

Value premium and macroeconomic variables

Elena Beccalli¹ | Nicola Doninelli¹ | Cesare Orsini²

¹School of Banking, Finance, and Insurance, Catholic University of the Sacred Heart of Milan, Milan, Italy

²Epsilon Associati Sgr S.p.A., Milan, Italy

Correspondence

Elena Beccalli, Catholic University of the Sacred Heart of Milan, Largo Gemelli 1, Milan 20123, Italy.

Email: elena.beccalli@unicatt.it

Abstract

This paper investigates the effect of macroeconomic expectations on the value premium. We introduce a two-pass estimation procedure to extrapolate the impact of investors' macroexpectations on the firm fundamental value of Rhodes-Kropf, Robinson, and Viswanathan. We find that the level and slope of the term structure affect valuation, revealing a heavily industry-dependent effect. The portfolios sorted on metrics orthogonal to macroeconomic variables show a clear association between the misvaluation component of value premium and size risk. By removing the influence of the macroeconomic conditions and size, we separate the portion of the value premium that rewards macroeconomic expectations.

KEYWORDS

macroeconomic risk, market-to-book decomposition, value premium

JEL CLASSIFICATION

G12, G14

We thank anonymous referees, Ettore Croci, Marzia De Donno, Giorgio Di Giorgio, Massimo Guidolin, Roberto Savona, Andrea Tarelli, and seminar participants at the European Financial Management Association 2021 Conference for helpful comments and suggestions.

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

© 2022 The Authors. *European Financial Management* published by John Wiley & Sons Ltd.

1 | INTRODUCTION

Value investors typically buy low price-to-book stocks and sell high price-to-book securities to harvest abnormal returns known as the value premium. Early attempts to understand the effect of macroeconomic conditions on the value premium have been quite unsuccessful (Lakonishok et al., 1994). More recently, Bergbrant and Kelly (2016) suggest little role for aggregate macroeconomic risks in explaining the returns to size, value, and momentum factors. Other studies use macroeconomic factors in asset pricing models but do not focus specifically on the value premium. According to Flannery and Protopapadakis (2002), macroeconomic indexes are excellent candidates to represent extra-market risk factors since they simultaneously affect cash flows and influence the risk-adjusted discount rate. For example, Chen et al. (2004) use industrial production and unexpected inflation in a celebrated five-factor model and Cochrane (1996) uses aggregate investment growth in his factor pricing model for stock returns. Petkova (2006) studies the connection between the Fama–French factors and innovations in state variables (such as the default spread, the market dividend-price ratio, the yield spread, and the 1-month Treasury bill rate) and finds that the average stock returns line up nicely against factor betas. Bianchi et al. (2017) recently show that macroeconomic shocks have considerable effects on the cross-section of US stock returns when risk exposures and idiosyncratic risk are time-varying.

In this study, we aim to investigate the relation between the value premium and a set of macroeconomic variables that the literature on asset pricing acknowledges to have an information content that plays a crucial role in influencing expectations on macroeconomic risk. To this end, we use Rhodes-Kropf, Robinson, and Viswanathan's (2005; RKR) market-to-book decomposition that they introduced to study the timing of merger waves. This decomposition breaks the market-to-book ratio into market-to-value and value-to-book components in which value is defined as a multiple-based estimate of the fundamental value of equity. As far as we know, Chang et al. (2013) and Golubov and Konstantinidi (2019; GK) are the first to apply the RKR decomposition to an asset pricing context. In particular, GK show that most of the premium is attributable to the market-to-value component while the cross-sectional loadings on value-to-book are not significantly different from zero. Moreover, they find that different exposures to cash-flow risk, long-run consumption risk, investment-specific technology shocks, operating leverage, and duration are not related to the cross-sectional distribution of market-to-values and provide evidence that supports common behavioral explanations of the price-to-book anomaly. Using a similar approach, Jaffe et al. (2020) report that after controlling for mispricing error, the RKR mispricing component predicts abnormal short-term and medium-term returns and that value investing no longer beats the growth approach. Chang et al. (2013) examine the association of a misvaluation factor (MSV^F) with common stock characteristics and empirically test the relation between MSV^F and future returns.¹ Hahn and Lee (2006) show that changes in the Default Spread and changes in the term spread capture most of the systematic risks proxied by Fama and French's (1993) size (SMB) and book-to-market (HML) factors.

We consider our investigation in many ways as complementary to the above studies. First, our paper aims to assess the impact of macrovariables on each individual sector by

¹Chang et al. (2013) directly focus on the RKR firm-level misvaluation and test the power of MSV^F to predict future macroeconomic conditions.

extrapolating in a bottom-up way the impact of the expectations contained in the macroeconomic variables on the value premium. Prior literature aims to provide a macroeconomic explanation of the value premium by focusing on a particular characteristic of value stocks (e.g., leverage, beta, etc.). The resulting empirical evidence often highlights consistency problems since macroeconomic expectations exhibit a complex and variable way of affecting returns of value stocks (Maloney & Moskowitz, 2021). A representative case of this lack of consistency is, in contradiction with the leverage interpretation of value premium, the poor performance of value stocks during the period 2009–2016 despite easing financial conditions. The lack of evidence on the connection between macroeconomic expectations and value premium suggests that such investigation cannot be grounded on a single characteristic. On the contrary, the relationship that links an economic sector to the performance of a macroeconomic variable tends to be more stable and subject to more sporadic shocks related to structural breaks in the economic activity (e.g., the advent of information technology). In short, while focusing on a single fundamental characteristic leads to problems of inconsistency, our analysis grasps more stable relationships by taking into account sectoral heterogeneity.

Second, provided that macroeconomic conditions hit stock prices differently depending on their economic sector, dissecting this heterogeneous effect helps explaining the mispricing component of the value premium. Moreover, market analysts normally estimate fundamental multiples on a sector basis; thus making a sector-based investigation very relevant also from a market practice point of view. By adopting a sector-based approach, we depart from the extant market-wide misvaluation analysis cited above by using a distinct approach that provides further evidence on the effect of macroeconomic conditions on each sector's fundamental multiple and their contribution to the market value.

Third, our paper advances Hahn and Lee (2006) by extending the range of factors explaining the sensitivity of value stocks to fluctuations in the business cycle. While Hahn and Lee (2006) just focus on the high level of debt as the primary explanation for such a sensitivity, our approach enables us to examine several firms' fundamental multiples and provides evidence on the significant influence of macroeconomic variables on net income and book value multiples. The need to move beyond the leveraged capital structure derives from the steady fall in the cost of debt experimented over the last decade: persistent low interest rates weaken the negative leverage's effect on the firm's market value.

Our results present relevant asset pricing implications. Using monthly data from 1975 to 2016, we investigate size, risk, and the returns of portfolios sorted in the market-to-book components. Consistent with GK, we find that the return difference between the low and high market-to-book portfolios almost entirely results from the firm-specific error component.

Furthermore, to investigate the effect of macroeconomic conditions on intrinsic values within each sector, we use the fundamental multiples suggested by RKR to directly dissect the sensitivity of these measures to the macroeconomic environment. Given that these multiples incorporate predictions on both growth and discount rates, their time-varying estimates should reflect the expectations on the macroeconomic scenario. To explore this connection in a regression setting, we first pick a set of leading macroeconomic variables that affect the expectational, nonfundamental component of stock prices: the term spread, the 10-year US Treasury yield, the ISM Manufacturing Purchasing Managers Index, and the Conference Board Leading Economic Index. These four variables are widely used in time series macroeconomic factor models, and very popular among practitioners as broad economic cycle indicators. We find that the slope of the term structure and the 10-year Treasury yield significantly influence the fundamental multiples with a consequential effect on the assessment of intrinsic value. Our

evidence indicates that depending on the sector, the deviations from the fundamental value are heavily conditioned by the level and slope of the term structure.

To study the nonmacro-related effect of value, we form decile portfolios ranked by the portion of fundamental value that is orthogonal to the one-dimensional space spanned by the macroeconomic variables and study their characteristics. Our key empirical finding is that the average size of the portfolios increases monotonically in the ranking. Thus, when we control for the influence of macroeconomic variables, the value premium (about 4%) in large part rewards size risk. Moving on, when controlling for both size and macroeconomic conditions, the return spread of the lowest and highest decile portfolios becomes about 1.5%, which is significantly smaller than the same size-adjusted differential when portfolios are built following the recipe of GK (return spread of about 1.8%). This decrease in respect to GK facilitates the understanding that a portion of the GK's misvaluation premium is attributable to macroeconomic conditions. These empirical findings show that macroeconomic conditions accounts for about 17% of the value premium. Therefore, explanations of the value premium should fully integrate the influence of macroeconomic conditions.

The rest of this study is organized as follows: Section 2 presents the RKR market-to-book decomposition, the data set, and a discussion on the results of a GK-type analysis based on the RKR market-to-book components. In Section 3, we compare the results of the previous section after we perform the same exercises by using our macroaware market-to-book decomposition. We then compare the asset pricing consequences of the two approaches. Section 4 contains the robustness checks. Section 5 is the conclusion.

2 | VALUE PREMIUM AND RKR MARKET-TO-BOOK DECOMPOSITION

Value strategies earn abnormal returns when compared to the prediction of a one-factor model like the CAPM or a two-factor model that includes size (Fama & French, 1992). The fierce classical debate on the reasons for this anomaly can be summarized in a single question: do these excess returns reflect behavioral biases or do they just reflect a compensation for additional risk?

According to the behaviorists, investors favor stocks that have performed well in the recent past. This preference allows contrarian strategies to profit from market overreaction by investing in neglected, value stocks (De Bondt & Thaler, 1985; Hwang & Rubesam, 2013). Lakonishok et al. (1994) argue that value investing exploits the suboptimal behavior of the average investor who excessively weights the recent realized performance and extrapolates past growth too far into the future. Doukas and Han (2021) present a sentiment-scaled CAPM model, providing an economic intuition of value premium based on the behavior of over-optimistic investors who tend to overprice growth (high-beta) stocks during high-sentiment periods. Wang (2020) argue that persistence in value anomaly is more consistent with behavioral explanations in which limits to arbitrage and slow-moving arbitrage capital cause mispricing to persist.

Under the risk-based explanation, the value premium reflects differences in risk attributable to, for example, the profile of assets in place of growth options (Zhang, 2005), cash flow uncertainty (Campbell & Vuolteenaho, 2004), distress risk (Fama & French, 1995, 1996), or asset risk and leverage (Choi, 2013; Obreja, 2013). Novy-Marx (2013) has recently challenged these traditional risk-based explanations by controlling for profitability, revealing that the

performance of value strategies is improved, especially among large stocks. Gerakos and Linnainmaa (2018) show that the bulk of the value premium is earned by those high book-to-value, conservative firms that have shrunk in size. Fama and French (2015) find that the value factor is unnecessary for describing the cross-section of average returns when other factors are added to their model, and Fama and French (2020) show that average value premium has dramatically declined but the hypothesis that their expected value remains constant cannot be rejected. Chang et al. (2013) and GK, using the multiples-based market-to-book decomposition of RKR, focus on the economic forces that give rise to return predictability and compare the competing explanations of the value anomaly.

2.1 | Returns data and sector classification

We obtain monthly data on stock returns and shares outstanding from January 1975 to December 2016 from the CRSP database. If a delisting return is missing, we set it equal to -30% as in Shumway (1997). The matching accounting items are from the Compustat database, and we exclude firm-year observations with SIC codes in the range 6000–6999 (financial firms) for consistency purposes. However, most of our tests start from 1981 as we require 5 years of prior data to preprocess the RKR market-to-book decomposition.

The resulting merged dataset contains a grand total of 119,403 firm-year observations. Our definition of sector follows the standard Fama–French 12-industry categorization. Further details on the industry breakdown are summarized in the online appendix in the Supporting Information; see Table A.1. This classification allows us to get at least 30 firms per industry (alternative definitions are considered in Section 4.1).

2.2 | RKR decomposition

The following is a basic multiplicative market-to-book identity:

$$\text{Market/Book} = \text{Market/Value} \times \text{Value/Book} \quad (1)$$

where Value is a measure of the fundamental value of the firm. Lee et al. (1999) and Dong et al. (2006), among others, estimate Value using a complete residual income model, and Bartram and Titman (2018) propose a purely statistical peer-implied fair value assessment. Our determination of Value is based on a simplified but quite objective residual income model that assumes the intrinsic value can be approximated by a linear function of book value of equity, net income, and leverage (see Section A.1 in the online appendix in the Supporting Information).

Taking logs on both sides of (1) we get:

$$m - b = (m - v) + (v - b), \quad (2)$$

where m is the log of the market value, b is the log of the book value, and v is the log of Value. The first term on the right-hand side, $m - v$, is a measure of the deviation in the stock price from the fundamental value, and $v - b$ denotes the difference between the fundamental value and the book value. If markets perfectly predict future cash flows, discount rates, and growth opportunities, $m - v$ should be zero. Expressing v as a linear function of the firm-level

accounting characteristics at a point in time, θ_{it} , and a vector of conditional accounting multiples, α , produces the RKR decomposition:

$$m_{it} - b_{it} = \underbrace{(m_{it} - v(\theta_{it}; \alpha_{jt}))}_{\text{firm-specific error}} + \underbrace{v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)}_{\text{industry error}} + \underbrace{v(\theta_{it}; \alpha_j) - b_{it}}_{\text{long-run deviation}}, \quad (3)$$

where α_{jt} is a vector of time t multiples, and α_j is a vector of long-run valuation multiples. The firm-specific error $m_{it} - v(\theta_{it}; \alpha_{jt})$, is the deviation in the market value from the fundamental value that is conditioned on time t and industry j .²

The term $v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$, the time-series sector-error, is the deviation in the contemporaneous firm valuations from the valuations that are implied by long-run industry multiples. This component measures the difference in the estimated fundamental value when the industry accounting multiples vector α_{jt} is not equal to the long-run industry multiples vector α_j . The last component is the deviation in the long-run industry multiples-based valuation from the book value of equity, $v(\theta_{it}; \alpha_j) - b_{it}$.

2.3 | Fundamental value estimation

As in CLR and GK, the vector of valuation multiples is obtained from³

$$m_{it} = \alpha_{0jt} + \alpha_{1jt} b_{it} + \alpha_{2jt} ni_{it}^+ + \alpha_{3jt} I_{<0} (ni_{it}^+) + \alpha_{4jt} LEV_{it} + \epsilon_{it}, \quad (4)$$

where m_{it} is the log of market value, b_{it} is the log of book value, ni_{it}^+ is the log of the absolute value of net income, LEV_{it} is book leverage, and ϵ_{it} is an error term. The dummy $I(<0)$ is used to separately estimate the earnings multiple for firms with negative net income.⁴ The market value is defined as the stock price multiplied by the number of shares outstanding. The book value is the book value of common equity⁵ (Compustat data item 60), and the net income is

²Cohen et al. (2003) claim that a large part of the cross-sectional variation in the market-to-book is due to differences in the future market-to-book and profitability. At the 1-year horizon, only 3% of this variation is due to stock returns, therefore the value-versus-growth classification contains poor information about future returns. These findings support the decomposition in Equation (3): if mb_{it} is sensitive to future profitability and the market-to-book, then the component of the market-to-book that is orthogonal to this information set is more important in predicting expected returns. From this perspective, the multiples contain time-varying expectations on the discount and growth rates that correspond to the risk characteristics at the industry level. As a result, $m_{it} - v(\theta_{it}; \alpha_{jt})$ contains information mostly related to firm-specific discount rates.

³The pricing measure of GK is based on the industry-adjusted values of several fundamental variables. They test for the possibility that the industry-level adjustment could be insufficient and that can lead to incorrect estimates of the firm's intrinsic value. In this case, variation in the market-to-value components corresponds to differences in risk. Otherwise, the deviations from the estimated fundamental value reflect over/undervaluation and therefore subsequent returns will drive the prices towards a central value.

⁴For descriptive statistics of the firm variables see Table A.2 in the online appendix in the Supporting Information.

⁵We tried more precise measures of the book value of common equity that included deferred taxes and investment tax credits and deduced the estimates of the preferred stock book value and found no material differences. Therefore, we stick to this less accurate, broader definition for replication purposes. If the Compustat item is not available, we eliminate the corresponding firm in the estimation process (for a different approach see Davis et al., 2000) by not replacing the missing point with the book value of assets minus total liabilities.

Compustat data item 172. Leverage is one minus the ratio of the book value to total assets (Compustat data item 6).

To estimate Equation (4), we group firms according to the Fama–French 12 industries and run 1-year cross-sectional regressions for each industry. The industry-year estimations capture the time-varying nature of the growth and discount rates that are embedded in the valuation multiples. Since the discount rates and growth opportunities vary by industry, a within-industry estimation of the α_k multiples takes care of this source of variability, so that the unexplained part of the market value can be more readily interpreted as an indicator of over/undervaluation. To eliminate the look-ahead bias, the model is estimated as of June 30 of each year, and we require at least a lag of 3 months for the accounting information to be considered publicly available. To estimate the long-run industry valuation multiples, we compute the 5-year time-series averages of the industry-year multiples. The first and the last portfolio formation dates are June 1981 and June 2015; return tracking ends in June 2016.

We determine each $v(\theta_{it}; \alpha_{jt})$ by using the fitted parameters from Equation (4)

$$v(\theta_{it}; \hat{\alpha}_{jt}) = \hat{\alpha}_{0jt} + \hat{\alpha}_{1jt} b_{it} + \hat{\alpha}_{2jt} ni_{it}^+ + \hat{\alpha}_{3jt} I_{<0}(ni_{it}^+) + \hat{\alpha}_{4jt} LEV_{it} \quad (5)$$

and to estimate $v(\theta_{it}; \bar{\alpha}_j)$ we first form the average $1/T \sum \hat{\alpha}_{jt} = \bar{\alpha}_j$ for each industry over a 5-year rolling window and then compute

$$v(\theta_{it}; \bar{\alpha}_j) = \bar{\alpha}_{0j} + \bar{\alpha}_{1j} b_{it} + \bar{\alpha}_{2j} ni_{it}^+ + \bar{\alpha}_{3j} I_{<0}(ni_{it}^+) + \bar{\alpha}_{4j} LEV_{it}. \quad (6)$$

Panel (a) of Table 1 presents the time-series averages of the multiples in Equation (4). The fitted coefficient $\hat{\alpha}_0$ can be interpreted as the value of the intangibles of the average firm from a certain industry at a point in time, that is, the component of the market value that is not influenced by the book value, net income, and leverage relative to the other firms in the industry. The results in Table 1 are logically consistent with this basic interpretation. In fact, *Utilities* and *Manufacturing* show the lowest values of $\hat{\alpha}_0$, while the *Telephone* and *TV Trasmision* and *Medical* sectors are the most affected by intangibles. By the same token, the estimates $\hat{\alpha}_1$ are generally higher where the intercepts are lower.

The loading for positive net income, $\hat{\alpha}_2$, is positive and larger than the coefficient for the absolute value of the negative net income. This coefficient indicates a relatively weaker effect of this regressor than the general low significance level of $\hat{\alpha}_3$, in absolute terms, also supports. As expected, the loading on leverage, $\hat{\alpha}_4$, is negative with substantial cross-sectional dispersion, given that some industries sustain high-debt loads while others benefit from an equity-tilted capital structure. However, the overall significance of this coefficient is low. Finally, the average R^2 indicates that the valuation model of Equation (4) explains between 63% and 85% of the variability in market value.

Panel (b) of Table 1 has a summary of some descriptive statistics for the decomposition in Equation (3) that we apply to our sample. The valuation model produces a grand mean firm-specific error of 0.06 with a standard deviation of 0.96; this component has a mean of

TABLE 1 Valuation multiples and the RKR decomposition

This table reports the sample of 119,403 firm-year observations from 1981 to 2016. Panel (a) summarizes the regression estimates of the model $m_{it} = \alpha_{0jt} + \alpha_{1jt} b_{it} + \alpha_{2jt} ni_{it}^+ + \alpha_{3jt} I_{<0}(ni)_{it}^+ + \alpha_{4jt} LEV_{it} + \epsilon_{it}$ where m_{it} is the log of market value, b_{it} is the log of book value, ni^+ is the log of the absolute value of the net income, LEV_{it} is the book leverage, and ϵ_{it} is an error term. The dummy $I(<0)$ is used to separately estimate the earnings multiples for firms with negative net income and the subscripts j, t and i denote the industry, the year and the firm, respectively. Codes 1–12 correspond to the Fama–French industry classification: (1) *Consumer Non-Durables*, (2) *Consumer Durables*, (3) *Manufacturing*, (4) *Oil and Gas*, (5) *Chemicals and Allied Products*, (6) *Business Equipment*, (7) *Telephone and TV Transmission*, (8) *Utilities*, (9) *Wholesale*, (10) *Healthcare*, (12) *Residual* excluding *Finance*. Reported coefficients are time-series averages of the estimated parameters. The Fama–MacBeth p values are shown in the row below and the R^2 time-series averages are also given for each industry. Panel (b) contains some descriptive statistics of the RKR components.

(a) Estimated fundamental multiples											
Fama and French industry classifications											
	1	2	3	4	5	6	7	8	9	10	12
$\hat{\alpha}_0$	1.53	2.02	1.33	1.76	1.78	1.57	2.15	1.30	1.44	1.90	1.93
p -value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.300	0.000	0.000	0.000
$\hat{\alpha}_1$	0.55	0.47	0.64	0.62	0.48	0.69	0.52	0.6	0.61	0.61	0.55
p -value	0.000	0.000	0.000	0.000	0.050	0.000	0.000	0.000	0.000	0.000	0.000
$\hat{\alpha}_2$	0.40	0.35	0.33	0.21	0.46	0.28	0.22	0.30	0.40	0.30	0.34
p -value	0.000	0.080	0.000	0.100	0.030	0.000	0.160	0.060	0.000	0.010	0.000
$\hat{\alpha}_3$	−0.16	−0.09	−0.11	−0.05	−0.07	−0.10	−0.03	−0.05	−0.17	−0.04	−0.10
p -value	0.180	0.310	0.100	0.410	0.450	0.080	0.480	0.300	0.070	0.220	0.150
$\hat{\alpha}_4$	0.14	0.09	−0.04	0.44	0.20	−0.09	0.55	0.36	−0.31	0.37	−0.31
p -value	0.300	0.520	0.320	0.380	0.380	0.270	0.350	0.240	0.340	0.230	0.250
R^2	0.80	0.74	0.85	0.75	0.81	0.82	0.63	0.84	0.83	0.81	0.75

(b) RKR decomposition										
	Mean	SD	1%	5%	25%	Median	75%	95%	99%	
$m_{it} - b_{it}$	0.65	1.12	−2.99	−0.93	0.11	0.64	1.23	2.34	3.56	
$m_{it} - v(\theta_{it}; \alpha_{jt})$	0.06	0.96	−3.24	−1.52	−0.36	0.13	0.6	1.44	2.2	
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$	0.10	0.40	−0.88	−0.52	−0.16	0.08	0.34	0.74	1.13	
$v(\theta_{it}; \alpha_j) - b_{it}$	0.54	0.62	−1.09	−0.41	0.18	0.53	0.88	1.52	2.18	

zero by construction as the ordinary least square residual from Equation (4). The average industry error is 0.1 with a SD of 0.4 while the mean long-run error is 0.54 with a SD of 0.62. All the three terms show a reasonable sample variation. Further, the firm-specific error has greater variation than the industry error and, again by construction, the three means add up to the mean of $m_{it} - b_{it}$.

2.4 | Attribution of the value premium to the RKR components

Table 2 presents the average monthly raw returns of 10 equally weighted and value-weighted portfolios that were sorted in the market-to-book and the three components of Equation (3). These portfolios are rebalanced every year in the month of July when the RKR decomposition model is estimated. In the first column of Panel (a) in Table 2, we find the usual strong negative relation between the market-to-book and the average returns. The cash neutral strategy, which is long in the bottom decile (equally weighted) portfolio and short in the top decile (equally weighted) portfolio, generates a highly statistically significant average monthly return of 2.35%. The same difference between the value-weighted portfolios is 0.88%, also statistically significant. The annualized Sharpe ratio of the long-short strategies for the equally weighted portfolios is approximately equal to one. Columns 2 to 4 use the three market-to-book components for sorting. The second column shows a sharp monotonic decline in returns from the Low to the High firm-specific residual portfolios and a substantial equally weighted long-short return of 3.35% (0.80% in the value-weighted case). The Sharpe ratio of this investment strategy is 1.37 that is significantly higher than one.

The sorting based on the industry-error component does not produce statistically significant excess returns. Conversely, the portfolios that were formed using the long-run error display average increasing returns in the long-run component and the related arbitrage strategy posts a statistically significant excess return (1.94%). These results are consistent with the findings on the post-issue stock price performance by Hertz and Li (2010).

To address the issue of size and the effect of small stocks⁶ on the performance of these strategies, in Panel (b) of Table 2 we sort the sample into portfolios that are based in the market-to-book and the three RKR components while controlling for size. We control for size by conducting market-to-book and its components sorts conditional on size following Fama and French (1993). Consistent with earlier studies, we use NYSE breakpoints of the French Data Library to form our portfolios every June 30. In the first column of Panel (b) in Table 2, the returns follow the usual pattern in which the average returns decrease with the market-to-book. The long-short strategy that is based on the top and bottom deciles (equally weighted) portfolios generates a statistically significant return of 1.31% (0.59% for the value-weighted portfolios), and the annualized Sharpe ratio is 0.65. The second column of the table shows a decline in the raw returns from the firm-specific component and a sizable positive return for the low firm-specific error portfolio in excess of the top decile portfolio (1.84%). The Sharpe ratio of this cash-neutral strategy is also quite large (0.92). The excess returns for the arbitrage strategies that use the sector-error and the long-run error variables are close to zero and not statistically significant.

The two-pass sort in the market-to-book and size in Panel (b) of Table 2 gives a clearer picture of the relative importance of the RKR characteristics: the market-to-book ratio essentially reduces to the firm-specific error component. The long-short returns that are associated with the size-adjusted portfolios are smaller than those obtained from the RKR components, and effectively isolate the size premium. Consistent with the literature, the value premium is larger for small stocks but still exists in all but the microcap deciles (Fama & French, 2008). The second columns in Panels (a) and (b) of Table 2 show a clear monotonic

⁶The percentage of microcaps (market cap less than \$300 million) in our sample is 56% on average and their combined weight is 5%.

TABLE 2 Returns of portfolios sorted on the RKRV components

This table reports the average monthly returns for 10 equally weighted (EW) portfolios sorted on the RKRV components $m_{it} - b_{it}$, $m_{it} - v(\theta_{it}; \hat{\alpha}_{jt})$, $v(\theta_{it}; \hat{\alpha}_{jt}) - v(\theta_{it}; \bar{\alpha}_j)$ and $v(\theta_{it}; \bar{\alpha}_j) - b_{it}$. The cash neutral positions are initiated on July 1 of each year by buying/selling the bottom/top decile portfolios sorted as of June 30, from 1981 to 2016. The value weighted (VW) arbitrage portfolio returns and annualized Sharpe ratios (for equally weighted portfolios) are also shown. The p -value is for the t -tests on the equality of the High and Low average returns. Panel (b) contains the size-adjusted figures.

(a) Decile portfolios sorted on the RKRV components				
Ranking	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it}; \hat{\alpha}_{jt})$	$v(\theta_{it}; \hat{\alpha}_{jt}) - v(\theta_{it}; \bar{\alpha}_j)$	$v(\theta_{it}; \bar{\alpha}_j) - b_{it}$
Low	2.82%	3.40%	1.66%	0.77%
2	1.85%	1.95%	1.13%	0.88%
3	1.39%	1.50%	1.31%	0.75%
4	1.08%	1.21%	1.25%	0.96%
5	1.01%	1.05%	1.00%	0.84%
6	0.87%	0.83%	1.29%	0.90%
7	0.86%	0.61%	1.06%	1.15%
8	0.75%	0.51%	0.89%	1.14%
9	0.33%	0.31%	0.74%	1.46%
High	0.48%	0.04%	1.16%	2.71%
Low-high (EW)	2.35%	3.35%	0.50%	-1.94%
p -value	0.000	0.000	0.465	0.001
Low-high (vw)	0.88%	0.80%	0.40%	-0.16%
p -value	0.024	0.033	0.365	0.764
Annualized Sharpe ratio	1.00	1.37	0.08	-0.77
(b) Size-adjusted decile portfolios sorted on the RKRV components				
Ranking	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it}; \hat{\alpha}_{jt})$	$v(\theta_{it}; \hat{\alpha}_{jt}) - v(\theta_{it}; \bar{\alpha}_j)$	$v(\theta_{it}; \bar{\alpha}_j) - b_{it}$
Low	2.03%	2.32%	1.52%	1.05%
2	1.65%	1.73%	1.10%	1.06%
3	1.30%	1.38%	1.05%	0.87%
4	1.11%	1.11%	1.35%	0.91%
5	1.18%	1.10%	1.17%	0.95%
6	0.95%	1.00%	1.22%	1.37%
7	0.92%	0.91%	1.03%	1.06%
8	0.98%	0.84%	0.97%	1.16%
9	0.70%	0.70%	0.89%	1.46%
High	0.72%	0.48%	1.30%	1.77%

(Continues)

TABLE 2 (Continued)

(b) Size-adjusted decile portfolios sorted on the RKRV components				
Ranking	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it}; \hat{\alpha}_{jt})$	$v(\theta_{it}; \hat{\alpha}_{jt}) - v(\theta_{it}; \bar{\alpha}_j)$	$v(\theta_{it}; \bar{\alpha}_j) - b_{it}$
Low-high (EW)	1.31%	1.84%	0.22%	-0.71%
<i>p</i> -value	0.010	0.000	0.723	0.161
Low-high (vw)	0.59%	0.58%	0.20%	-0.04%
<i>p</i> -value	0.092	0.131	0.744	0.985
Annualized Sharpe ratio	0.65	0.92	-0.01	-0.38

association between the portfolio returns and the market value at the estimated fundamental value. On the contrary, the value-to-book component is of no help in generating excess returns. This result supports our claim regarding the ability of the firm-specific error component to encode important information related to the expected returns.

Panels (a) and (b) of Table 3 summarize the sorted portfolio's performance in terms of alpha, confirming evidence discussed above on the predominance of the firm-specific component in the attribution of the value premium.

2.5 | Value premium, term spread and leverage

Prior literature aims to provide a theoretical justification to their empirical evidence relating the high level of leverage of value stocks to the value premium. To the extent that high book-to-market firms tend to have high financial leverage and cash flows problems (Fama & French, 1992), high book-to-market firms would be more vulnerable to worsening financial conditions (Choi, 2013). On this line, Hahn and Lee (2006) point out the higher level of firm leverage to theoretically support their evidence about positive loadings between the value premium and term spread. They associate an increase in the term spread with a decline in short interest rates that favors heavily indebted companies resulting in higher returns for value stocks.

While it could be consistent with the value being a proxy for highly leveraged firms, several factors complicate the interpretation proposed by Hahn and Lee (2006). First, there could be several reasons for an increase in the term spread in addition to a fall in short-term rates. For example, we could observe steepening in the yield curve due to market expectations of a generalized rise in interest rates to face inflation caused by a growth phase. In this case, a steeper yield curve means worsening financial conditions.

Second, as shown in Figure 1, comparing the value premium with the financial conditions index, we cannot recognize a consistent relationship supporting the hypothesis of underperforming value during tight financial conditions. Maloney and Moskowitz (2021) provide evidence of the inconsistency of the relationship between the value premium and the financial conditions.

Third, from 2009 to 2017, firms experimented a steady fall in the cost of debt, which coincided with the stream of interest cuts by the monetary policy. The decline in interest rates improves debt sustainability and interest coverage resulting in a premium for greater leverage ($\hat{\alpha}_4$ turns positive across almost all sectors, see Figure 2). In other words, we observe a positive relationship between the market value and the level of debt. While according to the debt-

TABLE 3 Alphas of portfolios sorted on the RKRV components

This table reports the alphas from the CAPM regression of portfolio returns. The dependent variable is the monthly return of decile portfolios formed on the basis of $m_{it} - b_{it}$, $m_{it} - v(\theta_{it}; \hat{\alpha}_{jt})$, $v(\theta_{it}; \hat{\alpha}_{jt}) - v(\theta_{it}; \alpha_j)$ and $v(\theta_{it}; \hat{\alpha}_j) - b_{it}$ in excess to the risk-free rate. The explanatory variable is the excess return to the risk-free rate on a market portfolio for which we use CRSP equal-weighted index. The risk-free rate is the 1-month Treasury bill rate. After the end of June rebalancing, equal-weighted monthly percent returns on the portfolios are calculated from July of year t to June of $t + 1$. The sample period is July 1981–June 2016. Column *Int.* contains the regression intercept, and column *p-value* reports the significance level of the related *t*-statistic. Panel (a) summarizes the results of the portfolios formed in the market-to-book components. Panel (b) summarizes the results of the portfolios formed in the market-to-book components, adjusting for size.

(a) Decile portfolios sorted on the RKRV components								
Ranking	$m_{it} - b_{it}$		$m_{it} - v(\theta_{it}; \hat{\alpha}_{jt})$		$v(\theta_{it}; \hat{\alpha}_{jt}) - v(\theta_{it}; \alpha_j)$		$v(\theta_{it}; \hat{\alpha}_j) - b_{it}$	
	Int. (%)	p-value	Int. (%)	p-value	Int. (%)	p-value	Int. (%)	p-value
Low	0.85	0.000	1.00	0.000	0.48	0.000	0.26	0.010
2	0.85	0.000	0.96	0.000	0.44	0.000	0.40	0.000
3	0.69	0.000	0.71	0.000	0.50	0.000	0.32	0.000
4	0.57	0.000	0.58	0.000	0.55	0.000	0.47	0.000
5	0.47	0.000	0.50	0.000	0.49	0.000	0.49	0.000
6	0.40	0.000	0.39	0.000	0.52	0.000	0.40	0.000
7	0.30	0.000	0.25	0.002	0.47	0.000	0.41	0.000
8	0.22	0.015	0.14	0.091	0.43	0.000	0.43	0.000
9	0.00	0.988	0.01	0.952	0.20	0.078	0.44	0.000
High	-0.05	0.705	-0.14	0.281	0.11	0.371	0.62	0.000
Low-high	0.90		1.14		0.37		-0.36	
(b) Size-adjusted decile portfolios sorted on the RKRV components								
Ranking	$m_{it} - b_{it}$		$m_{it} - v(\theta_{it}; \hat{\alpha}_{jt})$		$v(\theta_{it}; \hat{\alpha}_{jt}) - v(\theta_{it}; \alpha_j)$		$v(\theta_{it}; \hat{\alpha}_j) - b_{it}$	
	Int. (%)	p-value	Int. (%)	p-value	Int. (%)	p-value	Int. (%)	p-value
Low	0.41	0.001	0.44	0.000	0.31	0.008	0.25	0.012
2	0.59	0.000	0.54	0.000	0.34	0.002	0.27	0.011
3	0.46	0.000	0.51	0.000	0.40	0.000	0.35	0.000
4	0.45	0.000	0.42	0.000	0.39	0.000	0.26	0.004
5	0.36	0.000	0.39	0.000	0.45	0.000	0.32	0.000
6	0.29	0.001	0.35	0.000	0.33	0.000	0.37	0.000
7	0.18	0.055	0.27	0.003	0.28	0.003	0.28	0.001
8	0.14	0.170	0.10	0.283	0.25	0.021	0.28	0.003
9	0.06	0.586	0.01	0.919	0.17	0.147	0.28	0.006
High	-0.01	0.963	-0.07	0.583	0.00	0.974	0.27	0.022
Low-high	0.42		0.52		0.30		-0.02	

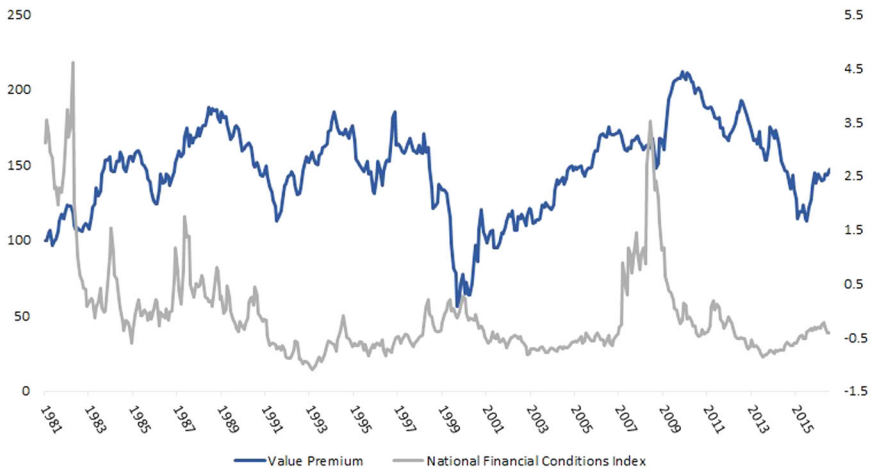


FIGURE 1 Value premium and financial conditions. The figure plots the cumulative performance of the value premium calculated as the return of the long-short strategy formed on the basis of $(m_{it} - b_t)$ (blue, left axis) for the period from July 1981 to June 2016, and the Chicago Fed National Financial Conditions Index (grey, right axis). The National Financial Conditions Index is constructed to have an average value of zero and an SD of one. Positive values of the index indicate financial conditions that are tighter than on average, while negative values indicate financial conditions that are looser than on average. *Source:* Federal Reserve Board via FRED. [Color figure can be viewed at wileyonlinelibrary.com]

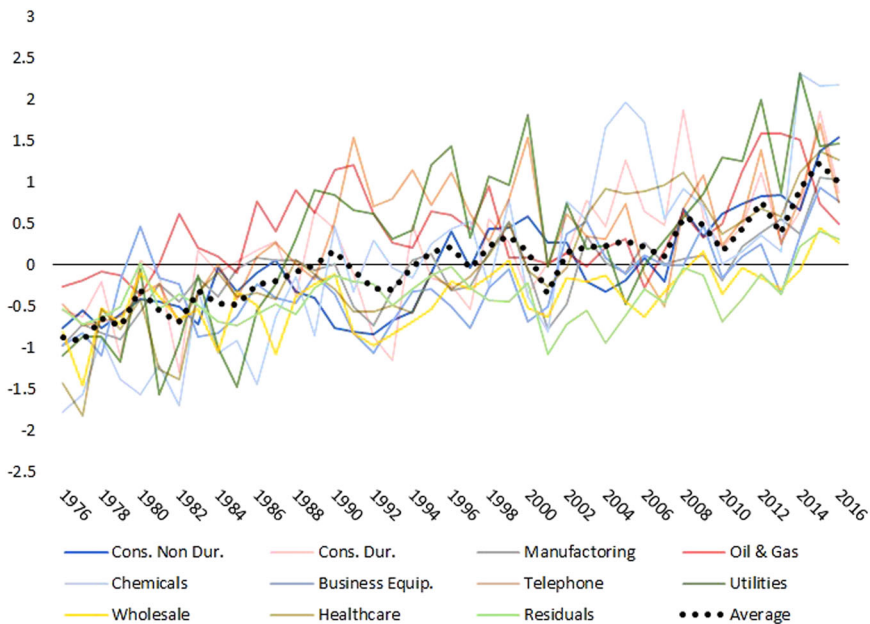


FIGURE 2 Market value and leverage. The evolution of the $\hat{\alpha}_4$ (leverage) fundamental multiple over the period from June 1976 to June 2016. The $\hat{\alpha}_4$ time-series for each industry result from the annual estimation of the cross-sectional regression in Equation (4). [Color figure can be viewed at wileyonlinelibrary.com]

related explanation, we should observe a favorable scenario for value (highly leveraged) stocks, during 2009–2016 the value premium exhibits a significant underperformance.

3 | THE EFFECT OF MACROECONOMIC VARIABLES ON THE VALUE PREMIUM

To design our macro dataset, we identify expectations for growth and inflation as the prominent factors affecting value premium. These two factors provide market participants with the coordinates to identify the current phase of the economic cycle and build their expectations. Specifically, if we consider any asset's price as the sum of expected nominal cash flows discounted to their present value, growth and inflation affect each component of this equation.

On the way to proxy expectations for growth and inflation, there exists interesting evidence on the ability of the bond and stock market to predict economic scenarios (Campbell, 1989), suggesting asset prices as good candidates to extrapolate the expectational component of macro information. Consistently, we use variables from financial market-related series (term spread, and the 10-year US Treasury yield) and standard macroeconomic variables (ISM Manufacturing Purchasing Managers Index, and the Conference Board Leading Economic Index), intending to obtain a data set containing proxies that differ based on their forward-looking nature.

3.1 | Variables

The term spread of the Treasury spot yield curve has had an impressive ability to forecast GDP growth since World War II, and inverted yield curves have been the most successful recession predictors. Chen (2009) argues that the shape of the term structure and inflation rates are effective predictors of a bear market. The term spread is also supported by evidence in the value-related literature; in fact, Hahn and Lee (2006) show that value stock returns are more sensitive (i.e., have higher betas) to changes in the term spread. Specifically, we define the term spread as the difference between the 10-year US Treasury yield and the 2-year note rate. We pick this alternative over the common 10-year Treasury yield minus the 3-month Treasury bill rate since we argue that the 2-year note yield more effectively reflects the expectations on future monetary policy measures (see Section A.2 in the online appendix in the Supporting Information).

The 10-year Treasury yield incorporates prominent information on inflationary expectations, economic growth projections, and current and future monetary policy. For example, Haubrich and Dombrosky (1996) provide persuasive arguments justifying this conclusion. A cautionary note concerns that our data set for interest rates is plagued by nonstandard monetary policy interventions that include different quantitative easing rounds. Given that these unorthodox policy actions drive government bond rates, in Section 4.2 we perform robustness checks exploring direct inflation expectations proxies.

The ISM Manufacturing Purchasing Managers Index (ISM PMI) is based on a monthly survey of senior executives' expectations on business activity and its recent trends. Koenig (2002) and Banerjee and Marcellino (2006) find evidence supporting PMI as a leading indicator for GDP changes. Considering the market practice, the ISM PMI is an essential reading of sentiment in the investment community; it is widely used to parse the economic cycle in different phases. The investor's understanding of the current phase of the business cycle will

likely affect the market risk appetite towards stocks with a certain characteristic driving their relative performance (e.g., cyclical vs. defensive, value vs. growth).

Finally, The Conference Board Leading Economic Index (LEI) is a composite of indicators covering a broad spectrum of the economy. The LEI components include both financial-market related indicators (e.g., stock prices, term spread) and real-activity indicators (e.g., new orders, new building permits). Its comprehensive nature makes the LEI Index a useful proxy for the economy's momentum.

The above four macroeconomic variables are used as time series factors in our regression analysis.⁷ To rule out potential criticisms related to omitted information, we conduct a battery of robustness checks (reported in Section 4.4) on a large data set of macroeconomic variables using dynamic factor analysis.

Yet, the macro information captured in the variables considered so far tendentially refers to the economic activity over a medium/long-term horizon. To also consider a macroeconomic variable qualified to capture the broad market uncertainty premia over a short-term horizon, we perform a robustness check (reported in Section 4.3) using the Cboe Volatility Index (VIX).

3.2 | Disentangling macroeconomic influence from valuation multiples

Accounting numbers are delayed, and therefore m_{it} anticipates the information carried by b_{it} . For this reason, α_1 is mainly influenced by the expected growth in earnings and by the rate used to discount the stream of future earnings. The earnings forecasts and discount rates could be affected by macroeconomic variables on a sector basis since the fundamental multiples are estimated every year for each sector. This may occur since the macroeconomic variables incorporate information that influences the expectations on future macroeconomic conditions that thus, become a proxy for macroeconomic risk.

To test the effect of the macroeconomic variable z_t on the estimated coefficients $\hat{\alpha}_k$ of Equation (4) we run the following regressions:

$$\hat{\alpha}_{kjt} = \psi^{\alpha_k} + \gamma^{\alpha_k} z_t + u_{jt}^{\alpha_k}, \quad (7)$$

where the subscripts k and j index the accounting variables and the sectors. This conditional set-up imposes a limited structure on the time-varying dynamics of growth and discount rates that drive the multiples.

We then plug the regression residuals of Equation (7) into Equation (5) to get

$$v(\theta_{it}; \hat{u}_{jt}^{\alpha_k}) = \hat{u}_{jt}^{\alpha_0} + \hat{u}_{jt}^{\alpha_1} b_{it} + \hat{u}_{jt}^{\alpha_2} ni_{it}^+ + \hat{u}_{jt}^{\alpha_3} I_{<0}(ni_{it}^+) + \hat{u}_{jt}^{\alpha_4} LEV_{it}, \quad (8)$$

that yields new short-run, time- t , fundamental value estimates. As when estimating the orthogonal long-run industry valuation multiples, we average the time-series of industry-year

⁷For further details on the macroeconomic variables and their transformations, see Table A.3 in the online appendix in the Supporting Information.

multiples $\hat{u}_{jt}^{\alpha_k}$ over a 5-year rolling window. Rewriting Equation (6) with the updated long-run multiples we get:

$$v(\theta_{it}; \bar{u}_{jt}^{\alpha_k}) = \bar{u}_{jt}^{\alpha_0} + \bar{u}_{jt}^{\alpha_1} b_{it} + \bar{u}_{jt}^{\alpha_2} ni_{it}^+ + \bar{u}_{jt}^{\alpha_3} I_{<0}(ni_{it}^+) + \bar{u}_{jt}^{\alpha_4} LEV_{it}. \quad (9)$$

Panel (a) of Table 4 gives the estimates of Equation (7) when the conditioning variable is the term spread.⁸ The *Chemicals* and *Business Equipment* industries are the most affected by fluctuations in the yield curve. For these sectors, there is a negative and logically appealing relation between the term spread and net income multiple $\hat{\alpha}_2$ and a positive relation between the slope of the term structure and the book value multiple $\hat{\alpha}_1$. During economic downturns, future earnings expectations are grim, and the book value identifies safer, mostly large-cap firms. The effect of the term spread on the $\hat{\alpha}_0$ coefficient for *Chemicals* and *Utilities* is different. In the *Chemicals* industry, the market value is significantly related to intangible assets (large positive $\hat{\alpha}_0$), and a steep yield curve reduces the positive contribution of the intangibles in the market value (negative $\hat{\gamma}^{\alpha_0}$ coefficient). This empirical evidence is consistent, for example, with a contraction in R&D during bad times. On the contrary, the $\hat{\gamma}^{\alpha_0}$ coefficient is positive for the *Utility* sector. The price of utility stocks that is unrelated to fundamentals captures the bond-like behavior of firms that are typically defensive and provide a stable stream of above average dividends. In a low-rate environment the market value of utilities depends even less on accounting fundamentals, with a larger intercept terms $\hat{\alpha}_0$. Panel (a) in Table 4 shows that the $\hat{\alpha}_4$ multiple is the most affected by the term spread, and $\hat{\gamma}^{\alpha_4}$ is large and positive. Steep yield curves are more common during expansionary monetary policy cycles with a clear effect on the cost of debt for leveraged firms. However, after 2001, the leverage multiple changes sign: firms experienced a steady fall in the cost of debt that resulted in a leverage premium, not a leverage discount.

Panel (b) of Table 4 shows the results from the regression of $\hat{\alpha}_k$ on the 10-year Treasury yield. In this case, the most interesting results involve $\hat{\alpha}_0$ and the net income multiples $\hat{\alpha}_2$ and $\hat{\alpha}_3$. The high government bond yields usually embody expectations for high inflation and strong economic growth. While this positive scenario is immediately reflected by the market value, its effect on the accounting numbers clearly lags. The intercept $\hat{\alpha}_0$, which is the part of the market value that is unexplained by the fundamental valuation, has the largest loadings on the 10-year government bond rate. These loadings also confirm the well-known prices-lead-earnings effect found by Beaver et al. (1980), Easton et al. (1992), and Kothari and Sloan (1992). The industries with a sizeable (in absolute value) $\hat{\alpha}_0$ are the most exposed to the economic cycle (*Consumer Durables*, *Consumer Nondurables*, *Business Equipment*, *Manufacturing*, and *Utilities*). The *Consumer Durables* sector is a cyclical industry with the largest positive $\hat{\gamma}^{\alpha_0}$ coefficient while the smallest loading corresponds to *Utilities*, which is a defensive industry. Utility stocks can be perceived as carry instruments; therefore, when long-term risk-free rates are high, investors will switch to safer fixed income alternatives.

As far as the multiples $\hat{\alpha}_2$ and $\hat{\alpha}_3$ are concerned, the results in Panel (b) of Table 4 exhibit a clear negative relation between the net income multiples and the 10-year Treasury yield. When

⁸Note that highly positive differentials between the 10-year and 2-year spot rates are common during recessions when short-term interest rates fall much faster than long-term yields (see Section A.2 in the online Appendix in the Supporting Information for a discussion).

TABLE 4 Estimates of regression (7) for the term spread and for the US 10-year Treasury yield

This table reports the results from the simple time-series regressions. The dependent variable is the accounting multiple $\hat{\alpha}_{kjt}$, where k indexes the accounting fundamental on which the multiple α_k is based ($k = 1$ for the book value, 2 for the net income, 3 for the negative net income, 4 for the book leverage, 0 for the constant). The subscripts j and t denote the industry and the year, respectively. The explanatory variable is the macroeconomic factor z_t . The simple regressions in Equation (7) are run for each industry j . In detail, for the industry j we run k regressions of $\hat{\alpha}_{kjt}$ on the macroeconomic variable z_t , obtaining the slope $\hat{\gamma}^{\alpha_k}$ and the intercept term $\hat{\psi}^{\alpha_k}$. Therefore, for industry j (columns) we have a slope and an intercept for each of the k accounting fundamentals (rows). The p -value for the t -test on each coefficient are reported in the row below. The k regressions are estimated on the whole sample from 1976 to 2015. We request White-corrected standard errors to correct for heteroskedasticity. Codes 1–12 correspond to the Fama–French industry classification: (1) *Consumer Non-Durables*, (2) *Consumer Durables*, (3) *Manufacturing*, (4) *Oil and Gas*, (5) *Chemicals and Allied Products*, (6) *Business Equipment*, (7) *Telephone and TV Transmission*, (8) *Utilities*, (9) *Wholesale*, (10) *Healthcare*, (12) *Residual* excluding *Finance*. Panel (a) shows the results for the term spread (*TERM*) and Panel (b) for the US 10-year Treasury yield (*US10YR*). To make the Treasury yield stationary, we apply a two-step transformation. First, we take the log of the level, then we remove the linear trend corresponding to the fall in interest rates due to the non-standard monetary policy interventions of the last decades.

(a) $\hat{\alpha}_{kjt} = \psi^{\alpha_k} + \gamma^{\alpha_k} TERM_t + u_{jt}^{\alpha_k}$											
Fama–French 12 industry classification											
	1	2	3	4	5	6	7	8	9	10	12
$\hat{\gamma}^{\alpha_0}$	0.11	0.18	0.04	0.05	−0.32	−0.04	0.13	0.24	0.11	−0.01	0.15
p -value	0.142	0.216	0.595	0.662	0.000	0.494	0.076	0.049	0.066	0.847	0.049
$\hat{\psi}^{\alpha_0}$	1.42	1.80	1.30	1.66	2.09	1.59	1.91	1.14	1.30	1.92	1.68
p -value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\hat{\gamma}^{\alpha_1}$	−0.01	0.01	0.02	0.00	0.11	0.04	−0.01	−0.03	0.00	0.00	0.00
p -value	0.689	0.702	0.286	0.900	0.000	0.045	0.591	0.423	0.928	0.843	0.801
$\hat{\psi}^{\alpha_1}$	0.56	0.46	0.61	0.62	0.37	0.63	0.54	0.63	0.60	0.61	0.56
p -value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\hat{\gamma}^{\alpha_2}$	0.00	−0.05	−0.01	−0.02	−0.06	−0.03	−0.04	0.00	0.00	0.01	−0.01
p -value	0.883	0.065	0.490	0.549	0.046	0.032	0.261	0.937	0.874	0.455	0.629
$\hat{\psi}^{\alpha_2}$	0.41	0.40	0.34	0.23	0.52	0.33	0.29	0.31	0.40	0.29	0.35
p -value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\hat{\gamma}^{\alpha_3}$	−0.03	0.04	0.00	−0.01	0.00	0.00	0.01	−0.05	0.00	0.02	−0.05
p -value	0.032	0.058	0.910	0.749	0.848	0.855	0.710	0.000	0.914	0.696	0.000
$\hat{\psi}^{\alpha_3}$	−0.13	−0.14	−0.11	−0.06	−0.08	−0.11	−0.06	−0.01	−0.18	−0.08	−0.05
p -value	0.000	0.000	0.000	0.062	0.089	0.000	0.000	0.000	0.000	0.384	0.000
$\hat{\gamma}^{\alpha_4}$	0.23	0.15	0.07	0.26	0.31	0.06	0.23	0.35	0.01	0.31	0.01
p -value	0.039	0.187	0.388	0.008	0.036	0.501	0.045	0.035	0.832	0.004	0.907
$\hat{\psi}^{\alpha_4}$	−0.09	−0.04	−0.09	0.16	−0.12	−0.19	0.18	0.03	−0.34	−0.20	−0.35
p -value	0.407	0.724	0.290	0.117	0.580	0.094	0.284	0.886	0.000	0.191	0.000

(b) $\hat{\alpha}_{kjt} = \psi^{\alpha_k} + \gamma^{\alpha_k} US10YR_t + u_{jt}^{\alpha_k}$

Fama-French 12 industry classification											
	1	2	3	4	5	6	7	8	9	10	12
$\bar{\gamma}^{\alpha_0}$	0.91	1.27	0.49	-0.44	-0.41	0.90	0.79	-1.32	0.18	0.29	0.79
<i>p</i> -value	0.001	0.017	0.055	0.407	0.449	0.001	0.057	0.032	0.408	0.308	0.002
$\bar{\psi}^{\alpha_0}$	1.35	1.95	1.29	1.58	1.74	1.45	1.81	0.56	1.39	1.90	1.76
<i>p</i> -value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\bar{\gamma}^{\alpha_1}$	-0.06	-0.20	0.06	0.14	0.23	-0.01	-0.16	0.13	0.24	0.00	-0.04
<i>p</i> -value	0.504	0.141	0.409	0.204	0.066	0.928	0.178	0.415	0.000	0.994	0.509
$\bar{\psi}^{\alpha_1}$	0.56	0.48	0.64	0.63	0.49	0.68	0.55	0.60	0.60	0.61	0.55
<i>p</i> -value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\bar{\gamma}^{\alpha_2}$	-0.05	-0.01	-0.14	-0.13	-0.35	-0.08	-0.01	-0.10	-0.31	-0.09	-0.10
<i>p</i> -value	0.478	0.915	0.035	0.222	0.007	0.209	0.922	0.508	0.000	0.196	0.065
$\bar{\psi}^{\alpha_2}$	0.39	0.34	0.32	0.19	0.43	0.29	0.23	0.29	0.41	0.30	0.34
<i>p</i> -value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\bar{\gamma}^{\alpha_3}$	0.13	-0.01	0.12	0.28	-0.03	0.16	0.06	0.29	0.16	-0.23	0.10
<i>p</i> -value	0.050	0.903	0.013	0.001	0.830	0.005	0.624	0.001	0.104	0.134	0.039
$\bar{\psi}^{\alpha_3}$	-0.17	-0.10	-0.11	-0.06	-0.04	-0.11	-0.04	-0.06	-0.19	-0.06	-0.10
<i>p</i> -value	0.000	0.000	0.000	0.001	0.190	0.000	0.177	0.001	0.000	0.065	0.000
$\bar{\gamma}^{\alpha_4}$	-0.30	-0.20	-0.32	0.35	1.11	-0.48	0.76	1.23	-0.49	0.64	-0.11
<i>p</i> -value	0.594	0.713	0.399	0.405	0.342	0.241	0.300	0.262	0.190	0.300	0.790
$\bar{\psi}^{\alpha_4}$	0.39	0.10	0.10	0.51	0.17	0.15	0.55	1.46	-0.11	0.06	-0.01
<i>p</i> -value	0.001	0.367	0.202	0.000	0.490	0.079	0.000	0.000	0.150	0.650	0.933

the long-term government bond yield increases, $\hat{\gamma}^{\alpha_2}$ decreases and that signals the lower importance of the fundamental-based valuation. This correspondence is even more significant for $\hat{\gamma}^{\alpha_3}$, which in many cases, is negative and hints at a contraction in the multiple $\hat{\alpha}_3$ in absolute terms. Moreover, the effect of this state variable is stronger on $\hat{\alpha}_3$ than on $\hat{\alpha}_2$ with an asymmetric effect of the Treasury rate in determining equity prices: in a high interest rate environment, the largest gap between the fundamental valuation and the market price occurs for the companies that report negative net income.

Panel (a) of Table 5 contains the outputs obtained from regressing $\hat{\alpha}_k$ on the ISM PMI. There is no statistically significant evidence that this sentiment indicator affects the RKRV valuation multiples, except for the $\hat{\gamma}^{\alpha_3}$ coefficient for the *Consumer Durables* sector and $\hat{\gamma}^{\alpha_0}$ for the Chemical industry. We show similar results in Panel (b) of Table 5 where the $\hat{\gamma}^{\alpha_k}$ coefficients are estimated using the LEI Index. The only industry that shows some dependence on this regressor is *Oil and Gas*: the book value multiple $\hat{\gamma}^{\alpha_1}$ increases and the constant term $\hat{\gamma}^{\alpha_0}$ decreases with the leading indicator.

TABLE 5 Estimates of regression (7) for the ISM Manufacturing Purchasing Managers Index and for the Conference Board Leading Economic indicator

This table reports the results from the simple time-series regressions. The dependent variable is the accounting multiple $\hat{\alpha}_{kjt}$, where k indexes the accounting fundamental on which the multiple α_k is based ($k = 1$ for the book value, 2 for the net income, 3 for the negative net income, 4 for the book leverage, 0 for the constant). The subscripts j and t denote the industry and the year, respectively. The explanatory variable is the macroeconomic factor z_t . The simple regressions in Equation (7) are run for each industry j . In detail, for the industry j we run k regressions of $\hat{\alpha}_{kjt}$ on the macroeconomic variable z_t , obtaining the slope $\hat{\gamma}^{\hat{\alpha}_k}$ and the intercept term $\hat{\psi}^{\hat{\alpha}_k}$. Therefore, for industry j (columns) we have a slope and an intercept for each of the k accounting fundamentals (rows). The p -value for the t -test on each coefficient are reported in the row below. The k regressions are estimated on the whole sample from 1976 to 2015. We request White-corrected standard errors to correct for heteroskedasticity. Codes 1–12 correspond to the Fama-French industry classification: (1) *Consumer Nondurables*, (2) *Consumer Durables*, (3) *Manufacturing*, (4) *Oil and Gas*, (5) *Chemicals and Allied Products*, (6) *Business Equipment*, (7) *Telephone and TV Transmission*, (8) *Utilities*, (9) *Wholesale*, (10) *Healthcare*, (12) *Residual* excluding *Finance*. Panel (a) shows the results for the ISM Manufacturing Purchasing Managers Index (PMI) and Panel (b) for the Conference Board Leading Economic Indicator (LEI).

(a) $\hat{\alpha}_{kjt} = \psi^{\alpha_k} + \gamma^{\alpha_k} PMI_t + u_{jt}^{\alpha_k}$											
Fama-French 12 industry classification											
	1	2	3	4	5	6	7	8	9	10	12
$\hat{\gamma}^{\alpha_0}$	-0.01	0.00	-0.02	-0.02	-0.03	-0.01	-0.02	0.00	-0.01	0.00	-0.01
p -value	0.628	0.911	0.080	0.200	0.042	0.639	0.378	0.959	0.454	0.926	0.605
$\hat{\psi}^{\alpha_0}$	1.53	1.98	1.34	1.72	1.79	1.55	2.03	1.37	1.41	1.91	1.83
p -value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\hat{\gamma}^{\alpha_1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
p -value	0.480	0.819	0.140	0.812	0.668	0.909	0.204	0.579	0.338	0.247	0.350
$\hat{\psi}^{\alpha_1}$	0.55	0.48	0.63	0.62	0.47	0.67	0.53	0.60	0.60	0.61	0.55
p -value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\hat{\gamma}^{\alpha_2}$	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00
p -value	0.893	0.628	0.494	0.517	0.860	0.686	0.210	0.566	0.931	0.235	0.900
$\hat{\psi}^{\alpha_2}$	0.41	0.35	0.33	0.21	0.46	0.30	0.25	0.31	0.41	0.30	0.34
p -value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\hat{\gamma}^{\alpha_3}$	0.00	0.01	0.00	-0.01	0.00	0.00	0.01	0.00	0.00	0.02	0.00
p -value	0.604	0.051	0.721	0.289	0.702	0.167	0.433	0.273	0.660	0.109	0.179
$\hat{\psi}^{\alpha_3}$	-0.16	-0.09	-0.11	-0.07	-0.07	-0.11	-0.05	-0.05	-0.18	-0.06	-0.09
p -value	0.000	0.000	0.000	0.004	0.021	0.000	0.154	0.012	0.000	0.090	0.000
$\hat{\gamma}^{\alpha_4}$	-0.01	-0.02	0.01	0.00	0.04	-0.01	0.00	0.00	-0.02	0.01	-0.02
p -value	0.797	0.285	0.339	0.792	0.239	0.415	0.993	0.979	0.124	0.854	0.219
$\hat{\psi}^{\alpha_4}$	0.12	0.11	-0.02	0.41	0.18	-0.13	0.40	0.37	-0.33	0.10	-0.34
p -value	0.238	0.348	0.745	0.000	0.290	0.074	0.001	0.015	0.000	0.376	0.000

(b) $\hat{\alpha}_{kjt} = \psi^{\alpha_k} + \gamma^{\alpha_k} LEL_t + u_{jt}^{\alpha_k}$

Fama–French 12 industry classification											
	1	2	3	4	5	6	7	8	9	10	12
$\hat{\gamma}^{\alpha_0}$	−0.01	0.00	−0.02	−0.06	−0.02	0.01	−0.01	−0.02	0.00	0.00	−0.01
<i>p</i> -value	0.524	0.916	0.204	0.016	0.218	0.519	0.753	0.407	0.941	0.684	0.504
$\hat{\psi}^{\alpha_0}$	1.57	2.00	1.38	1.79	1.80	1.55	2.08	1.40	1.42	1.91	1.87
<i>p</i> -value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\hat{\gamma}^{\alpha_1}$	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00
<i>p</i> -value	0.368	0.951	0.468	0.042	0.328	0.621	0.876	0.271	0.384	0.624	0.356
$\hat{\psi}^{\alpha_1}$	0.54	0.48	0.63	0.62	0.47	0.67	0.52	0.59	0.60	0.61	0.55
<i>p</i> -value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\hat{\gamma}^{\alpha_2}$	0.00	0.00	0.00	−0.01	0.00	0.00	0.00	−0.01	0.00	0.00	0.00
<i>p</i> -value	0.683	0.833	0.952	0.078	0.308	0.802	0.756	0.231	0.753	0.779	0.464
$\hat{\psi}^{\alpha_2}$	0.41	0.34	0.33	0.21	0.46	0.29	0.25	0.31	0.40	0.29	0.34
<i>p</i> -value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\hat{\gamma}^{\alpha_3}$	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
<i>p</i> -value	0.729	0.034	0.795	0.462	0.327	0.788	0.527	0.358	0.627	0.386	0.634
$\hat{\psi}^{\alpha_3}$	−0.15	−0.10	−0.11	−0.06	−0.08	−0.10	−0.05	−0.04	−0.18	−0.06	−0.09
<i>p</i> -value	0.000	0.000	0.000	0.008	0.009	0.000	0.198	0.014	0.000	0.186	0.000
$\hat{\gamma}^{\alpha_4}$	−0.01	−0.03	0.01	0.01	0.03	−0.02	0.00	0.02	−0.02	−0.01	−0.01
<i>p</i> -value	0.699	0.301	0.573	0.624	0.489	0.295	0.901	0.493	0.110	0.857	0.422
$\hat{\psi}^{\alpha_4}$	0.15	0.17	−0.02	0.41	0.17	−0.11	0.42	0.39	−0.30	0.14	−0.33
<i>p</i> -value	0.167	0.167	0.788	0.000	0.329	0.175	0.001	0.008	0.000	0.269	0.000

Overall, our regression-based tests confirm that the macroeconomic variables that are related to interest rates affect the valuation of stocks and show that this influence is very industry-dependent. We relegate to Sections 4.4 and 4.5 robustness checks to rule out potential concerns about the look-ahead bias and parameter estimation error, which could arise from the two steps of Equations (7) and (8).

3.3 | Comparing asset pricing implications

In this section, we compare the risk-return characteristics of the portfolios that are sorted according to GK and on the orthogonalized RKR components. Since the orthogonalized components are uncorrelated to the macroeconomic information, the returns of the resulting sorted portfolios are curtailed of the portion that rewards macroeconomic risk. Tables 6–12 show the raw and size-adjusted results in Panels (a) and (b), respectively.

TABLE 6 Average size, average volatility and ex ante β s for portfolios formed in the market-to-book components and size

This table reports the average size (ASI), average volatility ($\bar{\sigma}$), and average market exposure ($\bar{\beta}$) for 10 equal-weighted portfolios formed on $m_{it} - b_{it}$, $m_{it} - v(\theta_{it}; \hat{\alpha}_{jt})$, $v(\theta_{it}; \hat{\alpha}_{jt}) - v(\theta_{it}; \alpha_j)$ and $v(\theta_{it}; \hat{\alpha}_j) - b_{it}$ for a sample of 119,403 observations from 1981 to 2016. The long/short dollar neutral positions are taken on July 1 of each year in the bottom/top decile of the firms sorted as of June 30. The Average Size Index (ASI) expresses the average size of the stocks forming each portfolio using the ranking on market capitalization defined by the NYSE breakpoints and is calculated at the rebalancing dates. Column ASI shows the time-series average of this indicator on the portfolios formed from 1981 to 2016. At the end of June of each year, for each portfolio, we average the annual standard deviations of the returns of the constituent stocks, obtaining an average volatility measure at the portfolio level. Column $\bar{\sigma}$ contains the time-series average of this portfolio estimate. For each firm, we estimate the β coefficient on the CRSP value-weighted index over a 5-years rolling window. At the end of June of each year, we calculate the ex-ante β of each portfolio by averaging the β s of the constituents. Column $\bar{\beta}$ reports the time-series average of the portfolio systematic risk. Panel (a) summarizes the characteristics of the portfolios formed in the market-to-book components. Panel (b) summarizes the characteristics of the portfolios formed in the market-to-book components, adjusting for size.

(a) Decile portfolios sorted on the RKRV components												
Ranking	$m_{it} - b_{it}$			$m_{it} - v(\theta_{it}; \hat{\alpha}_{jt})$			$v(\theta_{it}; \hat{\alpha}_{jt}) - v(\theta_{it}; \alpha_j)$			$v(\theta_{it}; \hat{\alpha}_j) - b_{it}$		
	1	2	3	4	5	6	7	8	9	10	11	12
	ASI	$\bar{\sigma}$ (%)	$\bar{\beta}$	ASI	$\bar{\sigma}$ (%)	$\bar{\beta}$	ASI	$\bar{\sigma}$ (%)	$\bar{\beta}$	ASI	$\bar{\sigma}$ (%)	$\bar{\beta}$
Low	2.2	14.73	1.12	1.7	16.50	1.19	3.9	14.19	1.25	4.8	11.78	1.10
2	2.5	13.89	1.15	1.9	15.39	1.21	3.6	13.51	1.22	4.3	11.64	1.05
3	3.1	12.76	1.12	2.5	13.80	1.20	3.5	13.84	1.22	3.9	11.82	1.07
4	3.5	12.13	1.10	3.0	13.06	1.16	3.6	13.15	1.16	3.8	12.11	1.10
5	3.8	12.23	1.13	3.6	12.53	1.15	3.6	12.82	1.13	3.7	12.42	1.13
6	4.0	12.55	1.17	4.1	12.05	1.13	3.6	12.75	1.12	3.8	12.79	1.18
7	4.4	12.80	1.20	4.5	12.12	1.14	3.6	13.00	1.12	3.6	13.39	1.21
8	4.6	13.41	1.24	4.9	12.47	1.17	3.6	13.76	1.20	3.5	14.26	1.29
9	4.6	14.42	1.29	5.2	13.13	1.21	3.8	14.29	1.23	3.2	15.82	1.34
High	4.3	16.76	1.38	5.4	14.72	1.31	4.2	14.38	1.23	2.3	20.04	1.41
(b) Size-adjusted decile portfolios sorted on the RKRV components												
Ranking	$m_{it} - b_{it}$			$m_{it} - v(\theta_{it}; \hat{\alpha}_{jt})$			$v(\theta_{it}; \hat{\alpha}_{jt}) - v(\theta_{it}; \alpha_j)$			$v(\theta_{it}; \hat{\alpha}_j) - b_{it}$		
	1	2	3	4	5	6	7	8	9	10	11	12
	ASI	$\bar{\sigma}$ (%)	$\bar{\beta}$	ASI	$\bar{\sigma}$ (%)	$\bar{\beta}$	ASI	$\bar{\sigma}$ (%)	$\bar{\beta}$	ASI	$\bar{\sigma}$ (%)	$\bar{\beta}$
Low	3.7	12.85	1.13	3.7	13.58	1.20	3.7	13.99	1.28	3.7	12.59	1.12
2	3.7	13.57	1.20	3.7	13.57	1.20	3.7	13.33	1.23	3.7	12.22	1.05
3	3.7	12.93	1.15	3.7	12.93	1.15	3.7	13.14	1.21	3.7	11.94	1.03
4	3.7	12.56	1.13	3.7	12.56	1.13	3.7	13.12	1.16	3.7	12.22	1.09
5	3.7	12.44	1.13	3.7	12.44	1.13	3.7	12.97	1.13	3.7	12.61	1.14
6	3.7	12.57	1.14	3.7	12.57	1.14	3.7	12.95	1.12	3.7	13.13	1.18

TABLE 6 (Continued)

(b) Size-adjusted decile portfolios sorted on the RKR components												
	$m_{it} - b_{it}$			$m_{it} - v(\theta_{it}; \hat{\alpha}_{jt})$			$v(\theta_{it}; \hat{\alpha}_{jt}) - v(\theta_{it}; \bar{\alpha}_j)$			$v(\theta_{it}; \bar{\alpha}_j) - b_{it}$		
	1	2	3	4	5	6	7	8	9	10	11	12
Ranking	<i>ASI</i>	$\bar{\sigma}$ (%)	$\bar{\beta}$	<i>ASI</i>	$\bar{\sigma}$ (%)	$\bar{\beta}$	<i>ASI</i>	$\bar{\sigma}$ (%)	$\bar{\beta}$	<i>ASI</i>	$\bar{\sigma}$ (%)	$\bar{\beta}$
7	3.7	13.05	1.16	3.7	13.05	1.16	3.7	13.06	1.10	3.7	13.66	1.23
8	3.7	13.60	1.19	3.7	13.60	1.19	3.7	13.86	1.19	3.7	14.39	1.29
9	3.7	14.67	1.25	3.7	14.67	1.25	3.7	14.37	1.21	3.7	15.51	1.34
High	3.7	16.68	1.35	3.7	16.68	1.35	3.7	14.87	1.23	3.7	17.65	1.41

As for the GK replication, Table 6 gives results on risk. Specifically, it shows the time-series average of the ASI^9 , volatility, and the ex-ante beta for the GK portfolios. The first column of Panel (a) shows a positive relation between the market-to-book and the average size with the ASI increasing almost monotonically with the market-to-book. As a result, the average volatility differential between the Low and the High portfolios is small despite the fact that the betas of the two portfolios are very different. Column 4 shows an even more pronounced relation between the average size and the volatility for the firm-specific error sorted portfolios. Accordingly, in Column 11 the grouping with the highest $\bar{\sigma}$ is the High portfolio that is characterized by the smallest average size and the highest average beta.

Panel (b) has the results that were obtained by controlling for size that thus, produces portfolios with the same level of the ASI . As expected, Column 1 shows a positive and almost linear mapping between the average volatility and $\bar{\beta}$, for both the market-to-book and firm-specific portfolios. Column 11 displays similar results for the portfolios sorted on the long-run RKR component. Interestingly, a strong relation between the market-to-book and the beta persists after controlling for size and more so for the firm-specific and long-run components. This result is consistent with the negative long-run beta of the cash neutral market-to-book strategy found in Ang and Kristensen (2012).

We explore the portfolios' returns and risk when dissecting the influence of macroeconomic conditions from the RKR multiples by repeating the portfolio sorting analysis in the market-to-book components using the empirical setup illustrated in Equations (7)–(9) where firm value is derived from the $\bar{u}_{jt}^{\alpha_k}$ orthogonal multiples. We test only the term spread and 10-year Treasury yield cases since only these variables, according to the results in Table 4, have a significant conditioning effect on the $\hat{\alpha}_k$ multiples. Tables 7 and 8 present the average size, volatility, and the beta of the resulting portfolios.

As for the orthogonalized RKR components, Panel (a) of Table 7 presents the raw results. Column 1 shows a strong positive relation between the firm-specific error and the average size for each sorted portfolio when considering the term spread and the Treasury yield. However, the distribution of size is more polarized compared to the one shown in Columns 1 and 4 of Table 6. Namely, the ASI of the Low and High portfolio is close to one and nine, respectively. Therefore, the characteristics of the portfolios that are sorted on the deviations from the

⁹Since size adjustment is based on the NYSE break-points, we introduce a coherent measure of size, the Average Size Index (ASI), calculated in two steps. First, at the rebalancing dates, stocks are ranked by size and assigned a decile label based on the NYSE breakpoints. Then, a simple average of these integer values is taken within each portfolio.

TABLE 7 Average size, average volatility and ex-ante β s for portfolios formed in the market-to-book components orthogonal to the term spread

This table reports the average size (*ASI*), average volatility ($\bar{\sigma}$), and average market exposure ($\bar{\beta}$) for 10 equal-weighted portfolios formed on $m_{it} - b_{it}$, $m_{it} - v(\theta_{it}; \hat{u}_{jt})$, $v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$ and $v(\theta_{it}; \bar{u}_j) - b_{it}$ for a sample of 119,403 observations from 1981 to 2016. The long/short dollar neutral positions are taken on July 1 of each year in the bottom/top decile of the firms sorted as of June 30. The Average Size Index (*ASI*) expresses the average size of the stocks forming each portfolio using the ranking on market capitalization defined by the NYSE breakpoints and is calculated at the rebalancing dates. Column *ASI* shows the time-series average of this indicator on the portfolios formed from 1981 to 2016. At the end of June of each year, for each portfolio, we average the annual standard deviations of the returns of the constituent stocks, obtaining an average volatility measure at the portfolio level. Column $\bar{\sigma}$ contains the time-series average of this portfolio estimate. For each firm, we estimate the β coefficient on the CRSP value-weighted index over a 5-years rolling window. At the end of June of each year, we calculate the ex-ante β of each portfolio by averaging the β s of the constituents. Column $\bar{\beta}$ reports the time-series average of the portfolio systematic risk. Panel (a) summarizes the characteristics of the portfolios formed in the market-to-book components. Panel (b) summarizes the characteristics of the portfolios formed in the market-to-book components, adjusting for size.

(a) Portfolio formed in the market-to-book components									
Ranking	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$			$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$			$v(\theta_{it}; \bar{u}_j) - b_{it}$		
	1	2	3	4	5	6	7	8	9
	<i>ASI</i>	$\bar{\sigma}$ (%)	$\bar{\beta}$	<i>ASI</i>	$\bar{\sigma}$ (%)	$\bar{\beta}$	<i>ASI</i>	$\bar{\sigma}$ (%)	$\bar{\beta}$
Low	1.0	19.79	1.08	3.9	14.01	1.22	8.4	8.41	0.98
2	1.0	16.77	1.19	3.5	13.56	1.22	6.9	9.80	1.10
3	1.1	15.64	1.25	3.5	13.61	1.21	5.5	10.67	1.13
4	1.6	14.74	1.28	3.6	13.10	1.15	4.2	11.73	1.17
5	2.3	14.01	1.30	3.6	12.92	1.13	3.3	12.79	1.25
6	3.2	13.17	1.25	3.6	12.78	1.14	2.5	13.94	1.26
7	4.3	12.30	1.23	3.6	13.15	1.16	2.0	14.78	1.26
8	5.7	11.29	1.17	3.6	13.81	1.19	1.6	15.60	1.27
9	7.4	10.02	1.12	3.7	14.31	1.22	1.3	17.66	1.26
High	9.4	8.40	1.00	4.2	14.44	1.24	1.1	20.80	1.19
(b) Portfolio formed in the market-to-book components adjusting for size									
Ranking	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$			$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$			$v(\theta_{it}; \bar{u}_j) - b_{it}$		
	1	2	3	4	5	6	7	8	9
	<i>ASI</i>	$\bar{\sigma}$ (%)	$\bar{\beta}$	<i>ASI</i>	$\bar{\sigma}$ (%)	$\bar{\beta}$	<i>ASI</i>	$\bar{\sigma}$ (%)	$\bar{\beta}$
Low	3.7	16.00	1.23	3.7	13.99	1.26	3.7	11.76	1.12
2	3.7	13.29	1.23	3.7	13.29	1.23	3.7	11.81	1.09
3	3.7	12.97	1.19	3.7	12.97	1.19	3.7	11.75	1.10
4	3.7	13.00	1.15	3.7	13.00	1.15	3.7	12.11	1.13
5	3.7	13.08	1.13	3.7	13.08	1.13	3.7	12.58	1.16
6	3.7	12.97	1.13	3.7	12.97	1.13	3.7	13.18	1.20

TABLE 7 (Continued)

(b) Portfolio formed in the market-to-book components adjusting for size									
	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$			$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$			$v(\theta_{it}; \bar{u}_j) - b_{it}$		
	1	2	3	4	5	6	7	8	9
Ranking	<i>ASI</i>	$\bar{\sigma}$ (%)	$\bar{\beta}$	<i>ASI</i>	$\bar{\sigma}$ (%)	$\bar{\beta}$	<i>ASI</i>	$\bar{\sigma}$ (%)	$\bar{\beta}$
7	3.7	13.34	1.15	3.7	13.34	1.15	3.7	13.94	1.22
8	3.7	13.79	1.19	3.7	13.79	1.19	3.7	14.80	1.25
9	3.7	14.28	1.22	3.7	14.28	1.22	3.7	15.82	1.28
High	3.7	14.96	1.23	3.7	14.96	1.23	3.7	18.26	1.33

fundamental value disclose a significant relation between size and misvaluation. In addition, the differential in the average betas in the first sorting exercise disappears. Indeed, the betas of the extreme decile portfolios in Column 3 of Panel (a) are similar. This decline in the beta spread is also confirmed for the long-run component in Column 9 of Tables 7 and 8, but a differential remains. The average risk data for the firm-specific component sort in Panel (a) of Column 2 in Tables 7 and 8 follow roughly the same path as Table 6 with the Low portfolio having the highest average risk and the High portfolio having the lowest average volatility. In this case, however, the inverse relation between average volatility and the firm-specific component is more evident. Column 8 exhibits a considerable difference in the average volatility in which the top and bottom decile portfolios have the highest and the lowest average risk, respectively. These wide risk differentials can be attributable to the variance in the average size, as discussed before.

When moving to the size-adjusted results, Panel (b) in Tables 7 and 8 shows that the volatility spread between the High and Low portfolios decreases dramatically when size is neutralized and the average volatility lines up with the beta. Another consequence of size control is an upward shift on average portfolio beta that indicates an inverse relation between systematic risk and size. Further, the term spread and the 10-year Treasury yield do not influence the size and risk characteristics of the portfolios sorted on the industry-error component.

Tables 9 and 10 show the returns of the portfolios that are formed using the new setup. Comparing Panel (a) of Tables 9 and 10 with Panel (a) of Table 2, we observe a higher return for the Low-High arbitrage portfolio based on the firm-specific component. Turning to the long-run column, we find similar results and the differential return even increases in absolute value. The main reason behind this increase is the larger spread in size and average volatility. Moreover, while in the first sorting exercise the value weighting considerably reduces the performance of the cash-neutral strategy, in this case the abnormal return persists for both the firm-specific and long-run components. This persistence is explained by the considerable size dispersion from sorting on the orthogonalized components. Thus, a capital-weighting scheme that mitigates the return contribution of small firms does not eliminate the performance difference between the Low and High portfolios since they reward sharper size differentials.

Panel (b) of Tables 9 and 10 shows the size-adjusted results. First, we observe that the difference between the Low and High portfolio returns is smaller for each market-to-book component. For the firm-specific error, the difference decreases from 4.05% to 1.52% (Table 9) and from 4.11% to 1.58% (Table 10) and is still statistically significant. The return of the cash-

TABLE 8 Average size, average volatility and ex-ante β s for portfolios formed in the market-to-book components orthogonal to the US 10-Year Treasury Yield

This table reports the average size (*ASI*), average volatility ($\bar{\sigma}$), and average market exposure ($\bar{\beta}$) for 10 equal-weighted portfolios formed on $m_{it} - b_{it}$, $m_{it} - v(\theta_{it}; \hat{u}_{jt})$, $v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$ and $v(\theta_{it}; \bar{u}_j) - b_{it}$ for a sample of 119,403 observations from 1981 to 2016. The long/short dollar neutral positions are taken on July 1 of each year in the bottom/top decile of the firms sorted as of June 30. The Average Size Index (*ASI*) expresses the average size of the stocks forming each portfolio using the ranking on market capitalization defined by the NYSE breakpoints and is calculated at the rebalancing dates. Column *ASI* shows the time-series average of this indicator on the portfolios formed from 1981 to 2016. At the end of June of each year, for each portfolio, we average the annual standard deviations of the returns of the constituent stocks, obtaining an average volatility measure at the portfolio level. Column $\bar{\sigma}$ contains the time-series average of this portfolio estimate. For each firm, we estimate the β coefficient on the CRSP value-weighted index over a 5-years rolling window. At the end of June of each year, we calculate the ex-ante β of each portfolio by averaging the β s of the constituents. Column $\bar{\beta}$ reports the time-series average of the portfolio systematic risk. Panel (a) summarizes the characteristics of the portfolios formed in the market-to-book components. Panel (b) summarizes the characteristics of the portfolios formed in the market-to-book components, adjusting for size.

(a) Decile portfolios sorted on the RKR components									
Ranking	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$			$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$			$v(\theta_{it}; \bar{u}_j) - b_{it}$		
	1	2	3	4	5	6	7	8	9
	<i>ASI</i>	σ (%)	β	<i>ASI</i>	σ (%)	β	<i>ASI</i>	σ (%)	β
Low	1.0	19.82	1.08	3.9	14.12	1.24	8.4	8.45	0.98
2	1.0	16.70	1.19	3.6	13.70	1.23	6.9	9.80	1.09
3	1.1	15.64	1.25	3.6	13.37	1.19	5.5	10.73	1.14
4	1.6	14.78	1.28	3.6	13.09	1.17	4.3	11.69	1.17
5	2.3	14.03	1.30	3.7	12.89	1.14	3.2	12.77	1.24
6	3.2	13.12	1.25	3.7	12.74	1.13	2.5	13.93	1.26
7	4.3	12.29	1.23	3.6	13.20	1.14	2.0	14.77	1.26
8	5.7	11.32	1.17	3.5	13.84	1.19	1.6	15.63	1.26
9	7.4	10.01	1.12	3.7	14.24	1.19	1.3	17.63	1.25
High	9.4	8.43	1.01	4.1	14.52	1.25	1.2	20.82	1.20
(b) Size-adjusted decile portfolios sorted on the RKR components									
Ranking	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$			$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$			$v(\theta_{it}; \bar{u}_j) - b_{it}$		
	1	2	3	4	5	6	7	8	9
	<i>ASI</i>	σ (%)	β	<i>ASI</i>	σ (%)	β	<i>ASI</i>	σ (%)	β
Low	3.7	15.85	1.21	3.7	14.00	1.27	3.7	11.81	1.12
2	3.7	14.82	1.19	3.7	13.41	1.25	3.7	11.80	1.09
3	3.7	14.21	1.19	3.7	13.17	1.20	3.7	11.79	1.10
4	3.7	13.76	1.19	3.7	13.02	1.15	3.7	12.10	1.13
5	3.7	13.31	1.18	3.7	13.00	1.13	3.7	12.55	1.16
6	3.7	12.97	1.18	3.7	13.03	1.13	3.7	13.25	1.19

TABLE 8 (Continued)

(b) Size-adjusted decile portfolios sorted on the RKRV components									
	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$			$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$			$v(\theta_{it}; \bar{u}_j) - b_{it}$		
	1	2	3	4	5	6	7	8	9
Ranking	<i>ASI</i>	σ (%)	β	<i>ASI</i>	σ (%)	β	<i>ASI</i>	σ (%)	β
7	3.7	12.91	1.17	3.7	13.18	1.14	3.7	13.91	1.23
8	3.7	12.82	1.18	3.7	13.82	1.18	3.7	14.78	1.26
9	3.7	12.53	1.18	3.7	14.23	1.18	3.7	15.86	1.28
High	3.7	12.61	1.18	3.7	14.82	1.24	3.7	18.19	1.33

neutral strategy that is based on the industry-error sorted portfolios is marginally smaller but does not lose its significance. On the contrary, the Low–High return differential in the long-run component case increases considerably from -3.05% to -0.19% and from -3.06% to -0.38% for the term spread and the Treasury yield, respectively. Interestingly, by neutralizing the size effect, the significance of this excess return component is dramatically reduced. This piece of evidence confirms that differences in the average size explain the performance of the arbitrage strategy that depends on the long-run components.

As before, after removing the effect of size, the Low–High return difference of the firm-specific component decile portfolios declines but remains significant. In particular, the return of the long-short strategy based on the firm-specific component remains significant but decreases from 1.84% to 1.52% and to 1.58% when the effect of the two macroeconomic variables is taken away. This result is important since it shows that the excess return that is related to the RKRV mispricing component is related to the macroeconomic context. Tables 11 and 12 show the CAPM alpha of sorted portfolios, confirming the abovementioned evidence. In fact, excluding macroeconomic information generates a decrease in the alpha spread between Low and High portfolios compared to Table 3.

We can outline the key results of this section as follows. The empirical setup of Equation (7) allows us to estimate time-varying multiples that are orthogonal to the information carried by the macroeconomic variables. Then, these new market-to-book components rely on a measure of intrinsic value that is uncorrelated to the macroeconomic factors. The portfolios that are sorted on such orthogonal components show a clear relation between misvaluation and size. Again, by purging the sector-specific piece of valuation that is attributable to the macroeconomic context, we show that the premium earned by mispricing is mostly related to size risk. In addition, if we neutralize the link between size and misvaluation we obtain two additional results. First, the top and bottom size-adjusted portfolios that were formed on the firm-specific error show a smaller beta and a volatility differential when compared to the corresponding results in Table 6. Thus, after removing the macroeconomic effects and adjusting for size, the firm-specific error does not incorporate the beta differential between undervalued and overvalued firms. Second, the firm-specific excess return reduces when the macroeconomic conditions is removed from the information set. As a result, this reduction can be interpreted as the portion of the value premium that rewards this type of risk.

TABLE 9 Average monthly returns on portfolios sorted in the market-to-book components orthogonal to the term spread

This table reports the average monthly returns for 10 equally weighted (EW) portfolios sorted on the RKR components $m_{it} - b_{it}$, $m_{it} - v(\theta_{it}; \hat{u}_{jt})$, $v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$ and $v(\theta_{it}; \bar{u}_j) - b_{it}$. The cash neutral positions are initiated on July 1 of each year by buying/selling the bottom/top decile portfolios sorted as of June 30, from 1981 to 2016. The value weighted (VW) arbitrage portfolio returns and annualized Sharpe ratios (for equally weighted portfolios) are also shown. The p -value is for the t -tests on the equality of the High and Low average returns. Panel (b) contains the size-adjusted figures.

(a) Decile portfolios sorted on the RKR components			
Ranking	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$	$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$	$v(\theta_{it}; \bar{u}_j) - b_{it}$
Low	4.17%	1.56%	0.35%
2	2.44%	1.26%	0.40%
3	1.36%	1.35%	0.50%
4	1.00%	1.31%	0.65%
5	0.67%	0.92%	0.71%
6	0.55%	1.31%	0.99%
7	0.38%	0.91%	1.15%
8	0.30%	0.95%	1.31%
9	0.31%	0.85%	2.02%
High	0.13%	1.11%	3.39%
Low-high (EW)	4.05%	0.45%	-3.05%
p -value	0.000	0.491	0.000
Low-high (vw)	2.94%	0.31%	-1.15%
p -value	0.000	0.480	0.009
Annualized Sharpe ratio	1.56	0.07	-1.28
(b) Size-adjusted decile portfolios sorted on the RKR components			
Ranking	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$	$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$	$v(\theta_{it}; \bar{u}_j) - b_{it}$
Low	2.25%	1.41%	1.24%
2	1.48%	1.25%	1.09%
3	1.33%	1.14%	1.15%
4	1.33%	1.26%	0.92%
5	1.09%	1.35%	1.04%
6	0.99%	1.11%	1.04%
7	0.89%	0.94%	1.12%
8	0.78%	0.88%	1.19%
9	0.79%	0.94%	1.40%
High	0.73%	1.34%	1.43%

TABLE 9 (Continued)

(b) Size-adjusted decile portfolios sorted on the RKRV components			
Ranking	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$	$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$	$v(\theta_{it}; \bar{u}_j) - b_{it}$
Low-high (EW)	1.52%	0.07%	-0.19%
<i>p</i> -value	0.002	0.957	0.759
Low-high (vw)	-0.01%	0.11%	0.43%
<i>p</i> -value	0.986	0.783	0.238
Annualized Sharpe ratio	0.83	-0.08	-0.13

4 | ROBUSTNESS CHECKS

Tables summarizing the results we present in this Section are reported in the online appendix in the Supporting Information.

4.1 | Long-run multiples estimation and industry classification

The RKRV study uses full sample estimates to get the sector-error component. As Hertzell and Li (2010) point out, this choice introduces a look-ahead bias in the original RKRV specification for the industry-average valuation because it includes forward-looking accounting information that is not available to time t investors. Following GK, we use a 5-year rolling window to avoid the look-ahead bias, although different options are available to remain consistent with our out-of-sample exercise. For example, we could opt for an expanding window as in Hertzell and Li (2010). We settle for a fixed rolling window because each observation is equally weighted when averaged.

Logically, a short window width could affect the reliability of the industry misvaluation measures. As Hertzell and Li (2010) observe, the volatility of the estimated multiples could increase with the window width. Thus, we compare our long-run multiples with estimates using a 10-year rolling window. The 10-year estimates are almost identical to our 5-year figures and the correlation between the two is almost perfect.¹⁰ Clearly, using larger windows would mean fewer portfolios to examine in our out-of-sample analysis.

Table A.5 shows the portfolio returns using both the full sample and the long-run multiples of the expanding window. The forward-looking information that is incorporated in the original RKRV specification leads to a marginal increase in the magnitude of the long-short returns for both the industry-error and the long-run components. The expanding window methodology generates almost identical results.

To further assess the effect due to the potential instability of the 5-year rolling window, in Table A.6, we consider portfolios that are sorted on the sum of the sector short-run and long-run errors, $v(\theta_{it}; \alpha_j) - b_{it}$ by gathering additional evidence on the robustness of the GK method.

¹⁰For details on this correlation see Table A.4 in the online appendix in the Supporting Information.

TABLE 10 Average monthly returns on portfolios sorted in the market-to-book components orthogonal to the US 10-Year Treasury Yield

This table reports the average monthly returns for 10 equally weighted (EW) portfolios sorted on the RKR components $m_{it} - b_{it}$, $m_{it} - v(\theta_{it}; \hat{u}_{jt})$, $v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$ and $v(\theta_{it}; \bar{u}_j) - b_{it}$. The cash neutral positions are initiated on July 1 of each year by buying/selling the bottom/top decile portfolios sorted as of June 30, from 1981 to 2016. The value weighted (VW) arbitrage portfolio returns and annualized Sharpe ratios (for equally weighted portfolios) are also shown. The p -value is for the t -tests on the equality of the High and Low average returns. Panel (b) contains the size-adjusted figures.

(a) Decile portfolios sorted on the RKR components			
Ranking	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$	$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$	$v(\theta_{it}; \bar{u}_j) - b_{it}$
Low	4.23%	1.51%	0.35%
2	2.40%	1.25%	0.40%
3	1.33%	1.18%	0.53%
4	1.05%	1.22%	0.64%
5	0.65%	1.18%	0.72%
6	0.56%	1.23%	0.97%
7	0.39%	0.98%	1.05%
8	0.26%	0.89%	1.38%
9	0.32%	0.89%	2.00%
High	0.11%	1.21%	3.41%
Low-high (EW)	4.11%	0.30%	-3.06%
p -value	0.000	0.670	0.000
Low-high (VW)	3.02%	0.24%	-1.21%
p -value	0.000	0.596	0.008
Annualized Sharpe ratio	1.52	0.03	-1.26
(b) Size-adjusted decile portfolios sorted on the RKR components			
Ranking	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$	$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$	$v(\theta_{it}; \bar{u}_j) - b_{it}$
Low	2.27%	1.46%	1.25%
2	1.51%	1.12%	1.12%
3	1.34%	1.13%	1.10%
4	1.42%	1.19%	0.96%
5	1.05%	1.51%	1.03%
6	1.01%	1.02%	1.00%
7	0.80%	0.97%	1.13%
8	0.77%	0.87%	1.24%
9	0.79%	0.97%	1.16%
High	0.69%	1.38%	1.63%

TABLE 10 (Continued)

(b) Size-adjusted decile portfolios sorted on the RKRV components			
Ranking	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$	$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$	$v(\theta_{it}; \bar{u}_j) - b_{it}$
Low-high (EW)	1.58%	0.08%	-0.38%
<i>p</i> -value	0.001	0.917	0.544
Low-high (VW)	0.03%	0.04%	0.40%
<i>p</i> -value	0.923	0.992	0.259
Annualized Sharpe ratio	0.90	-0.05	-0.21

To deal with potential concerns regarding the Fama–French 12-industry classification, we replicate our results by adopting the alternative Bloomberg Industry Classification System (BICS). Table A.7 provides the details of this categorization, and Table A.8 has a summary of our findings from using the BICS classification.

4.2 | The role of inflation

The consequences of several nonstandard monetary policy interventions deployed after the 2008–2009 financial crisis could interfere with the relation between inflation expectations and the 10-year Treasury yield. Therefore, we replicate our results by measuring inflation with the 1-year Consumer Price Index (CPI) inflation rate. This index estimates the realized inflation but is also closely related to inflation expectations.¹¹

Panel (a) of Table A.9 shows the results from regressing $\hat{\alpha}_k$ on the 1-year CPI inflation rate. The most affected multiple is $\hat{\alpha}_0$ for the 10-year Treasury yield case. However, the number of industries in which the inflation rate significantly affects $\hat{\alpha}_k$ is lower. The signs of the $\hat{\gamma}^{\hat{\alpha}_0}$ for each industry are the opposite of those reported in Panel (b) of Table 4. When inflation rises, the nominal interest rates go up that results in an increase in the demand for bonds; this demand reduces the short-term demand for stocks since stocks and bonds usually compete in portfolio allocations. This fall in demand for equities, which is unrelated to fundamental value, results in a compression of $\hat{\alpha}_0$ and $\hat{\gamma}^{\hat{\alpha}_0}$ that is negative. In all, the results in Table A.9 show that the 10-year Treasury yield assimilates the expected inflation.

4.3 | Short-term broad market uncertainty (VIX)

The macroeconomic variables we select to perform our empirical strategy incorporate expectations mainly related to a medium or long-term time horizon. To address potential concerns about the lack of short-term information, we reiterate our exercise with a shorter

¹¹The correlation coefficient between the 1-year CPI inflation rate and the University of Michigan inflation expectation series is 0.91 for our sample (*p*-value less than 0.001). The time-series of the Michigan inflation expectations are from <https://fred.stlouisfed.org/series/MICH>.

TABLE 11 Alphas portfolios sorted in the market-to-book components orthogonal to the term spread

This table reports the alphas from the CAPM regression of portfolio returns. The dependent variable is the monthly return of decile portfolios formed on the basis of $m_{it} - b_{it}$, $m_{it} - v(\theta_{it}; \hat{u}_{jt})$, $v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$ and $v(\theta_{it}; \bar{u}_j) - b_{it}$ in excess to the risk-free rate. The explanatory variable is the excess return to the risk-free rate on a market portfolio for which we use CRSP equal-weighted index. The risk-free rate is the 1-month Treasury bill rate. After the end of June rebalancing, equal-weighted monthly percent returns on the portfolios are calculated from July of year t to June of $t + 1$. The sample period is July 1981–June 2016. Column *Int.* contains the regression intercept, and column *p-value* reports the significance level of the related *t*-statistic. Panel (a) summarizes the results of the portfolios formed in the market-to-book components. Panel (b) summarizes the results of the portfolios formed in the market-to-book components, adjusting for size.

(a) Decile portfolios sorted on the RKR components						
Ranking	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$		$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$		$v(\theta_{it}; \bar{u}_j) - b_{it}$	
	<i>Int.</i> (%)	<i>p-value</i>	<i>Int.</i> (%)	<i>p-value</i>	<i>Int.</i> (%)	<i>p-value</i>
Low	1.97	0.000	0.59	0.000	0.30	0.013
2	0.87	0.000	0.47	0.000	0.24	0.031
3	0.56	0.000	0.46	0.000	0.26	0.009
4	0.32	0.000	0.57	0.000	0.32	0.001
5	0.19	0.035	0.50	0.000	0.32	0.000
6	0.18	0.052	0.45	0.000	0.32	0.000
7	0.19	0.052	0.43	0.000	0.41	0.000
8	0.21	0.038	0.39	0.000	0.58	0.000
9	0.22	0.037	0.24	0.023	0.73	0.000
High	0.21	0.064	0.10	0.415	0.90	0.000
Low-high	1.76		0.49		-0.60	
(b) Size-adjusted decile portfolios sorted on the RKR components						
Ranking	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$		$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$		$v(\theta_{it}; \bar{u}_j) - b_{it}$	
	<i>Int.</i> (%)	<i>p-value</i>	<i>Int.</i> (%)	<i>p-value</i>	<i>Int.</i> (%)	<i>p-value</i>
Low	0.56	0.000	0.51	0.000	0.33	0.003
2	0.38	0.000	0.28	0.004	0.40	0.000
3	0.27	0.001	0.40	0.000	0.38	0.000
4	0.30	0.000	0.37	0.000	0.45	0.000
5	0.33	0.000	0.36	0.000	0.37	0.000
6	0.32	0.000	0.26	0.004	0.36	0.000
7	0.27	0.001	0.23	0.015	0.25	0.005
8	0.21	0.015	0.23	0.025	0.16	0.083
9	0.30	0.001	0.19	0.102	0.16	0.147
High	0.36	0.000	0.08	0.554	0.10	0.482
Low-high	0.20		0.42		0.22	

TABLE 12 Alphas portfolios sorted in the market-to-book components orthogonal to the US 10-Year Treasury Yield

This table reports the alphas from the CAPM regression of portfolio returns. The dependent variable is the monthly return of decile portfolios formed on the basis of $m_{it} - b_{it}$, $m_{it} - v(\theta_{it}; \hat{u}_{jt})$, $v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$ and $v(\theta_{it}; \bar{u}_j) - b_{it}$ in excess to the risk-free rate. The explanatory variable is the excess return to the risk-free rate on a market portfolio for which we use CRSP equal-weighted index. The risk-free rate is the 1-month Treasury bill rate. After the end of June rebalancing, equal-weighted monthly percent returns on the portfolios are calculated from July of year t to June of $t + 1$. The sample period is July 1981–June 2016. Column *Int.* contains the regression intercept, and column *p-value* reports the significance level of the related *t*-statistic. Panel (a) summarizes the results of the portfolios formed in the market-to-book components. Panel (b) summarizes the results of the portfolios formed in the market-to-book components, adjusting for size.

(a) Decile portfolios sorted on the RKR components						
Ranking	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$		$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$		$v(\theta_{it}; \bar{u}_j) - b_{it}$	
	<i>Int.</i> (%)	<i>p-value</i>	<i>Int.</i> (%)	<i>p-value</i>	<i>Int.</i> (%)	<i>p-value</i>
Low	2.04	0.000	0.52	0.000	0.30	0.013
2	0.86	0.000	0.46	0.000	0.25	0.026
3	0.57	0.000	0.51	0.000	0.26	0.011
4	0.37	0.000	0.53	0.000	0.32	0.001
5	0.15	0.104	0.55	0.000	0.32	0.000
6	0.20	0.029	0.43	0.000	0.32	0.000
7	0.18	0.069	0.43	0.000	0.42	0.000
8	0.18	0.067	0.43	0.000	0.57	0.000
9	0.23	0.033	0.28	0.010	0.75	0.000
High	0.20	0.083	0.11	0.418	0.91	0.000
Low-high	1.84		0.41		-0.61	
(b) Size-adjusted decile portfolios sorted on the RKR components						
Ranking	$m_{it} - v(\theta_{it}; \hat{u}_{jt})$		$v(\theta_{it}; \hat{u}_{jt}) - v(\theta_{it}; \bar{u}_j)$		$v(\theta_{it}; \bar{u}_j) - b_{it}$	
	<i>Int.</i> (%)	<i>p-value</i>	<i>Int.</i> (%)	<i>p-value</i>	<i>Int.</i> (%)	<i>p-value</i>
Low	0.64	0.000	0.39	0.002	0.33	0.003
2	0.42	0.000	0.32	0.002	0.39	0.000
3	0.29	0.001	0.35	0.000	0.40	0.000
4	0.29	0.000	0.43	0.000	0.42	0.000
5	0.29	0.000	0.36	0.000	0.41	0.000
6	0.32	0.000	0.25	0.007	0.34	0.000
7	0.30	0.000	0.32	0.001	0.23	0.007
8	0.22	0.014	0.24	0.024	0.14	0.140
9	0.28	0.003	0.18	0.134	0.18	0.111
High	0.31	0.001	0.11	0.422	0.13	0.364
Low-high	0.33		0.27		0.19	

horizon macroproxy. We use the Cboe VIX as the barometer of the broad stock market uncertainty. This metric, measuring the 1-month implied volatility index of options on the S&P500, is closely followed by financial professionals, and its relevance in macroeconomic contexts has been established in previous research (Bloom, 2009; Corradi et al., 2013; Wang & Yen, 2017).

Panel (a) of Table A.10 shows the results from regressing $\hat{\alpha}_k$ on the VIX Index. The results across sectors suggest that the effect of the implied volatility on the fundamental multiples is not statistically significant. This evidence is due to the peculiar dynamics of the VIX index; in fact, this indicator tends to fluctuate around median values with irregular spikes in the occurrence of risk-off scenarios in the stock market. The information content of this variable peaks when the index exhibits extreme values; however, these periods have a short duration with a fairly fast reversion to median levels. This characteristic downsizes the impact of VIX on the fundamental multiples time series, especially in our investigation that is based on annual data.

4.4 | Multiple regressions

In our baseline analysis, we ran simple regressions on the macroeconomic variables. Our main objective was to highlight that valuation multiples are affected by some of these variables and that this effect varies significantly by industry. We want to keep our empirical analysis as robust and transparent as possible since most of the information carried by the macroeconomic variables overlaps and we have no interest in mining new factors. Nevertheless, as Ludvigson and Ng (2009) point out, some macroeconomic leading indexes may be latent and difficult to approximate with a few observable series. Similarly, Breeden et al. (1989) attribute the empirical failure of macroeconomic factor models to measurement issues (Breeden et al., 1989). Hence potential concerns could arise about the omission or imperfect measurement of variables that contain relevant information.

Therefore, we extend Equation (7) and run multiple regressions on a set of orthogonal factors that we extracted from a large macroeconomic data set specifically built to study the link between forecastable variations in excess bond returns and macroeconomic fundamentals¹² (Ludvigson & Ng, 2009).

As in Ludvigson and Ng (2009), we get eight common factors and label them according to the correlation¹³ of each factor with the set of macroeconomic variables. The real factor ($F1$) loads on employment and production measures but also on the indexes of capacity utilization and new manufacturing orders. The second factor ($F2$) displays a high correlation with several interest rate spreads. The third and fourth factors correlate with measures of price pressure and nominal interest rates. Factors ($F6$) and ($F7$) can be interpreted as indicators of monetary conditions, and $F5$ is a housing activity factor. The eighth factor is highly correlated with the stock market dynamics. According to the evidence from Ludvigson and Ng (2009), this factor is mainly correlated with the stock market dividend yield and with a pure market sentiment component which is unrelated to expected cash flows.

¹²Ludvigson and Ng (2009) use a dynamic factor analysis to estimate a set of common factors from a large panel of 132 measures of economic activity. These indexes are representative of broad categories of macroinformation.

¹³The labeling is based on the marginal R^2 of the regressions of each of the 132 series in the panel data set on each estimated factor for the full sample of data.

We test a multiple version of Equation (7):

$$\hat{\alpha}_{kjt} = \psi^{\alpha_k} + \gamma^{\alpha_k} F_t + u_{jt}^{\alpha_k}, \quad (10)$$

where again, the subscript k indexes the accounting variables for which the coefficient $\hat{\alpha}_k$ is estimated, and F_t is the vector of factors. As we did in the case of Equation (7), we group firms according to the Fama–French 12 industries, and within each industry we perform a time-series regression of $\hat{\alpha}_k$ on F_t . In the estimation process we select a model from a range of possible specifications that include nonlinear transformations of the factors by using the AIC criterion.

Our estimates focus on the eight selected factors, but the combination of a dynamic factor analysis applied to a large data set and a statistical criterion for choosing parsimonious models should ensure that our analysis is less dependent on a predetermined choice.

Table A.11 gives the results for the specifications with the lowest AIC criterion. The most affected multiple is $\hat{\alpha}_0$ highlighting a remarkable impact of both real growth ($F1$) and monetary policy information ($F6$ and $F7$) on the intangible portion of the market value. The realized inflation ($F3$ and $F4$) and the stock market ($F8$) factors have a meaningful effect on $\hat{\alpha}_0$ as well. This evidence is consistent with the idea that the market value portion that is unrelated to fundamentals is strongly affected either by information on real growth, nominal pressures, and market sentiment. The leverage multiple $\hat{\alpha}_4$ is also importantly affected by the real factor ($F1$), but in this case, the information on monetary policy ($F6$) becomes a relevant factors and, as we expected, the information on interest rate spreads ($F2$) becomes crucial. The five factors ($F2$, $F3$, $F4$, $F6$, and $F7$) capturing information on financial conditions, inflation, money supply, and financial market dynamics tend to exhibit a broader and pervasive effect than real factors. The monetary policy factors ($F6$ and $F7$) show a meaningful influence on sectors most exposed to business cycle swings, as *Durables*, *Manufacturing*, *Chemicals*, *Business Equipment*, *Telephone*, and *Wholesales*. This empirical evidence appears to be reasonable if we consider the upward pressure on the fundamental multiples generated by an easing on interest rates, or the widespread increase in valuations due to a market exuberance phase, especially for cyclical industries.

The five factors that are associated with a broader influence on the valuation multiples are among the critical drivers of the 10-year bucket of the US curve. Thus, we can establish a reasonable equivalence between the joint effect of the five orthogonal factors and the effect on pricing of the 10-year Treasury yield.

We repeat the portfolio sorting exercise with the market-to-book components that are based on the fundamental values that are orthogonal to the macroeconomic factors. Table A.12 shows the connection between the firm-specific error and the average size, the inverse relation between size and volatility, and the positive volatility differential between the top and bottom portfolios in the multiple regression setting. In Table A.13, we find a lower difference in excess returns between the two extreme portfolios compared to Panel (b) of Table 2, but the main finding was already there in the earlier framework. To conclude, the application of more complex, multiple regressions does not add much to the overall picture based on simple regressions.

To alternatively test the influence of macrofactors, we follow a further identification strategy centered around portfolio returns instead of firm fundamental value. Specifically, we regress the long-short monthly returns of strategies formed on the basis of log market-to-book

$m_{it} - b_{it}$ and its components—firm-specific error ($m_{it} - v(\theta_{it}; \alpha_{jt})$), sector error ($v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$), and long-run ($v(\theta_{it}; \alpha_j) - b_{it}$)—running this model:

$$r_t^{LS} = \kappa + \beta F_t + v_t, \quad (11)$$

where r_t^{LS} is the monthly return of the strategy which goes long the lowest sorted portfolio and short the highest one and F_t is the vector of factors. We perform this exercise for portfolios sorted in the market-to-book components from the RKR decomposition. Results in Table A.14 confirm that financial and inflation factors ($F3$, $F6$ and $F7$) have a wider impact with respect to real factors.

4.5 | Look-ahead bias

The adjustment for the effect of macrovariables on the three components in regression (7) relies on an estimation on the entire sample. To rule out potential concerns on look-ahead biases in the results, we perform the portfolio sorting exercise in a pure out-of-sample fashion. We split the sample into two parts, use data from 1981 to 2001 as the initial estimation sample and the remaining observations from 2001 to 2016 as the out-of-sample period. Specifically, we first estimate regression (7) and Equations (8) and (9) using data from July 1981 to June 2001; then, we obtain the first portfolio formation in July 2001. We proceed in this recursive estimation procedure, re-estimating Equations (7), (8) and (9) using all previous observations, until the end of the sample in 2016.

Tables A.15 and A.16 report risk and return characteristics of portfolios sorted on the RKR decomposition over the subsample period ranging from 2001 to 2016. Panel (a) of Table A.16 confirms that the value premium is almost entirely attributable to the firm-specific component, even if we adjust for size as in Panel (b).

Tables A.17 and A.18 give the results deriving from applying the pure out-of-sample methods to the term spread. We find a confirmation of the baseline result, a significant relationship between the mispricing component and size in panel (a) of Table A.17. When we adjust for size, we obtain a compression in Low–High differential return in panel (b) of Table A.18 compared to results in panel (b) of Table A.16. Again, the suppression of the information component relating to the macroeconomic conditions significantly affects the differential returns of the top and bottom portfolios.

4.6 | Parameter estimation error

The two-pass procedure we use to include the effect of macroeconomic variables on the firm fundamental value could raise concerns about potential parameter estimation error. To address this point, we investigate the effect of macrovariables more directly, including the firm's sensitivity to macroeconomic variables as an additional regressor in Equation (4). For this purpose, we specify an augmented version of Equation (4) as follows:

$$m_{it} = \alpha_{0jt} + \alpha_{1jt} b_{it} + \alpha_{2jt} ni_{it}^+ + \alpha_{3jt} I_{<0} \left(ni_{it}^+ \right) + \alpha_{4jt} LEV_{it} + \alpha_{5jt} \beta_{zit} + \epsilon_{it}, \quad (12)$$

where β_{zit} represents the loading of firm i at time t on the macrovariable z ¹⁴. As done in Equation (4), to estimate Equation (12), we group firms according to the Fama–French 12 industries and run 1-year cross-sectional regressions for each industry. Table A.19 reports the results deriving from running Equation (12) with the term spread and Treasury Yield. Specifically, the table shows the number of times (in percentage) in which in the cross-sectional regressions alpha5 was statistically significant. Results for the term spread and the Treasury Yield confirm the evidence we obtain from Equation (4): the industries where macroexpectations exhibit a statistically significant influence on the firm's market value overlap with the most impacted by the macroeconomic variables in Panels (a) and (b) of Table 4. This result confirms the ability of the two-pass procedure (Equations 6 and 7) to capture the heavy sector-dependent macroeffect.

5 | CONCLUSIONS

To investigate the effects of macroeconomic conditions on the value premium, we refer to the market-to-book decomposition of Rhodes-Kropf et al. (2005) (RKR) and the model specification of Golubov and Konstantinidi (2019). Our investigation complements GK by exploring the macroeconomic sector-specific effects on the RKR valuation multiples and by considering the asset pricing implications of these results. The need for a sector-based investigation is consistent with the established industry practice of estimating the fair value metrics on a sector basis. As Chang et al. (2013) point out, there is the possibility that the industry level adjustment and the fundamental variables chosen by RKR are not sufficient to capture the cross-sectional variation in the intrinsic value. However, the RKR original specification is justified, at least in part, by adopting the residual income model and a standard, nonstatistical categorization.

To incorporate the effect of macroeconomic conditions we pick a set of leading macroeconomic variables that previous studies have shown to affect the expectational, nonfundamental component of stock prices. These macroeconomic variables carry information that influences the investors' expectation on the macroeconomic scenario, thus becoming proxies for macroeconomic risk. We find that these macroeconomic variables, especially those related to term structure of interest rates, affect valuation. Moreover, the effect is very industry-specific. Therefore, while other studies recognize that the time-varying nature of the sector multiples reflects the dynamics of discount rates and growth opportunities, we take a step forward by uncovering the information content that is embedded in the panel of RKR metrics.

To explore the asset pricing consequences of these findings, we first estimate the time-varying fundamental multiples that are orthogonal to the information conveyed by the macroeconomic variables. Thus, the resulting new market-to-book components rely on a

¹⁴The β_z is the slope coefficient from regressing returns of firm i on the macroeconomic variable z according to the following time-series regression

$$r_{it} = \beta_0 + \beta_m R_{mt} + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \beta_{MOM} MOM_t + \beta_z z_t + \varepsilon_t \quad (13)$$

where r_i is the excess return over the risk-free rate for firm i , R_m is the excess return over the risk-free rate of the market portfolio, HML, SMB and MOM are the excess returns of value, size and momentum factors from the Fama–French Data Library and z is the macroeconomic variable. Estimations are performed on 24–60 monthly returns (as available) in the 5 years before June of year t .

measure of intrinsic value unaffected by macroeconomic conditions. The decile portfolios that are sorted on such orthogonal components have a clear monotonic relation between misvaluation and size. Thus, when we control for the influence of macroeconomic conditions, the value premium (about 4%) rewards in large part the size risk. In addition, when controlling for both size and macroeconomic conditions, the return spread of the lowest and highest decile portfolios significantly decreases when compared to the return difference that is obtained by using the original GK method (approximately 1.5% vs. 1.8%). This reduction in the return spread can be interpreted as the portion of the GK's misvaluation premium that is attributable to macroeconomic conditions. Overall, the firm-specific excess return is reduced when macroeconomic risk is removed from the information set; more precisely, macroeconomic risk accounts for about 17% of the full value premium.

Our evidence suggests that explanations of the value premium should fully integrate the role of macroeconomic risk. These results are also relevant for the practice of fundamental investing as they indicate the opportunity to account for the macroeconomic conditions to enhance the performance of value strategies.

ACKNOWLEDGMENT

Open Access Funding provided by Università Cattolica del Sacro Cuore within the CRUI-CARE Agreement.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from CRSP, Compustat and Bloomberg. Restrictions apply to the public availability of these data, which were used under license for this study. Data can be obtained from the corresponding author with the permission of the aforementioned third parties. The Stata code used to generate the results is available at [10.17632/63sms5tr7z.1](https://doi.org/10.17632/63sms5tr7z.1).

REFERENCES

- Ang, A., & Kristensen, D. (2012). Testing conditional factor models. *Journal of Financial Economics*, 106, 132–156.
- Banerjee, A., & Marcellino, M. (2006). Are there any reliable leading indicators for us inflation and gdp growth? *International Journal of Forecasting*, 22, 137–151.
- Bartram, S. M., & Titman, D. (2018). Agnostic fundamental analysis works. *Journal of Financial Economics*, 128(1), 125–147.
- Beaver, W., Lambert, R., & Morse, D. (1980). The information content of security prices. *Journal of Accounting and Economics*, 2, 3–28.
- Bergbrant, M. C., & Kelly, P. (2016). Macroeconomic expectations and the size, value, and momentum factors. *Financial Management*, 45(4), 809–844.
- Bianchi, D., Guidolin, M., & Ravazzolo, F. (2017). Macroeconomic factors strike back: A Bayesian change-point model of time-varying risk exposures and premia in the U.S. cross-section. *Journal of Business & Economic Statistics*, 35(1), 110–129.
- Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77(3), 623–685.
- Breeden, D. T., Gibbons, M., & Litzenberger, R. (1989). Empirical tests of the consumption-oriented capm. *The Journal of Finance*, 44(2), 118–173.
- Campbell, J. Y. (1989). Forecasts of economic growth from the bond and stock markets. *Financial Analysts Journal*, 45(5), 38–45.

- Campbell, J. Y., & Vuolteenaho, T. (2004). Bad beta, good beta. *The American Economic Review*, 94(5), 1249–1275.
- Chang, E. C., Luo, Y., & Ren, J. (2013). Pricing deviation, misvaluation comovement, and macroeconomic conditions. *Journal of Banking & Finance*, 37(12), 5285–5299.
- Chen, N., Roll, R., & Ross, S. A. (2004). Economic forces and the stock market. *The Journal of Business*, 59(3), 383–403.
- Chen, S. (2009). Predicting the bear stock market: Macroeconomic variables as leading indicators. *Journal of Banking & Finance*, 33(2), 221–223.
- Choi, J. (2013). What drives the value premium? The role of asset risk and leverage. *Review of Financial Studies*, 26(11), 2845–2875.
- Cochrane, J. H. (1996). A cross-sectional test of an investment-based asset pricing model. *Journal of Political Economy*, 104(3), 572–621.
- Cohen, R. B., Polk, C., & Vuolteenaho, T. (2003). The value spread. *The Journal of Finance*, 58(2), 609–642.
- Corradi, V., Distaso, W., & Mele, A. (2013). Macroeconomic determinants of stock volatility and volatility premiums. *Journal of Monetary Economics*, 60(2), 203–220.
- Davis, J. L., Fama, E. F., & French, K. R. (2000). Characteristics, covariances, and average returns: 1929 to 1997. *The Journal of Finance*, 55(1), 389–406.
- De Bondt, W. M. F., & Thaler, R. (1985). Does the stock market overreact. *The Journal of Finance*, 40(3), 793–805.
- Dong, M., Hirshleifer, D., Richardson, S., & Teoh, S. H. (2006). Does investor misvaluation drive the takeover market? *The Journal of Finance*, 61(2), 725–762.
- Doukas, J. A., & Han, X. (2021). Sentiment-scaled capm and market mispricing. *European Financial Management*, 27(2), 208–243.
- Easton, P., Harris, T., & Ohlson, J. (1992). Aggregate accounting earnings can explain most of security returns: The case of long-event Windows. *Journal of Accounting and Economics*, 15, 119–142.
- Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2), 427–465.
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33, 3–56.
- Fama, E. F., & French, K. R. (1995). Size and book-to-market factors in earnings and returns. *The Journal of Finance*, 50(1), 131–155.
- Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, 51(1), 55–84.
- Fama, E. F., & French, K. R. (2008). Average returns, b/m, and share issues. *The Journal of Finance*, 63(6), 2971–2995.
- Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116, 1–22.
- Fama, E. F., & French, K. R. (2020). *The value premium*. Fama-Miller Working Paper, 20.1.
- Flannery, M. J., & Protopapadakis, A. A. (2002). Macroeconomic factors do influence aggregate stock returns. *The Review of Financial Studies*, 15, 751–782.
- Gerakos, J., & Linnainmaa, J. T. (2018). Decomposing value. *The Review of Financial Studies*, 31, 1825–1854.
- Golubov, A., & Konstantinidi, T. (2019). Where is the risk in value? Evidence from a market-to-book decomposition. *The Journal of Finance*, 74(6), 3135–3186.
- Hahn, J., & Lee, H. (2006). Yield spreads as alternative risk factors for size and book-to-market. *The Journal of Financial and Quantitative Analysis*, 41(2), 245–269.
- Haubrich, J., & Dombrosky, A. M. (1996). Predicting real growth using the yield curve. *Economic Review*, 32, 26–35.
- Hertzel, M., & Li, Z. (2010). Behavioral and rational explanations of stock price performance around seos: Evidence from a decomposition of market-to-book ratios. *Journal of Financial and Quantitative Analysis*, 45, 935–958.
- Hwang, S., & Rubesam, A. (2013). A behavioral explanation of the value anomaly based on time-varying return reversals. *Journal of Banking & Finance*, 37, 2367–2377.
- Ilmanen, A. (1995). *Market's rate expectations and forward rates (understanding the yield curve, part 2)*. Fixed-Income Research, Salomon Brothers.

- Jaffe, J. F., Jindra, J., Pedersen, D. J., & Voetmann, T. (2020). Can mispricing explain the value premium? *Financial Management*, 49(3), 615–633.
- Koenig, E. F. (2002). Using the purchasing managers' index to assess the economy's strength and the likely direction of monetary policy. *Economic and Financial Policy Review*, 1(6), 1–14.
- Kothari, S., & Sloan, R. (1992). Information in prices about future earnings: Implications for earnings response coefficients. *Journal of Accounting and Economics*, 15, 143–171.
- Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *The Journal of Finance*, 49(5), 1541–1578.
- Lee, C. M. C., Myers, J., & Swaminathan, B. (1999). Does investor misvaluation drive the takeover market? *The Journal of Finance*, 61(2), 725–762.
- Ludvigson, C. S., & Ng, S. (2009). Macro factors in bond risk premia. *The Review of Financial Studies*, 22(12), 5027–5067.
- Maloney, T., & Moskowitz, T. J. (2021). Value and interest rates: Are rates to blame for value's torments? *The Journal of Portfolio Management*, 47(6), 65–87.
- Mele, A. (2021). *Financial Economics. Classics & Contemporary*. MIT Press.
- Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108, 1–28.
- Obreja, I. (2013). Book-to-market equity, financial leverage, and the cross-section of stock returns. *Review of Financial Studies*, 26, 1146–1189.
- Petkova, R. (2006). Do the Fama-French factors proxy for innovations in predictive variables? *The Journal of Finance*, 61(2), 581–612.
- Rhodes-Kropf, M. D., Robinson, T., & Viswanathan, S. (2005). Valuation waves and merger activity: The empirical evidence. *Journal of Financial Economics*, 77, 561–603.
- Shumway, T. (1997). The delisting bias in crsp data. *The Journal of Finance*, 52(1), 327–340.
- Wang, F., Yan, X. S., & Zheng, L. (2020). Time-series and cross-sectional momentum in anomaly returns. *European Financial Management*, 27(4), 736–771.
- Wang, Y., & Yen, K. (2017). Macroeconomic determinants of stock volatility and volatility premiums. *European Financial Management*, 25(2), 380–406.
- Zhang, L. (2005). The value premium. *The Journal of Finance*, 60(1), 67–103.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Beccalli, E., Doninelli, N., & Orsini, C. (2023). Value premium and macroeconomic variables. *European Financial Management*, 29, 1336–1374.
<https://doi.org/10.1111/eufm.12397>