) for global government bonds. At the 2-year horizon, the coefficient estimates range from 6.86% ($t^{hd} = 1.94$) for commodities to 15.60% ($t^{hd} = 2.80$) for global government bonds. The value spread captures a considerable fraction of the variation in 2-year value returns at R^2s of 16.86% for industries, 8.91% for commodities, 27.32% for currencies, 33.92% global government bonds, and 5.21% for global stock indexes.[11] Similar to what we find for US individual equities, the ratio of the coefficient on the value spread relative to the intercept is quite large in all asset classes. This ratio is about one for currencies and commodities. The ratio is considerably larger than one in the remaining asset classes, which is partly due to the fact that the unconditional value effects are small in some cases. For instance, the unconditional average value return is only 4 bps per month for industries, which is consistent with the literature. We show that the industry value premium is large conditionally and varies over time with the value spread, just like it does in all the other classes we study. In fact, comparing the unconditional evidence in Panel A to the conditional evidence in Panel B, we conclude that the conditional variation in value premia is actually more similar across asset classes than is the unconditional value premium.

3.2 Pooled Predictive Regressions

We next employ pooled tests for the following value strategies: US individual equities (book-to-market excluding financials and industry-adjusted book-to-market), industries, commodities, currencies, global government bonds, and global stock indexes. These pooled tests provide insight on the joint time variation in expected value premia implied by time

11 Table C.II of Online Appendix shows similar evidence for global government bonds when we use the alternative value measure (5-year change in yield instead of −5-year return) and slightly weaker when using synthetic bond futures returns.

variation in the value spread. Panel A of Table III presents the results for the following regression:

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

where c denotes an asset class and $x \in \{H - L, Rank\}$. We add in these pooled tests a longer 4-year horizon, $h = 48$ months, because pooling increases statistical power.[12]

In Panel A of Table III, we find that the joint evidence for value return predictability is strong for both types of portfolios. For instance, for the high-minus-low portfolio, the coefficient on the value spread is significant, with a t-statistic above three at the monthly horizon and a t-statistic above five for horizons that are over a quarter. 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 81–147% (23–77%) larger than the unconditional value premium in the pool of high-minus-low (rank-weighted) value strategies. For instance, the coefficient estimate is 6.41% at the annual horizon, which is relative to an unconditional average value premium of 2.64% (the intercept). Consistent with these coefficient estimates, the R^2 increases with the horizon, and exceeds 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 the evidence in Figure 2. In this figure, we predict future value returns over consecutive semiannual periods after portfolio formation. We find that the coefficient on the value spread is decreasing as time passes, but remains positive and marginally significant up to about four-and-a-half years after portfolio formation.

In Panel B of Table III, we present an alternative way of looking at the joint strength of the value return predictability. We regress in the time series the across-asset class average value return on the across-asset class average value spread. We again see coefficient estimates on the value premium that are statistically significant and economically large. The R^2s at the 24- and 48-month horizons are even larger at over 35%, since averaging smooths out some noise in the individual value strategies. These results testify to the joint strength of the value premium predictability, but they also suggest that there is a common variation in value premia across asset classes.

We run the same tests, but exclude the value strategies for individual equities. We see in Panels C and D in Table III that value returns in the alternative asset classes are jointly strongly predictable by the value spread, with a ratio of coefficient-to-intercept that is well above one in both the pooled and average-on-average specification. Finally, in Table C.V of Online Appendix, we show that the value spread predicts value returns in the pool of asset classes in both subsamples (split around June 1994). This result suggests that value return predictability is not solely driven by the highly popularized value episodes around the dot-com bubble in the late 1990s and around the recent global financial crisis.

Next, we examine whether our results are explained by time-varying exposure to a market benchmark, as in a conditional capital asset pricing model (CAPM). The literature shows that an unconditional CAPM does not explain the value premium. However, Campbell and Vuolteenaho (2004) find that the value spread is a significant time series predictor of equity market returns. Hence, if the market beta of value strategies varies over time with the value spread, this could explain the time series variation in value premia. To

12 Because the value spread is mean zero in all asset classes, the coefficient estimate b_h is identical when we include asset class fixed effects in Equation (4).

Table III. Predicting value returns with the value spread: pooled tests

This table reports results from joint tests that pool the value strategies across asset classes. Panel A reports regression results for the pooled predictive regression, $R_{c,t+1:t+h} = a_h + b_h VS_{c,t} + \varepsilon_{c,t+1:t+h}$. Value is measured in each asset class c as explained in Table I. For the sake of comparison across asset classes, value spreads, $VS_{c,t}$, are standardized to have mean equal to 0 and variance equal to 1, whereas value returns are standardized to have a standard deviation of 15% annually. Panel B reports results of a time series regression of the cross-sectional average value return (over the seven strategies) on the cross-sectional average value spread: $\overline{R_{t+1:t+h}} = a_h + b_h \overline{VS_t} + \varepsilon_{t+1:t+h}$. Panels C and D report results for the same two specifications, but exclude the two value strategies in individual equities. 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 Hodrick (1992) 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 1972–2017, but some alternative asset classes enter the sample only after 1972.

	$H-L$					*Rank*				
h	a	b	t_a	t_b	R^2	a	b	t_a	t_b	R^2
Panel A: Pooled predictive regression										
1	0.21	0.38	2.15	3.39	0.75	0.26	0.32	2.51	2.69	0.56
3	0.61	1.23	2.32	4.86	2.47	0.78	1.07	2.63	3.55	1.77
6	1.26	2.73	2.55	5.66	5.60	1.61	2.44	2.72	3.99	4.10
12	2.64	6.41	2.86	6.16	12.74	3.45	5.93	2.90	4.50	9.70
24	5.84	14.40	2.90	5.63	22.06	7.82	13.83	3.17	4.27	18.81
48	15.23	31.76	2.86	6.22	26.20	19.54	27.69	3.38	5.52	21.36
Panel B: Average value return on average value spread										
1	0.25	0.35	2.48	2.16	2.04	0.29	0.30	2.80	1.90	1.29
3	0.73	1.14	2.43	2.39	6.47	0.87	0.95	2.78	2.06	3.88
6	1.53	2.37	2.54	2.68	14.27	1.83	2.01	2.90	2.33	7.87
12	3.30	5.30	2.74	3.51	30.06	3.96	4.66	3.16	3.02	17.00
24	7.75	12.42	3.27	4.98	48.53	9.32	11.91	3.76	4.43	35.11
48	20.57	27.88	4.61	7.08	53.25	23.81	24.19	5.04	5.45	43.74
Panel C: Excluding value in individual equities (pooled)										
1	0.20	0.28	2.13	2.80	0.43	0.22	0.26	2.29	2.58	0.37
12	2.31	5.44	2.53	5.88	9.64	2.61	5.31	2.54	5.30	8.76
24	5.15	11.74	2.81	6.09	16.05	5.68	11.23	2.81	5.10	14.98
Panel D: Excluding value in individual equities (average-on-average)										
1	0.22	0.24	2.19	1.91	0.87	0.23	0.23	2.28	1.92	0.70
12	2.80	4.03	2.33	3.31	21.61	2.87	4.02	2.33	3.43	16.25
24	6.99	8.38	3.01	4.17	36.43	6.82	8.28	2.93	4.06	28.87

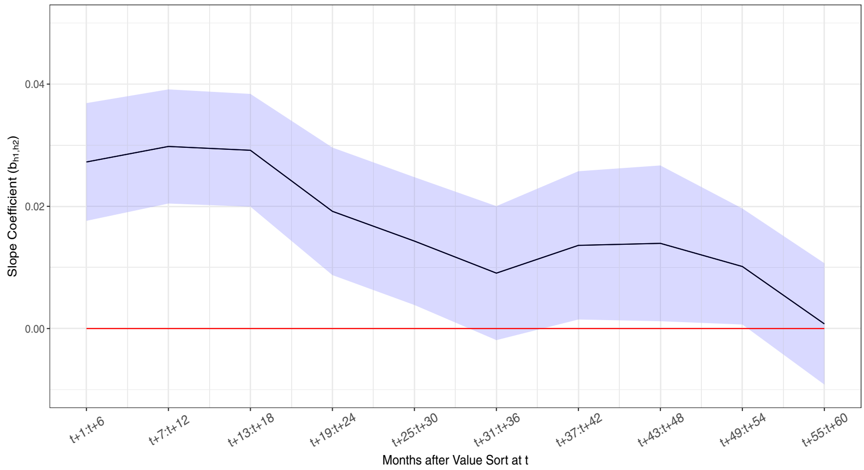

Figure 2. Semiannual future value returns on the value spread at time t. This figure presents the coefficient estimates (± 2 standard errors) from pooled predictive regressions of nonoverlapping semiannual value returns on the value spread: $R_{c,t+h_1:t+h_2} = a_{h_1,h_2} + b_{h_1,h_2} \text{VS}^x_{c,t} + e_{c,t+h_1:t+h_2}$. The semiannual value returns range from 6 months ($h_1 = 1, h_2 = 6$) to 6 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, (ii) individual equities: industry adjusted book-to-market, (iii) US industries, (iv) commodities, (v) currencies, (vi) global government bonds, and (vii) global stock indexes. The value spread is standardized.

see whether this is the case, we run the pooled predictive regression of value returns on the value spread, but control for market exposure in each asset class. We consider a model with constant betas, as well as a model that allows the market beta in each asset class c to vary over time with the value spread: $\beta_{MKT,c,t} = \beta_{0,c} + \beta_{1,c} VS_{c,t}$. The results are reported in Table IV. In Panel A, we use the CRSP value-weighted stock market portfolio—the most common proxy for the CAPM market portfolio in the literature—as the benchmark in all asset classes. In Panel B, we use an equal-weighted portfolio of the securities in each alternative asset class as the benchmark.

In the first test with constant betas, we find that the estimated coefficient on the value spread is similarly large in economic magnitude and significance to what we report in Panel A of Table III. This finding is intuitive: since the unconditional market betas of the value strategies are small, time variation in expected market returns alone cannot explain the large amount of time variation in value premia we find. The model with time-varying betas shows that the interaction between time variation in market betas and time variation in the market risk premium cannot explain our findings either. There is no consistent pattern across asset classes in the coefficients $\beta_{1,c}$, which are mostly insignificant. Hence, the predictability of value returns due to the value spread is again largely unaffected. We conclude that our results are not driven by the predictive relation between market returns and the value spread and thus a conditional CAPM. In line with this conclusion, Table C.VI of Online Appendix shows that the value spread is not a robust predictor of market returns in the pool of asset classes we study.

Table IV. Does the CAPM explain time variation in value returns?

This table reports the results of pooled predictive regressions as in Table III, but now we control for exposure to a market benchmark. We consider an unconditional specification: $R_{c,t+1} = a + bVS_{c,t} + \beta_{0,c}R_{MKT,c,t+1} + \varepsilon_{c,t+1}$ as well as a conditional alternative: $R_{c,t+1} = a + bVS_{c,t} + \beta_{0,c}R_{MKT,c,t+1} + \beta_{1,c}R_{MKT,c,t+1} \cdot VS_{c,t} + \varepsilon_{c,t+1}$, where $VS_{c,t}$ is the value spread in asset class *c*. $\beta_{0,c}$ captures the unconditional market exposure and $\beta_{0,c} + \beta_{1,c}VS_{c,t}$ captures the conditional market exposure of each value strategy. 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. Value returns are calculated from two portfolio strategies: high-minus-low (*H* – *L*) or rank-weighted (*Rank*). *t*-statistics are Driscoll and Kraay (1998) with one lag. The full sample period is 1972–2017.

	a	b	$\beta_{0,ExFin.}$	$\beta_{1,ExFin.}$	$\beta_{0,IndAdj.}$	$\beta_{1,IndAdj.}$	$\beta_{0,Inds.}$	$\beta_{1,Inds.}$	$\beta_{0,Com.}$	$\beta_{1,Com.}$	$\beta_{0,Cur.}$	$\beta_{1,Cur.}$	$\beta_{0,Bonds}$	$\beta_{1,Bonds}$	$\beta_{0,EqInd.}$	$\beta_{1,EqInd.}$	R^2
Panel A: Common market benchmark: CRSP market portfolio																	
High-minus-Low ($H-L$)																	
Unconditional	0.22	0.38	−0.20		−0.03		−0.13		0.03		0.03		0.11		0.17		2.20
	(2.30)	(3.43)	(−3.33)		(−0.51)		(−2.45)		(0.62)		(0.38)		(1.94)		(2.54)		
Conditional	0.22	0.34	−0.23	0.06	−0.06	0.07	−0.11	−0.05	0.03	−0.03	0.02	0.12	0.13	0.04	0.17	0.04	2.82
	(2.27)	(3.35)	(−3.94)	(0.95)	(−1.18)	(0.96)	(−2.21)	(−1.22)	(0.71)	(−0.72)	(0.38)	(1.85)	(1.72)	(0.34)	(2.42)	(0.53)	
Rank-weighted (*Rank*)																	
Unconditional	0.28	0.32	−0.26		−0.03		−0.14		0.05		0.00		0.08		0.22		2.72
	(2.71)	(2.74)	(−4.25)		(−0.52)		(−2.75)		(1.07)		(0.01)		(1.38)		(3.47)		
Conditional	0.27	0.30	−0.28	0.03	−0.06	0.06	−0.13	−0.03	0.06	−0.07	0.00	0.12	0.10	0.05	0.22	0.02	3.23
	(2.65)	(2.68)	(−4.86)	(0.40)	(−1.05)	(0.79)	(−2.75)	(−0.56)	(1.31)	(−1.72)	(0.03)	(1.76)	(1.38)	(0.55)	(3.46)	(0.25)	
Panel B: Asset class-specific market benchmark																	
High-minus-low ($H-L$)																	
Unconditional	0.30	0.37	−0.20		−0.04		−0.14		−0.20		−0.24		−0.95		0.33		4.11
	(3.11)	(3.48)	(−3.38)		(−0.68)		(−2.68)		(−3.23)		(−1.83)		(−3.37)		(4.53)		
Conditional	0.29	0.34	−0.22	0.05	−0.07	0.06	−0.12	−0.07	−0.14	−0.12	−0.24	0.08	−0.96	0.45	0.32	0.09	4.94
	(3.09)	(3.47)	(−3.95)	(0.70)	(−1.26)	(0.76)	(−2.37)	(−1.55)	(−2.06)	(−2.12)	(−1.88)	(0.57)	(−3.56)	(1.85)	(4.47)	(1.25)	
Rank-weighted (*Rank*)																	
Unconditional	0.35	0.32	−0.25		−0.02		−0.15		−0.24		−0.33		−0.65		0.39		4.96
	(3.40)	(2.79)	(−3.88)		(−0.27)		(−2.94)		(−3.76)		(−2.57)		(−2.40)		(5.95)		
Conditional	0.34	0.30	−0.24	0.00	−0.03	0.03	−0.14	−0.05	−0.19	−0.13	−0.33	0.10	−0.68	0.66	0.38	0.06	5.77
	(3.39)	(2.84)	(−4.19)	(0.00)	(−0.54)	(0.40)	(−2.88)	(−0.85)	(−2.63)	(−2.82)	(−2.65)	(0.65)	(−2.62)	(2.63)	(6.03)	(0.78)	

4. Out-of-Sample Value Timing and Rotation

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

4.1 Value Timing in Individual Equities

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

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

Thus, $VS_{t,His}$ indicates whether the average value spread over the last 12 months is historically large. We take an annual average to accommodate that return predictability using the value spread strengthens with the horizon. To ensure that our dynamic strategies are not extreme, we truncate the standardized signal at ± 2.

Table V presents summary performance statistics for three strategies: a unit weight strategy that captures the unconditional value premium, a linear timing strategy where $VS_{t,His}$ dollars are invested in both the long and short position of the value strategy, and a combined strategy where $1 + VS_{t,His}$ dollars are invested in the long and short position. We consider 2×2 variations of these strategies: using either (i) the book-to-market signal excluding financials or the industry-adjusted book-to-market ratio and (ii) the high-minus-low decile portfolio or the rank-weighted portfolio. To make the results comparable across strategies, we standardize each return series to have an ex ante annualized standard deviation of 15%. In particular, we follow Moskowitz et al. (2012) and estimate ex ante variance using an exponential weighting scheme: $\sigma^2_{R_{t+1}} = \sum_{i=0}^{\infty}(1-\delta)\delta^i(R_{t-i} - \hat{R}_{t+1})^2$, where δ is chosen so that the center of mass of the weights is 2 years and $\hat{R}_{t+1}$ is the exponentially-weighted average return computed similarly. We then rescale the return on the position as follows: $R_{t+1,15\%} = \frac{R_{t+1}}{\sigma_{R_{t+1}}} \times \frac{15\%}{\sqrt{12}}$.

We next compare the performance of the linear timing strategy to the unit weight strategy. For the high-minus-low decile book-to-market strategy that excludes financials, we find an average return for the linear timing strategy of 60 bps ($t = 2.77$) per month, which is 62 bps higher than the average return of the unit weight strategy. For the alternative value strategies, this difference ranges from 25 bps (industry-adjusted book-to-market, rank-weighted value strategy) to 49 bps (excluding financials, rank-weighted value strategy). Because this increase in average returns is not accompanied by a proportional increase in standard deviation, the Sharpe ratio of the linear timing strategies is relatively large as well, ranging from 0.34 to 0.41 (annualized). For comparison, over the alternative value strategies, the largest Sharpe ratio for the unit weight strategy is 0.24 (industry-adjusted book-to-market, rank-weighted value strategy). In the combined strategy, the returns of its two components are summed, which yields attractive average returns ranging from 56 bps to 87 bps, but Sharpe ratios that are similar to the linear timing strategies. In all, these results suggest that investors can use the information in the value spread to time value in the stock market. Moreover, this timing strategy is an attractive complement to an unconditional value strategy.

These conclusions are supported further when we look at alphas relative to the market portfolio (of large stocks accounting for 90% of total market cap in CRSP), as well as the

Table V. Value timing in individual equities

This table reports unconditional performance statistics for the monthly returns of a strategy that times value using the signal: $VS_{t,His} = \frac{\sum_{s=0}^{11} VS_{t-s}/12 - \sum_{s=12}^{t-1} VS_{t-s}/(t-12)}{\sigma(VS_{1:t-12})}$. $VS_{t,His}$ 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 in both the long and short position of the value strategy, and, finally, a combined strategy that invests $1 + VS_{t,His}$. We consider 2×2 variations of each value strategy: using either the book-to-market signal excluding financials or the industry-adjusted book-to-market ratio and either the high-minus-low decile portfolio or the rank-weighted portfolio. To make these different value strategies comparable, we scale each value return series ex ante to have an annualized standard deviation of 15%. The sample period is 1972–2017.

	Avg. ret.	t	Sharpe	αCAPM	t_α^{CAPM}	α^{FF3}	t_α^{FF3}
			Panel A: High-minus-Low (H – L)				
Ind. Equities ($BM_{Ex.fin.}$)							
Unit weight	−0.02	−0.08	0.00	0.17	0.89	−0.39	−2.60
Linear timing	0.60	2.77	0.12	0.53	2.42	0.59	2.73
Combined	0.58	2.34	0.10	0.71	2.79	0.20	0.91
Ind. Equities ($BM_{Ind.adj.}$)							
Unit weight	0.20	1.03	0.04	0.24	1.20	−0.18	−1.09
Linear timing	0.60	2.66	0.11	0.55	2.39	0.48	2.12
Combined	0.80	3.04	0.13	0.79	2.93	0.30	1.27
			Panel B: Rank-weighted (*Rank*)				
Ind. equities ($BM_{Ex.fin.}$)							
Unit weight	0.04	0.19	0.01	0.28	1.47	−0.32	−2.35
Linear timing	0.52	2.35	0.10	0.53	2.33	0.50	2.23
Combined	0.56	2.03	0.09	0.81	2.94	0.18	0.74
Ind. equities ($BM_{Ind.adj.}$)							
Unit weight	0.31	1.61	0.07	0.34	1.70	−0.17	−1.10
Linear timing	0.56	2.29	0.10	0.58	2.31	0.47	1.94
Combined	0.87	2.90	0.12	0.92	2.97	0.31	1.14

Fama and French (1993) three-factor model. We find that the CAPM alpha of the linear-timing strategies is large at about 55 bps and significant. This number is relative to a CAPM alpha for the unit weight strategy, which ranges from an insignificant 17 bps to a marginally significant 34 bps. This result suggests that conditional value strategies are attractive on top of an indexed market strategy and more so than an unconditional value strategy. The three-factor alpha of the linear timing strategies is also large and significant, at over 47 bps. This result suggests that the conditional value strategies using only the largest stocks are attractive even relative to unconditional value strategies using all stocks in the CRSP file.

In Table C.VII of Online Appendix, we present results for the same strategies using alternative market cap cutoffs of 75% and 95%. Although there is some variation in magnitude, we find again that conditioning on the value spread improves performance relative to a unit weight value strategy and typically also relative to a market strategy and the Fama–

French three-factor model. With the 95% cutoff, we use on average 740 stocks per month (relative to 495 using the 90% cutoff), which increases transaction costs. Including these relatively smaller stocks does increase the unconditional value premium, which is consistent with the literature. Interestingly, with the 75% cutoff, we use on average only 212 stocks per month, which lowers the transaction costs considerably.

4.2 Value Timing and Rotation in the Pool of Value Strategies

We next examine value timing and rotation in the pool of asset classes. To start, we run a pooled regression of value returns on a dummy variable that indicates whether the current value spread in an asset class is above the historical average:

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

where c denotes an asset class and $x \in \{H-L, Rank\}$, and $VS^{x}_{c,t,His}$ is defined as in Equation (5). The subscript indicates that we standardize each return series to have an ex ante annualized standard deviation of 15% to ensure comparability across asset classes.

Table VI presents the results. For the 1-month horizon, we find that the coefficient estimate of b is large and significant at 60 bps ($t = 2.91$) and 57 bps ($t = 2.53$) 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 52 bps and 55 bps per month, respectively. These returns translate to annualized Sharpe ratios of about 0.4. In comparison, the Sharpe ratio of investing when $VS_{c,t,His} \leq 0$ is negative, although small and insignificant. This evidence suggests that investing in value in a typical asset class is only attractive when the value spread in that asset class is historically large. Finally, the regression results for longer horizons suggest that strategies that rebalance at a lower frequency than every single month, are likely more attractive.

We next examine strategies that rotate value across asset classes. As a benchmark, we consider an unconditional value strategy where $1/N_t$ is invested in each of N_t available value strategies (out of the maximum of seven) in each sample month t. Next, we consider a value rotation strategy where asset classes are overweighted (underweighted) when the value spread is high (low) relative to the other asset classes. We consider two alternative weighting schemes. The first rotation strategy takes a position in each asset class c in month t equal to:

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

where the scalar q_t ensures that the total weight in the long and short position equals 1. In the second strategy, with weights denoted $w^{rot,2}_{c,t}$, an equal weight is invested in each asset class with $VS_{c,t,His}$ above (below) the mean value spread across asset classes. We calculate performance measures for these two long-short rotation strategies, as well as for a combination with the unconditional strategy.

The first block of results in Panel A in Table VII is for the high-minus-low portfolios. We find that the two rotation strategies outperform the unconditional strategy. For instance, the average return and annualized Sharpe ratio of the linear rotation strategy equal 68 bps ($t = 3.12$) and 0.52, respectively, which is large relative to 8 bps ($t = 0.74$) and 0.12 for the unconditional strategy. The equal-weighted rotation strategy performs similarly at

Table VI. Out-of-sample pooled predictive regression

This table reports results for pooled predictive regressions of returns of the seven value strategies on a dummy variable indicating whether the current value spread in an asset class is historically high or low. 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 equals one when the historically standardized value spread in asset class c (see Equation (5)) is positive, and zero otherwise. 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 ex ante annualized standard deviation of 15%. We perform this standardization in each month using only backward-looking information as detailed in Table V. 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 in the pooled regression at the monthly horizon ($a + b$ for $h = 1$). 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 1972–2017, but some alternative asset classes enter the sample only after 1972.

Panel A: Pooled regression on high-value spread dummy

	$H-L$					$Rank$				
h	a	b	t_a	t_b	R^2	a	b	t_a	t_b	R^2
1	−0.09	0.60	−0.70	2.91	0.41	−0.02	0.57	−0.12	2.53	0.37
3	−0.28	1.83	−0.83	3.36	1.15	−0.01	1.61	−0.03	2.55	0.87
6	−0.68	4.01	−1.08	3.77	2.56	0.03	3.23	0.03	2.48	1.57
12	−1.36	8.27	−1.03	3.64	4.76	−0.07	7.27	−0.04	2.67	3.34
24	−4.49	21.12	−1.42	3.56	9.82	−0.99	16.98	−0.26	2.64	6.03
48	−16.53	63.35	−1.84	3.99	17.26	−6.28	46.94	−0.64	3.43	10.07

Panel B: Implied performance

	$H-L$				$Rank$			
	Avg. ret.	St. dev.	t	Sharpe	Avg. ret.	St. dev.	t	Sharpe
Invest when $VS_{c,t,His} > 0$	0.52	4.52	3.70	0.11	0.55	4.61	3.90	0.12
Invest when $VS_{c,t,His} \leq 0$	−0.09	4.43	−0.86	−0.02	−0.02	4.35	−0.16	−0.00

an average return of 63 bps ($t = 3.30$) and has a Sharpe ratio of 0.55. In the second block of results for the rank-weighted value strategies, we find that the value rotation strategies outperform the unconditional strategies as well, albeit by a slightly smaller margin. The Sharpe ratio is about 0.45 for the two rotation strategies and 0.23 for the unconditional strategy. Similar to the case of individual equities, we find that the combined strategies (unconditional value plus value rotation) perform about as well as the rotation strategies in Sharpe ratio. We conclude that the value spread can be used by investors to rotate value across asset classes in real time and this strategy is attractive relative to a strategy that invests unconditionally in value in all asset classes. Thus, investing in value is most attractive in asset classes with value spreads that are large compared to other asset classes.

Table IV also reports the abnormal return, or α, of the rotation strategies relative to an equal-weighted portfolio of the market strategies in each asset class (as shown in Panel B of

Table VII. Rotating value strategies across asset classes

This table reports unconditional performance statistics for monthly returns of strategies that rotate value across asset classes. These strategies overweight (underweight) those asset classes where the value spread is high (low) relative to the other asset classes. As a benchmark, we consider an unconditional value strategy that invests, in each sample month t, $1/N_t$ in each of the N_t available value strategies (out of the maximum of seven). The first rotation strategy takes a position in each asset class c in month t equal to $w_{c,t}^{rot,1} = q_t(VS_{c,t,His} - Mean(VS_{c,t,His}))$, where the scalar q_t ensures that the total weight in the long and short position equals one. The second strategy, with weights denoted $w_{c,t}^{rot,2}$, invests an equal weight in each asset class with $VS_{c,t,His}$ above (below) the mean value spread across asset classes. We calculate performance measures for these two long-short rotation strategies (denoted $Rotation_{Long-Short}$) as well as for a combination with the unconditional strategy (denoted $Combined_{Long-Short}$). The reported α is relative to an unconditional market strategy, which equally weights the market portfolio in each asset class (defined as in Table IV). The value strategy returns are scaled in each asset class to have a standard deviation of 15% using only backward-looking information. Panel B reports the fraction of the long and short leg of the two rotation strategies that is invested in each asset class (on average over time). Panel C decomposes the average return of the long-short rotation strategy across asset classes. Because we lose the first 120 months in the asset classes with the longest history as burn-in period for the value signal and we require at least four asset classes with available data, the full out-of-sample period is 1982–2017.

Panel A: Performance of value rotation strategies

	Linear Weight ($w_{c,t}^{rot,1}$)						Equal weight ($w_{c,t}^{rot,2}$)					
	Avg. ret.	St. dev.	t	Sharpe	α	t_α	Avg. ret.	Std. dev.	t	Sharpe	α	t_α
High-minus-low ($H-L$)												
Unconditional	0.08	2.20	0.74	0.04	0.09	0.81	0.08	2.20	0.74	0.04	0.09	0.81
$Rotation_{Long-Short}$	0.68	4.51	3.12	0.15	0.56	2.49	0.63	3.96	3.30	0.16	0.55	2.83
Combined	0.76	4.93	3.19	0.15	0.64	2.64	0.71	4.44	3.31	0.16	0.64	2.92
Rank-weighted ($Rank$)												
Unconditional	0.15	2.32	1.37	0.07	0.16	1.35	0.15	2.32	1.37	0.07	0.16	1.35
$Rotation_{Long-Short}$	0.60	4.58	2.71	0.13	0.49	2.15	0.53	4.05	2.71	0.13	0.49	2.42
Combined	0.75	5.09	3.07	0.15	0.64	2.55	0.68	4.67	3.04	0.15	0.64	2.78

Panel B: Percentage of allocation to each asset class in $Rotation_{Long-Short}$

	ExFin.	IndAdj.	Inds.	Com.	Cur.	Bonds	EqInd.	Sum	ExFin.	IndAdj.	Inds.	Com.	Cur.	Bonds	EqInd.	Sum
$H-L_{Long}$	0.03	0.05	0.05	0.22	0.31	0.05	0.28	1.00	0.07	0.07	0.09	0.22	0.30	0.08	0.18	1.00
$Rank_{Long}$	0.06	0.04	0.03	0.21	0.32	0.04	0.29	1.00	0.11	0.05	0.07	0.22	0.29	0.07	0.19	1.00
$H-L_{Short}$	0.20	0.20	0.23	0.12	0.14	0.09	0.03	1.00	0.20	0.20	0.21	0.12	0.11	0.11	0.04	1.00
$Rank_{Short}$	0.16	0.19	0.27	0.12	0.15	0.09	0.02	1.00	0.17	0.22	0.22	0.12	0.11	0.12	0.03	1.00

Panel C: Contribution to Avg. Ret. in $Rotation_{Long-Short}$

	ExFin.	IndAdj.	Inds.	Com.	Cur.	Bonds	EqInd.	Sum	ExFin.	IndAdj.	Inds.	Com.	Cur.	Bonds	EqInd.	Sum
$H-L$	0.11	0.16	0.01	0.00	0.27	0.02	0.11	0.68	0.14	0.13	0.03	0.03	0.23	0.00	0.08	0.63
$Rank$	0.06	0.11	0.04	0.02	0.19	0.04	0.14	0.60	0.09	0.07	0.03	0.00	0.24	−0.01	0.11	0.53

Table IV). Note, this aggregate market benchmark is well-diversified and presents a tough benchmark for the dynamic strategy to beat. The value rotation strategies have lower α's than average returns, suggesting that there is some market exposure. However, the reduction is generally small (about 10 bps), such that the remaining abnormal return is economically large ($>$ 49 bps) and statistically significant. We conclude that rotation strategies may be an attractive addition to a portfolio that diversifies unconditionally across these markets. In contrast, the unconditional value strategy obtains an α that is about one-third in magnitude of the rotation strategy and is insignificant in all four cases.

In Panel B of Table VII, we present the fraction of months in which the long and short leg of the rotation strategies invest in each asset class. We see that the strategies diversify across different asset classes over time: no asset class is present in either leg for more than one-third of the sample. We next decompose the average return of the long-short rotation strategies across asset classes. For both rotation strategies, we find in Panel C that about 60% of the average return is derived from the alternative asset classes. Currencies are the asset class with the largest contribution. The value strategies using individual equities and equity indexes also contribute substantially. Thus, we conclude that not only US individual equities, but also the alternative asset classes, contribute to the benefits of value rotation.

Table C.VIII in Online Appendix presents the results from timing strategies for the alternative asset classes (analogous to Table V). We find that the return from a linear timing strategy is non-negligible economically (ranging from about 20 to 30 bps per month) for industries, currencies, global government bonds, and global stock indexes. These effects are insignificant, however, partly due to the shorter sample period dictated by data availability. This result highlights an important difference between value timing and rotation. Even if timing value in a specific asset class is difficult, the value spread in that asset class may contain valuable information for rotating value across asset classes. Indeed, the evidence in Table VII suggests that comparing the value spread in currencies to other asset classes provides valuable information to determine when to go long (or short) the currency value strategy.

5. Common Value and Economic Drivers of Value Return Predictability

In this section, we investigate (i) the strength of comovement between the expected returns of value strategies in different asset classes, and (ii) whether this comovement is driven by economic fundamentals. Throughout this section, we discuss the results for the high-minus-low value strategies. By and large, identical results for the rank-weighted strategies are reported in Tables C.IX, C.X, and C.XI of Online Appendix.

5.1 Common versus Asset Class-Specific Value

We start by investigating how much predictability in value strategies is common across the different asset classes. In Table VIII, we present the results from a pooled predictive regression on the two components of the value spread defined in Section 2.4. The common component, denoted VS_t^{Com}, is the first principal component of value spreads. The asset class-specific component, denoted VS_t^{Spec}, is the residual from a regression of the value spread in each asset class on the common component.

In isolation, the coefficient estimates on the common as well as the asset class-specific component of the value spread are statistically and economically significant at all horizons. Thus, both contain information about future value returns. The estimated coefficients are

Table VIII. Common and asset class-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. Panel A reports the results of a pooled predictive regression on the common component of the value spread (the first principal component of the value spread in seven asset classes): $R_{c,t+1:t+h} = a_h + b_{h,Com} VS_t^{Com} + \varepsilon_{t+h}$. Panel B reports results for the asset class-specific components, which are defined as the residual in a regression of the value spread in asset class c on VS_t^{Com}: $R_{c,t+1:t+h} = a_h + b_{h,Spec} VS_{c,t}^{Spec} + \varepsilon_{t+h}$. Panel C reports the results of a pooled regression that includes the two components simultaneously. t-statistics are calculated using Driscoll and Kraay (1998) standard errors with h lags. The sample is 1972–2017, but some alternative asset classes enter the sample only after 1972.

h	a	b_{Com}	b_{Spec}	t_a	$t_{b_{Com}}$	$t_{b_{Spec}}$	R^2
Panel A: Common value							
1	0.25	0.39		2.37	2.02		0.35
3	0.73	1.28		2.63	2.71		1.18
6	1.50	2.78		2.87	3.08		2.61
12	3.17	6.43		3.25	4.16		5.79
24	7.13	16.17		3.53	5.39		12.84
48	17.43	38.58		3.85	8.83		18.45
Panel B: Specific Value							
1	0.21		0.28	2.13		2.38	0.21
3	0.61		0.96	2.26		3.40	0.73
6	1.26		2.29	2.38		4.50	1.92
12	2.64		5.67	2.41		5.49	4.84
24	5.84		10.75	2.07		5.46	5.94
48	15.23		21.20	1.80		3.29	5.62
Panel C: Common and specific value							
1	0.25	0.39	0.28	2.38	2.02	2.37	0.56
3	0.73	1.28	0.96	2.64	2.72	3.36	1.92
6	1.50	2.78	2.29	2.91	3.10	4.49	4.53
12	3.17	6.43	5.67	3.31	4.18	5.74	10.63
24	7.13	16.17	10.75	3.52	5.25	5.97	18.78
48	17.43	38.58	21.20	3.83	8.64	3.40	24.07

identical in a joint test, because the two components are orthogonal.[13] More interesting is the relative contribution of each component to the total R^2 in the joint test. This R^2 ranges from 0.56% at the monthly horizon to 10.63% at the annual horizon, 18.78% at the 2-year horizon, and 24.07% at the 4-year horizon. At these horizons, the common component contributes 0.35, 5.79, 12.84, and 18.45% of the explained variation, respectively. In other words, about 60% of the predictability of value returns in the pool of value strategies

13 One can decompose the value spread arbitrarily in two orthogonal components that obtain a joint regression R^2 identical to what we present here. However, such arbitrary components will in general not predict value returns in isolation, especially a component that is restricted to not vary across asset classes.

is driven by the common component at horizons from 1 month up to 1 year. At horizons of 2 and 4 years, the common component contributes even more at about 68% and 77%, respectively. Recall that the common component explains about half of the variation in value spreads. We thus find that it explains an even larger share of the predictability of value returns; for instance, more than two-thirds at long horizons. The asset class-specific components contribute relatively more at short horizons. This latter finding is consistent with the idea that limits to arbitrage prohibit the fast movement of money across asset classes.

In Tables C.XII and C.XIII of Online Appendix, we show that these conclusions are not sensitive to the definition of the common component. A first alternative definition uses the first principal component from a standard principal component analysis performed on the panel of value spreads. However, in this case, the panel is balanced 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. A second alternative definition is the average value spread over the asset classes with available data in month t.[14] The advantage of this definition is that the common component is directly observable and does not suffer from errors-in-variables bias. The disadvantage of this decomposition is that we assume equal loadings on the common component across asset classes. The correlation between our measure of the common component and this alternative measure is large, at 0.95, which suggests that this disadvantage should not affect the results much. For both alternative definitions and all horizons, we find that the common component contributes about two-thirds of the predictability of value returns.

Overall, these results suggest that the common component of the value spread contributes more than the asset class-specific component to value return predictability. A component of the value spread that is common across asset classes and determines about two-thirds of the variance of expected returns to 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, p. 1060): "It is not enough to simply generate temporary price movements in individual securities."

5.2 Economic Drivers of the Components of Value

In this subsection, 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 following form:

$$VS_t^{Com} = k_0 + k_1' Z_t + u_t^{Com} \text{ and} \tag{8}$$

$$VS_{c,t}^{Spec} = k_0 + k_1' Z_t + u_{c,t}^{Spec}, \tag{9}$$

where Z_t is a particular set of state variables or risk proxies. We report the results from Equations (8) and (9) in Panels A and B of Table IX, respectively.

Intermediaries are the marginal investors in many asset markets. Hence, their marginal value of wealth is a plausible pricing kernel for a broad set of securities and may drive common variation in expected returns. Recent intermediary-based asset pricing models (e.g., 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

14 The asset class-specification component is then simply the difference between the value spread in an asset class and common value.

Table IX. 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; the dividend yield; a global recession dummy; the default spread; real uncertainty; and, the Chicago Fed National Activity Index). Panel A reports results from time series regressions of the common component of the value spread on the risk proxies, $VS_t^{Com} = k_0 + k_1^{'} Z_t + u_t^{Com}$. 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). For Specifications 3 and 5, we also run the regression in innovations, which are estimated using an AR(1)-model for both common value and the state variables. Panel B regresses the asset class-specific components of the value spread on the full set of risk proxies (as in Specification 7), $VS_{c,t}^{Spec} = k_0 + k_1^{'} Z_t + u_t^{Spec}$. t-statistics are calculated using Newey and West (1987) standard errors with twelve lags. The full sample period is 1972–2017, 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
				Panel A: Common value				
1	0.52							53.02
	(6.81)							
2		0.45						40.09
		(9.56)						
3	0.39	0.27						64.39
	(6.70)	(3.83)						
4			0.59					68.70
			(10.00)					
5	0.16	0.16	0.38					73.80
	(2.94)	(2.16)	(5.37)					
6				0.46				9.88
				(2.57)				
7	0.02	0.09	0.43	0.21	0.07	0.08	0.01	78.73
	(0.30)	(1.27)	(5.91)	(2.85)	(1.07)	(1.11)	(0.26)	
3 (in AR(1)-innovations)	0.61	0.12						41.21
	(6.87)	(2.96)						
5 (in AR(1)-innovations)	0.22	0.04	0.58					57.32
	(3.23)	(1.30)	(6.58)					
				Panel B: Asset class-specific value				
Ind. equities ($BM_{Ex.Fin.}$)	−0.11	0.00	0.03	−0.04	0.08	0.08	−0.02	8.64
	(−1.27)	(0.07)	(0.44)	(−0.58)	(1.46)	(1.50)	(−0.99)	
Ind. equities ($BM_{Ind.Adj.}$)	0.10	−0.08	−0.12	−0.14	0.14	0.04	0.02	40.73
	(1.60)	(−2.59)	(−2.15)	(−2.89)	(2.76)	(0.78)	(0.91)	
Industries	−0.30	0.09	0.29	0.03	−0.01	−0.12	−0.03	47.63
	(−4.98)	(2.64)	(4.79)	(0.35)	(−0.23)	(−2.63)	(−1.33)	
Commodities	0.15	−0.10	−0.18	−0.16	−0.42	0.52	0.15	19.29
	(0.78)	(−1.21)	(−0.99)	(−0.88)	(−2.85)	(4.19)	(2.05)	
Currencies	0.08	0.21	0.08	−0.35	0.15	−0.26	−0.15	12.35
	(0.45)	(1.21)	(0.38)	(−1.37)	(0.92)	(−1.64)	(−1.54)	
Government bonds	−0.25	0.11	1.57	0.06	−0.09	−0.02	−0.19	35.07
	(−1.11)	(0.41)	(3.24)	(0.28)	(−0.51)	(−0.10)	(−2.16)	
Stock indexes	0.67	0.09	−0.43	0.22	−0.23	−0.73	−0.03	44.34
	(2.42)	(0.34)	(−1.01)	(1.22)	(−1.47)	(−4.50)	(−0.35)	

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 of Table IX. We find a strong relation, with variation in leverage accounting for almost 50% of the overall variation in common value. 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 (Adrian et al., 2014; He et al., 2017).

Next, guided by theory (Brunnermeier and Pedersen, 2009) and empirical evidence (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 of Table IX, we find that illiquidity also explains considerable variation in common value with an R^2 of almost 40%. Jointly, leverage and illiquidity explain 64% of the variation in common value (row 3). Both variables enter significantly, with economically large coefficients. For a standard deviation increase in leverage and illiquidity, common value increases by 0.39 and 0.27 standard deviations, respectively.

Recent literature acknowledges that financial intermediary leverage is endogenous and its cycles may simply reflect movements in aggregate risk aversion (Campbell and Cochrane, 1999; Menzly et al., 2004; Santos and Veronesi, 2016).[15] 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. In row 4 of Table IX, we find that the dividend yield explains lots of variation in common value, with an R^2 of almost 69%. This result is consistent with the idea that the value spread widens when risk aversion is high. We then investigate the extent to which leverage and liquidity are just a manifestation of time-varying risk aversion (as proxied by the dividend yield). We see in Row 5 that intermediary leverage, illiquidity, and the dividend yield are all significant and jointly capture about three-quarters 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 (Santos and Veronesi, 2016), the magnitude and statistical significance of the individual coefficients fall upon joint inclusion of the variables.

Based on the evidence so far, we conclude that common value is large when, in bad times, intermediaries' balance sheets get shocked or aggregate risk aversion is high, or both. Consistent with this result, we see in Row 6 of Table IX that common value is higher by about 0.46 standard deviations during global recessions. In Row 7, we find that this conclusion is also robust to controlling for additional state variables. Following Koijen et al. (2017), who link the value spread in equities to business cycle risk, we include the Chicago Fed National Activity Index. We also include the Jurado et al. (2015) real uncertainty index. As pointed out by Nagel (2016), liquidity may be in part 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 BAA–AAA corporate bond default spread, a popular proxy for cyclical variation in risk premia. In this "kitchen sink" regression, all three

15 Leverage is measured as the inverse of the squared intermediary capital ratio, as in He, Kelly, and Manela (2017). This 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).

additional state variables are insignificant and the R^2 increases only marginally relative to the three-variable model in Row 5 (79% vs. 74%). In all, the common value spread is high in bad times, which are modeled well as a combination of high leverage, illiquidity, and a large dividend yield.

This conclusion holds true also in changes.[16] Rows 8 and 9 in Table IX display the results obtained when using innovations from an AR(1) model in the common component and the state variables. We find that the innovations in common value are driven positively and significantly by innovations in these state variables. Innovations in leverage and liquidity together explain 41% of the variation in innovations in common value, whereas adding innovations in the dividend yield increases the R^2 to 57%. Among the three state variables, the dividend yield (liquidity) is relatively more (less) important.

For the asset class-specific components in Panel B in Table IX, 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 asset class-specific value spread in some asset classes, with R^2s ranging from 9% for the equity value strategy excluding financials to 48% for industries. However, the loadings on individual risk proxies vary dramatically across asset classes, in both magnitude and significance.

Next, we examine how much of the predictive ability of the common component of the value spread is captured by the part that is correlated with the risk proxies (the predicted value spread in the kitchen sink specification, $k_0 + k_1' Z_t$, of Equation (8)) and how much by the part that is orthogonal (the residual, u_t^{Com}). Focusing on the decomposition of R^2, we see in Panel A of Table X that both the explained and orthogonal parts are significant in predicting value returns. The fraction of value return variation attributed to the explained part of common value increases in horizon and ranges from about two-thirds (at short horizons) to three-fourths (at the 4-year horizon). Consistent with the association between these risk proxies and common value, we show in Table C.XIV of Online Appendix that the first principal component of the risk proxies predicts value returns significantly in isolation. However, it is common value that dominates in predicting value returns in a joint test. Panel B of Table X provides the results of a decomposition of the asset class-specific value return predictability. In contrast to the case of common value, we find that the part of the asset class-specific component of the value spread that is orthogonal to the risk proxies is relatively more important for predicting value returns than the explained part.

5.3 The Role of the Equity Value Spread

Although the value spread also predicts value returns outside US individual equities, it is an interesting question as to how much of the value return predictability across asset classes is associated with variation in the value spread in US individual equities. The fact that the dividend yield is the state variable with the largest correlation to common value suggests that US individual equity valuations are relatively important. To answer this question, we conduct a pooled regression of value returns in all asset classes on the equity value spread. We report the results in Panels A and B of Table C.XV of Online Appendix. We find that the equity value spread predicts returns about as well as the common component (see Table VIII). When we exclude the two equity value returns from the test assets (Panels C and D), the value spread remains marginally significant (at the 1- and 2-year horizons) in both specifications, but the fraction of explained variation drops considerably. Thus, we

16 We thank an anonymous referee for suggesting this analysis.

Table X. Value return predictability net of risk proxies

In Panel A of this table, we present the results from pooled predictive regressions of high-minus-low value returns on the explained and orthogonal components of common value; $R_{c,t+1:t+h} = a_h + b_{Com,Orth}(VS^{Com}_{c,t} - \widehat{VS^{Com}_{c,t}}) + b_{Com,Expl}\widehat{VS^{Com}_{c,t}} + \varepsilon_{c,t+1:t+h}$. The explained component of common value (denoted $\widehat{VS^{Com}_{c,t}}$) is pre-estimated by regressing the common component on the full set of risk proxies used in Table IX, and saving the predicted value. The orthogonal component of common value is the residual from this time series regression. In Panel B, we similarly decompose the asset class-specific components of the value spread into the part explained by the risk proxies and the part that is orthogonal. *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 1972–2017, but some alternative asset classes enter the sample only after 1972.

h	a	$b_{Com,Orth}$	$b_{Com,Expl}$	t_a	$t_{Com,Orth}$	$t_{Com,Expl}$	R^2	$R^2_{Com,Orth}$	$R^2_{Com,Expl}$
Panel A: Common value									
1	0.24	0.35	0.53	2.35	1.70	1.38	0.36	0.24	0.13
3	0.72	1.18	1.66	2.57	2.06	2.10	1.21	0.82	0.39
6	1.49	2.63	3.43	2.81	2.30	2.38	2.64	1.88	0.77
12	3.12	5.88	8.74	3.18	3.33	2.97	5.97	3.90	2.08
24	7.04	15.01	20.99	3.49	5.42	3.14	13.11	8.92	4.20
48	17.36	37.36	43.54	3.83	8.81	3.20	18.52	13.89	4.63
Panel B: Asset class-specific value									
1	0.21	0.11	0.34	2.13	0.50	2.51	0.24	0.01	0.23
3	0.61	0.63	1.08	2.26	1.14	3.29	0.76	0.08	0.68
6	1.26	1.33	2.63	2.38	1.24	4.52	2.05	0.17	1.88
12	2.64	4.52	6.09	2.41	2.22	4.62	4.91	0.82	4.09
24	5.84	12.40	10.14	2.07	5.35	3.67	5.99	2.14	3.85
48	15.23	34.98	15.80	1.81	5.50	1.64	6.55	4.30	2.24

find weak evidence for across-asset class value return predictability due to the equity value spread. This finding implies that our measure of common value extracts additional relevant information from the value spreads in the alternative asset classes.

5.4 Interpretation

The evidence in this section suggests that the majority of value return predictability in different asset classes is driven by a single common component. These results for common value call for a general framework, where investors shy away in bad times from holding different risky assets, such as individual equities, global stock indexes, industries, and commodities with low valuation ratios. Consequently, value spreads widen simultaneously when discount rates (and thus expected value returns) are high. The motivation is that common value return predictability is closely associated with 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.

Our analysis of the asset class-specific components of the value spread indicates the presence of additional risk and mispricing factors in time-varying value premia. For risk, we find that correlation between risk proxies, such as leverage and uncertainty, and asset class-specific value contributes to the predictability of value returns. The loadings of specific value on these risk proxies vary across asset classes, which point to heterogeneity in risk exposure as an important driver of asset class-specific value return predictability. For mispricing, we show that 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. Limits to arbitrage may impair the ability of investors to undo mispricing specific to different asset classes.

In Table C.XVI of Online Appendix, we show that common value is relatively more important in the recent subsample post-1994, which is broadly consistent with these interpretations. Common value is strongly associated with proxies for the risk of financial intermediaries and financial intermediation has become progressively more important over time. Moreover, if limits to arbitrage partially drive the asset class-specific components of value return predictability, one would expect these components to become less important over time.

6. Conclusion

Value premia are strongly time-varying and comove across asset classes. We show that returns to value strategies in US individual equities, industries, commodities, currencies, global government bonds, and global stock indexes are predictable in the time series using the value spread. This predictability is statistically significant and economically large. Our coefficient estimates suggest that expected value returns vary by at least as much as their unconditional level. To understand the drivers of this time variation, we decompose the value spread into a common component, defined as the first principal component of value spreads, and asset class-specific components. While the common component captures about half of the total variation in value spreads, it captures more—about two-thirds—of the total variation in expected value returns across asset classes. The dividend yield, intermediary leverage, and an illiquidity premium capture the bulk of the time variation in common value. Furthermore, common value return predictability is persistent and indicates that expected value returns are countercyclical. Thus, we argue that the main source of common variation in value premia is compensation for risk. On the contrary, both risk and mispricing contribute to the asset class-specific components of value return predictability.

These findings are new to the literature and are only detected in a joint examination of different asset classes. Our results confirm the basic intuition that risk premia comove strongly across asset classes, for which empirical evidence to date is scarce.

Supplementary Material

Supplementary data are available at *Review of Finance* online.

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