Strategies Can Be Expensive Too! The Value Spread and Asset Allocation in Global Equity Markets

Adam Zaremba

Poznan University of Economics and Business, Poland

University of Dubai, UAE

adam.zaremba@ue.poznan.pl

Mehmet Umutlu

Department of International Trade and Finance

Yasar University, Turkey

mehmet.umutlu@yasar.edu.tr

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Abstract

Is the value spread useful for forecasting returns on quantitative equity strategies for country selection? To test this, we examine a sample of 120 country-level equity strategies replicated within 72 stock markets for the years 1996–2017. The value spread is a powerful and robust predictor of strategy returns in the cross-section, subsuming other methods based on momentum, reversal, or seasonality. Going long (short) the strategies with the broadest (narrowest) value spread produces significant four-factor model alphas, markedly outperforming an equal-weighted benchmark of all of the strategies. The results are robust to many considerations.

Keywords: value spread, country-level anomalies, country-selection strategies, asset allocation, asset pricing, international investment, return predictability, equity anomalies, the cross-section of returns.

JEL-codes: G12, G15.

1. Introduction

The finance literature includes reports of the preponderance of equity anomalies that have been discovered. The papers of Green, Hand, and Zhang (2016), Harvey, Liu, and Zhu (2016), Hou, Xue, and Zhang (2017), and Jacobs and Müller (2017) review hundreds of return-predictive signals that help to find the most promising equities. In addition, many of these return patterns also exist in other asset classes, including bonds, commodities, and currencies (Asness, Moskowitz, and Pedersen 2013, Asness, Ilmanen, Israel, and Moskowitz 2016, Keloharju, Linnainmaa, and Nyberg 2016, Koijen, Moskowitz, Pedersen, and Vrugt 2016). Importantly, many of these patterns also work well in the cross-section of country returns (Zaremba and Andreu 2018) so today, in the world of exchange-traded funds (ETFs), these anomalies could be efficiently used to allocate money across various international equity markets.

Alas, the large number of country asset allocation anomalies poses another challenge: how can an investor pick the best strategies from so many factors? The anomaly returns are certainly not stable through time; some of the anomalies lose profitability temporarily and many of them tend to vanish altogether (McLean and Pontiff 2016, Jacobs and Müller 2017). So how can we choose the most promising anomalies? The finance literature offers us a few tools. Avramov, Cheng, Schreiber, and Shemer (2017) show that the strategies with the best (worst) performance in the previous month continue to overperform (underperform). Zaremba and Szyszka (2016) and Ehsani (2017) document that this anomaly-level momentum effect also extends to longer periods. Arnott, Beck, and Kalesnik (2016) argue that the quantitative strategies also display a long-run reversal in returns. Keloharju, Linnainmaa, and Nyberg (2016) document that the phenomenon of cross-sectional seasonality in stock market anomalies—the strategies that produced high (low) returns in the same calendar month in the past—continue to perform well (poorly) in the future. In this research, we aim to extend the array of the strategy-rotation approaches with a new tool—the value spread.

The value spread of a long-short anomaly portfolio is the difference in valuation ratios between the long and the short sides of the trade (Cohen, Polk, and Vuolteenaho 2003). Put simply, it can be intuitively understood as a measure of how cheap or expensive a given strategy currently is. So far, the value spread has been examined predominantly either for prediction of the aggregate market return (Liu and Zhang 2008), or to forecast the performance of the value versus growth strategy (Asness, Friedman, Krail, and Liew 2000, Cohen, Polk, and Vuolteenaho 2003, Ilmanen, Nielsen, and Chandra 2015). In the latter application, in essence, it shows how much cheaper the value stocks are in comparison to the growth stocks. Also, Michou (2009) tested the value spread for its ability to indicate the future performance of small and large companies. We significantly extend this approach, showing that the value spread can be used to select the future winners from a broad array of strategies which could be used for country asset allocation.

Summing up, the major aim of this paper is to examine the usefulness of the value spread as a tool for selecting strategies for international country asset allocation. To this end, we first develop a sample of 120 quantitative country selection strategies, replicating anomalies in individual equities. We perform our examinations within a sample of 72 country indices for the period 1996 to 2017. We start with cross-sectional tests, to examine the predictive power of the value spread through future returns in the cross-section. Subsequently, we form long-short portfolios of anomalies that go long (short) in the country-level anomalies with the widest (narrowest) value spread and we evaluate the portfolio performance with various models.

This study contributes in a few ways. First, we add to the literature on the applications of the value spread. So far, it has been used almost solely for predicting either entire stock market profitability (Liu and Zhang 2008) or the profitability of the value investing strategy (Asness, Friedman, Krail, and Liew 2000, Cohen, Polk, and Vuolteenaho 2003, Ilmanen, Nielsen, and Chandra 2015). We show it could be efficiently used as a tool for active rotation among various strategies.

Second, we extend the array of return patterns in the cross-section of anomaly returns. In addition to the previously documented immediate momentum (Avramov, Cheng, Schreiber, and Shemer 2017), long-term momentum (Zaremba and Szyszka 2016, Ehsani 2017), long-run reversal (Arnott, Beck, and Kalesnik 2016), and cross-sectional seasonality (Keloharju, Linnainmaa, and Nyberg 2016), the difference in valuation of various sides of the trade is an independent and powerful predictor of future anomaly returns.

Last, but not least, we bring all of these considerations to a new global level. Previous studies on anomaly selection (e.g., Avramov, Cheng, Schreiber, and Shemer 2017, Zaremba and Szyszka 2016, Arnott, Beck, and Kalesnik 2016, Keloharju, Linnainmaa, and Nyberg 2016) concentrated on implementation in individual stocks. As far as we know, this is the first comprehensive examination of approaches for picking country-level equity allocation strategies, which could be easily implemented with, for instance, ETFs or liquid future contracts.

The basic results of our investigations can be summarized as follows. First, the value spread is a strong predictor of future returns in the cross-section. It holds for various portfolio specification and returns measurement methods. The value spread plays a significant role in future returns, even after controlling for other known return predictive signals such as short-, medium-, and long-term past returns, as well as cross-sectional seasonality. Second, forming a portfolio of country allocation strategies that go long (short) the strategies with the broadest (smallest) value spreads delivers significant positive raw and abnormal returns, outperforming an equal-weighted benchmark of all of the anomalies considered. The country-level anomalies with the widest spreads outperform the strategies with the narrowest spreads, providing a monthly four-factor alpha of 0.35%–0.62%, depending on the portfolio construction methods. The results are robust to various considerations, including subsample and subperiod analysis, alternative weighting and portfolio construction methods, long-only versus long-short portfolio, as well as implementation in the ETF universe. They are also not subsumed by any other strategy-picking methods.

The remainder of the study is organized as follows. Section 2 presents data sources and research methods used in this study. This also includes the detailed description of the estimation of the value spread, the cross-sectional tests and time-series portfolio examinations, as well as an outline of robustness checks. Section 3 describes the results of our research. Finally, Section 4 concludes the paper.

2. Data and Methods

In this research, we conduct cross-sectional and time-series tests to examine the practical predictive abilities of the value spread. In this section, we first describe the data sources and the preparation of the sample of country-level anomalies. Subsequently, we present our definition of the value spread, and the tests used to evaluate its performance. Finally, we outline the robustness checks applied in this paper.

2.1. Data

This research is based on data from the Bloomberg database. We perform our examinations within a sample of 72 equity indices calculated by MSCI. We use monthly observations from the period April 1996 to April 2017.[1] We include an index in the sample in

[1] Our study period of returns is limited by data availability. Importantly, we also use earlier data when it is necessary for the calculation of some strategies, for instance, past returns for price-based variables (e.g., reversal or momentum).

month *t* when we are able to obtain its return in month *t* and total market value at the end of *t*-1. An overview of the sample is presented in Table 1.

[Insert Table 1 here]

We collect initial data in local currencies and subsequently convert them to U.S. dollars to form a pooled sample. To remain consistent with the U.S. dollar framework, we proxy the risk-free rate in all of our calculations with the one-month treasury bill rate.[2]

Numerous retur predictive variables strategies tested in this paper rely on country-level financial ratios and fundamental variables. To calculate these, we weight the accounting and price data of the relevant companies according to the index weighting scheme, and subsequently compute the necessary ratios.[3]

2.2. The Sample of Country-Level Strategies

To test the predictive power of the anomalies, in the first step, we develop a sample of country-level strategies. Our study is based on a sample of 120 individual international equity strategies. To avoid any arbitrariness in the anomaly selection, we closely follow the approach of Zaremba and Andreu (2018), replicating precisely the same anomalies with identical portfolio formation procedures. Zaremba and Andreu (2018) perform a replication of 120 equity strategies at the level of single-country indices. Their selection is predominantly motivated by earlier review studies, e.g., Hou, Xue, and Zhang (2017) and Jacobs and Müller (2017), but also imposes some additional screens on these anomalies. For instance, they require the anomaly strategies to be computable using data from standard databases, such as Bloomberg, with data that could be transformed to the country level with the use of one-way sorts. The full list of the examined anomalies is presented in Table 2, and the details of the

[2] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[3] The country-level ratios are obtained directly by Bloomberg. Moreover, when a variable is based on accounting data, to compute return in month *t*, we use data from month *t*-5 so as to avoid look-ahead bias.

implementation procedures are provided in Table A1 of the online Appendix. The 120 anomalies fall into nine major categories based on the underlying economic rationales: value versus growth, momentum, quality, investment, liquidity, skewness and extreme risk, low-risk, reversal, and seasonality.

The formation procedure of the anomaly portfolios is identical for all of the anomalies. To obtain a return in month *t*, we sort all the equity indices on anomaly-related return-predicting variables at the end of month *t*-1 and, subsequently, we determine the 25th and 75th percentiles which are used as breakpoints. Next, we use all the country indices from the top and bottom quartiles of the rankings to form equal-weighted portfolios. Finally, we build monthly-rebalanced long-short zero-investment portfolios, assuming a long (short) position in the portfolio with higher (lower) expected returns based on the available earlier empirical evidence.

In line with the findings of Zaremba and Andreu (2018), we document that only 30 anomalies (25% of the sample) deliver significant and positive means of returns; 75% of the strategies fail in this replication exercise. Again, the detailed results are displayed in Table 2.

2.3. The Value Spread

In this paper, we examine the predictive power of the value spread for the future returns on the country-level long-short anomaly portfolios. The economic intuition behind the value spread is relatively straightforward. There is lot of theoretical and empirical evidence that valuation ratios are indicative of future returns: stocks with high fundamental-to-price ratios tend to outperform stocks with low fundamental-to-price ratios.[4] Hence, in a given long-short portfolio, the spread between the long and short sides of the trade should be indicative of the future long-short portfolio performance, expressing the relative valuation of the long and short potfolios. The exisiting empirical research, which focuses primarily on the value versus growth

[4] A review of evidence and theoretical explanations can be found, for instance, in Zaremba and Shemer (2016).

strategy, generally supports these concepts (Asness, Friedman, Krail, and Liew 2000, Cohen, Polk, and Vuolteenaho 2003, Ilmanen, Nielsen, and Chandra 2015).

In line with these considerations, our conjecture is that the expected return on a given strategy is high when the long side of the trade is attractively priced (or cheap) in comparison with the short side of the trade. What we call a value spread is the measure that we use to evaluate the degree of the cheapness of the long side relative to the short side. We define it as the difference between valuation ratios of the long and short sides of the zero-investment anomaly portfolio. A high difference indicates that the long portfolio is attractively priced compared to the short portfolio, thus, predicting high future returns. Analogously, a low difference forecasts poor performance of a given strategy.

The earlier studies examining the usefulness of the value spread vary in terms of both calculation techniques and underlying valuation ratios. Regarding the calculation techniques, two alternative approaches are commonly used. The first technique is to use the difference in valuation ratio breakpoints, or percentiles used to form the quantile portfolios. For example, Kim (2012) computes the value spread as the difference between the 15th and 85th percentiles of E/P ratios. The alternative approach, employed for instance by Ilmanen, Nielsen, and Chandra (2015), is to use the weighted average valuations of the long and short sides of the portfolio. In this paper, we opt for the latter method because by using data on all of the stocks in the portfolios instead of the breakpoint values only, it provides a more comprehensive and precise measure of relative valuations.

The second key to methodological choice is the valuation ratio to be used. The earlier studies employ an array of measures including earnings-to-price ratio, book-to-market ratio, operating cash flow-to-enterprise value ratio, or sales-to-enterprise value ratios (e.g., Cohen, Polk, and Vuolteenaho 2003, Lu and Zhang 2008, Kim 2012, Ilmanen, Nielsen, and Chandra 2015). In this study, we employ the EBITDA-to-enterprise value ratio (*EBEV*) as our primary measure. Our basic motivation is that among various popular valuation measures, the *EBEV* ratio has been found to be the best predictor of future returns (Gray and Vogel 2012), and its dominance has been confirmed in both U.S. and international markets (Loughran and Wellman 2011, Gray and Carliste 2012, Walkshäusl and Sebastian 2015, Crawford, Gray, Vogel, and Xu 2017). Importantly, also at the index level the *EBEV* seems to be the most reliable of the well-known valuation variables used for country equity selection (Zaremba and Shemer 2016, Zaremba and Andreu 2018): the high *EBEV* countries significantly outperform the low *EBEV* countries. Nonetheless, to evaluate robustness, we also examine a broad range of alternative valuation measures that we discuss in detail in the subsection devoted to the robustness checks.

To sum up, in our baseline approach we calculate the value spread used to predict the anomaly returns in month *t* using the following formula:

$$VS_t = \sum_{a=1}^{n} w_{a,t-1}^{L} EBEV_{a,t-1}^{L} - \sum_{b=1}^{m} w_{b,t-1}^{S} EBEV_{b,t-1}^{S}, \qquad (1)$$

where VS_t is the value spread of a given long-short anomaly portfolio for month *t*; superscripts *L* and *S* denote the securities in the n-component long and m-component short sides of the portfolio, respectively; $w_{a,t-1}^{l}$ ($w_{b,t-1}^{s}$) is the weight of the country index *a* (*b*) in the portfolio *L* (*S*) at the end of month $t-1$; and $EBEV_{a,t-1}^{L}$ ($EBEV_{b,t-1}^{S}$) is the *EBEV* ratio of the index *a* (*b*) in the portfolio *L* (*S*) at the end of month $t-1$.

The time-series average values of the value spread measures are reported in the last column of Table 2. Not surprisingly, the VS_t tends to be particularly high for the value strategies (Panel A). On the other hand, for momentum (Panel B) and quality (Panel C) long-short portfolios oftenwise display negative strategies, pointing out that they are tilted towards highly priced equity markets.

2.4. Cross-Sectional Tests

We start our investigation of the predictive abilities of the value spreads with standard cross-sectional monthly regressions following those of Fama-MacBeth (1973):

$$R_{i,t} = \beta_{0,t} + \sum_{j=1}^{J} \beta_{j,t} K_{i,j,t-1} + \varepsilon_{i,t}, \quad (2)$$

where $R_{i,t}$ is the return on an anomaly portfolio i in month t, and $\beta_{0,t}$ and $\beta_{j,t}$ are regression parameters. Our basic return predictor $K_{i,j,t-1}$ is the value spread VS_t, as defined as in equation (1). Nonetheless, to isolate the predictive abilities of the value spreads, we also control for other variables that have been proved to be useful for forecasting the returns on investment strategies and equity anomalies. Avramov, Cheng, Schreiber, and Shemer (2017) found the previous month's return on equity anomalies helps to predict their performance. Zaremba and Szyszka (2016) showed that the classical momentum effect, based on annual returns, could also be applicable. Arnott, Beck, and Kalesnik (2016) suggested the existence of long-run reversals in quantitative strategies. Finally, Keloharju, Linnainmaa, and Nyberg (2016) found that the effect of cross-sectional seasonality is also present in the equity anomalies—the anomalies that performed well (poorly) on average in the same calendar month in the past, continue to overperform (underperform) in the future. Motivated by these studies, we closely follow their methodological approach and include four additional control variables: $StMom_{i,t}$—the anomaly return in month t-1; $LtMom_{i,t}$—the average anomaly return in month t-12 to t-2; $LtRev_{i,t}$—the average anomaly return in month t-60 to t-12; and $SeasMom_{i,t}$—the average anomaly return in the same calendar month during the past trailing 20 years.

As an additional robustness check, we follow Avramov, Cheng, Schreiber, and Shemer (2017) and also apply the Fama-MacBeth regressions to the four-factor model-adjusted returns. To this end, applying the four-factor model of Carhart (1997), we calculate benchmark-adjusted returns based on the procedure used in Jacobs (2015, p. 69, equation [1]) and substitute them for $R_{i,t}$ in equation (2). The details of the implementation of the four-factor model are presented in the next subsection.

2.5. Time-Series Tests

Having documented the basic cross-sectional relationships in the first pass, we continue with examining whether they can be translated into profitable strategies by forming one-way portfolios. Thus, each month we sort the country-level anomaly portfolios on their value spreads. Subsequently, we calculate long-short quintile portfolios that are long (short) in the quantile of anomalies with the highest (lowest) value spreads. The quantile portfolios include 20% of the anomaly portfolios available in a given month, which amounts to approximately 24 strategies on average. The portfolios are reviewed and rebalanced on a monthly basis.

To control for the interactions between the value spread and other variables that were reported to have predictive abilities over anomaly returns, we also calculate portfolios from two-way sorts. Hence, we sort the anomalies independently on the value spread (*VS*) and four alternative variables described in the previous section: *IMom*, *LtMom*, *LtRev*, and *SeasMom,* and determine the 33rd and 66th percentiles. The intersection of both independent sorts produces nine portfolios that are subsequently further investigated.

To evaluate the risk-adjusted performance of the portfolios of anomalies from single and double sorts, we apply two different models. The first model is the four-factor model of Carhart (1997). The regression equations in this model represent the relationship between excess returns and four factors:

$$R_t = \alpha_{4F} + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD_t + \varepsilon_t, \tag{3}$$

Where R_t is the return on a long-short portfolio of anomalies; $\beta_{MKT,i}$, $\beta_{SMB,i}$, $\beta_{HML,i}$, $\beta_{UMD,i}$, and $\alpha_{4F,i}$ are the model's estimated parameters—$\beta_{MKT,i}$, $\beta_{SMB,i}$, $\beta_{HML,i}$, and $\beta_{UMD,i}$ are measures of exposure to MKT_t (market risk), SMB_t (small minus big), HML_t (high minus low), and UMD_t (up minus down), respectively, whereas α_{4Fi} represents the average abnormal return; and $\varepsilon_{i,t}$ is the error term. The four factors in the model represent the returns of a market portfolio and the payoffs on well-established size, value, and momentum strategies. In order to be consistent with our study of country equity indices, we closely follow Zaremba (2015) to calculate the asset pricing factors on the basis of indices instead of individual equities. The details of this procedure are reported in Table A2 in the Appendix, and the basic statistical properties of the factor returns are displayed in Table A3 in the Appendix.

The second model that we employ is an ad-hoc benchmark model. In this approach, we are interested in seeing whether our anomaly-selection strategies based on value spreads outperform an equal-weighted portfolio of all of the anomalies that we consider:

$$R_t = \alpha_{B,i} + \beta_{BEN} BEN_t + \varepsilon_{i,t}, \tag{4}$$

where BEN_t is the return on the benchmark, or the equal-weighted portfolio of all of the anomalies considered in the study, which can also be interpreted as a sort of market portfolio in the universe of country-level strategies.[5] Again, β_{BEN} and α_B are regression parameters, analogous to equation (3). The details of the implementation and the performance of the *BEN* factor are presented also in Tables A2 and A3 of the Appendix. In the evaluations with models (3) and (4), we are particularly interested in seeing whether our anomaly-picking strategies deliver abnormal returns, i.e., whether α_{4F} and α_B differ significantly from zero.

2.6. Further Robustness Checks

To assure the validity of our results, we conduct a battery of additional robustness tests. The checks are applied at various stages of our research.

Alternative breakpoints in individual strategy portfolios. Our default approach assumes forming long-short individual strategy portfolios based on quartiles (25% of the equity markets). For robustness, we also test portfolios based on 20% and 30% of the equity indices.

[5] The individual anomaly portfolios included in the benchmark are always identical to the ones constituting the tested one-way or two-way sorted portfolios. For instance, if we implement some robustness checks with the use of alternative breakpoints or weighting methods, the benchmark portfolio is always formed consistently.

Equal-weighted versus value-weighted portfolios. In addition to the equally-weighted anomaly portfolios, we also test capitalization-weighted strategies.

Long-short versus long-only portfolios. Long-short portfolios capture the cross-sectional patterns very well. Nevertheless, their applicability may be reduced in cases of constrained liquidity and limited short-sale availability, even in the more realistic approach of capitalization-weighting. Also, Stambaugh, Yu, and Yuan (2012) indicate that anomalous returns tend to be stronger on the short side of the trade. Therefore, we also examine the performance of portfolios of long-only versions of these anomalies, selecting them by valuation of the long-leg only.

Alternative breakpoints in portfolios of multiple anomalies. Our basic approach assumes forming long-short quintile portfolios of anomalies (approximately 24 strategies). For robustness, we also test portfolios of 12 strategies (10% breakpoint) and 36 strategies (30% breakpoint).

Insignificant versus significant anomalies. In our basic approach, we use all of the 120 strategies in our examinations. This method aims to avoid look-ahead bias because investors ex-ante are not sure which strategies will prove successful. It also allows us to avoid arbitrariness in the selection of the sample of strategies, as this set of 120 anomalies stems from an external paper by Zaremba and Andreu (2018). Nonetheless, for robustness, we limit our scope only to the anomalies that displayed significant and positive returns in Table 2 and replicate our tests within this subsample.

Exclusion value anomalies. The value anomalies – by their nature – are characterized by a large value spread. Hence, we examine also the anomaly selection strategies within a narrowed sample excluding value anomalies (Group 1: Value in Table 2, anomalies [1]-[13]) from the research sample.

Alternative valuation measures. Besides the default *EBEV* ratio serving as a basis for the value spread estimation, we examine an array of alternative valuation ratios: earnings-to-price (*EP*), book-to-market (*BM*), cash flow-to-price (*CFP*), sales-to-price (*SP*), sales-to-enterprise value (*SEV*), EBITDA-to-price (*EBP*), dividend yield (*DY*), gross profit-to-enterprise value (*GPEV*). Subsequently, we compute the value spread using an adapted version of formula (1) and replicate our tests.

Index-based versus ETF-based portfolios. We replicate our tests within a sample of iShares single country exchange-traded funds (ETFs). We regard this sample as more realistic, thus providing a better investor perspective. The drawback of this approach is that the ETF sample covers 42 equity markets, mostly developed and big emerging ones, and frequently displays shorter time series. The description of the ETF sample is provided in Table A4 of the Appendix.

Performance within subsamples. As mentioned earlier, to assure that the value spread strategy works not only in full sample, but also in the subsamples, we examine two-way sorts on the value spread and the *IMom*, *LtMom*, *LtRev*, and *SeasMom* variables. To form the subsamples, we use measures that were found to predict future returns because we want to make sure that the value spreads contain unique information not captured by the other variables.

Performance within subperiods. We examine the performance of our basic value spread-based long-short portfolio anomalies within various subperiods of the full research period. First, Davis (1994) and Loughran (1997), among others, find that the valuation-based strategies may be influenced by the January effect; they have disappointing returns in January. Thus, we test the performance in January and non-January months separately. Second, Jacobs (2015) suggests that the effect of an aggregate measure of market-wide limits on arbitrage may influence anomaly payoff profits. Following this concept, we examine the performance within periods of low and high arbitrage constraints. We use four different measures of limits on arbitrage which were employed previously in studies by Jacobs (2015), among others: (a) the CBOE Volatility Index (*VIX*), which expresses the implied volatility of short-term index options on the SandP 500 Index; (b) BAA spread (*Credit*), i.e., the difference between the yield on U.S. corporate bonds with BAA ratings and the 10-year maturing U.S. treasury bond; (c) term spread (*Term*), i.e., the difference between the yields on U.S. 10-year and 2-year benchmark treasury bonds; and (d) TED spread (*TED*), calculated as the difference between the 3-month US$ LIBOR and the 3-month U.S. benchmark T-Bill rate.[6] For each of the variables, we determine the median value. Subsequently, we examine the performance of our strategy separately in the subperiods when the *VIX*, *Credit*, *Term*, and *TED* variables were above and below the long-term median at the end of *t*-1.[7]

Third, the behavioral finance view on market anomalies is that they are driven by investor irrationality that could not be quickly arbitraged away. Thus, besides the limits on arbitrage, the second major pillar of the behavioral explanation is investor sentiment (see Stambaugh, Yu, and Yuan, 2012). Hence, we examine the performance of the value-spread portfolios of high and low investor sentiment. Our base measure of the market-wide sentiment is the Baker and Wurgler (2006) sentiment index (*BW*).[8] For robustness, we follow Jacobs (2015) and also use two alternative measures: the Index of Consumer Expectations computed by the University of Michigan (*MICE*) and the Conference Board Consumer Confidence Index (*CBCC*). Again, we use the same procedure as for the limits on arbitrage to determine the periods of above-median and below-median market-wide sentiment.[9]

[6]TED spread is calculated as the difference between the 3-month US$ LIBOR and the 3-month U.S. benchmark T-Bill rate. All the data are obtained from Bloomberg.

[7] Naturally, this approach cannot be used directly as an asset allocation strategy because we do not know *ex-ante* the median values. Nonetheless, it provides a general picture of the behavior of the momentum strategy.

[8] The data are retrieved from the website of Jeffrey Wurgler: http://people.stern.nyu.edu/jwurgler/.

[9] All data are sourced from Bloomberg. For further information on *CBCC*, see: https://www.conference-board.org/data/coansumerconfidence.cfm; for *MICE*: http://www.sca.isr.umich.edu/. Regarding the U.S. nature of our data, see footnote 7 regarding the limits on arbitrage.

Fourth, Cooper, Gutierrez, and Hameed (2004) suggest that anomaly payoffs may differ in periods following bear and bull markets. Drawing on this research, we examine the usefulness of value spreads in these two types of subperiod. Consistent with Cooper, Gutierrez, and Hameed (2004), for month *t*, we define the bull (bear) markets as having a positive (negative) mean return during the preceding 36-month period.

3. Results

In this section, we start with the description of the cross-sectional relations between the value spread and future anomaly returns. Next, we uncover the performance of the portfolios of strategies from sorts on the value spread.

3.1. Basic Cross-Sectional Relations

Table 3 reports the results of simple regressions following Fama and MacBeth (1973) of returns on the value spreads. For robustness, we report the outcomes for both equal-weighted and capitalization-weighted portfolios. Also, we test variants based on three different breakpoints: 20%, 25%, and 30%, as well as applying the regressions to both raw returns and the four-factor model-adjusted returns. The evidence is unequivocal: the value spreads are strongly linked to future returns. The predictive power of the value spread is robust to alternative weighting-schemes, return measurement approaches, and portfolio formation techniques. The relation explains, on average, 7.9% to 19.3% of the cross-sectional variation in the next-month returns, depending on the particular methodological choice.[10]

[Insert Table 3 here]

[10] Because our baseline approach for the calculation of the value spread relies on *EBEV*, we replicate the Fama-Macbeth regressions based on model-adjusted returns (Panel B) with the HML factor calculated based on *EBEV* instead of *BM*. The results were qualitatively consistent and the *t*-statistics corresponding to the regressions coefficients are in the range of 1.708 – 1.919 (2.725 – 2.810) for the equal-weighted (value-weighted) portfolios.

Table 4 provides additional insights into the cross-sectional relations between the future returns and the value spread. In this case, we control for other variables predicting anomaly performance that have previously been documented in the literature: short-term and long-term momentum, long-term reversal, and cross-sectional seasonality. For brevity, we limit the presentation to our basic approach (raw returns on equal-weighted quartile portfolios), because the alternative approaches display no qualitative difference. The predictive power of the value spread is significant after controlling for any single other return predictive variable (specifications [2] to [4]), as well as after controlling for all of the variables together (specification [6]). Interestingly, apart from the long-run momentum effect, no other variable is confirmed as a significant predictor of future returns. Even the cross-sectional seasonality, which has been found by Keloharju, Linnainmaa, and Nyberg (2016) to be a very strong return pattern, turns out to be unimportant. Only the sorts on the mean return in months *t*-12 to *t*-2 remain significant when considered jointly with the value spreads. This observation matches with the findings of Asness, Moskowitz, and Pedersen (2013), which suggest that value and momentum are two truly ubiquitous cross-sectional patterns in returns.

[Insert Table 4]

3.2. Performance of Portfolios of Strategies

Having documented the cross-sectional patterns in returns, we test whether they can be translated into profits via equity portfolios. Table 5 shows the monthly returns on the one-way sorted portfolio of the long-short anomalies. Consistent with the evidence in Tables 3 and 4, the portfolios of anomalies with the broadest value spreads markedly outperform the strategies with the narrowest value spreads. In consequence, the mean returns on the portfolios going long the top anomalies and short the bottom anomalies are positive, significant, and vary from 0.60% to 0.95% (Panel A of Table 5). Furthermore, the elevated returns remain significant after controlling for the factors of Carhart's (1997) model, although admittedly the *T-B* portfolios display significant *SMB* and *HML* exposures (Panel B of Table 5).[11] Finally, Panel C of Table 5 displays the results of the application of the benchmark model. The portfolios of anomalies with the widest spreads appears to show slightly higher exposure than those with the narrowest spreads. Nevertheless, the difference is not very large, and the *T-B* portfolios reveal no significant benchmark exposure. In consequence, even in the benchmark model, the long-short portfolios of anomalies produce significant abnormal returns that range from 0.58% to 0.83% per month.[12]

[Insert Table 5 here]

Table 6 presents the results of the robustness tests for the anomaly-picking strategies by examining portfolios formed using alternative methods. In specifications I and II, the equal-weighted quintile portfolios of anomalies were formed using anomalies based on alternative breakpoints: 20% and 30%. These modifications do not affect the results qualitatively; the anomalies with the broadest value spreads outperform the anomalies with the narrowest value spreads. The mean returns on the *T-B* portfolio amount to 0.74–0.78% and the abnormal returns adjusted for the four-factor model (benchmark model) equal 0.46–0.47% (0.66–0.74%). Specification III shows the results for the capitalization-weighted portfolios. These may be regarded as more realistic from the investors' perspective because more liquid stocks are

[11] Our default calculation method of the value spread relies on *EBEV*, so we replicate the evaluations of the portfolios from one-way sorts with the four-factor model where the *HML* factor is calculated based on *EBEV* instead of *BM.* Theoretically, the *EBEV*-based *HML* fator should better explain the returns on one-way sorted portfolios of anomalies, effectively decreasing the alphas and their significance. The results are qualitatively consistent; the alphas are lower, though, still positive and significantly different from zero. The alphas on the *T-B* portfolios formed of 12, 24, and 36 strategies amount to 0.25%, 0.29%, and 0.37%, respectively, with the corresponding *t*-statistic of 1.98, 1.78, amd 1.82, respectively.

[12] Avramov, Chordia, Jostova, and Philipov (2012) and Zaremba (2016) argue that also the credit risk is a priced factor at the global level. Thus, for robustness, we extend the four-factor and menchmark models with the additional risky minus safe (RMS) factor. The RMS factor represents the sovereign spread and is formed using identical technique as the HML portfolio, but the book-to-market ratio is replaced with a credit risk measure. Following Zaremba (2016), the credit risk is proxied by the Economist Intelligence Unit Sovereign Risk measures sourced from Bloomberg. The examination of the portfolios with these augmented five-factor and two-factor models displays no qualitative changes. For brevity, we report it Table A5 of the Online Appendix.

overweighted in this approach. Yet the outperformance of the anomalies with the largest value spreads is even larger, with the average return amounting to 1.15%, and remains significant after adjusting for the factor models. Furthermore, specification IV shows an even more realistic approach by focusing on only the long side of these anomaly portfolios. However, even if the *T-B* portfolios deliver abnormal and significant returns with this technique, the returns are noticeably lower. The alphas from the four-factor (benchmark) model equal to 0.33% (0.43%) per month. Finally, specification V limits our consideration to only those anomalies that display significant means of monthly returns in Table 2. This operation also noticeably decreases the abnormal returns by about half, compared to our basic approach. The decline may result from the lower cross-sectional dispersion of payoffs in the more limited sample and, thus, lower profit opportunities. Nevertheless, the anomalies with the broadest spreads still outperform the anomalies with the smallest spreads by a significant monthly raw (abnormal) return of 0.35% (0.27–0.47%). Eventually, specification VI exhibits the results of the tests conducted within a narrowed sample of anomalies that excludes the value anomalies. Notably, the results are not qualitatively different from our baseline outcomes, and the *T-B* portfolios yields an average monthly return (four-factor model alpha) of 0.63% (0.40%) with the corresponding *t*-statistic of 3.62 (2.27).

[Insert Table 6 here]

Table 7 displays a set of additional robustness checks. In this approach, we use alternative valuation measures to calculate the value spreads obtained from equation (1). We use a variety of ratios including *EP*, *BM*, *CFP*, *SP*, *SEV*, *EBP*, *DY*, and *GPEV*. The bird's-eye view on the outcomes confirms that our results hold not only for the spreads based on *EBEV*, but also for those based on several different definitions.

[Insert Table 7 here]

When we consider the means of raw monthly returns on the long-short portfolios of anomalies, in all cases the values are positive and significant. Nonetheless, the profitability of these ratios is not equal; so, indeed, some of them perform better than others. The worst performers are multiples based on sales: the *SP* and *SEV*. For these two ratios, the means of raw returns are low but still significant, amounting to 0.33–0.38%. However, after adjusting for the four-factor model, the payoffs decrease by about half and lose their significance (although the alphas from the benchmark model are still significant, indicating that the strategies still outperform an equal-weighted portfolio of all the anomalies). All the remaining valuation multiples display significant means and alphas, with the top performance being the *GPEV*. For this variable, the mean return equals 0.73% monthly, and the alpha from the four-factor (benchmark) model amounts to 0.50% (0.59%). This observation matches the findings of Cakici, Chatterjee, and Tang (2017), who also found the *GPEV* a particularly reliable predictor of general equity returns.

So far, we have discussed the results implemented within the universe of single-country equity indices. This approach provides a broad and comprehensive international sample, but may be regarded as not fully realistic because not all of the countries are covered by easily accessible liquid futures or index funds. Furthermore, there may be some discrepancy between the returns on these instruments and the underlying equity indices. Therefore, we replicate our basic tests associated with Table 3 within the universe of single country-iShares ETF administered by BlackRock. The outcomes of this exercise are shown in Table 8.

[Insert Table 8 here]

Our ETF data are more limited regarding time and geographical coverage, and exclude the least efficient countries. Nonetheless, the anomaly picking strategies continue to work very well. The anomalies with the broadest value spreads still overperform, leading to high returns on the *T-B* portfolios. These long-short portfolios of anomalies based on ETFs produced significant and positive raw and factor-adjusted returns. The means of returns ranged from 0.56% to 0.72% (*t*-statistics from 3.22 to 3.80) and the abnormal returns from the four-factor (benchmark) model amounted to 0.35–0.49% (0.66–0.83%). Summing up, the value spread-based strategies passet practicality tests employing ETFs very well.

Besides alternative anomaly and portfolio construction and implementation methods, we test the performance of the anomaly-picking strategy based on value spreads within various subsections of the entire universe. Specifically, we examine the performance within subsamples of anomalies from sorts on *IMom*, *LtMom*, *LtRev*, and *SeasMom* to see whether, even after controlling for the influence of these variables, the value spreads retain their predictive abilities. This exercise is linked to the examinations with the multiple Fama-MacBeth (1973) regressions in Table 3, but reveals a more practical flavor.

[Insert Table 9 here]

The outcomes in Table 9 confirm the evidence from the Fama-MacBeth regressions. The portfolios formed on value spreads still deliver an impressive performance, both in the full sample, as well as in the subsamples. Literally, in each of the subsamples tested in Table 9, the broad value spreads guaranteed a superior performance. This is reflected in significant and positive raw returns and alphas from the four-factor model on the long-short portfolios of anomalies implemented within the subsamples. Regardless of the past returns during 1, 12, or 60 months, or the average payoffs in the same calendar month in the past, the value spread-based strategy always worked well, delivering high returns.

Finally, having conducted the subsample analysis, we re-examine the performance of our basic anomaly picking strategy (equal-weighted quartile portfolios of anomalies) within subperiods. Table 10 reports the means of returns and alphas within various subperiods. We divide the full sample using various indicators to assure the validity of our results.

[Insert Table 10 here]

The consideration of various measures of limits on arbitrage (*VIX*, *credit*, *term*, *TED*) does not exert a clear influence on the results. The raw and abnormal returns are positive and significant during the periods of both above-median and below-median limits on arbitrage. The accounting for the sentiment index computed by Baker and Wurgler (2006) leads to the conclusion that the best performance is observable during periods of high market-wide sentiment. For instance, the means of raw returns amount to 1.13% in the high investor sentiment months, and to an insignificant 0.42% in the low sentiment months. This observation supports the hypothesis of Stambaugh et al. (2012), who suggest that behavioral biases driving the regularities in equity returns are particularly pronounced in high sentiment periods. Nonetheless, the other indicators do not confirm these results, so they should be treated with caution.

When we consider performance in various calendar months, we find that the seasonal anomalies also seem to play a role for the performance of the value spread-based strategy. The payoffs are clearly higher in January (R = 1.21%, t-stat = 3.51) than in the other months (R = 0.31%, t-stat = 1.30). This observation is consistent with the arguments of Davis (1994) or Loughran (1997) that the value-related strategies overperform in January.

The bear and bull markets do not seem to have much influence on the performance of the value spread-based approach. The raw and abnormal returns are approximately equal following periods of both long-run price increases and declines. Hence, it appears that the arguments raised by Cooper, Gutierrez, and Hameed (2004) regarding the momentum effect do not play a significant role for value.

4. Concluding Remarks

In this study, we have offered and evaluated a new application of the value spread as a tool for the selection of country asset allocation strategies. The breadth of the value spread can predict the future returns in the cross-section. We show that equity strategies with a wide value spread markedly outperform strategies with a narrow value spread. In other words, if you wonder which strategy might produce decent payoffs in the future, pay attention to the value spread.

Our results not only provide additional insights into asset pricing, but they have a direct practical implication. Besides momentum or seasonality in anomalies, we offer a new strategy rotation approach. Focusing on the strategies with the broadest value spreads and standing off the techniques with narrow value spreads delivers significant and robust abnormal returns.

Future research on the topics discussed in this paper could be pursued in at least two directions. First, the value-related strategies have their parallels in many other asset classes, including bonds, currencies, and commodities (Asness et al., 2013). It would be interesting to see whether the value spread approach could be "transferred" to these investment venues. Second, our spread approach could also be extended to other fundamental measures that help to predict future returns such as profitability or investment. Perhaps constructing a "profitability spread" or an "investment spread" would also help to identify winning strategies.

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Tables

Table 1

Descriptive Statistics of Country Equity Markets

Country	R	Vol	Skew	Kurt	N	Country	R	Vol	Skew	Kurt	N
Argentina	1.19	11.91	0.23	2.40	220	Malaysia	0.89	6.22	0.88	5.73	220
Australia	0.70	6.12	-0.49	1.44	252	Mauritius	1.48	6.62	-0.26	5.21	179
Austria	0.40	7.55	-0.75	3.54	252	Mexico	0.92	7.50	-0.71	2.39	252
Bahrain	-1.23	6.73	-0.70	2.92	135	Morocco	0.39	5.44	0.32	1.33	220
Bangladesh	0.32	7.28	-0.64	2.82	89	Netherlands	0.57	5.93	-0.75	1.74	252
Belgium	0.55	6.18	-1.38	6.13	252	New Zealand	0.54	6.45	-0.41	0.81	252
Brazil	1.31	10.74	-0.01	0.88	220	Nigeria	0.11	7.50	-0.58	0.74	91
Bulgaria	-0.47	9.73	-0.64	5.10	143	Norway	0.67	7.69	-0.68	2.52	252
Canada	0.69	5.93	-0.64	2.38	252	Oman	0.03	5.63	-1.20	4.95	143
Chile	0.78	6.22	-0.30	1.69	220	Pakistan	1.64	8.45	-1.19	7.58	179
China	0.55	9.68	0.52	3.42	252	Peru	1.45	8.26	-0.26	1.42	220
Colombia	1.43	9.13	-0.13	0.43	220	Philippines	0.65	7.23	-0.03	0.63	220
Croatia	0.67	7.68	0.36	3.55	179	Poland	0.81	9.57	-0.10	0.59	220
Czech Republic	1.15	8.11	0.00	1.10	220	Portugal	0.26	6.55	-0.40	0.75	252
Denmark	0.96	5.84	-0.61	1.99	252	Qatar	0.48	7.81	-0.44	1.90	135
Egypt	1.30	9.89	0.29	1.84	252	Romania	0.86	11.07	-0.71	3.94	137
Estonia	1.11	8.90	0.38	6.16	179	Russia	1.69	11.43	0.62	3.41	220
Finland	1.07	9.14	0.01	1.52	252	Saudi Arabia	-1.86	12.22	0.06	-1.00	28
France	0.56	5.92	-0.43	0.76	252	Serbia	-0.55	12.76	-0.18	4.72	107
Germany	0.63	6.74	-0.47	1.51	252	Singapore	0.42	7.38	-0.16	2.34	252
Greece	-0.23	10.88	-0.29	0.97	252	Slovenia	0.45	6.74	-0.05	1.89	179
Hong Kong	0.62	7.09	0.06	2.81	252	South Africa	1.01	7.41	-0.34	0.18	220
Hungary	0.86	9.82	-0.46	1.81	220	Spain	0.75	7.13	-0.25	0.97	252
India	0.89	8.49	0.04	0.93	252	Sri.Lanka	1.26	9.53	1.93	9.54	179
Indonesia	1.55	10.45	0.17	1.72	220	Sweden	0.87	7.37	-0.21	1.54	252
Ireland	0.15	6.48	-0.81	1.87	252	Switzerland	0.58	4.78	-0.46	0.76	252
Israel	0.59	6.62	-0.15	1.39	220	Taiwan	0.56	7.48	0.19	0.92	220
Italy	0.37	6.90	-0.15	0.35	252	Thailand	1.18	9.08	0.21	3.05	220
Japan	0.00	5.16	0.04	0.11	252	Trinidad and Tobago	0.44	3.01	0.24	1.89	101
Jordan	0.30	5.62	0.05	2.47	220	Tunisia	0.51	5.00	0.61	4.01	155
Kazakhstan	1.19	13.92	3.40	22.10	137	Turkey	1.51	14.08	0.56	2.99	220
Kenya	1.88	7.97	-0.17	2.51	179	UEA	0.29	10.30	0.06	1.28	143
Korea	1.15	8.92	0.27	0.80	220	UK	0.39	4.61	-0.36	1.35	252
Kuwait	-0.07	6.45	-0.05	1.09	135	Ukraine	-1.37	12.23	-0.19	0.95	131
Latvia	0.21	6.13	0.02	0.32	74	USA	0.59	4.37	-0.63	1.01	252
Lebanon	0.89	8.29	1.42	6.81	179	Vietnam	0.38	11.09	1.13	4.37	125
Lithuania	0.56	7.76	1.72	14.25	107						

Note. The table presents the performance of the country equity markets examined in this study based on MSCI indices. *R* is the averege monthly excess return over risk-free rate, *Vol* is the standard deviation of monthly excess returns, *Skew* denotes the skewness, *Kurt* denotes the kurtosis, and *N* indicates the number of monthly observations.

Table 2

The Anomaly Portfolios

No.	Strategy	R	*t*-stat	$\overline{VS}$
	Panel A: Value			
1	Earnings-to-price ratio	0.18	*(0.85)*	0.123
2	Book-to-market ratio	0.34	*(1.22)*	0.180
3	Cash flow-to-price ratio	0.56***	*(2.89)*	0.187
4	Free cash flow yield	0.57***	*(2.82)*	0.137
5	Sales-to-price ratio	0.61***	*(2.69)*	0.183
6	EBITDA-to-EV ratio	0.79***	*(3.65)*	0.251
7	Sales-to-EV ratio	0.71***	*(3.76)*	0.205
8	EBITDA-to-price ratio	0.67***	*(2.79)*	0.224
9	Gross profit-to-EV ratio	0.84***	*(2.74)*	0.292
10	Gross profit-to-market equity ratio	0.55*	*(1.86)*	0.273
11	Assets-to-market ratio ratio	0.19	*(0.98)*	0.099
12	5-year sales growth	0.11	*(0.67)*	-0.093
13	Dividend yield	0.13	*(0.65)*	0.027
	Panel B: Momentum			
14	Short-term momentum	0.40	*(1.44)*	-0.016
15	Long-term momentum	0.65***	*(2.68)*	-0.015
16	Intermediate momentum	0.65***	*(3.15)*	0.000
17	Return consistency-enhanced momentum	-0.09	*(-0.29)*	-0.017
18	Risk-adjusted momentum	0.47**	*(1.98)*	-0.002
19	Momentum acceleration	0.06	*(0.30)*	-0.001
20	6-month moving average (ratio)	0.35	*(1.35)*	-0.016
21	12-month moving average (ratio)	0.57*	*(1.95)*	-0.032
22	52-week high (ratio)	0.40	*(1.34)*	-0.025
23	Lagged 52-week high (ratio)	0.21	*(0.72)*	-0.004
24	Residual momentum (CAPM)	0.32	*(1.53)*	-0.010
25	Residual momentum (three-factor model)	0.15	*(0.67)*	-0.008
26	Residual momentum (five-factor model)	0.00	*(0.01)*	-0.001
27	Volatility-adjusted residual momentum (CAPM)	0.17	*(0.78)*	-0.007
28	Volatility-adjusted residual momentum (three-factor model)	0.15	*(0.69)*	-0.005
29	Volatility-adjusted residual momentum (five-factor model)	0.14	*(0.67)*	-0.021
30	Alpha momentum (CAPM)	0.13	*(0.55)*	-0.028
31	Alpha momentum (three-factor model)	-0.03	*(-0.05)*	-0.023
32	Alpha momentum (five-factor model)	-0.17	*(-0.70)*	-0.016
33	Returns signal momentum	0.48**	*(2.21)*	-0.022
34	Skewness-enhanced momentum	0.42*	*(1.84)*	-0.015
	Panel C: Quality			
35	Change in dividend yield	-0.22	*(-1.05)*	-0.015
36	Change in absolute dividends	-0.19	*(-1.12)*	-0.072
37	Return on assets	0.12	*(0.57)*	-0.009
38	Change of ROA	0.14	*(0.73)*	-0.068
39	Return on equity	0.07	*(0.33)*	-0.070

No.	Strategy	R	*t*-stat	$\overline{VS}$
	Panel C continued			
63	Cash flow-to-debt ratio	0.52**	*(2.48)*	0.104
64	EBITDA-to-debt ratio	0.59***	*(3.07)*	0.166
65	Sales growth (1 year)	0.03	*(0.02)*	0.094
66	Net debt-to-capitalization value ratio	0.27	*(1.30)*	0.026
67	Balance sheet leverage	0.27	*(1.08)*	0.121
68	Earnings surprise	-0.35	*(-1.63)*	-0.102
69	Revenue surprise	-0.13	*(-0.62)*	-0.146
	Panel D: Investment			
70	Asset growth	0.35*	*(1.80)*	-0.073
71	Hiring rate	0.21	*(1.24)*	0.095
72	Capital investments	-0.20	*(-0.67)*	-0.113
73	Investment change (1 year)	-0.01	*(0.05)*	-0.036
74	Investment change (2 years)	-0.11	*(-0.49)*	0.021
75	Investment change (3 years)	0.28	*(1.07)*	0.060
76	Composite equity issuance	-0.19	*(-0.81)*	0.000
77	Change in common shareholder equity	0.16	*(0.93)*	-0.064
78	Abnormal capital expenditures	-0.20	*(-0.86)*	-0.038
	Panel E: Liquidity			
79	Turnover	0.58***	*(2.65)*	0.126
80	Turnover ratio	0.34	*(1.48)*	0.118
81	Turnover ratio variability	0.53**	*(2.11)*	0.154
82	Turnover variability	0.38	*(1.43)*	0.080
83	Amihud measure	0.44**	*(2.13)*	0.125
84	Annual turnover	0.29	*(1.23)*	0.117
85	Total market capitalization	0.50**	*(2.47)*	0.117
	Panel F: Low-Risk			
86	Beta	-0.10	*(-0.27)*	-0.020
87	Volatilty	-0.44	*(-1.55)*	-0.041
88	Oil beta	-0.36	*(-1.52)*	-0.026
89	Idiosyncratic volatility (CAPM)	-0.15	*(-0.63)*	-0.051
90	Idiosyncratic volatility (three-factor model)	-0.18	*(-0.85)*	-0.040
91	Idiosyncratic volatility (four-factor model)	-0.22	*(-1.01)*	-0.040
92	Idiosyncratic volatility (five-factor model)	-0.16	*(-0.72)*	-0.042
93	Idiosyncratic volatility (model-free)	-0.12	*(-0.57)*	-0.042
94	Dispersion	-0.22	*(-1.06)*	-0.048
95	Range	-0.26	*(-0.84)*	-0.086
96	Systematic volatility	0.04	*(0.14)*	-0.018
97	Downside beta	-0.29	*(-1.12)*	0.000
98	Exposure to idiosyncratic volatility (CAPM)	-0.11	*(-0.44)*	0.009
99	Exposure to idiosyncratic volatility (three-factor model)	0.03	*(0.22)*	0.008
100	Exposure to idiosyncratic volatility (model free)	-0.13	*(-0.52)*	-0.007

40	Change of ROE	0.26	*(1.44)*	-0.052	101	Exposure to dispersion	-0.13	*(-0.62)*	0.015
41	Cash flow-to-assets ratio	0.47***	*(2.75)*	0.138		*Panel G: Reversal*			
42	Gross profit-to-assets ratio	0.70***	*(2.64)*	0.255	102	Long-term reversal (36 months)	-0.19	*(-0.75)*	0.020
43	Gross margin	0.26	*(0.72)*	-0.029	103	Long-term reversal (48 months)	-0.18	*(-0.92)*	0.023
44	Profit margin	-0.20	*(-0.89)*	-0.037	104	Long-term reversal (60 months)	0.01	*(0.06)*	0.034
45	Change in profit margin	0.06	*(0.39)*	-0.056	105	Short-term reversal	-0.24	*(-1.03)*	0.015
46	Asset turnover	0.46**	*(2.06)*	0.149	106	Stock-reversal month (*t*-13) to (*t*-18)	0.40*	*(1.77)*	0.013
47	Change in asset turnover	-0.01	*(-0.20)*	-0.010		*Panel H: Seasonality*			
48	Gross margin growth minus sales growth	0.17	*(0.37)*	-0.054	107	Seasonality momentum (5 years)	0.10	*(0.51)*	-0.017
49	Earnings volatility	0.50**	*(2.38)*	0.131	108	Seasonality momentum (20 years)	0.20	*(0.82)*	-0.010
50	Cash flow volatility	0.38*	*(1.86)*	0.185	109	The other January effect	0.18	*(0.81)*	0.002
51	Leverage	-0.07	*(-0.29)*	0.042		*Panel I: Skewness and Extreme Risk*			
52	Change in leverage	0.35**	*(2.11)*	-0.026	110	Total skewness	0.31*	*(1.70)*	-0.040
53	Cash holdings	0.17	*(1.03)*	0.027	111	Systematic skewness	-0.03	*(-0.12)*	0.027
54	Sales-to-cash ratio	0.40**	*(2.05)*	0.133	112	Idiosyncratic skewness (CAPM)	-0.02	*(-0.19)*	-0.025
55	Current ratio	-0.24	*(-1.38)*	0.021	113	Idiosyncratic skewness (three-factor model)	-0.06	*(-0.51)*	-0.017
56	Change in current ratio	-0.18	*(-1.00)*	-0.028	114	Idiosyncratic skewness (four-factor model)	-0.06	*(-0.32)*	-0.004
57	Operating accruals	0.40**	*(2.03)*	0.127	115	Idiosyncratic skewness (five-factor model)	0.00	*(-0.10)*	-0.017
58	Total accruals	0.23	*(0.87)*	0.095	116	Downside volatility	0.21	*(0.72)*	-0.034
59	Percent operating accruals	0.22	*(1.04)*	0.108	117	Value at risk	0.06	*(0.31)*	0.000
60	Percent total accruals	0.32	*(1.27)*	0.116	118	Kurtosis	0.21	*(1.24)*	-0.008
61	Net operating assets growth	0.24	*(1.18)*	0.023	119	Maximum daily return	-0.31	*(-1.11)*	-0.072
62	Net operating assets change	0.02	*(0.11)*	0.048	120	Minimum daily return	-0.34	*(-1.10)*	-0.051

Note. This table presents the average monthly returns on the long-short equal-weighted quartile portfolios of MSCI country equity indices. *No.* is the running number. *Strategy* is the symbol of a strategy utilized used in the article. *R* indicates the average monthly return on the long-short anomaly portfolio and the values in parentheses are bootstrap *t*-statistics. $\overline{VS}$ denotes the time-series average of the value spread for the individual anomalies. Asterisks *, **, and *** indicate values that are significantly different from zero at the 10%, 5%, and 1% levels, respectively. The description of the individual strategies, along with the source literature and implementation detailes, is presented in Table A1 in the Online Appendix. The sample of anomalies is sourced from Zaremba and Andreu (2018).

Table 3

Result of the Simple Fama-MacBeth Regressions

	Equal-weighted portfolios			Capitalization-weighted portfolios		
	20%-breakpoint	25%-breakpoint	30%-breakpoint	20%-breakpoint	25%-breakpoint	30%-breakpoint
Panel A: Raw returns						
β_1	0.054***	0.057***	0.057***	0.097***	0.098***	0.102***
	(2.819)	*(2.890)*	*(2.801)*	*(3.707)*	*(3.546)*	*(3.393)*
R^2	0.118	0.124	0.129	0.164	0.177	0.193
Panel B: Four-factor model-adjusted returns						
β_1	0.024*	0.024*	0.022	0.043**	0.044**	0.047**
	(1.793)	*(1.803)*	*(1.585)*	*(2.164)*	*(2.164)*	*(2.137)*
R^2	0.079	0.080	0.082	0.115	0.118	0.128

Note. This table presents the simple monthly regressions following Fama and MacBeth (1973), with corresponding *t*-statistics applied to returns on anomaly portfolios listed in Table 2 and Table A1 in the Appendix:

$$R_{i,t} = \beta_{0,t} + \beta_{1,t}K_{i,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is the return on the long-short anomaly portfolio *i* in month *t*, and $\beta_{0,t}$ and $\beta_{1,t}$ are regression parameters. In this simple regression, we use only one predictor $K_{i,t-1}$: the value spread of the long-short anomaly portfolio based on *EBEV* (EBITDA-to-enterprise value ratio). The present values are average $\beta_{1,t}$ coefficients, whereas the values in parentheses are corresponding *t*-statistics. R^2 are average cross-sectional coefficients of determination. Asterisks *, **, and *** indicate values significantly different from zero at the 10%, 5%, and 1% levels, respectively. Panel A displays the results of the Fama-MacBeth regressions applied to raw returns, whereas Panel B concentrates on the regressions applied to abnormal returns from the four-factor model.

Table 4

Results of the Multiple Fama-MacBeth Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
VS	0.057***	0.070***	0.066***	0.052***	0.051***	0.056***
	(2.890)	*(4.073)*	*(3.690)*	*(2.741)*	*(2.715)*	*(3.565)*
IMom		0.077				-0.106
		(1.501)				*(-1.812)*
LtMom			0.109*			0.231***
			(1.739)			*(3.191)*
LtRev				-0.098		0.011
				(-0.760)		*(0.114)*
SeasMom					0.016	0.023
					(0.357)	*(0.605)*
R^2	0.124	0.281	0.279	0.257	0.211	0.504

Note. This table presents the monthly multiple regressions following Fama and MacBeth (1973), with corresponding *t*-statistics applied to raw returns on anomaly portfolios listed in Table 2 and Table A1 in the Appendix:

$$R_{i,t} = \beta_{0,t} + \sum_{j=1}^{J} \beta_{j,t} K_{i,j,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is the return on the long-short anomaly portfolio *i* in month *t*, and $\beta_{0,t}$ and $\beta_{j,t}$ are regression parameters. We consider five return predictors $K_{i,j,t-1}$: the value spread of the long-short anomaly portfolio based on the EBITDA-to-enterprise value ratio (*VS*), immediate momentum, i.e., the return in month *t*-1 (*IMom*), long-term momentum, i.e., the average return in months *t*-12 to *t*-2 (*LtMom*), long-run reversal, i.e., the cumulative return in months *t*-60 to *t*-13 (*LtRev*), and seasonality momentum, i.e., the average return in the same calendar month in the previous trailing 20 years, as available (*SeasMom*). The reported values are average $\beta_{j,t}$ coefficients, whereas the values in parentheses are corresponding *t*-statistics. R^2 are average cross-sectional coefficients of determination. Asterisks *, **, and *** indicate values significantly different from zero at the 10%, 5%, and 1% levels, respectively.

Table 5

Performance of the One-Way Sorted Portfolios of Country-Level Strategies

	12 strategies (10%)			24 strategies (20%)			36 strategies (30%)		
	Bottom	Top	T-B	Bottom	Top	T-B	Bottom	Top	T-B
				Panel A: Basic statistics					
R	-0.25**	0.71***	0.95***	-0.21*	0.55***	0.76***	-0.14	0.46***	0.60***
	(-1.97)	*(4.94)*	*(3.94)*	*(-1.96)*	*(4.96)*	*(3.84)*	*(-1.59)*	*(4.86)*	*(3.70)*
Vol	2.42	2.49	4.46	2.01	2.00	3.68	1.73	1.74	3.13
				Panel B: Four-factor model					
α_{4F}	-0.09	0.52***	0.62***	-0.07	0.38***	0.45**	-0.02	0.33***	0.35**
	(-0.81)	*(4.36)*	*(2.74)*	*(-0.68)*	*(4.22)*	*(2.53)*	*(-0.27)*	*(3.99)*	*(2.31)*
MKT	-0.14***	-0.01	0.13*	-0.11***	-0.02	0.09*	-0.09***	-0.03	0.07
	(-3.69)	*(-0.33)*	*(1.94)*	*(-4.16)*	*(-0.49)*	*(1.75)*	*(-4.60)*	*(-1.06)*	*(1.63)*
SMB	-0.29***	0.33***	0.62***	-0.22***	0.29***	0.51***	-0.16***	0.24***	0.41***
	(-6.09)	*(6.13)*	*(6.50)*	*(-6.90)*	*(6.41)*	*(7.16)*	*(-6.60)*	*(5.90)*	*(7.07)*
HML	-0.24***	0.32***	0.57***	-0.21***	0.28***	0.48***	-0.18***	0.26***	0.44***
	(-7.86)	*(4.03)*	*(5.50)*	*(-7.22)*	*(5.26)*	*(6.87)*	*(-7.69)*	*(6.74)*	*(8.17)*
UMD	0.08	0.02	-0.06	0.11***	0.05	-0.07	0.12***	0.06*	-0.06
	(1.53)	*(0.46)*	*(-0.66)*	*(2.92)*	*(1.23)*	*(-0.97)*	*(3.53)*	*(1.71)*	*(-1.05)*
R^2	0.402	0.303	0.393	0.437	0.342	0.410	0.466	0.358	0.427
				Panel C: Benchmark model					
α_B	-0.33**	0.50***	0.83***	-0.34***	0.37***	0.71***	-0.29**	0.29***	0.58***
	(-2.07)	*(3.58)*	*(2.92)*	*(-2.62)*	*(3.09)*	*(3.01)*	*(-2.55)*	*(2.71)*	*(2.70)*
BEN	0.48*	1.24***	0.75	0.79***	1.08***	0.29	0.87***	1.02***	0.16
	(1.76)	*(3.27)*	*(1.27)*	*(2.99)*	*(3.42)*	*(0.51)*	*(3.61)*	*(3.88)*	*(0.31)*
R^2	0.016	0.119	0.010	0.072	0.142	-0.001	0.122	0.167	-0.003

Note. This table presents the monthly returns on the portfolios of equal-weighted country-level anomalies based on MSCI single-country indices. *Top* (*Bottom*) is the portfolio of the anomalies that display the highest (lowest) value spread calculated based on *EBEV* (EBITDA-to-enterprise value ratio). *T-B* is the portfolio that is long (short) in the *Top* (*Bottom*) anomaly portfolio. We present three variants of the quantile portfolios based on 10% (12 anomalies), 20% (24 anomalies), and 30% (36 anomalies) of the anomalies. Panel A displays the basic portfolio statistics: *R* is the mean monthly return, and *Vol* is the monthly standard deviation of returns. Panel B shows the coefficient estimates of the the four-factor model of Carhart (1997): *MKT* (market portfolio), *SMB* (small minus big), *HML* (high minus low), *UMD* (up minus down), and α_{4F} (alpha, or the intercept from the model). Panel C presents the coefficient estimates of the ad-hoc benchmark model: *BEN* (benchmark coefficient) and α_B (alpha from the model). The values in parentheses are bootstrap (for *R*) and Newey-West (1987) adjusted (for α_{F4} and α_B) *t*-statistics. Means, volatilities, and intercepts are expressed in%. The symbols *, **, and *** indicate values significantly different from zero at the 10%, 5%, and 1% levels, respectively.

Table 6

One-Way Sorted Portfolios of Country-Level Strategies—Alternative Formation Techniques

	Anomaly portfolios formed based on 20%-breakpoint			Anomaly portfolios formed based on 30%-breakpoint			Capitalization-weighted anomaly portfolios			Long-only anomaly portfolios			Significant anomalies only			Value anomalies excluded		
	Bottom	Top	T-B	Bottom	Top	T-B	Bottom	Top	T-B	Bottom	Top	T-B	Bottom	Top	T-B	Bottom	Top	T-B
	(I)			(II)			(III)			(IV)			(V)			(VI)		
Panel A: Basic characteristics																		
R	-0.20*	0.59***	0.78***	-0.23**	0.51***	0.74***	-0.52***	0.63***	1.15***	0.32	0.91**	0.59***	0.43***	0.77***	0.35*	0.42***	-0.22*	0.63***
	(-1.78)	*(4.92)*	*(3.81)*	*(-2.39)*	*(4.82)*	*(4.05)*	*(-3.27)*	*(4.03)*	*(3.83)*	*(1.07)*	*(2.38)*	*(3.69)*	*(2.73)*	*(5.20)*	*(1.78)*	*(4.36)*	*(-1.96)*	*(3.62)*
Vol	2.18	2.22	4.02	1.82	1.90	3.41	2.74	2.55	5.00	4.66	5.96	2.69	2.47	2.68	4.14	1.75	2.05	3.38
SR	-0.31	0.92	0.67	-0.44	0.93	0.75	-0.65	0.86	0.79	0.24	0.53	0.77	0.60	1.00	0.29	0.83	-0.36	0.65
Panel B: Four-factor model																		
α_{4F}	-0.05	0.42***	0.47**	-0.10	0.36***	0.46***	-0.31**	0.37**	0.69***	-0.20**	0.14	0.33**	0.30***	0.57***	0.27*	0.31***	-0.09	0.40**
	(-0.44)	*(4.07)*	*(2.45)*	*(-1.10)*	*(4.42)*	*(2.85)*	*(-2.42)*	*(2.56)*	*(2.63)*	*(-2.34)*	*(1.28)*	*(2.50)*	*(2.59)*	*(4.43)*	*(1.74)*	*(3.62)*	*(-0.82)*	*(2.27)*
MKT	-0.11***	-0.02	0.09	-0.09***	-0.02	0.08	-0.19***	0.05*	0.24***	1.00***	1.13***	0.13***	-0.02	-0.04	-0.02	-0.02	-0.11***	0.10**
	(-3.87)	*(-0.63)*	*(1.54)*	*(-4.08)*	*(-0.52)*	*(1.50)*	*(-6.26)*	*(1.80)*	*(4.38)*	*(44.51)*	*(44.67)*	*(4.42)*	*(-0.60)*	*(-0.98)*	*(-0.33)*	*(-0.60)*	*(-4.22)*	*(2.05)*
SMB	-0.22***	0.31***	0.52***	-0.21***	0.28***	0.49***	-0.29***	0.32***	0.62***	0.10***	0.41***	0.32***	0.01	0.32***	0.31***	0.29***	-0.22***	0.51***
	(-5.86)	*(5.32)*	*(6.42)*	*(-7.46)*	*(6.68)*	*(7.87)*	*(-6.66)*	*(7.19)*	*(8.28)*	*(2.73)*	*(9.61)*	*(6.85)*	*(0.22)*	*(5.64)*	*(4.13)*	*(6.79)*	*(-6.38)*	*(7.35)*
HML	-0.22***	0.31***	0.53***	-0.19***	0.26***	0.45***	-0.23***	0.34***	0.57***	-0.01	0.33***	0.34***	-0.10***	0.40***	0.49***	0.18***	-0.21***	0.39***
	(-7.52)	*(5.80)*	*(7.03)*	*(-7.47)*	*(5.20)*	*(7.19)*	*(-4.93)*	*(9.60)*	*(8.03)*	*(-0.22)*	*(8.03)*	*(10.06)*	*(-3.22)*	*(5.21)*	*(5.90)*	*(5.46)*	*(-7.31)*	*(7.33)*
UMD	0.12***	0.04	-0.08	0.10***	0.04	-0.06	0.15***	0.02	-0.13	0.08***	0.04	-0.04	0.37***	0.02	-0.36***	0.09***	0.12***	-0.03
	(3.01)	*(0.91)*	*(-1.16)*	*(3.01)*	*(1.11)*	*(-0.92)*	*(2.82)*	*(0.32)*	*(-1.31)*	*(2.76)*	*(0.74)*	*(-0.75)*	*(8.91)*	*(0.33)*	*(-4.59)*	*(2.70)*	*(3.03)*	*(-0.40)*
R^2	0.415	0.336	0.398	0.444	0.342	0.418	0.421	0.360	0.408	0.930	0.909	0.426	0.461	0.343	0.433	0.281	0.450	0.368
Panel C: Benchmark model																		
α_B	-0.33**	0.40***	0.74***	-0.34***	0.33***	0.66***	-0.58***	0.49***	1.07***	-0.25***	0.18**	0.43***	0.11	0.58***	0.47*	0.23**	-0.35***	0.58**
	(-2.14)	*(3.33)*	*(2.83)*	*(-2.86)*	*(3.06)*	*(3.09)*	*(-3.37)*	*(3.03)*	*(3.27)*	*(-2.89)*	*(2.00)*	*(2.68)*	*(0.71)*	*(3.94)*	*(1.78)*	*(2.13)*	*(-2.69)*	*(2.38)*
BEN	0.83***	1.10***	0.27	0.55**	0.93***	0.39	0.62	1.36***	0.74	0.90***	1.16***	0.26***	1.90***	1.13***	-0.76	1.10***	0.80***	0.30
	(2.96)	*(2.98)*	*(0.44)*	*(2.50)*	*(3.28)*	*(0.79)*	*(1.40)*	*(3.84)*	*(0.93)*	*(47.04)*	*(61.45)*	*(7.88)*	*(4.62)*	*(2.61)*	*(-0.93)*	*(4.88)*	*(2.94)*	*(0.64)*
R^2	0.068	0.119	0.000	0.050	0.140	0.004	0.018	0.120	0.006	0.929	0.945	0.229	0.290	0.085	0.013	0.191	0.071	0.000

Note. This table presents the monthly returns on the long-short portfolios of equal-weighted country-level anomalies based on MSCI single-country indices. *Top* (*Bottom*) is the portfolio of the anomalies that display the highest (lowest) value spread calculated based on *EBEV* (EBITDA-to-enterprise value ratio). *T-B* is the portfolio that is long (short) in the *Top* (*Bottom*) anomaly portfolio. The portfolios are based on 20% (24) of the anomalies. Panel A displays the basic portfolio statistics: *R* is the mean monthly return, and *Vol* is the monthly standard deviation of returns. Panel B shows the coefficient of the the four-factor model of Carhart (1997): *MKT* (market portfolio), SMB (small minus big), *HML* (high minus low), *UMD* (up minus down), and α_{4F} (alpha, or the intercept from the model). Panel C presents the coefficient of the four-ad-hoc benchmark model: *BEN* (benchmark coefficient) and α_B (alpha from the model). The values in parentheses are bootstrap (for *R*) and Newey-West (1987) adjusted (for α_{F4} and α_B) *t*-statistics. Means, volatilities, and intercepts are expressed in%. The symbols *, **, and *** indicate values significantly different from zero at the 10%, 5%, and 1% levels, respectively. The different sections (I-VI) of the table display various alterations in the portfolio construction: I – using 20% breakpoint in the anomaly portfolios instead of 25%, II – using 30% breakpoint in the anomaly portfolios instead of 25%, III – weighting anomaly portfolio components on firm capitalizations instead of equally, IV – using long-only leg of these anomaly portfolios, V – using anomalies with significant positive returns only, IV – the value anomalies (Group 1 in Tabl 2, anomalies [1]–[13]) are excluded from the sample.

Table 7

Performance of the Portfolios of Country-Level Strategies from Sorts on Alternative Definitions of the Value Spread

	EP	BM	CFP	SP	SEV	EBP	DY	GPEV
				Panel A: Basic statistics				
R	0.46**	0.51***	0.52***	0.33*	0.38**	0.61***	0.37**	0.73***
	(2.49)	*(2.62)*	*(2.83)*	*(1.65)*	*(2.12)*	*(3.03)*	*(2.12)*	*(3.89)*
Vol	4.03	3.96	3.36	3.65	3.42	3.77	3.46	3.22
SR	0.40	0.45	0.54	0.31	0.39	0.56	0.37	0.79
				Panel B: Four-factor model				
α_{4F}	0.28*	0.32*	0.32*	0.18	0.20	0.38**	0.39**	0.50***
	(1.74)	*(1.74)*	*(1.84)*	*(0.94)*	*(1.09)*	*(1.97)*	*(2.55)*	*(3.01)*
MKT	0.04	-0.04	0.05	0.02	0.07*	0.02	-0.20***	0.04
	(0.52)	*(-0.72)*	*(1.11)*	*(0.33)*	*(1.70)*	*(0.32)*	*(-3.44)*	*(0.68)*
SMB	0.44***	0.39***	0.36***	0.10	0.24***	0.33***	0.20***	0.56***
	(6.47)	*(5.46)*	*(5.00)*	*(1.10)*	*(3.17)*	*(4.07)*	*(2.59)*	*(7.87)*
HML	0.52***	0.59***	0.43***	0.46***	0.42***	0.56***	0.40***	0.36***
	(10.57)	*(6.47)*	*(5.28)*	*(4.97)*	*(5.15)*	*(7.70)*	*(6.71)*	*(5.21)*
UMD	-0.16**	-0.21***	-0.12**	-0.24***	-0.23***	-0.15**	-0.27***	0.03
	(-2.28)	*(-3.23)*	*(-2.22)*	*(-3.88)*	*(-4.31)*	*(-2.53)*	*(-3.56)*	*(0.36)*
R^2	0.398	0.453	0.370	0.374	0.419	0.424	0.358	0.341
				Panel C: Benchmark model				
α_B	0.60**	0.54**	0.46**	0.43*	0.45*	0.60**	0.43*	0.59***
	(2.26)	*(2.06)*	*(2.40)*	*(1.83)*	*(1.83)*	*(2.49)*	*(1.92)*	*(2.61)*
BEN	-0.82	-0.15	0.40	-0.58	-0.38	0.04	-0.35	0.88**
	(-1.22)	*(-0.20)*	*(0.84)*	*(-1.01)*	*(-0.79)*	*(0.06)*	*(-0.39)*	*(1.96)*
R^2	0.017	-0.003	0.003	0.008	0.002	-0.004	0.001	0.033

Note. This table presents the monthly returns on the portfolios of equal-weighted country-level anomalies based on MSCI single-country indices. The portfolios go long (short) 20% of the anomalies with the broadest (narrowest) value spread based on different ratios: earnings-to-price (*EP*), book-to-market (*BM*), cash flow-to-price (*CFP*), sales-to-price (*SP*), sales-to-enterprise value (*SEV*), EBITDA-to-price (*EBP*), dividend yield (*DY*), gross profit-to-enterprise value (*GPEV*). Panel A displays the basic portfolio statistics: *R* is the mean monthly return of the long-short anomaly portfolio, and *Vol* is the monthly standard deviation of returns. Panel B shows the coefficient of the four-factor model of Carhart (1997): *MKT* (market portfolio), *SMB* (small minus big), *HML* (high minus low), *UMD* (up minus down), and α_{4F} (alpha, or the intercept from the model). Panel C presents the coefficient of the four-ad-hoc benchmark model: *BEN* (benchmark coefficient) and α_B (alpha from the model). The values in parentheses are bootstrap (for *R*) and Newey-West (1987) adjusted (for α_{F4} and α_B) *t*-statistics. Means, volatilities, and intercepts are expressed in%. The symbols *, **, and *** indicate values significantly different from zero at the 10%, 5%, and 1% levels, respectively.

Table 8

Performance of the One-Way Sorted Portfolios of Strategies Based on Single-Country ETFs

	12 strategies (10%)			24 strategies (20%)			36 strategies (20%)		
	Bottom	Top	T-B	Bottom	Top	T-B	Bottom	Top	T-B
				Panel A: Basic statistics					
R	-0.23*	0.48***	0.71***	-0.29***	0.44***	0.72***	-0.19**	0.37***	0.56***
	(-1.89)	*(4.14)*	*(3.22)*	*(-2.81)*	*(4.49)*	*(3.80)*	*(-2.19)*	*(4.75)*	*(3.65)*
Vol	2.15	1.84	3.62	1.78	1.52	3.11	1.55	1.33	2.64
				Panel B: Four-factor model					
α_{4F}	-0.12	0.37***	0.49**	-0.15*	0.29***	0.44***	-0.08	0.26***	0.35***
	(-1.14)	*(2.94)*	*(2.33)*	*(-1.91)*	*(3.43)*	*(2.89)*	*(-1.17)*	*(3.59)*	*(2.68)*
MKT	-0.09***	0.08***	0.17***	-0.08***	0.04**	0.12***	-0.08***	0.02	0.10***
	(-2.65)	*(3.16)*	*(3.18)*	*(-3.59)*	*(2.11)*	*(3.10)*	*(-3.77)*	*(1.27)*	*(2.87)*
SMB	-0.34***	0.08	0.42***	-0.25***	0.17***	0.41***	-0.19***	0.17***	0.36***
	(-4.56)	*(1.41)*	*(3.58)*	*(-5.42)*	*(4.27)*	*(5.27)*	*(-5.85)*	*(4.32)*	*(5.70)*
HML	-0.16***	0.22***	0.38***	-0.12***	0.18***	0.30***	-0.11***	0.14***	0.25***
	(-3.12)	*(3.56)*	*(4.17)*	*(-3.90)*	*(4.83)*	*(4.71)*	*(-4.69)*	*(3.88)*	*(5.36)*
UMD	0.14**	0.00	-0.14	0.15***	0.01	-0.14*	0.13***	0.03	-0.10
	(2.45)	*(-0.08)*	*(-1.44)*	*(3.65)*	*(0.25)*	*(-1.85)*	*(3.79)*	*(0.87)*	*(-1.56)*
R^2	0.384	0.230	0.346	0.463	0.282	0.403	0.494	0.234	0.392
				Panel C: Benchmark model					
α_B	-0.31**	0.44***	0.75***	-0.40***	0.43***	0.83***	-0.33***	0.33***	0.66***
	(-2.33)	*(4.24)*	*(3.64)*	*(-3.69)*	*(3.95)*	*(4.02)*	*(-3.60)*	*(3.73)*	*(3.73)*
BEN	0.79**	0.38	-0.41	1.11***	0.10	-1.00	1.34***	0.37	-0.97
	(2.39)	*(1.17)*	*(-0.68)*	*(3.48)*	*(0.27)*	*(-1.45)*	*(3.88)*	*(1.22)*	*(-1.50)*
R^2	0.041	0.010	0.000	0.126	-0.002	0.031	0.248	0.023	0.041

Note. This table presents the monthly returns on the portfolios of equal-weighted country-level anomalies based on ETFs. *Top* (*Bottom*) is the portfolio of the anomalies that display the highest (lowest) value spread calculated based on *EBEV* (EBITDA-to-enterprise value ratio). *T-B* is the portfolio that is long (short) in the *Top* (*Bottom*) anomaly portfolio. We present three variants of the quantile portfolios based on 10% (12 anomalies), 20% (24 anomalies), and 30% (36 anomalies) of the anomalies. Panel A displays the basic portfolio statistics: *R* is the mean monthly return, and *Vol* is the monthly standard deviation of returns. Panel B shows the coefficient of the four-factor model of Carhart (1997): *MKT* (market portfolio), *SMB* (small minus big), *HML* (high minus low), *UMD* (up minus down), and α_{4F} (alpha, or the intercept from the model). Panel C presents the coefficient of the four-ad-hoc benchmark model: *BEN* (benchmark coefficient) and α_B (alpha from the model). The values in parentheses are bootstrap (for *R*) and Newey-West (1987) adjusted (for α_{F4} and α_B) *t*-statistics. Means, volatilities, and intercepts are expressed in%. The symbols *, **, and *** indicate values significantly different from zero at the 10%, 5%, and 1% levels, respectively.

Table 9

Performance of the Two-Way Sorted Portfolios of Country-Level Strategies

		Panel A: Mean excess returns				Panel B: Four-factor model alphas			
		Value spread							
		Bottom	Medium	Top	T-B	Bottom	Medium	Top	T-B
Short-term momentum: 1-month return	Bottom	-0.18	0.06	0.34***	0.52***	-0.07	0.05	0.19	0.26*
		(-1.30)	*(0.89)*	*(2.74)*	*(3.30)*	*(-0.45)*	*(0.43)*	*(1.55)*	*(1.65)*
	Medium	-0.10	0.21***	0.42***	0.51***	-0.02	0.16*	0.32***	0.33**
		(-1.27)	*(2.93)*	*(4.37)*	*(3.51)*	*(-0.27)*	*(1.91)*	*(3.09)*	*(2.23)*
	Top	0.08	0.26**	0.58***	0.47***	0.12	0.14	0.49***	0.35**
		(0.17)	*(2.33)*	*(3.58)*	*(2.92)*	*(0.79)*	*(1.06)*	*(3.08)*	*(2.00)*
	T-B	0.25	0.20	0.24		0.19	0.09	0.30	
		(0.80)	*(0.88)*	*(0.93)*		*(0.72)*	*(0.42)*	*(1.29)*	
Long-term momentum: 1-month lagged 11-month return	Bottom	-0.37***	0.03	0.34***	0.74***	-0.18	0.13	0.28**	0.48***
		(-2.61)	*(0.39)*	*(2.87)*	*(4.38)*	*(-1.26)*	*(1.26)*	*(2.51)*	*(2.74)*
	Medium	-0.08	0.13	0.45***	0.53***	-0.02	0.09	0.35***	0.36**
		(-0.83)	*(1.64)*	*(4.18)*	*(3.58)*	*(-0.18)*	*(1.19)*	*(3.30)*	*(2.26)*
	Top	0.10	0.31*	0.66***	0.63***	0.07	0.08	0.44***	0.39**
		(0.34)	*(1.86)*	*(3.72)*	*(3.82)*	*(0.57)*	*(0.60)*	*(3.36)*	*(2.26)*
	T-B	0.44	0.28	0.25		0.22	-0.05	0.13	
		(1.46)	*(0.96)*	*(0.85)*		*(1.10)*	*(-0.24)*	*(0.66)*	
Long-run reversal: 12-month lagged 48-month return	Bottom	-0.24**	0.21*	0.36***	0.60***	-0.20	0.15	0.20*	0.39**
		(-2.11)	*(1.72)*	*(2.82)*	*(3.52)*	*(-1.36)*	*(1.31)*	*(1.80)*	*(2.41)*
	Medium	-0.01	0.16**	0.45***	0.45***	0.04	0.06	0.34***	0.30*
		(-0.21)	*(2.49)*	*(4.79)*	*(3.35)*	*(0.40)*	*(0.86)*	*(3.44)*	*(1.82)*
	Top	-0.12	0.16	0.49***	0.58***	-0.03	0.14	0.46***	0.48***
		(-0.93)	*(1.16)*	*(3.39)*	*(3.66)*	*(-0.25)*	*(1.16)*	*(3.18)*	*(2.84)*
	T-B	0.13	-0.05	0.14		0.18	-0.01	0.26	
		(0.66)	*(-0.26)*	*(0.57)*		*(0.80)*	*(-0.05)*	*(1.42)*	
Seasonality: average same-calendar month return	Bottom	-0.09	0.18**	0.37***	0.47***	0.07	0.12	0.30**	0.23*
		(-0.71)	*(1.99)*	*(3.34)*	*(3.27)*	*(0.67)*	*(0.96)*	*(2.25)*	*(1.67)*
	Medium	-0.07	0.11	0.47***	0.53***	-0.01	0.04	0.35***	0.35**
		(-0.77)	*(1.30)*	*(4.45)*	*(3.11)*	*(-0.07)*	*(0.47)*	*(4.14)*	*(2.35)*
	Top	-0.12	0.14	0.44***	0.56***	-0.06	0.07	0.27**	0.34*
		(-0.94)	*(1.11)*	*(3.45)*	*(3.35)*	*(-0.41)*	*(0.77)*	*(2.25)*	*(1.95)*
	T-B	-0.03	-0.04	0.06		-0.14	-0.05	-0.03	
		(-0.22)	*(-0.36)*	*(0.16)*		*(-0.68)*	*(-0.29)*	*(-0.17)*	

Note. This table presents the monthly returns on the equal-weighted portfolios from two-way of country-level anomalies based on MSCI single-country indices. The anomalies are sorted into tertiles on value spread calculated with the use of *EBEV* (EBITDA-to-enterprise value ratio) and one of the following variables: short-term momentum (1-month return), long-term momentum (1-month lagged 11-month return), long-run reversal (12-month lagged 48-month return), and cross-sectional seasonality (average same-calendar month return during the past 20 years, as available). *T-B* is the portfolio that is long (short) in the *Top* (*Bottom*) anomaly portfolio. Panel A displays average monthly returns, whereas Panel B alphas from the four-factor model. The values in parentheses are bootstrap (for *R*) and Newey-West (1987) adjusted (for α_{F4} and α_B) *t*-statistics. Means and intercepts are expressed in%. The symbols *, **, and *** indicate values significantly different from zero at the 10%, 5%, and 1% levels, respectively.

Table 10

Performance of the Portfolios of Country-Level Strategies from One-Way Sorts on Value Spreads within Subperiods

Subperiod	R	α_{4F}	α_B
High *VIX* volatility index	0.73** *(2.37)*	0.56** *(2.01)*	0.74* *(1.73)*
Low *VIX* volatility index	0.79*** *(3.53)*	0.29* *(1.75)*	0.60*** *(3.95)*
High *BAA* credit spread	0.70** *(2.08)*	0.42* *(1.78)*	0.73* *(1.94)*
Low *BAA* credit spread	0.82*** *(3.23)*	0.40* *(1.82)*	0.49* *(1.80)*
High *term* spread	0.57* *(1.86)*	0.40* *(1.76)*	0.62* *(1.81)*
Low *term* spread	0.94*** *(3.69)*	0.51** *(2.14)*	0.77** *(2.11)*
High *TED* spread	0.58* *(1.95)*	0.37 *(1.41)*	0.60 *(1.42)*
Low *TED* spread	0.93*** *(3.30)*	0.56** *(2.40)*	0.77** *(2.42)*
High Baker and Wurgler sentiment index	1.13*** *(3.81)*	0.51* *(1.85)*	0.92** *(2.09)*
Low Baker and Wurgler sentiment index	0.42 *(1.54)*	0.37 *(1.36)*	0.46 *(1.26)*
High University of Michigan Index of Consumer Expectations	0.89*** *(3.09)*	0.42 *(1.63)*	0.82** *(2.37)*
Low University of Michigan Index of Consumer Expectations	0.62** *(2.01)*	0.54* *(1.80)*	0.61* *(1.65)*
High Conference Board Consumer Confidence Index	0.71** *(2.49)*	0.42* *(1.81)*	0.65** *(2.09)*
Low Conference Board Consumer Confidence Index	0.81*** *(2.67)*	0.50** *(2.07)*	0.77** *(2.20)*
January	1.21*** *(3.51)*	0.69** *(2.40)*	1.22*** *(3.01)*
February - December	0.31 *(1.30)*	0.09 *(0.38)*	0.10 *(0.29)*
Bull markets	0.51** *(2.57)*	0.34* *(1.92)*	0.53** *(1.97)*
Bear markets	1.47*** *(2.98)*	0.75* *(1.81)*	1.30** *(2.54)*

Note. This table presents the performance of the portfolios of equal-weighted country-level anomalies based on MSCI single-country indices. The portfolios go long (short) 20% of the anomalies, amounting to approximately 24, with the broadest (narrowest) value spread *EBEV* (EBITDA-to-enterprise value ratio). *R* is the mean monthly return of the long-short anomaly portfolio, and α_{4F} and α_B are alphas from the four-factor model and the benchmark models, respectively. The values in parentheses are bootstrap (for *R*) and Newey-West (1987) adjusted (for α_{F4} and α_B) *t*-statistics. Averages, volatilities, and intercepts are expressed in%. The symbols *, **, and *** denote values significantly departing from zero at the 10%, 5%, and 1% levels, respectively. The performance is measured in various subperiods of the main sample (see Section II of the paper for details).