VERSOR

Versor[10]

A decade of quantitative research in 10 white papers

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Firm Overview

Versor is a quantitative investment firm where data, innovation, and market expertise drive every decision. Headquartered in New York, Versor's investment team merges decades of quantitative research with an ethos that fosters ingenuity and innovation. Leveraging modern statistical methods and vast datasets, Versor works to create diversified sources of absolute returns across multiple asset classes.

Alpha forecast models, portfolio construction, and the trading process rely on the ingenuity and mathematical expertise of 50+ investment professionals, which is underpinned by a rigorous scientific, hypothesis-driven framework. Versor implements state of the art technology infrastructure for risk management, portfolio optimization, and trade execution, developed over 250+ human work years.

Versor upholds client interests with 100% employee ownership and substantial co-investment from partners. Versor offers two categories of investment products: Hedge Funds and Alternative Risk Premia. Both product lines are designed to provide superior risk-adjusted returns while exhibiting low correlation to traditional and alternative asset classes.

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Preface

As Versor celebrates its 10th anniversary, we are thrilled to present a collection of 10 of our white papers. These papers draw upon the vast quantitative investment expertise of our Founding Partners. In the enclosed research papers, we summarize our work for major hedge fund and alternative risk premia strategies: equity market neutral, merger arbitrage, global macro, trend following, and systematic value. We invite you to explore these hedge fund and risk premia strategies from a fresh perspective.

The first section delves into return convexity of futures-based strategies. Investors looking for positive convexity were previously attracted to trend following. We show that trend following strategies have lost convexity. Fortunately, investors can employ expertly constructed cross-sectional signals without market exposure as an alternative source of positive return convexity. The papers also highlight the appeal of alternative investments that offer attractive opportunities for portfolio diversification through low correlation with bond and stock markets. These papers discuss limitations of simple trend-following approaches and emphasize the need for liquid alternatives that build on artificial intelligence, machine learning, and modern technology.

The second section unravels the seemingly intuitive world of merger arbitrage. Versor demonstrates the importance of a nuanced approach with strong risk management at the center. A sophisticated strategy can pinpoint which deals are likely to terminate, which are likely to receive a competing bid, and predict all crtical aspects of mergers. Interestingly, merger arbitrage has strong ESG characteristics – a sought-after feature for many modern investors. Our research shows that mergers are associated with increasing ESG scores for both target and acquirer companies.

The third section focuses on systematic value strategies. Although value investing remains a popular concept, 2017 through early 2021 proved very challenging for these strategies. However, value portfolios experienced a notable uptick in performance in late 2021 and throughout 2022. The papers highlight metrics that are useful in gauging the attractiveness of value investing. Based on these metrics, the paper argues that sophisticated market-neutral implementations are well positioned to capture remaining (and recurring) value investing opportunities while exhibiting low correlation to traditional markets.

The fourth section presents the case for alternative risk premia. Sophisticated implementations of alternative risk premia can deliver strong risk-adjusted returns in a way that is efficient and attractive for the end investor.

This selection of our white papers represents some of our detailed research on hedge fund and alternative risk premia investment strategies. We hope the papers provide you with new insights on liquid alternative investments.

We have enjoyed 10 years of innovation, client service, and success. We thank you for your support.

Deepak Gurnani

Deepak Gurnani

Founder and Managing Partner

Section 1

Futures Strategies - Uncorrelated Alpha

1. Has Trend Gone Flat? Return Convexity in Trend Following

Deepak Gurnani Ludger Hentschel

April 2022

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Executive Summary

Historically, the returns generated by CTA or "trend-following" hedge funds have exhibited an unusual and attractive combination of high average returns and positive convexity.

We document that, over time, the returns of CTA funds have lost some of both of these appealing characteristics, especially return convexity. The long-term trend signal favored by the largest CTA funds have lost more convexity than short-term trend signals that require faster trading.

Any portfolio that successfully implements time-series forecasts exhibits positive convexity and positive returns: A successful time-series signal tends to predict positive returns when markets rise and leads to profitable long positions. By the same token, such a signal tends to predict negative returns when markets fall and leads to profitable short positions.

Based on this logic, we show how to enhance the performance characteristics of trend-following portfolios with additional, newer signals not based on past trends. We demonstrate that such portfolios have been able to improve upon the positive return convexity previously associated with CTA strategies.

Interestingly, cross-sectional signals without market exposure can also provide return convexity. A primary source of convexity for cross-sectional signals is higher returns during volatile periods with large market returns. Strategies that generate larger returns during volatile periods than during calm periods are likely to have positive convexity.

Investors looking for positive convexity and positive returns during less volatile times were previously attracted to trend-following. They should now consider enhanced portfolios that also implement non-trend signals to enhance portfolio convexity.

1. Introduction

Historically, the returns generated by CTA or "trend-following" hedge funds have exhibited an unusual and attractive combination of high average returns and positive convexity. As a result, CTA funds have been able to generate positive returns in periods with large positive and large negative equity market returns without incurring offsetting negative returns during more normal market environments. As Fung and Hsieh (2001) document, this payoff profile resembles being long options, which earn positive returns during volatile periods, or purchasing a form of portfolio insurance – but without the premium costs associated with insurance strategies.

Many investors find it challenging to maintain allocations to insurance strategies if those strategies earn negative returns during extended calm periods. Of course, that also means that these investors go without the benefit of the insurance during periods of market stress. Historically, trend-following allocations have been easier to maintain because they did not charge an obvious premium.

We document that – over time – the returns of CTA funds have lost some of both of these appealing characteristics. Clearly, that makes CTA returns less appealing than they used to be. We can link the returns of CTA funds to trend-following signals and show that the average returns and convexity associated with these signals has declined over time. In particular, the long-term trend signals favored by the largest CTA funds that make up the SG Trend index have lost more convexity than shorter-term trend signals that require faster trading.

While it is possible that these declines in convexity and average returns are temporary, they have now lasted for many years. This must give rise to concerns that a secular change has affected the returns to trend-following strategies.

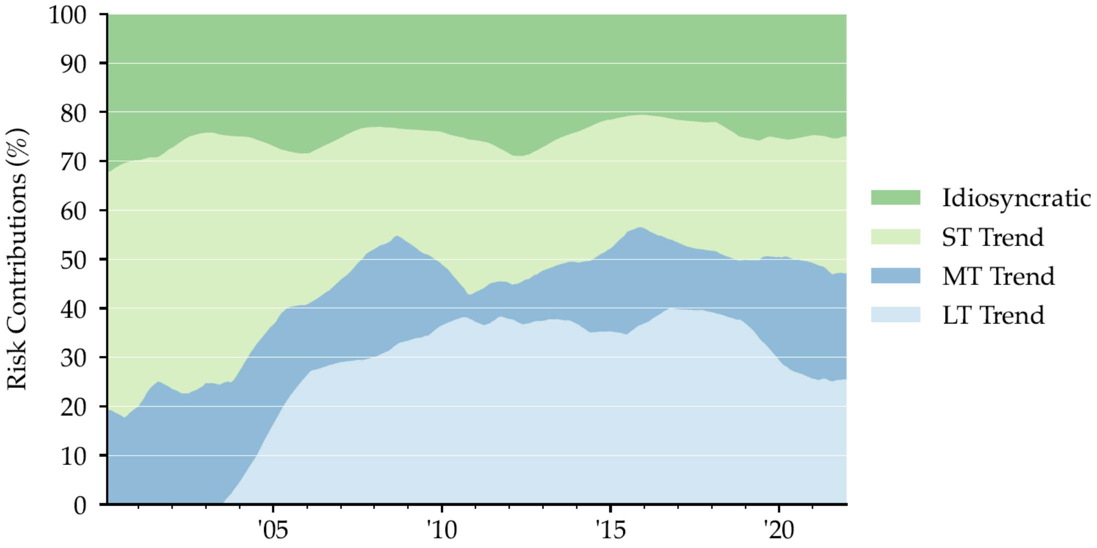
Basic logic implies that any successful time-series portfolio should exhibit positive convexity and positive returns. A successful time-series signal tends to predict positive returns when markets rise and leads to profitable long positions. By the same token, such a signal tends to predict negative returns when markets fall and leads to profitable short positions. Note that a successful time-series does not have to be always correct about the sign of the return. If a time-series signal has predictive power on average, it should lead to positive returns with positive convexity.

Interestingly, cross-sectional signals without market exposure can also provide return convexity. A primary source of convexity for cross-sectional signals is better performance during volatile periods with large market returns. Strategies that generate larger returns during volatile periods than during calm periods are likely to have positive convexity. Although such "long gamma" strategies are relatively easy to construct with options, these option strategies generally involve upfront premium payments that reduce their profitability. During extended calm periods, these premium costs can lead to material losses, which in turn can lead investors to abandon the strategy. Due to their premium costs and the associated challenges of maintaining allocations, we do not consider options-based strategies.

Based on this logic, we stress the importance of enhancing the performance characteristics of trend-following portfolios with additional, newer signals that enhance return convexity. We show how to measure return convexity and how to construct portfolios with attractive convexity.

The remainder of the paper proceeds as follows: Section 2 demonstrates that CTA fund returns are largely driven by trend-following signals; section 3 describes how to measure the convexity of portfolio returns; section 4 shows that, over time, the returns to trend-following signals have become smaller and less convex; section 5 introduces additional signals that have had higher and more convex returns than trend following signals; section 6 introduces a framework for trading off average performance against

Figure 1: CTA Investment Styles



The figure shows risk contributions to the SG Trend index from different investment styles. The SG Trend index is composed of the 10 largest CTA funds. The estimates stem from return-based style analysis of monthly SG Trend index returns from January 2000 to December 2021. The investment styles include simulated long-term, medium-term, and short-term trend-following. The simulated trend-following strategies invest in roughly 100 futures contracts across the 4 major asset classes: equities, fixed income, commodities, and currencies.

The idiosyncratic contributions contain risk from SG Trend index return components that we cannot attribute to trend-following.

The replicating portfolios consisting of the simulated trend-following returns capture about 70 to 80 percent of the return risk of the SG Trend index returns. That corresponds to a return correlation of approximately 90 percent.

Source: Data received from Société Générale. Internally prepared by Versor Investments.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss. These results are based on simulated or hypothetical returns that have inherent limitations. No representation is being made that any account is likely to achieve results similar to those shown. Please see additional important disclosures in the back.

convexity; section 7 illustrates portfolio combinations of signals with strong returns and high convexity; section 8 describes performance of trend-following strategies in 2021; and section 9 concludes.

2. CTA Hedge Funds and Trend-Following

While it is generally accepted that CTA hedge fund returns are driven by trend-following strategies, many investors underestimate how central these strategies are to CTA funds. We show that more than 90 percent of return variation for CTA funds can be explained by a blend of short-, medium-, and long-term trend-following signals in futures markets covering commodities, equity indexes, fixed income, and currencies.

Figure 1 shows the results of returns-based style analysis for the SG Trend index, which is an average of the returns for the 10 largest CTA hedge funds.[1] The style analysis blends short-, medium-, and long-term trend-following strategies to find the portfolio returns that most closely resemble the return to the SG Trend index. The estimation allows the exposures to the different investment strategies to vary over time, in case managers join or leave the index or in case continuing managers change their investment style.

[1] See Sharpe (1992) for a description of returns-based style analysis.

As the figure shows, trend-following investment strategies account for approximately 75 percent of the overall return risk in the SG Trend index, leaving relatively little room for other investment styles among the CTA funds included in the index. Equivalently, the returns of the pure trend-following replicating portfolio have a correlation of nearly 0.9 with the SG Trend index. Among the trend-following styles, long-term trend-following now contributes the largest amount of risk. This contrasts with the large risk share of short-term trend-following styles in the early 2000s, when many of the included CTA funds were much smaller. We attribute this preference for long-term trends among the largest CTA funds to the potentially large market impact associated with the faster trading required for short-term trend signals. Very large CTA funds likely find it prohibitively expensive to implement these short-term trends.

2.1 Simulated Trend-Following

The trend-following strategies we consider use time-series momentum and moving-average cross-over signals. The signals are based on lookback periods from 1 to 12 months. The long-term trend signals use lookback periods between 6 and 12 months. The medium-term trend signals use lookback periods between 3 and 6 months. The short-term trend signals use lookback periods less than 3 months.

We simulate the strategies and their returns by investing in liquid futures contracts across the 4 major asset classes: equity index futures, fixed-income futures, commodity futures, currency futures and forwards. There are about 100 futures contracts in total, fairly evenly split across the asset classes.

We construct trend signals based on past returns. Within each asset class, we allocate similar risk to all contracts by deflating positions by the risk of the corresponding contract. Finally, we use equal long-term risk budgets to allocate across asset classes.

3. Measuring Convexity in Returns

Convexity measures a nonlinear response in investment returns with respect to a reference returns. We focus on equity market returns as the reference returns. This focus is natural for investors with large risk allocations to equity markets.

3.1 Convexity with Respect to Equity Market Returns

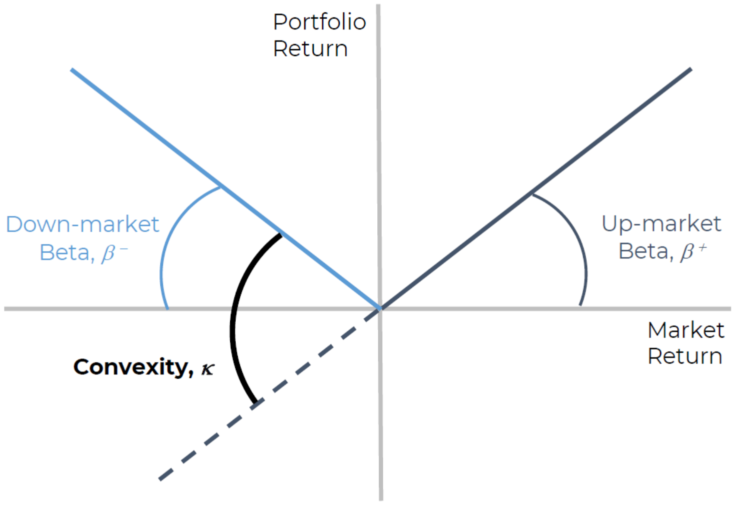
The main measure of market exposure is beta, measuring the linear dependence of portfolio returns on market returns,

$$r_t = \alpha_0 + \beta_0 r_{m,t} + \epsilon_t. \tag{1}$$

Throughout the analytical discussion, we use returns measured in excess of the risk-free rate, $r_{f,t}$. Here, r_t is a portfolio excess return, $r_{m,t}$ is the excess return on the market portfolio, β_0 measures the portfolio's market exposure, α_0 is the portfolio's average excess return not attributable to market exposures, and ϵ_t is an unidentified return contribution in period t. We generally estimate the coefficients α_0 and β_0 via regression.

Clearly, the market exposure captured by β_0 is constant over time. Also, it does not vary with market returns. Jensen (1972) and Henriksson and Merton (1981) discuss that such constant measures of market exposure cannot identify whether a portfolio manager or investment strategy has market timing ability. To allow for market timing, we can model different market exposures, depending on whether market returns are positive or negative,

Figure 2: Convexity in Returns



The figure illustrates the effects of market timing with higher exposures, β^+, during periods with positive market returns and lower exposures, β^-, during periods with negative market returns. We define convexity as the difference between the up-market and down-market exposures, $\kappa = \beta^+ - \beta^-$.

Source: Internally prepared by Versor Investments.

$$r_t = \alpha + \beta^+ r^+_{m,t} + \beta^- r^-_{m,t} + \epsilon_t. \tag{2}$$

As described by Henriksson and Merton (1981), β^+ measures the average market exposure during periods with positive market returns $r^+_{m,t} \geq 0$ and β^- measures the average market exposure during periods with negative market returns $r^-_{m,t} \leq 0$. As before, we can estimate these coefficients using regressions. In these regressions, the independent variables are $r^+_{m,t} \equiv \max\{0, r_{m,t}\}$ and $r^-_{m,t} \equiv \min\{0, r_{m,t}\}$.[2]

As in a standard market regression, the intercept term α indicates the average portfolio return conditional on zero excess returns for the equity market. The regressions impose the constraint that this excess return is the same during positive and negative market regimes. This restriction attributes return variation across market regimes to differences in market exposures, not differences in idiosyncratic returns. Freely estimating separate intercepts and exposures in both market regimes is unattractive because the different intercepts produce potentially large discontinuities in expected portfolio returns at $r_{m,t} = 0$.

The difference in market exposures during up markets and down markets is a natural measure of return convexity:

$$\kappa \equiv \beta^+ - \beta^-. \tag{3}$$

Figure 2 illustrates this definition of convexity in returns. A portfolio that displays constructive market timing has less market exposure during down markets than during up markets: $\beta^- < \beta^+$. Ideally, we might wish for positive exposures during up markets, $\beta^+ > 0$, and negative exposures during down markets, $\beta^- < 0$. However, as long as the difference in market exposures is positive, the portfolio exhibits positive convexity and constructive market timing.

[2] A constraint built into this direct approach is that we pre-determine the breakpoint between positive and negative equity environments. The point of zero excess return is a natural division between positive and negative equity regimes. However, the approach generalizes to any process that identifies positive and negative market regimes, so that we can use the appropriate returns in the regression. For example, one could use the Hamilton (1989) regime-switching framework to determine market regimes. If the two market regimes have different volatilities, it may be appropriate to use generalized least squares estimation methods.

Importantly, this measure separates convexity from average or overall market exposures. There may be cases where we wish to manage the average beta to a particular value, like 0 or 1. For any choice of overall market exposure, β, it seems clear that investors would prefer a portfolio with more convexity, "all else equal". A portfolio with more convexity provides better insurance during periods of poor market returns.

Note that keeping the other portfolio characteristics equal as we vary convexity, may correspond to changes in the regression coefficients. For example, the expected excess return on the portfolio is

$\mu = \alpha + \beta^{+}\mu_m - \kappa\mu_m^{-}$,

where μ_m is the average excess return on the equity market and $\mu_m^{-} = Er_m^{-}$ is the average value of r_m^{-}. Since $\mu_m^{-} \leq 0$, increasing convexity directly increases the average return on the portfolio. To maintain a constant average return as convexity rises, expected portfolio returns at $r_{m,t} = 0$, given by α, have to decline. Of course, if an investment strategy can increase convexity and average returns, all the better.

By defining convexity as the difference between two betas we ensure that convexity inherits some useful properties familiar from market betas. First, the convexity of a portfolio is equal to the corresponding weighted average of convexities of the constituent assets. Second, because convexity is a difference of betas, the market portfolio has zero convexity with respect to its own returns. Third, the risk-free asset has zero convexity. Fourth, convexity is proportional to leverage. These properties imply that we can use hedge positions in the market portfolio in order to remove market beta from the portfolio without affecting the portfolio's convexity.

As for linear market exposures, there are applications where we prefer a measure that does not depend on leverage. In these situations, correlation provides a scale-free measure of linear exposure. Since convexity is the difference of two linear exposures, the scale-free measure of convexity is

$$\nu = \kappa \frac{\sigma_m}{\sigma}, \tag{4}$$

where κ is the convexity measure from equation 3, σ_m is the standard deviation of market returns and σ is the standard deviation of the portfolio returns.

An equivalent representation of the market timing regression in equation 2 that can be analytically more convenient is

$$r_t = \alpha + \beta^{+} r_{m,t} - \kappa r_{m,t}^{-} + \epsilon_t. \tag{5}$$

Estimating this form via standard regression methods conveniently produces standard errors for the convexity estimate.

If we estimate a standard market regression, like equation 1, for a portfolio with a convex investment strategy, the regression produces a beta estimate

$$\hat{\beta} \approx \beta^{+} - \frac{\kappa}{2}, \tag{6}$$

if the distribution of market excess returns $r_{m,t}$ is approximately symmetric about 0.[3]

[3] This result follows directly from the standard omitted variable bias calculations for linear regressions. (See Wooldridge (2010), for example.The bias term is $-\kappa\,\mathrm{Cov}(r_{m,t}, r_{m,t}^{-})/\mathrm{Var}(r_{m,t})$. Inspection reveals that the covariance calculation produces zeros for all $r_{m,t} \geq 0$ and standard variance terms for all $r_{m,t} \leq 0$. By symmetry, the covariance is half of the variance of the market excess returns.

3.2 Convexity and Return Horizon

Like market beta, convexity estimates can vary with return horizons. This is a property of return covariances. Moreover, if convexity is generated by dynamic trading strategies, like trend following, then slower strategies may display little convexity over short return horizons but material convexity over long return horizons. Obviously, "long" and "short" return horizons must be considered relative to the speed of the trading strategy.

Given the typical speeds of trend following signals and the other signals we investigate, we focus on monthly returns in our empirical analysis. We have also analyzed quarterly and annual returns. For the signals we use here, quarterly and annual return horizons produce qualitatively similar results.

Longer return horizons reduce the number of available non-overlapping observations. Such a reduction in sample size generally reduces statistical significance of results. This can be offset by using overlapping return periods while making the appropriate adjustments to the statistical estimates. To avoid these complications, we focus on non-overlapping monthly returns in our empirical analysis.

3.3 Convexity with Respect to Other Returns

There may be scenarios where we would like to measure convexity with respect to other returns. Mechanically, this is straightforward. We simply replace the market excess return on the right side of the regressions, $r_{m,t}$, with the excess return of interest. Everything else stays the same.

For an investment strategy that tries to time a particular asset, a natural reference return is the long-only excess return to that asset. Any successful timing strategy should have positive convexity with respect to the return of the traded asset: the strategy should be less long during periods of negative asset returns. In this context, testing for positive convexity is equivalent to testing for timing skill.

For an investment strategy that operates in a particular asset class, an natural reference return is the return to that asset class. For example, an investment strategy that attempts to time the bond market should have positive convexity with respect to a bond market benchmark return.

3.4 Convexity and Skewness

If the reference returns $r_{m,t}$ and forecast errors ϵ_t are symmetrically distributed, then an investment strategy with positive convexity generates returns with positive skewness.[4] Barberis and Huang (2008) and Harvey and Siddique (2000) argue that investors find positively skewed returns appealing.

Unfortunately, it becomes harder to link convexity to skewness if the reference returns are not symmetric. Bessembinder (2018) and Albuquerque (2012) show that returns for individual stocks generally have strong positive skewness; Campbell and Hentschel (1992) and Albuquerque (2012) show that daily and monthly returns for equity market indexes have negative skewness. However, Kim and White (2004) argue that standard estimates of higher moments are easily contaminated by outliers and that robust estimates of skewness for equity market index returns show less evidence of asymmetry in the return distribution.

Although negative skewness of equity market returns would make it difficult to say how much convexity is required for a market-timing strategy to have positively skewed returns, positive convexity generally implies less negatively skewed returns.

[4] Potters and Bouchaud (2005) and Martin and Zou (2012) derive the positive skewness induced by trend-following trading strategies for unpredictable asset returns.

4. Trend-Following Over Time

Using both the SG Trend returns and the simulated returns to the trend-following signals, we now show that the convexity and average returns to these strategies have declined over time.

We estimate convexity κ for the different trend-following strategies using regressions. By running these regressions for rolling estimation periods, we can investigate how convexity has changed over time.

We measure equity market returns using the S&P 500 index. The results are qualitatively similar for other broad equity market indexes.

Figure 3 graphs coefficient estimates from rolling regressions for the SG Trend index. For each day, we estimate regression coefficients based on 5 years of trailing monthly returns. The red line shows point estimates of β^-, the slope coefficient during negative market environments. The green line shows point estimates of β^+, the slope coefficient during positive market environments. The blue line shows convexity, the difference between the estimates: $\kappa = \beta^+ - \beta^-$. The shaded areas around these lines indicate 95% confidence intervals. Ideally, we would like to see the point estimates for the betas and their confidence intervals to remain on either side of 0: negative for β^- and positive for β^+. This would indicate positive convexity for the returns. Strikingly, this was the case for many years early in the sample.

Starting about 10 years ago, however, the SG Trend returns apparently lost their positive convexity. Over the most recent decade, the convexity estimates have lost their statistical significance and have generally turned negative. In particular, market exposures during negative market environments now appear to be positive instead of negative. This is the opposite of what many investors expect from CTA managers.

Figure 4 repeats this process for simulated portfolios based on short-, medium-, and long-term trend-following, respectively. As the figure shows, the long-term trend-following signals display very little evidence of positive convexity. In contrast, the short-term signals generally exhibit positive convexity. The medium-term signals appear to have lost positive convexity over time. Since figure 1 shows that the managers in the SG Trend index have shifted from short-term to long-term trend-following signals, the difference in convexity among trend-following signals also explains why the SG Trend index has lost much of its earlier convexity.

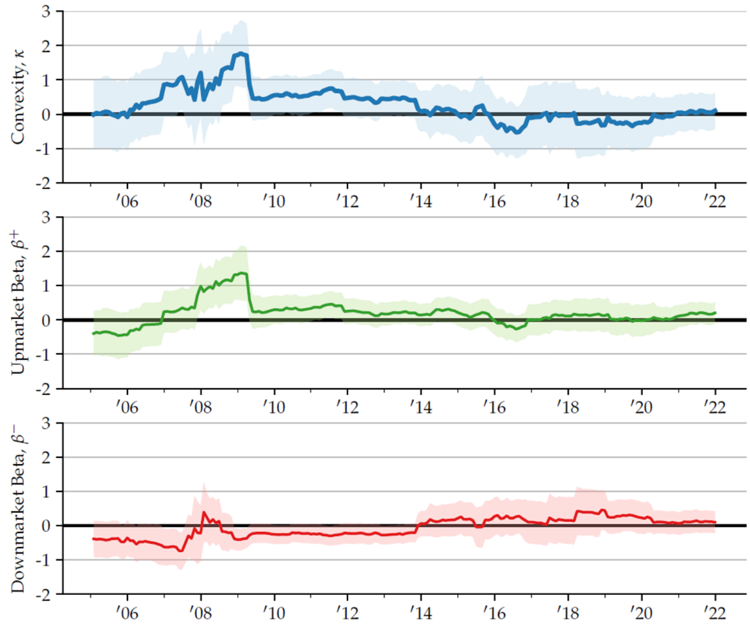
This is striking evidence that positive convexity is not a feature of all trend-following investment styles. Investors interested in convexity must not presume that CTA funds universally provide returns with positive convexity. Clearly, differences in investment style matter.

5. Convex Signals

Trend-following signals are not the only signals that can generate positive convexity. Any signal that successfully predicts future returns allows us to be short during negative return environments and long during positive return environments. This generates returns with positive convexity in a long-short portfolio. Based on this logic, adding effective time-series signals to a trend-following portfolio can enhance the positive convexity of the portfolio.

Interestingly, cross-sectional, non-directional investment strategies can also generate positive convexity. An important source of this type of convexity is market volatility: Strategies that generate larger returns during volatile periods are likely to have positive convexity. Conversely, strategies that generate lower

Figure 3: Convexity in CTA Returns



The figure shows rolling estimates of market exposures and convexity for the SG Trend index.

The SG Trend index is an index of the 10 largest CTA hedge funds. The lines show estimates of market exposure during periods of positive excess returns for the market, β^{+} in green, during periods of negative excess returns for the market, β^{-} in red, and convexity $\kappa = \beta^{+} - \beta^{-}$ in blue. The shaded areas around the lines indicate plus or minus 2 standard errors around the estimates, covering roughly 95 percent confidence intervals. The estimates are based on 5 years of rolling monthly returns. The return sample spans 264 months from January 2000 to December 2021.

Source: Data received from Bloomberg and Société Générale. Internally prepared by Versor Investments.

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returns during volatile periods are likely to have negative convexity.

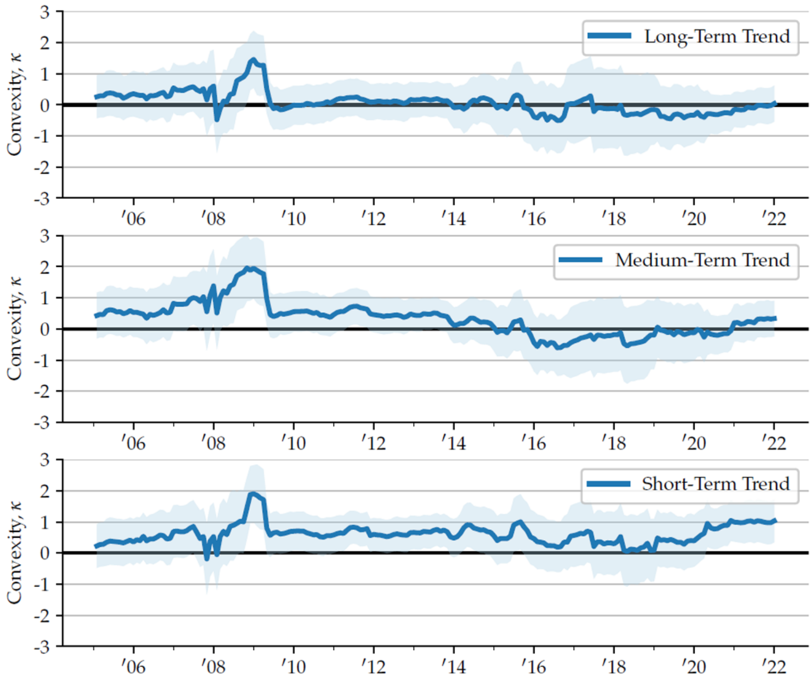
We now describe a collection of signals for futures trading and their convexity. For convenience, we follow the common approach of classifying signals into “value”, “momentum”, or “carry” groups.

5.1 Time-Series Signals

Time-series signals assess each asset in isolation and then establish a long or short position for that asset, depending on the signal. In this construction, the portfolio may be long many equity index futures or commodities at one point in time but short the same assets at another point in time. While a time-series portfolio may have low market exposures over the course of time, it can be materially net long or net short at any point in time.

Value: We use a range of asset-class-specific valuation criteria to assess each asset. If an asset appears expensive relative to its own past valuation measures, we establish a short position. Similarly, if an asset appears cheap relative to its own past valuation measures, we establish a long position. The valuation measures include inventories for commodities, real interest rates for fixed income, price-earnings ratios for equities, and purchasing power parity for currencies, among others. These trades generally profit when unusual valuations return to more normal levels.

Figure 4: Convexity in Trend-Following Returns



The figure shows rolling estimates of convexity for simulated trend-following strategies. The top panel shows results for long-term trend signals. The middle panel shows results for medium-term trend signals. The bottom panel shows results for short-term trend signals.

In each panel, the lines show estimates convexity $\kappa = \beta^{+} - \beta^{-}$. The shaded areas around the lines indicate plus or minus 2 standard errors around the estimates, covering roughly 95 percent confidence intervals.

The estimates are based on 5 years of rolling monthly returns. The return sample spans 264 months from January 2000 to December 2021. The simulated returns are levered to the same annual volatility as the SG Trend index returns.

The short-term trend signals use lookback periods up to 3 months. The medium-term signals use lookback periods between 3 and 6 months. The long-term trend signals use lookback periods between 6 and 12 months.

The simulated returns include estimated transaction costs but no management fees. Source: Data received from Bloomberg.

Carry: In futures trading, carry signals use estimates of the (negative of the) slope near the front-end of the futures curve as return predictions. We calculate carry based on the difference between the spot price and the near futures price, or the difference between the near and next futures prices. These differences are the equivalents of yield spreads. We go long assets with a positive yield spread and short assets with a negative yield spread. These trades generally profit when the yield spreads are large relative to return volatility.

Momentum: We use past returns as return predictions. The trend-following signals we described previously are the core of this signal family. We go long assets with positive past returns. These trades generally profit when past return trends continue into the future.

Table 1: Convexity for Different Strategies

Portfolio	Full Sample		2002-2011		2012-2021	
Panel A: Trend-Following Signals						
SG Trend	0.36	(0.16)	0.52	(0.24)	0.04	(0.22)
LT Trend	0.07	(0.16)	0.13	(0.21)	-0.06	(0.27)
MT Trend	0.34	(0.16)	0.41	(0.22)	0.04	(0.25)
ST Trend	0.62	(0.16)	0.53	(0.21)	0.76	(0.25)
Panel B: Time-Series Signals						
Carry TS	0.17	(0.16)	0.52	(0.20)	-0.50	(0.26)
Value TS	0.30	(0.16)	0.21	(0.22)	0.53	(0.26)
Momentum TS	0.47	(0.16)	0.53	(0.22)	0.34	(0.24)
Panel C: Cross-Sectional Signals						
Carry CS	-0.04	(0.16)	0.25	(0.24)	-0.49	(0.18)
Value CS	0.32	(0.16)	0.57	(0.24)	-0.12	(0.22)
Momentum CS	-0.23	(0.17)	-0.33	(0.24)	0.10	(0.22)

The table shows convexity estimates for different investment strategies. The values in parentheses are standard errors for the estimates.

Panel A shows trend-following strategies. The SG Trend index is an index of the 10 largest CTA hedge funds. The LT Trend returns are based on trend-following signals with look-back periods from 6 to 12 months. The MT Trend returns are based on trend-following signals with look-back periods from 3 to 6 months. The ST Trend returns are based on trend-following signals with look-back periods up to 3 months.

Panel B shows time-series strategies based on value, carry, and momentum themes.

Panel C shows cross-sectional strategies based on value, carry, and momentum themes. The cross-sectional construction results in market-neutral portfolios in each asset class.

The full sample contains 240 monthly returns from January 2002 to December 2021. The pre-2011 sample contains 120 monthly returns from January 2002 to December 2011. The post-2011 sample contains 120 monthly returns from January 2012 to December 2021.

For comparison, the table levers all strategies to the same volatility as the SG Trend index.

The simulated returns include estimated transaction costs but no management fees.

Source: Data received from Bloomberg and Société Générale. Internally prepared by Versor Investments.

5.2 Cross-Sectional Signals

The time-series signals we describe above can also be converted into a cross-sectional implementation. For the cross-sectional version we compare signal values within asset classes to form market-neutral, long-short portfolios in each asset class. Creating separate cross-sections within each asset class makes the signal values more comparable. The differences between the time-series and cross-sectional constructions produce returns with relatively low correlations, even if the underlying signals are very similar.[5]

Value: We use the same asset-class-specific valuation criteria as above but now compare the values across contracts in the same asset class instead of over time. We establish large long positions in the

[5] For additional descriptions of the cross-sectional signals and portfolio construction, see Gurnani and Hentschel (2021).

most attractive asset, large short positions in the least attractive asset, and intermediate positions in the other assets, according to their valuation scores. As a result, a cross-sectional portfolio is market neutral at each point in time. These trades generally profit when the difference in valuation ratios compresses.

Carry: Similarly, we use the carry signals above to create long-short portfolios in each asset class. These trades generally profit when the differences in carry spreads compress.

Momentum: Finally, we use the momentum signals to create long-short portfolios in each asset class. These trades generally profit when the assets with the strongest past price trends continue to have the highest returns. Note that such a cross-sectional portfolio can earn positive returns even if all the assets in an asset class experience negative returns.

5.3 Convexity Over Time

We now show that many – but not all – of these signals have exhibited higher convexity than trend signals, especially in recent years. To conserve space, we summarize convexity in table 1 across 3 periods: the full sample, the period up to December 2011, and the period from January 2012 onward.

As we showed in figure 4 already, table 1 confirms that short-term trend-following signals consistently have the highest convexity among the trend-following signals. Among the other time-series signals, the Value strategies stand out with consistently high convexity. Similarly, time-series momentum has attractive convexity in all 3 sample periods. Among the cross-sectional signals, Value produces attractive convexity. Cross-sectional carry and momentum, however, are less consistent.

For simplicity, we show a small number of signal families that group a much larger number of underlying signals. If we look through to the underlying granular signals, however, we can find individual signals with attractive convexity in most of the groups. For example, it turns out that cross-sectional carry signals have poor convexity in currencies. However, cross-sectional carry signals have more attractive convexity in commodities. Nonetheless, the group averages shown in table 1 are broadly representative of the underlying signals.

6. The Sharpe-Convexity Frontier

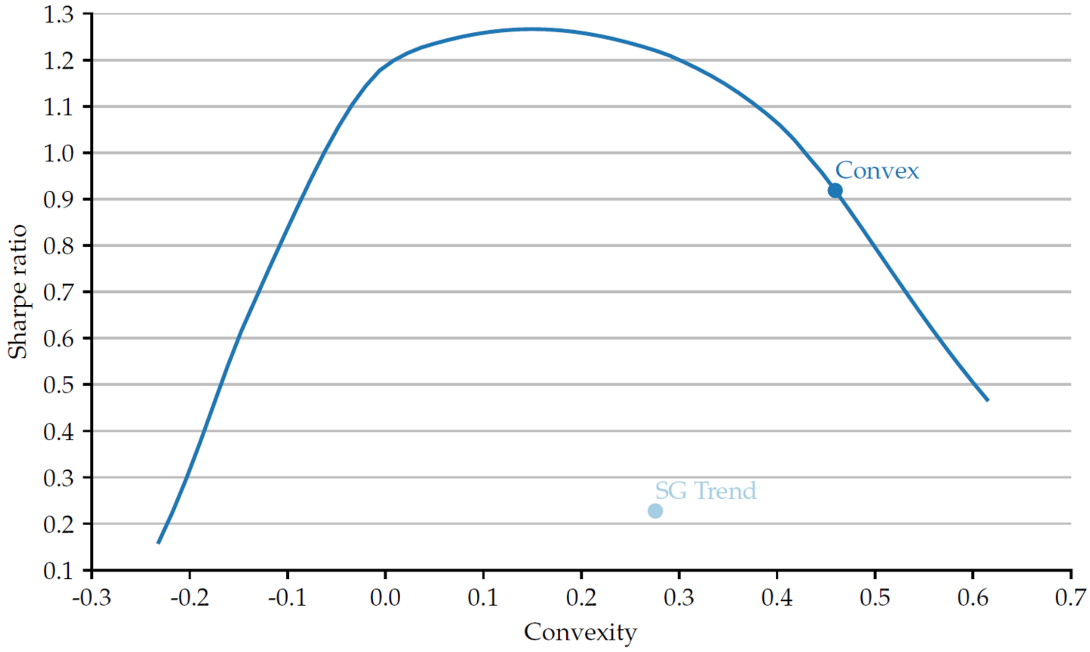
Given a collection of investment strategies, we can search for portfolios of these strategies that provide the strongest returns and highest convexity of returns. We formally search for such portfolios by finding the portfolio with the maximum Sharpe ratio for a given convexity. We can summarize the results of these searches on a “Sharpe ratio and convexity frontier” and then choose the portfolio with the most attractive combination of Sharpe ratio and convexity.

The Sharpe ratio is a natural measure of performance if the portfolio has a market beta close to zero. If the portfolio has material market exposures, we can hedge out this overall beta without affecting convexity.

Figure 5 shows an example Sharpe-convexity frontier. From the constituent strategies, we can build portfolios with different convexity levels. For a given level of convexity, we can then find the portfolio with the maximum Sharpe ratio. The blue line illustrates the resulting Sharpe-convexity frontier for the simulated strategies from table 1, excluding the SG Trend index.

The light blue circle on the frontier marks a convex portfolio for which we present further analysis. We intentionally select a portfolio with higher convexity and Sharpe ratio than the SG Trend index.

Figure 5: Sharpe-Convexity Frontier



The figure shows the frontier of maximum Sharpe ratio for a given convexity based on combinations of 9 underlying strategies.

The simulated underlying strategies include: long-term, medium-term, and short-term trend following, time-series implementations of value, carry, and momentum, as well as cross-sectional implementations of value, carry, and momentum.

All of the simulated strategies are levered to the same long-term risk as the SG Trend index. The composite strategies on the frontier, however, have lower risk due to diversification.

The estimates of convexity and Sharpe ratios are based on 240 monthly returns from January 2002 to December 2021.

The figure marks the "convex" portfolio we use for further analysis. For comparison, the figure also marks the SG Trend index levered to the same risk as the convex portfolio. This leverage changes the convexity but not the Sharpe ratio.

The simulated returns include estimated transaction costs but no management fees.

Source: Data received from Bloomberg and Société Générale. Internally prepared by Versor Investments.

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However, there are several such portfolios along the frontier above and to the right of the SG Trend index. We choose a portfolio away from the end of the frontier.

Nearby portfolios are qualitatively similar. For comparison, the figure also shows the convexity and Sharpe ratio of the SG Trend index.[6]

6.1 Interpretation

The frontier allows us to separate the portfolio with the highest Sharpe ratio from all other portfolios with the same level of return convexity. Conversely, we can find the portfolio with the highest convexity for a given Sharpe ratio.

The mean-variance efficient frontier is a familiar analogue. There, we search for the portfolio with

[6] For comparison, we lever the SG Trend index to the same risk as the selected "convex" portfolio. This leverage affects the convexity but not the Sharpe ratio.

maximum return for a given risk level. Here, we search for the portfolio with the maximum Sharpe ratio for a given convexity. We use the Sharpe ratio as a performance measure, instead of returns, since the portfolio constituents can use leverage and may have different levels of risk and return. The Sharpe ratio removes the effects of this leverage and accounts for risk.

For the mean-variance frontier, we prefer portfolios with lower risk and higher returns. They are in the upper left of the familiar frontier diagram. For the Sharpe-convexity frontier, we prefer portfolios with higher convexity and higher Sharpe ratios. They are in the upper right of the frontier diagram.

For a portfolio employing a weighted average of underlying strategies, the portfolio convexity is the weighted average of the strategy convexities. This is directly analogous portfolio betas being equal to the weighted average beta of the constituents. In contrast, the Sharpe ratio of a portfolio is not a weighted average of the constituent Sharpe ratios, just like the portfolio risk is not a weighted average of the constituent risk levels.

As for the mean-variance frontier, the full Sharpe-convexity frontier contains dominated portfolios. For portfolios to the left of the maximum Sharpe ratio portfolio, we can find portfolios with the same Sharpe ratio and higher return convexity. We prefer these portfolios on the right side of the frontier. Figure 5 includes the left side for illustration.

Among the non-dominated portfolios on the right side of the frontier, however, there is not a single “best” portfolio. Here, there generally are tradeoffs between higher Sharpe ratios or higher convexity.

Conceptually, we can trace the Sharpe-convexity frontier by first finding the portfolio with maximum Sharpe ratio absent the convexity constraint. That portfolio is at the peak of the Sharpe-convexity constraint and has a convexity we can compute. From there, we can find additional portfolios with maximum Sharpe ratio subject to gradually increasing or decreasing required convexity levels. In that sense, the portfolios on either side of the peak are more constrained. As a result, they have lower Sharpe ratios.

From this mental calculation, we can see that the portfolios along the Sharpe-convexity frontier trace a path in mean-standard-deviation space. The path starts from the tangency portfolio without convexity constraints. As we require higher or lower convexity levels, the constrained frontier moves down in mean-standard-deviation space. As a result, the constrained Sharpe ratio falls.

Unlike the mean-variance frontier, the Sharpe-convexity frontier does not follow a particular functional form. The rate of decline from the peak Sharpe ratio can be different on the left and right side of the frontier. (We mostly care about the right side.) The steepness of the decline depends on the return characteristics of the available assets.

The frontier in figure 5 is an illustration built on the 9 signal portfolios described above. This is a fairly limited set of underlying strategies. The approach can handle an arbitrary number of strategies. With a larger number of strategies, the Sharpe-convexity frontier generally expands vertically and horizontally, making more attractive portfolios available. Of course, this also changes the trade-off between available Sharpe ratios and available convexity.

6.2 Optimization

To find the portfolio with maximum Sharpe ratio for a given level of convexity, we find the maximum Sharpe ratio portfolio subject to linear constraints on the portfolio weights. The constraints are:

- The portfolio has a specified level of convexity, say z.

- The weights sum to 1.
- The weights are positive.

Formally, we search for a portfolio ω that solves

$$\max_{\omega} \ \theta(\omega) = \omega'\mu\ (\omega'\Sigma\omega)^{-1/2} \tag{7}$$

$$s.t. \quad \omega'\kappa = z$$

$$\omega'\iota = 1$$

$$\omega_i \geq 0 \ \forall i,$$

where μ is the vector of expected excess returns associated with the strategies, Σ is the covariance matrix of strategy returns, κ is a vector of convexity levels associated with the strategies, z is a number we choose and hold fixed for a given optimization, ι is a conformable vector of ones, and ω_i is element i of the weight vector ω.

When we repeat this process for a range of convexity levels z, we find the portfolios along the Sharpe-convexity frontier. Generally, the most interesting range of convexity lies between the lowest convexity of the available strategies and the highest level of convexity of the available strategies.[7]

The final constraint rules out leverage. Like the familiar market beta, convexity is proportional to portfolio leverage. To avoid artificial increases in convexity due to leverage, we focus on optimizations that don't permit leverage.

Like mean-variance optimizations with inequality constraints, these optimizations generally do not have analytical solutions. However, they can be solved iteratively using numerical methods. In particular, any portfolio optimization method that can find a maximum Sharpe ratio portfolio subject to standard portfolio constraints can solve the optimizations in equation 7.

Since the optimizations required for the Sharpe-convexity frontier are mean-variance optimizations, we can exploit experience with mean-variance optimizations in order to improve estimates of the Sharpe-convexity frontier. A well-known concern for mean-variance optimizations is that they may produce concentrated portfolios if they employ mean returns with large dispersion compared to the dispersion in risk characteristics. The corresponding portfolios have very large *ex ante* – but not *ex post* – Sharpe ratios. Naturally, the portfolios along the Sharpe-convexity frontier can become similarly concentrated under the same circumstances. Safeguards that are useful in mean-variance optimization are similarly effective here. Three approaches in wide-spread use are shrinkage of the expected returns, position limits, and shrinkage of the covariance matrix.[8] We use position limits by constraining the weights to be positive and less than 1.

7. Convex Portfolios

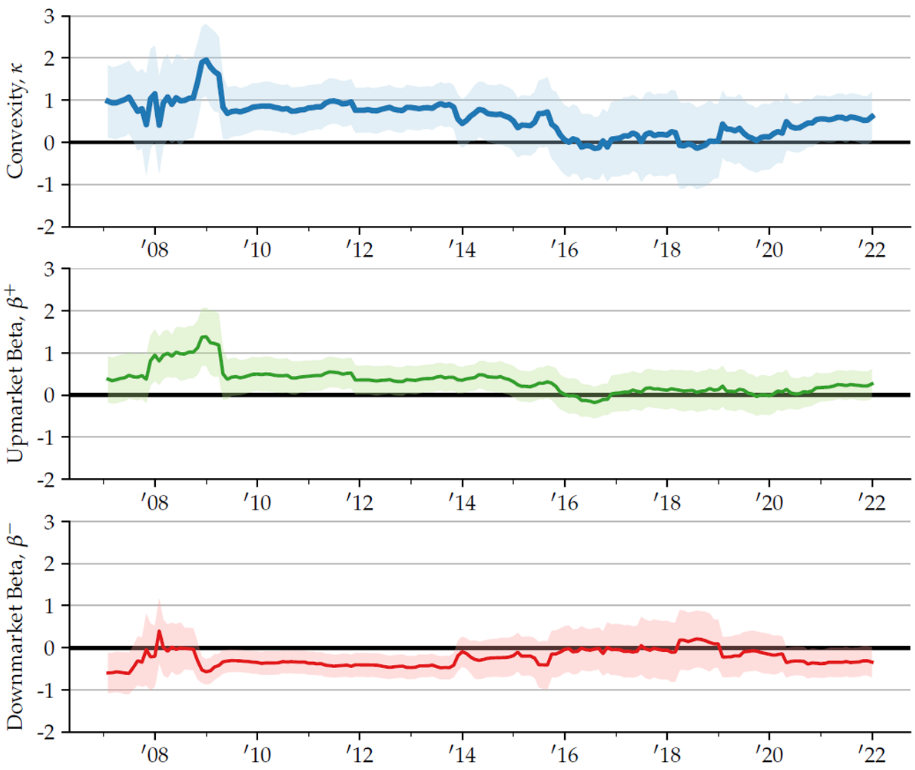
Given the collection of signals from section 5, we can construct a composite signal that targets high returns with high convexity. As table 1 and figure 5 show, several of the new signals have higher convexity than trend-following signals. As a result, adding the new signals allows us to find portfolios with higher convexity than pure trend-following.

Figure 6 shows the rolling convexity estimates for the portfolio marked on the frontier in figure 5. Since we are interested in portfolios with high convexity, we intentionally did not choose the strategy with

[7] These are not strict limits. If we allow negative allocations or leverage, then the portfolios can attain convexity outside of the range of convexities associated with the individual strategies.

[8] Common shrinkage methods for expected returns include statistical approaches based on James and Stein (1961), and financial approaches based on Black and Litterman (1992). Common shrinkage methods for the covariance matrix include Ledoit and Wolff (2004). Jagannathan and Ma (2003) show that position limits are closely related to covariance shrinkage.

Figure 6: Convex Portfolio



The figure shows rolling estimates of market exposures and convexity for a simulated convex portfolio. The lines show estimates of market exposure during periods of positive excess returns for the market, β^+ in green, during periods of negative excess returns for the market, β^- in red, and convexity $\kappa = \beta^+ - \beta^-$ in blue. The shaded areas around the lines indicate plus or minus 2 standard errors around the estimates, covering roughly 95 percent confidence intervals.

The portfolio blends a range of signals in order to find an attractive combination of Sharpe ratio and convexity. The signals are described in section 5. The portfolio construction along the Sharpe-convexity frontier is outlined in section 6.

The estimates are based on 5 years of rolling monthly returns. The return sample spans 240 months from January 2002 to December 2021.

The simulated returns include estimated transaction costs but no management fees. Source: Data received from Bloomberg. Internally prepared by Versor Investments.

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maximum Sharpe ratio. As the figure shows, however, we can start from the portfolio with maximum Sharpe ratio and materially increase convexity without large reductions in the Sharpe ratio. Comparing the estimates in figure 6 to those shown in figure 3 for the SG Trend index demonstrates that the enhanced portfolio consistently exhibits higher convexity. As the graphs show, the convex portfolio has materially more negative beta during negative equity markets than the SG Trend index.

Finally, table 2 summarizes the long-term performance characteristics of the convex trading strategy illustrated above and trend-following strategies. The table demonstrates that the convex portfolio has higher performance in addition to higher convexity. Of course, finding such a strategy was the purpose of constructing the Sharpe-convexity frontier. The table compares 5 strategies: the simulated convex portfolio, simulated long-term trend following, simulated medium-term trend following, simulated

Table 2: Convexity for Different Strategies

	Convex	LT Trend	MT Trend	ST Trend	SG Trend
Panel A: Full Sample					
Return	12.22	10.87	9.63	7.58	4.56
Risk	12.44	12.44	12.44	12.44	12.44
Sharpe	0.87	0.75	0.65	0.47	0.21
Convexity	0.62	0.07	0.34	0.61	0.37
Beta	-0.09	-0.12	-0.11	-0.16	-0.00
Max DD	-15.33	-16.77	-19.29	-24.08	-23.40
Panel B: 2002-2011					
Return	20.01	15.67	15.63	12.99	6.36
Risk	13.27	12.16	12.95	12.14	14.08
Sharpe	1.44	1.16	1.08	0.92	0.26
Convexity	0.72	0.13	0.46	0.53	0.55
Beta	-0.10	-0.12	-0.18	-0.14	-0.08
Max DD	-9.78	-16.24	-13.06	-11.22	-18.02
Panel C: 2012-2021					
Return	4.42	6.08	3.62	2.16	2.77
Risk	11.16	12.61	11.71	12.59	10.58
Sharpe	0.30	0.38	0.21	0.06	0.16
Convexity	0.44	-0.06	0.04	0.76	0.03
Beta	-0.02	-0.09	0.03	-0.16	0.12
Max DD	-15.33	-16.77	-19.29	-24.08	-23.40

The table shows performance characteristics for different simulated investment strategies and the SG Trend index. The columns show results for a convex strategy constructed from a collection of trend and non-trend signals, long-term trend following, medium-term trend following, short-term trend following, and the SG Trend index. The simulated strategies are levered to the same risk as the SG Trend returns.

All simulated strategies invest in about 100 liquid futures contracts across 4 major asset classes: equities, fixed income, commodities, and currencies.

The performance statistics in the rows are the annualized mean return in percentage points, the annualized standard deviation of returns in percentage points, the Sharpe ratio, the convexity of returns with respect to the S&P 500, the equity beta with respect to the S&P 500, and the maximum drawdown.

Panel A shows results for the full sample of 240 monthly returns from January 2002 to December 2021. Panel B shows results for 120 monthly returns from January 2002 to December 2011. Panel C shows results for 120 monthly returns from January 2012 to December 2021.

The simulated returns include estimated transaction costs but no management fees.

Source: Data received from Bloomberg and Société Générale. Internally prepared by Versor Investments.

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short-term trend following, and the SG Trend index. As the table, shows, intelligently incorporating other signals into trend-following strategies can materially raise the Sharpe ratio and convexity compared to pure trend-following strategies.

The table shows a direct comparison based on identical simulation assumptions for all of the simulated strategies. To facilitate this comparison, all of the simulated strategies have been levered to the same long-term volatility as the SG Trend index.

In addition to the higher convexity, the convex portfolio has a higher Sharpe ratio than any of the purely trend-following strategies. This demonstrates that the Sharpe-convexity frontier can help us identify portfolios that increase convexity without sacrificing average returns.

8. Trend in 2021

Interestingly, trend-following strategies generally had a positive year in 2021, as we were writing this paper. For example, the SG Trend index returned 9.1 percent in 2021, its third-highest return in 10 years. While some have interpreted this as a revival of trend-following strategies, we caution that this performance likely was driven by material exposures to the least convex strategy components, which had exceptionally good performance in 2021.

The large exposures to long-term trend following shown in figure 3 suggest that some of the SG Trend returns can be attributed to positive market exposures during a period of rising equity markets. Unfortunately, the figure shows that these positive market exposures are not accompanied by positive convexity. Absent convexity, strategies with positive market exposures are likely to produce negative returns during periods of market drawdowns. Of course, this is not what most investors have historically expected from trend-following strategies.

To illustrate this point, we show the long-term convexity of several signals, their 2021 returns, and their long-term returns. Table 3 shows these summary statistics. Signals like long-term trends in equities have strongly negative convexity after the financial crisis but realized exceptional returns in 2021, as global equity markets collectively moved up.

Figure 7 illustrates a striking negative association between 2021 returns and signal convexity. The 2021 signal returns are marked in light blue. The light blue line shows the linear relation between 2021 returns and long-term signal convexity. In contrast, the dark blue markers show the long-term returns for the same signals. The dark blue line graphs the linear relation between long-term returns and long-term signal convexity. Clearly, 2021 demanded a material premium for positive convexity. Long-term, however, strategies with positive convexity do not earn lower average returns. The dark blue markers and line illustrate that there is no long-term association between average return and convexity.

While 2021 was a strong year for strategies with negative convexity, we caution that such strategies are unlikely to match investor expectations for trend-following portfolios. Most investors in trend-following portfolios expect these strategies to deliver positive convexity.

Relying on long-term trend signals in the most liquid asset classes, like equities and fixed income, is likely to lead to investor disappointment during periods of weak equity markets. Yet, those appear to be the most important signals for the very large CTA funds that make up the SG Trend index. Futures strategies striving for positive convexity must allocate material risk to shorter-term trend signals and non-trend signals.

Table 3: Convexity and 2021 Returns

	Convexity	Avg Return	2021 Return
Panel A: Developed Equities			
LT Trend	-0.40	1.15	21.31
MT Trend	-0.18	1.65	14.87
ST Trend	0.34	-1.29	2.45
Panel B: Commodities			
LT Trend	-0.18	1.91	2.44
MT Trend	0.10	1.74	18.04
ST Trend	0.24	-0.32	5.17
Panel C: Fixed Income			
LT Trend	0.15	6.52	-18.98
MT Trend	0.15	3.05	-15.03
ST Trend	0.37	4.17	7.09
Panel C: Developed Currencies			
LT Trend	0.11	-0.27	-7.91
MT Trend	-0.04	1.92	-2.88
ST Trend	0.10	0.52	-8.27

The table shows a range of signals, their long-term convexity, their long-term annualized average returns, and their 2021 returns. The full sample consists of monthly returns from January 2002 to December 2021.

All strategies simulate investments in about 100 liquid futures contracts across 4 major asset classes: equities, fixed income, commodities, and currencies. All strategies are levered to the same risk as the SG Trend index, 13.5 percent.

The simulated returns include estimated transaction costs but no management fees.

Source: Data received from Bloomberg. Internally prepared by Versor Investments.

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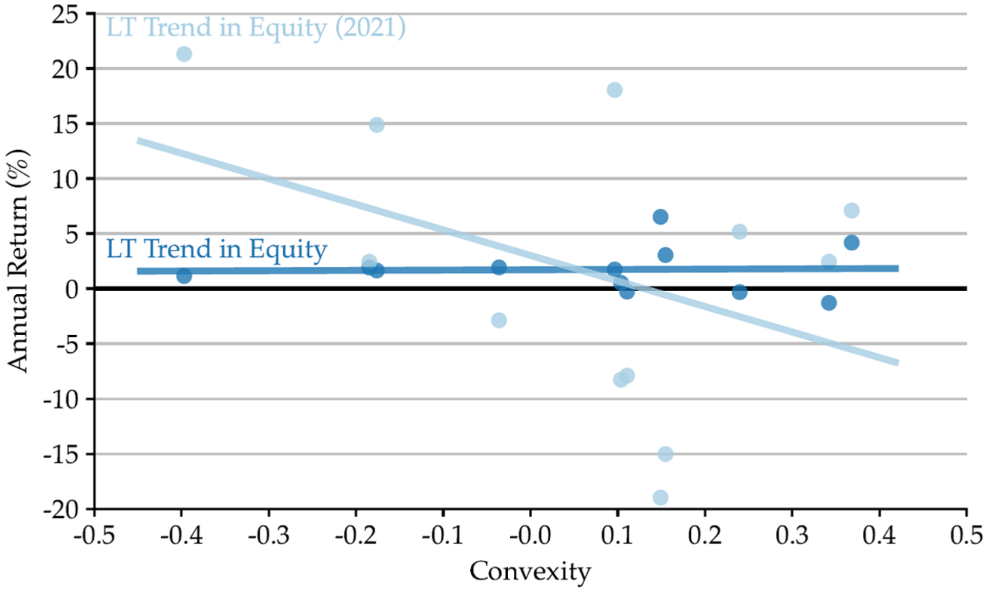
Figure 7: Returns and Convexity: Long-Term and 2021



The figure shows annualized average strategy returns for 2021 in light blue and from 2009 to 2021 in dark blue. All underlying return data are monthly. The horizontal axis shows the corresponding long-term convexities. Since convexity for several of these signals appears to be lower post 2008 than pre 2008, the figure uses data from January 2009 to December 2021.

All returns are levered to the same long-term volatility as the SG Trend index.

The lines indicate the best linear fit between average return and convexity over each of the two sample periods.

The text annotates the data points associated with long-term trend in equities, which has displayed material negative convexity since 2009.

The simulated returns include estimated transaction costs but no management fees.

Source: Data received from Bloomberg. Internally prepared by Versor Investments.

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9. Summary

We show how to measure convexity in portfolio returns and demonstrate that the trend-following signals responsible for CTA hedge fund returns have lost some of their positive convexity over time. This is especially true for the long-term trend signals favored by the largest CTA hedge funds.

Since any successful timing signal generates returns with positive convexity, we show that portfolios that combine effective non-trend signals with some trend-following signals may produce returns with superior returns and convexity compared to pure trend-following portfolios. We introduce the Sharpe-convexity frontier that isolates the portfolios with the maximum Sharpe ratio for a given level of convexity. This frontier allows investors to make efficient choices among portfolios with high Sharpe ratios and high convexity. Although these portfolio choices generally require a tradeoff between Sharpe ratios and convexity, the frontier separates the attractive portfolios from the rest.

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A Appendix: 2022 Update

We wrote the paper in early 2022, before markets produced the exceptional returns for 2022. Given the unusual magnitudes of equity and trendfollowing returns, it is interesting to update the main results from the paper. Despite the unusual returns in 2022, the main results are qualitatively unchanged.

In 2022, inflation in most developed economies rose to levels not seen in decades. The major central banks responded by raising interest rates from near zero at the beginning of 2022 to 4 percent, or higher, by the end of the year. The sharp increase in interest rates was partly responsible for a sharp decline in global equity markets. The S&P 500 lost 18.1 percent for the year.

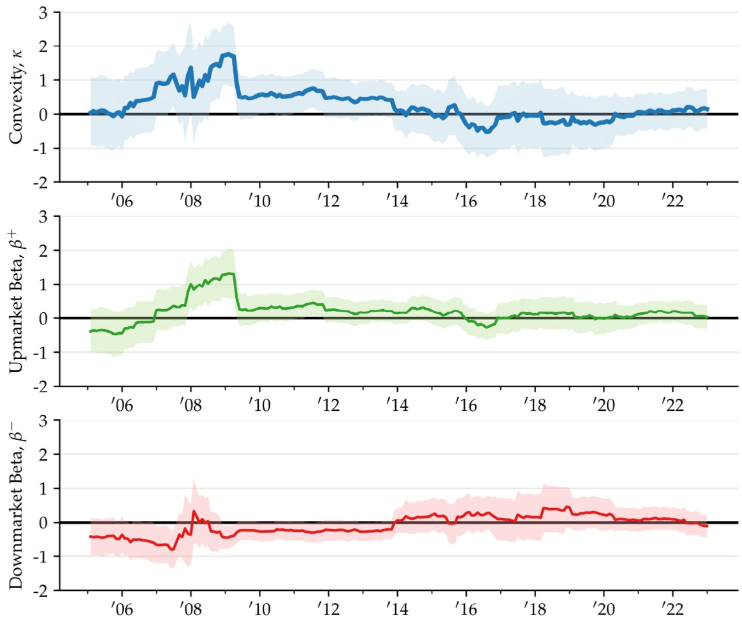
These dramatic price movements immediately raise questions about the performance of trend-following strategies during a period when positive return convexity is most valuable. Interestingly, the SG Trend index had its strongest year on record (since 2001): The SG Trend index rose 27.4 percent in 2022. Unfortunately, this marks only the second time that the SG Trend index has shown positive returns during an S&P 500 drawdown of more than 10 percent. There have been 6 such periods since the beginning of the SG Trend index.

As Figure 8 shows, these returns resulted only in small changes of our rolling convexity estimates for the SG Trend index. When comparing the end of 2022 to the end of 2021, the upside and downside beta for the SG Trend index had fallen by similar amounts, increasing the overall convexity estimate from 0.11 to 0.14. This variation is well within the confidence bounds for the estimates. The rolling convexity estimate for the SG Trend index remains statistically indistinguishable from 0.

Trend-following investors should be pleased that trend following provided offsets to large equity market losses in 2022. However, we so no reason to believe that 2022 marks a structural change from the longer-term poor return convexity of the largest trend-following managers included in the SG Trend index.

Investors should continue to look for better sources of return convexity.

Figure 8: Convexity in CTA Returns Through 2022



The figure shows rolling estimates of market exposures and convexity for the SG Trend index. The SG Trend index is an index of the 10 largest CTA hedge funds.

The lines show estimates of market exposure during periods of positive excess returns for the market, β^{+} in green, during periods of negative excess returns for the market, β^{-} in red, and convexity $\kappa = \beta^{+} - \beta^{-}$ in blue. The shaded areas around the lines indicate plus or minus 2 standard errors around the estimates, covering roughly 95 percent confidence intervals. The estimates are based on 5 years of rolling monthly returns. The return sample spans 276 months from January 2000 to December 2022.

Source: Data received from Bloomberg and Société Générale. Internally prepared by Versor Investments.

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2. Global Macro: Portfolio Diversification for Turbulent Times

Deepak Gurnani Ludger Hentschel

January 2021

Contents

Executive Summary

Following more than a decade of global monetary expansion, investors are concerned that global bond and equity values may be stretched. In such an environment, alternative investments uncorrelated with bonds and stocks can offer attractive opportunities for portfolio diversification. Within alternative investment strategies, cross-sectional Global Macro strategies seem especially well positioned to benefit from the asset return dispersion that may come with a delinking of international monetary policy.

Global Macro strategies can be classified into discretionary and systematic styles. Systematic Global Macro implements a consistent investment style that trades equity, fixed income, currency, commodities, and futures markets using investment rules that react to large volumes of market and economic data. The rules are determined by a combination of the managers' insights and historical patterns in the data.

For the systematic Global Macro hedge funds in the SG Macro Trading–Quantitative index, we show that directional trend-following strategies dominate their portfolios. While trend-following strategies can be attractive, they are quite distinct from systematic cross-sectional strategies. Hence, investors interested in cross-sectional strategies within systematic Global Macro strategies must carefully select managers offering such investments.

Simulated returns for our Global Macro strategy based on cross-sectional alpha forecast models confirm that the strategy has historically done well during periods of equity market declines and high return dispersion. This includes the most recent period of market turmoil in the first quarter of 2020, when the Versor Systematic Global Macro strategy was up while equity markets were down about 20%.

1. Introduction

Following years of strong market gains on the back of international monetary expansion, investors are concerned that global equity and bond valuations may now be stretched and present significant downside risks. In such an environment, alternative investment strategies truly uncorrelated with equity and bond markets offer attractive opportunities for portfolio diversification. Within alternative investment strategies, Global Macro strategies seem especially well positioned to benefit from the asset return dispersion that may come with a delinking of international monetary policy.

We made this case in early 2018, in an earlier version of this paper.[1] In light of the market volatility of 2020, this version updates our earlier results. We are pleased that high-quality cross-sectional Global Macro strategies have performed in line with our earlier predictions: During the first quarter of 2020 global equity markets declined roughly 20% while the Versor Systematic Global Macro strategy we discuss here was up. Based on these developments, we think it is worthwhile to state our case once more and include more recent results.

For more than 10 years, the world's major central banks have jointly exercised extraordinarily lenient monetary policy, first in the extended aftermath of the global financial crisis and most recently in response to the Covid-19 pandemic. This monetary expansion has produced record-low bond yields and has contributed to record-high equity prices. A long stretch of low market volatility and asset return dispersion likely was a collateral effect but has recently been upended by the economic uncertainty associated with Covid-19.

There are signs that these coordinated policy efforts may begin to diverge as different central banks are setting policy to suit their respective economies at different points in the post-crisis expansion and Covid-19 contraction.

Investors are rightfully concerned that less expansionary monetary policy may contribute to material increases in bond yields and declines in equity prices. However, differences in economic cycles and monetary policy may also lead to significant differences in the timing of such market declines across regions and countries.

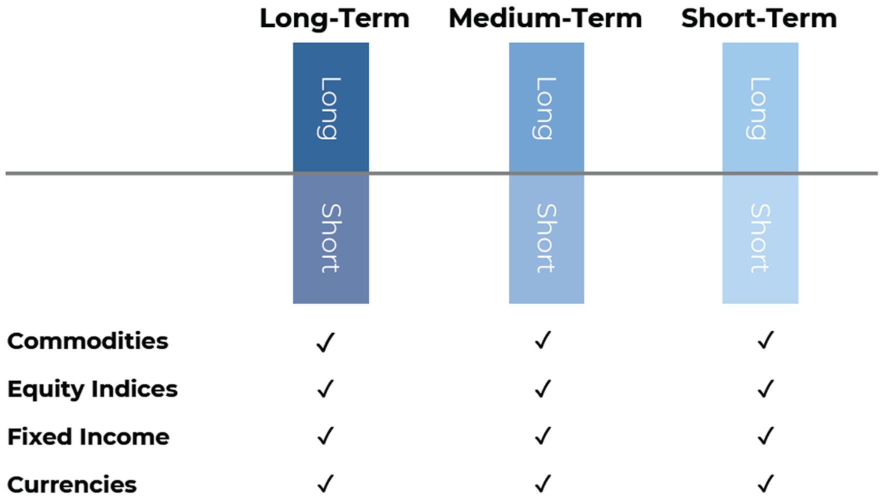
If market declines are accompanied by increases in inflation, such a scenario could be even more challenging for pension plans. In such a scenario, higher inflation would lead to an increase in inflation-indexed liabilities, market declines would lead to a decrease in assets, and the net effect could be a notable deterioration in funding ratios.

While there may be differences in equity and bond returns, if both are negative they do not offer much diversification in this scenario. An attractive investment strategy in this scenario would be uncorrelated with stocks and bonds and would be able to profit from increased volatility and dispersion in asset prices. Global Macro fits this description and is one of the most liquid and scalable alternative investment strategies.

Among Global Macro strategies, non-directional, cross-sectional strategies may be especially attractive since they can profit from asset return dispersion even in the absence of protracted price trends.

[1] See Gurnani and Hentschel (2018).

Figure 1: Versor Global Macro Signals and Universe



The figure shows a high-level summary of the signals used by the Versor Systematic Global Macro strategy to construct long-short portfolios in futures and currency forwards. The signals are diversified across long-term, medium-term, and short-term investment horizons ranging from a year to a few days.

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2. Global Macro

Global Macro strategies can be broadly divided into discretionary and systematic styles.

2.1 Discretionary

Discretionary Global Macro managers trade equity, fixed income, currency, commodities, and futures markets primarily based on the managers' economic views of various markets and instruments.

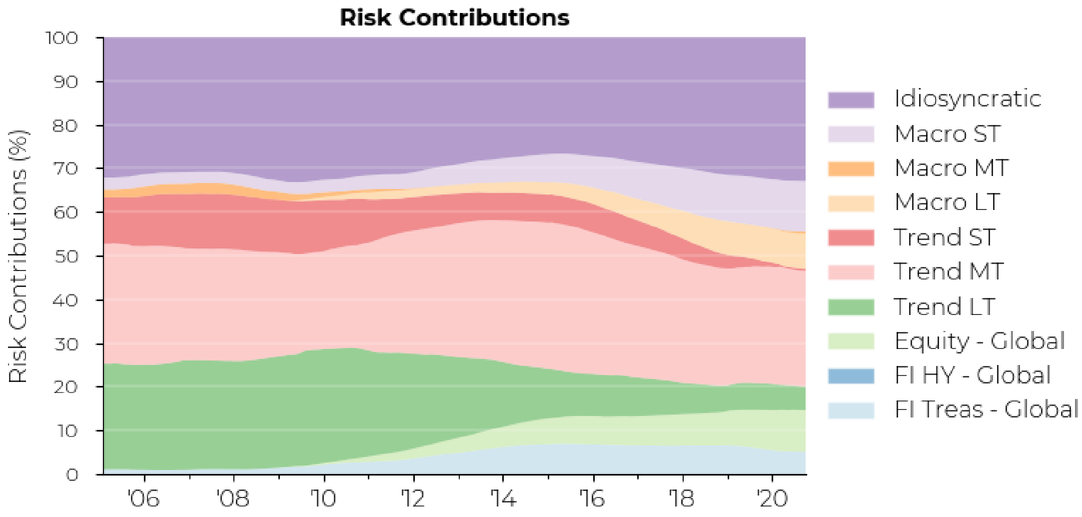
2.2 Systematic

Systematic Global Macro managers trade equity, fixed income, currency, commodities, and futures markets using systematic investment rules based on large volumes of market and economic data. The rules are determined by a combination of the managers' insights and historical patterns in the data.

3. Versor Global Macro

Versor implements a fully systematic, purely cross-sectional Global Macro strategy that trades based on a large number of alpha forecast models in 4 asset classes: equities, fixed income, commodities, and currencies. The forecasts generally differ by asset class and can be most usefully grouped into short-, medium-, and long-term forecasts. The portfolio trades liquid futures and currency forwards. Figure 1 summarizes the alpha forecast models and asset classes. In each asset class, the portfolio is long the most attractive assets and short the least attractive assets. This disciplined long-short portfolio construction means that the portfolio has no net exposure to any of the asset classes. In particular, the portfolio has no net exposure to equity markets or bond markets.

Figure 2: Macro Signals in SG Macro Trading–Quantitative



The figure shows the estimated risk contributions from several factors to the SG Macro Trading– Quantitative index. The risk contributions are derived from returns-based style analysis with time-varying exposures. The factors are short-term, medium-term, and long-term cross-sectional Macro, short-term, medium-term, and long-term Trend, as well as MSCI World equity, Barclays High Yield global fixed income, and Barclays Treasuries global fixed income. The estimation uses monthly data from January 2005 to September 2020.

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Versor constructs and combines alpha forecast models based on the firm's extensive experience and research. The research process subjects the team's hypotheses about return predictions to rigorous analysis and sophisticated statistical tests. The predictive models are based on a broad range of data including market data, economic statistics, and alternative data, like news flow and sentiment.

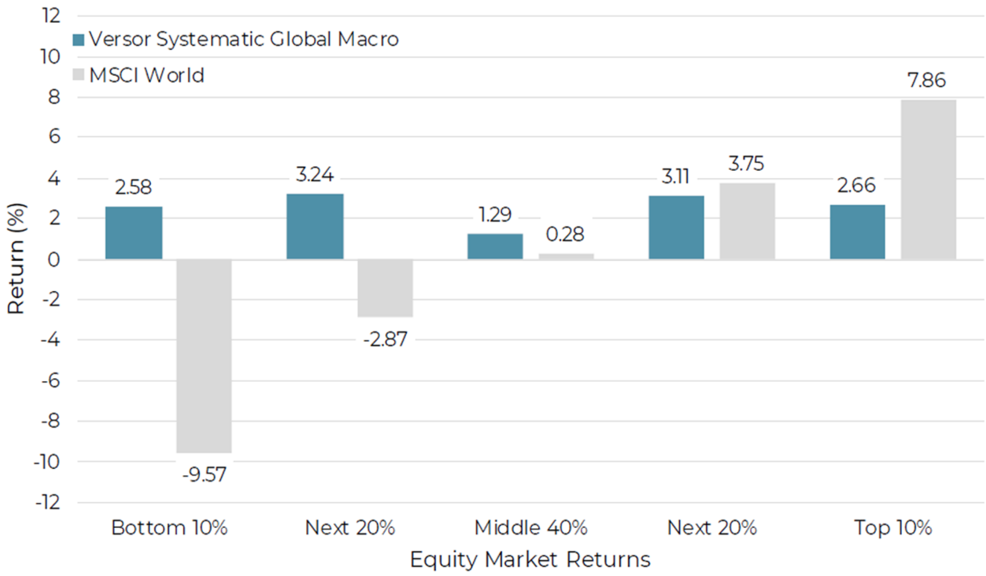
3.1 Short-Term Forecasts

Versor Global Macro short-term alpha forecast models look for price differences within an asset class that should revert to more normal relationships over holding periods up to 2 months. One example of these forecasts is based on unusual price relations between spot and futures prices and unusual shapes of the futures curves. These trades generally profit when the price differences are large relative to return volatility.

3.2 Medium-Term Forecasts

Versor Global Macro medium-term alpha forecast models look for price differences within an asset class that should revert to more normal relationships over holding periods between 2 and 4 months. One example of these forecasts is based on continuing momentum in past price movements. Importantly, such cross-sectional momentum forecasts are different from time-series Trend signals. Trend signals generally are net long equity instruments following market rallies and net short equity instruments following market declines. In contrast, cross-sectional momentum forecasts always construct market neutral long and short portfolios, regardless of recent market movements. As a result, the returns from Trend and cross-sectional Global Macro strategies only have low correlation and are both good portfolio diversification strategies.

Figure 3: Global Macro Performance in Different Equity Market Regimes



The figure shows the simulated performance of the Versor Systematic Global Macro investment style during periods with different equity returns. The figure groups monthly equity returns into 5 buckets. The lighter, grey bars show the average monthly equity returns for each group. The darker, blue bars show the matching average monthly returns for the simulated Global Macro investment style during the same months. The figure uses monthly returns from January 2002 to September 2020. The simulated Global Macro returns are net of estimated transaction costs and 90bps of fees.

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3.3 Long-Term Forecasts

Versor Global Macro long-term alpha forecast models look for price differences within an asset class that should revert to more normal relationships over holding periods between 4 and 6 months. One example of these forecasts is based on fundamental valuation metrics for equity indexes, macroeconomic indicators for fixed income and currencies, and inventory levels for commodities. These trades generally profit when unusual or extreme prices return to more normal levels.

3.4 Prevalence of Styles

Interestingly, the cross-sectional forecasts driving the Versor Global Macro trades are demonstrably different from those implemented by systematic Global Macro hedge funds in general. Using simulated historical returns to these investment styles, we perform returns-based style analysis on the SG Macro Trading–Quantitative index returns.[2] We estimate time-varying exposures of the index to trend-following and cross-sectional macro forecasts. Figure 2 shows that the returns from these forecasts account for about 70% of the total risk in the SG Macro Trading–Quantitative index returns. However, most of the risk in the SG Macro Trading–Quantitative index stems from short-term, medium-term, and long-term directional Trend strategies. Only a small part of the risk stems from any of the cross-sectional macro investment styles.

[2] Sharpe (1992) describes how to estimate historical exposures to different investment styles using returns-based style analysis.

Since the Versor Systematic Global Macro strategy is built entirely around cross-sectional forecasts and does not employ any trend-following signals, it is very different from the investment styles employed by the funds that make up the SG Macro Trading–Quantitative index. As a result, the purely cross-sectional Versor Systematic Global Macro strategy offers strong diversification from more common Global Macro investment styles.

Moreover, investors looking for market-neutral, cross-sectional sources of returns in futures markets cannot rely on the headline descriptor "systematic Global Macro". They must carefully choose from the relatively small number of managers offering this investment style.

4. Performance Characteristics

Global Macro based on cross-sectional forecasts has performed well during periods of equity market declines and high volatility. This makes Global Macro an attractive portfolio diversification strategy.

4.1 Strong Performance During Market Stress

Although cross-sectional forecasts are not primary risk drivers for most Global Macro funds in the SG Macro Trading–Quantitative index, they are valuable for investors, especially in the face of declining equity markets.

Figure 3 summarizes the performance of simulated Global Macro based on cross-sectional alpha forecast models during different equity market regimes. For illustration, we segment monthly equity market returns, as measured by the MSCI World index, into 5 groups. The figure shows monthly average equity returns for each group in grey bars. The leftmost group contains the 10% of months with the lowest equity returns. The rightmost group contains the 10% of months with the highest equity returns. The middle groups likewise sort months by equity returns and collect them into groups with the remaining 20%, 40%, and 20% of months. The central groups are intentionally larger to focus attention on the more extreme outcomes.

The blue bars show the average monthly returns for the simulated Global Macro strategy during the months corresponding to the equity returns in each group. In the 10% of months with the lowest equity returns, -9.57% on average, the Global Macro strategy returned 2.58%. Based on the graph, the Global Macro strategy has similarly attractive returns regardless of the equity market environment. This is also borne out by the correlation between the monthly returns for equities and Global Macro, which is -0.04.

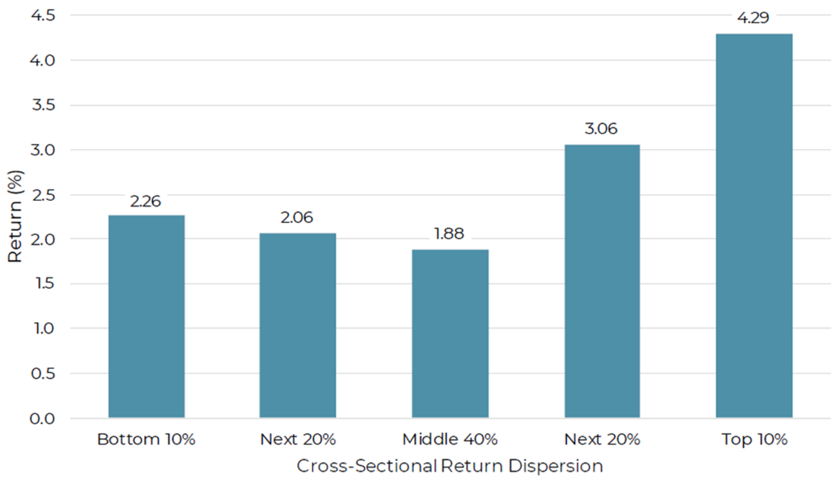
The Covid-19 related market stress during first quarter of 2020 was an interesting test of Global Macro performance during negative equity environments: Equity markets declined by roughly 20% while Versor's systematic Global Macro strategy was up for the quarter.

4.2 Dispersion Offers Opportunity for Global Macro

If global monetary expansion slows or reverses and does so at different points in different regions, this may well give rise to increased market volatility and higher dispersion across asset prices. Such periods of high volatility and dispersion offer opportunities for above-average Global Macro returns.

To illustrate this effect, Figure 4 shows average monthly cross-sectional Global Macro returns, where months are grouped by the average dispersion of returns within asset classes during the month. The grouping criteria are as in Figure 3 but here we apply them to average dispersion instead of returns.

Figure 4: Macro Signals in SG Macro Trading–Quantitative



The figure shows the simulated performance of the Versor Systematic Global Macro investment style during periods with different asset return dispersion. The figure groups monthly returns into 5 buckets according to the average return dispersion within asset classes during each month. The figure uses monthly returns from January 2002 to September 2020. The simulated Global Macro returns are net of estimated transaction costs and 90bps of fees.

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5. Summary

A systematic Global Macro portfolio based on cross-sectional forecasts offers attractive diversification to portfolios dominated by equity risk, especially in an environment with increased uncertainty and potential equity market drawdowns. The Versor Global Macro portfolio systematically implements a broad range of cross-sectional forecasts with different time-horizons in liquid futures or forwards on commodities, equity indexes, fixed income, and currencies. Simulations for this strategy show an attractive return profile during periods of negative equity returns and high return dispersion.

Importantly, most systematic Global Macro hedge funds focus on directional trend-following signals. These are quite distinct from purely cross-sectional implementations. Investors looking to diversify their portfolios with the latter style need to carefully choose their Global Macro managers.

6. References

Gurnani, Deepak, and Ludger Hentschel, 2018, Global Macro: Portfolio diversification for turbulent times,Versor Investments, New York, NY.

Sharpe, William F., 1992, Asset allocation: Management style and performance measurement, *Journal of Portfolio Management* Winter, 7–19.

3. CTA Trend Following – This Time is Different?

Deepak Gurnani Ludger Hentschel

June 2017

Contents

Executive Summary

Recent investor interest in CTA trend-following has been high. Concurrently, over the last 2-3 years, performance of many large CTA funds has been disappointing, in absolute terms and compared to historical returns for the strategy. Is this a case of "This time is different"?

In this paper, we share some of our insights into CTA trend-following, focusing on the environment and performance of CTA trend-following during the last 2-3 years. We demonstrate that there has been an increase in trend shifts across assets, asset classes, and trend horizons. Pinpointing the reasons for this change is beyond the scope of this paper but the transition in the environment coincides with a period of unusual global monetary policy and net asset growth in CTA trend-following and other systematic strategies.

In this challenging environment, Versor's Trend strategy has generated positive returns and materially outperformed the large CTA hedge funds included in the SG Trend Index. Versor has generated these returns through a differentiated and sophisticated investment process with large capacity. Versor's edge is the combination of sophisticated signals, dynamic risk allocation, and efficient trade execution.

We don't know if "This time is different". However, we do know that simple trend-following approaches no longer work in the current environment. CTA funds need to adapt their investment processes to the more frequent changes in trend and market volatility. CTA funds that fail to adapt presumably will continue to underperform.

The large dispersion in recent returns has confirmed that trend following is not a "generic" strategy and that choosing an appropriate manager matters. Especially for funds that can adapt to this new environment, we remain confident about the prospects for CTA trend-following risk premia going forward.

1. Introduction

Over the last several years, investor interest in CTA trend-following has been high. However, the environment for trend-following strategies has been challenging, as indicated by the low returns for CTA indexes. Much of that challenge has come from trends shifting across assets, asset classes, and signal horizons. We don't know if "This time is different". However, we do know that simple trend-following approaches no longer work in the current environment. CTA funds need to adapt their investment processes to the more frequent changes in trends and market volatility. CTA funds that fail to adapt presumably will continue to underperform. Thus, while investors may hope that the environment will improve, they should also invest in trend-following strategies that can prosper without a change in the environment.

Our research into alternative risk premia, including trend-following, goes back more than 20 years. For a recent example, see Gurnani and Hentschel (2010). Several years ago, we launched alternative risk premia products, including Versor Trend, that allow investors to benefit from these insights directly.

We show that the live performance of the Versor Trend alternative risk premia product has materially exceeded that of the largest CTA hedge funds that constitute the SG Trend index. This is empirical confirmation of our investment philosophy that sophisticated alternative risk premia strategies can outperform high-quality hedge fund portfolios in similar strategies.

We demonstrate that annualized outperformance of Versor Trend 1x and 2x versus the SG Trend Index has been roughly 4% and 10%, respectively, on a risk-adjusted basis. (Versor Investments can customize risk levels for Versor Trend.) These excess returns vastly exceed the fee differentials between our alternative risk premia products and hedge funds and hence must be driven by excess returns gross of fees.

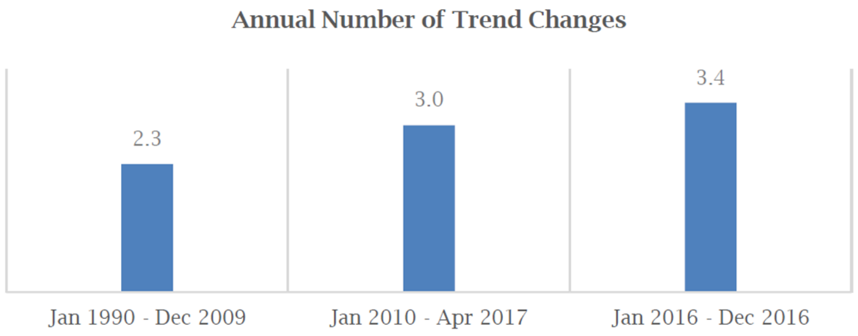
Versor's edge is the combination of sophisticated signals, dynamic risk allocation, and efficient trade execution. Versor's alternative risk premia products are sophisticated systematic investment strategies offered at low, fixed fees. There now exist several competing alternative risk premia products, with more continuing to enter. Initially, some investors considered these products to be "generic". The realized returns for these alternative risk premia have had large dispersion, however, demonstrating that alternative risk premia products come in many different forms.

We argue that deep hedge fund experience, and risk management expertise in particular, is an important ingredient in successful alternative risk premia products. Yet, alternative risk premia products offered by hedge funds are subject to conflicts of interest that should trouble investors. Obviously, a hedge fund manager has incentives to keep the best ideas for the high-fee hedge fund instead of offering them in a lower-fee alternative risk premia product. An obvious way to avoid this conflict is to choose alternative risk premia products from asset managers without competing hedge fund products but with hedge fund experience.

2. Trend-Following Returns

We define the trend-following strategy, at its core, as a collection of sophisticated trend-following signals applied to a large set of diverse, liquid futures contracts, using dynamic risk allocations in

Figure 1: Number of Trend Changes Per Year



The figure shows the average number of times trend signals changed sign over 3 periods: January 1990 to December 2009, January 2010 to April 2017, and calendar year 2016. The trend signals and their changes are based on a constant blend of short-, medium-, and longterm trend signals.

These results are based on simulated or hypothetical performance results that have certain inherent limitations. Unlike the results shown in an actual performance record, these results do not represent actual trading.

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order to ensure diversification across signals, contracts, and asset classes. The strategy is long or short different futures contracts at different points in time.

Investors increasingly recognize that such a strategy has attractive returns that have approximately zero correlation with traditional asset returns and exhibit positive convexity.[1] These features allow trend-following exposures to mitigate major portfolio risks while making positive return contribution. Many other strategies that offer portfolio insurance require investors to sacrifice returns in normal investment environments.

Historically, investors have invested in trend-following via CTA hedge funds. Some of the largest hedge funds in the world are CTA managers. More recently, firms like Versor Investments have offered trend-following strategies in the form of alternative risk premia with more attractive transparency, liquidity, and fees.

The Versor Trend strategy invests in a diverse set of more than 60 liquid futures contracts across the four major asset classes: commodities, equities, fixed income, and exchange rates. The trades for each contract are driven by a collection of distinct trend-following signals. These signals indicate long positions when recent prices are higher than previous prices and short positions when recent prices are lower than previous prices.[2] The signals estimate price trends using a variety of metrics over different periods, with comparison periods ranging from approximately 1 month to approximately 1 year.

The Versor Trend process sizes these long and short positions using portfolio construction and risk management techniques that consider liquidity, transaction costs, and the volatility of signals, contracts, and asset classes, as well as their correlations. The objective is to maximize returns net of costs within a target risk range while maintaining liquidity and avoiding portfolio concentration in individual signals or contracts.

2.1 Recent Performance

Trend-following performance over recent years has been hampered by trends that have shifted more frequently across assets, asset classes, and signal durations. Since 2010, the average duration of trends

[1] Fung and Hsieh (2001) describe and document the positive convexity in trend-following returns. A successful trend-following strategy earns positive returns by being long an asset during periods of rising prices and also earns positive returns by being short the same asset during periods of falling prices. This naturally creates convexity in the returns of the trend-following strategy.

[2] Due to the expiration of individual futures contracts, we adjust futures prices before comparing them across expiration dates.

Table 1: Realized Performance from 12/19/2014 to 4/30/2017

	Versor Trend 1x	SG Trend	HFRX CTA
Panel A: Summary Statistics			
Return	2.36	-2.33	-1.10
Risk	8.51	10.49	8.19
Sharpe Ratio	0.25	-0.24	-0.16
Panel B: Relative Performance			
Versor Alpha (% pa)		4.06	3.43
Versor Beta vs index		0.74	0.84
Panel C: Correlation			
Versor correlation vs index		0.91	0.76

The table shows summary statistics based on realized daily returns for the Versor Trend 1x strategy from December 19, 2014 to April 30, 2017. For comparison, the table shows summary statistics for two separate benchmarks: the SG Trend index and the HFRX Systematic Diversified CTA index. Both indexes track the performance of CTA hedge funds.

Panel A shows realized annualized returns, annualized risk, and annualized Sharpe ratios. All returns are net of fees and actual transaction costs.

Panel B shows the annualized realized alpha of the Versor Trend strategy relative to the beta-adjusted benchmark returns. The panel also shows the betas. We estimate alphas and betas by regressing the Versor Trend returns in excess of the risk-free interest rate on index returns in excess of the risk-free interest rate.

Panel C shows the realized correlation of the Versor Trend strategy with the 2 benchmark series, based on daily returns.

Reported actual returns are unaudited preliminary estimates, subject to revision and net of 0.75% per annum management fees. Returns for the strategy are estimated by applying a notional capital allocation (and applicable expenses) to the P/L associated with the portion of the Versor Alternative Risk Premia Master Fund Ltd allocated to the strategy. Performance results reflect the reinvestment of income. Please note that the returns could be materially different from those stated above in case the strategy was managed in a dedicated standalone fund. The fee structure is for the Day 1 Investor Share Class. Certain investors may have higher management and performance fees depending on applicable share class. Versor also manages other accounts using the same investment strategy. Returns for the other accounts may differ from the returns shown here, depending on differences in risk levels and investment restrictions, timing of cash flows and fee structures. Please see important disclosures at the end.

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has shortened. To summarize this effect, we compute the number of times per year trend-following signals switched from long to short or vice versa. We count these switches for a composite signal that blends short-, medium-, and long-term trend signals. Of course, we hold the weights across the signal durations constant.

From 1990 through 2009, trends switched direction an average of 2.3 times per year. Since 2010, trends have switched direction an average of 3.0 times per year. During 2016, the number of direction changes reached 3.4 per year, the highest average for any calendar year since 1990. Figure 1 shows these changes graphically.

The difference between pre- and post-2009 represents a large and highly unusual change. While trend patterns vary over time, the post 2009 increase in the number of annual direction changes is 2.6 standard deviations above the 1990-2009 norm. This is a 30% increase in the number of direction changes and a 25% decline in the associated average duration of the signals. However, as we will show, simply using faster trend signals would not have addressed this issue since trends were also weak or absent from many assets for extended periods.

Naturally, most trend-following strategies find it harder to generate attractive returns when trends

Table 2: Pro Forma Performance from 12/19/2014 to 4/30/2017

	Versor Trend 2x	SG Trend	HFRX CTA
Panel A: Summary Statistics			
Return	5.46	-2.33	-1.10
Risk	17.05	10.49	8.19
Sharpe Ratio	0.31	-0.24	-0.16
Panel B: Relative Performance			
Versor Alpha (% pa)		9.77	8.51
Versor Beta vs index		1.46	1.67
Panel C: Correlation			
Versor correlation vs index		0.91	0.76

The table shows summary statistics based on pro forma daily returns for the Versor Trend 2x strategy from December 19, 2014 to April 30, 2017. The returns are computed by applying 2x leverage to the realized returns net of transaction costs of the Versor Trend strategy. For comparison, the table shows summary statistics for two separate benchmarks: the SG Trend index and the HFRX Systematic Diversified CTA index. Both indexes track the performance of CTA hedge funds.

Panel A shows realized annualized returns, annualized risk, and annualized Sharpe ratios. All returns are net of fees and actual transaction costs.

Panel B shows the annualized realized alpha of the Versor Trend strategy relative to the beta-adjusted benchmark returns. The panel also shows the betas. We estimate alphas and betas by regressing the Versor Trend returns in excess of the risk-free interest rate on index returns in excess of the risk-free interest rate.

Panel C shows the realized correlation of the Versor Trend strategy with the 2 benchmark series, based on daily returns.

Reported actual returns are unaudited preliminary estimates, subject to revision and net of 0.75% per annum management fees. Performance results reflect the reinvestment of income. Please note that the returns could be materially different from those stated above in case the strategy was managed in a dedicated standalone fund. The fee structure is for the Day 1 Investor Share Class. Certain investors may have higher management and performance fees depending on applicable share class. Versor has generated pro forma results for running the Trend 2x strategy at 16-20% annualized volatility. There are no assurances, however, that the actual performance from running the strategy at higher volatility levels will be in line with the pro forma results shown here. In fact, the actual returns could be much lower than those shown here. Versor does not manage any capital in the Trend 2x strategy. The pro forma results for the Trend 2x strategy are estimated from the live performance of the Trend 1x strategy, using the process described below. The target volatility of the Trend 2x strategy is 16-20% annualized (twice that of the Trend 1x strategy). The excess returns for the Trend 1x strategy are calculated by subtracting the US T-Bill return from the total return. The excess return is then multiplied by two (the ratio of the volatilities of the two strategies) to arrive at the excess return for the Trend 2x strategy. The pro forma returns for the Trend 2x strategy are computed by adding the US T-Bill return to the excess returns. This process is repeated for each day and has the net effect of increasing the profits in profitable periods for the Trend 1x strategy and conversely increasing the losses during periods where Trend 1x strategy suffers losses. Please see important disclosures at the end.

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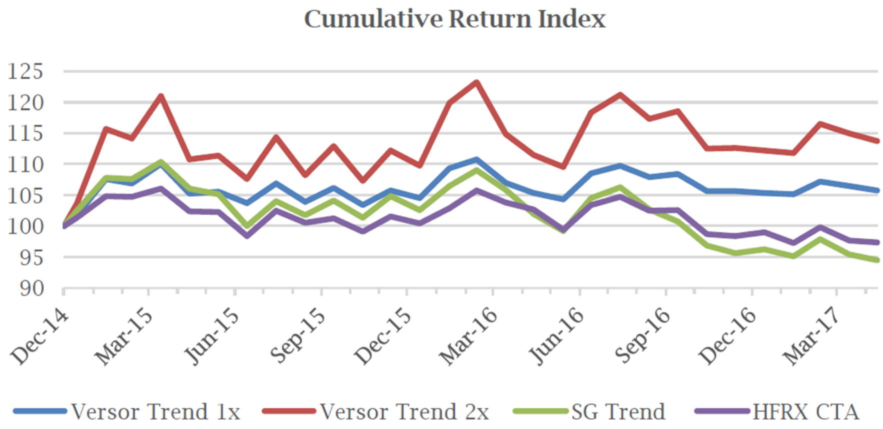
shift in this fashion. Investors speak of getting “whipsawed”. Since these shifting trends may be here to stay it is important for investors to find trend-following implementations that can succeed in this environment.

We launched the Versor Trend 1x strategy on December 19, 2014. Table 1 shows performance statistics net of fees, expenses, and transaction costs, from inception until April 30, 2017, a period of nearly two and a half years. The table also includes information for the SG Trend Index and the HFRX Systematic Diversified CTA index. Both indexes measure returns for CTA hedge funds net of fees and transactions costs. The SG Trend index includes the largest CTA funds by assets under management. The HFRX CTA index includes managers selected by HFRX.

We offer the Versor Trend strategy at a range of customized risk levels. For reference, we show performance for a baseline “1x” portfolio with a risk target of 8-10% in table 1 and for a pro forma “2x”

Figure 2: Cumulative Performance



The figure shows cumulative monthly performance from December 19, 2014 to April 30, 2017. From top to bottom at the right, the returns are for the Versor Trend 2x strategy in red, the Versor Trend 1x strategy in blue, the HFRX CTA index in purple, and the SG Trend index in green. All returns are net of fees and transaction costs. The Versor Trend 2x returns are pro forma returns based on applying 2x leverage to the Versor Trend 1x returns.

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portfolio with a risk target of 16-20% in table 2. For brevity, we focus our discussion on table 2. Apart from the natural effects of leverage, the results in both tables are similar.

Overall, the live Versor Trend returns have generated strong returns and materially exceeded the index returns over this period. Panel A of table 2 shows that the Versor Trend 2x portfolio has outperformed the SG Trend index by nearly 8% annualized and the HFRX CTA index by nearly 7% annualized. Importantly, Versor Trend 2x has had positive returns of 5.46% annualized during a challenging period for CTA managers, when both indexes have lost money.

Panel A of table 2 also shows that Versor Trend 2x runs higher risk than either index. To adjust for these risk differences, panel B of table 2 shows the results from regressing Versor returns in excess of the risk-free interest rate on index returns in excess of the risk-free rate. The betas from separate return regressions are 1.46 and 1.67 for the SG Trend and HFRX CTA indexes, respectively. The same regressions yield intercepts that confirm that Versor Trend 2x has materially outperformed the indexes on a beta or risk adjusted basis. In annualized terms, the outperformance has been 9.77% versus the SG Trend index and 8.51% versus the HFRX CTA index.

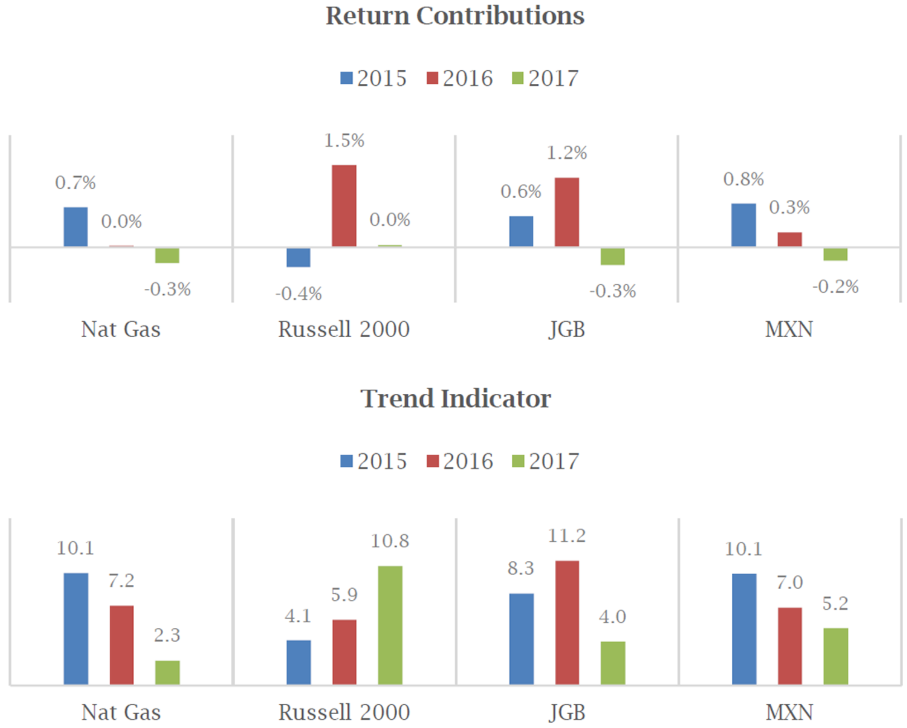
Unfortunately, we do not know fees and expenses for the managers constituting either index. Even at a full "2 and 20" fee for the hedge funds, however, this performance differential greatly exceeds the fee differential.

Panel C of table 2 shows that correlations between Versor Trend and the CTA indexes is 0.91 and 0.76, respectively. These correlations are so high that it is clear that Versor Trend and the hedge funds in the indexes are pursuing comparable strategies—albeit with distinctly different outcomes.

Figure 2 compares cumulative returns for the Versor Trend strategy and the benchmark indexes. The cumulative return graph illustrates the high correlation between the Versor Trend returns and the benchmark returns. The graph also shows the consistent outperformance of the Versor strategy.

By the design of the index, the SG Trend index includes the 10 largest CTA trend-following mangers. In

Figure 3: Dynamic Allocations to Assets with Trends



The top panel of the figure shows return contributions, net of transaction costs, to overall portfolio returns for Versor Trend 1x from four futures contracts, one from each asset class: Natural Gas, Russell 2000 small-cap equities, Japanese 10-year government bonds, and the Mexican peso vs US dollar exchange rate. The bars show returns contributions by calendar year. The contributions for 2017 are up to April 30, 2017.

The bottom panel shows trend indicators for the same assets and periods. The trend indicator measures the strength of the trend, regardless of sign, divided by the variability of the trend.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

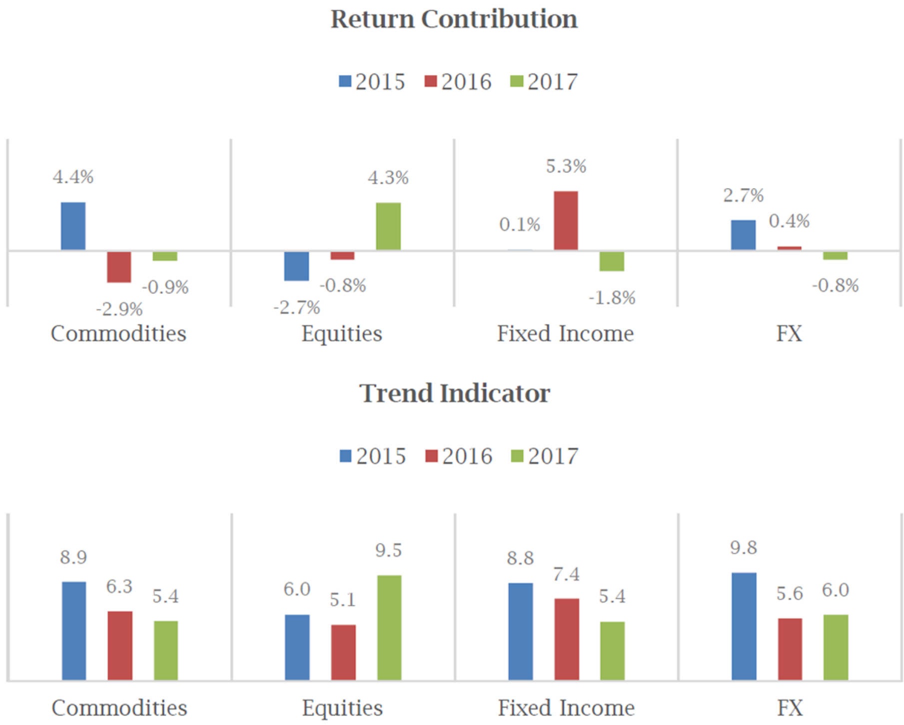
fact, the size of these CTA hedge funds has triggered investor concerns that the largest CTA managers have shifted their focus from asset management to asset gathering and that this has negatively affected returns. The index performance during the Versor Trend live trading period seems to warrant this concern. Yet, the HFRX CTA index generally includes smaller managers and has delivered very similar performance, so that manager size may not be the only impediment to recent CTA hedge fund performance.

2.2 Dynamic Risk Allocations Add Value

The performance of the Versor Trend strategy shows that a sophisticated trend-following strategy can earn attractive returns in an environment of less reliable trends. Key features that allow the Versor Trend strategy to sustain performance in an environment with less stable trends are a broad array of signals to detect trends, the ability to dynamically allocate risk to assets and asset classes with strong trends, and the ability to dynamically manage overall portfolio risk so exposures can shrink and grow with the overall opportunity set.

Figure 3 illustrates this idea with four contracts, one from each asset class. For each contract, the the top panel of the figure shows the return contribution to the Versor Trend portfolio by calendar year. The bottom panel of the figure shows a trend indicator that adjusts signal strength by volatility. The

Figure 4: Dynamic Allocations to Asset Classes with Trends



The top panel of the figure shows return contributions, net of transaction costs, to overall portfolio returns for Versor Trend 1x from asset class allocations. The bars show returns contributions by calendar year. The contributions for 2017 are up to April 30, 2017.

The bottom panel shows trend indicators for the same asset classes and periods. The trend indicator measures the strength of the trend, regardless of sign, divided by the variability of the trend. The trend indicator for each asset class is an average of the trend indicators for the futures contracts in the Versor Trend investable universe belonging to the asset class.

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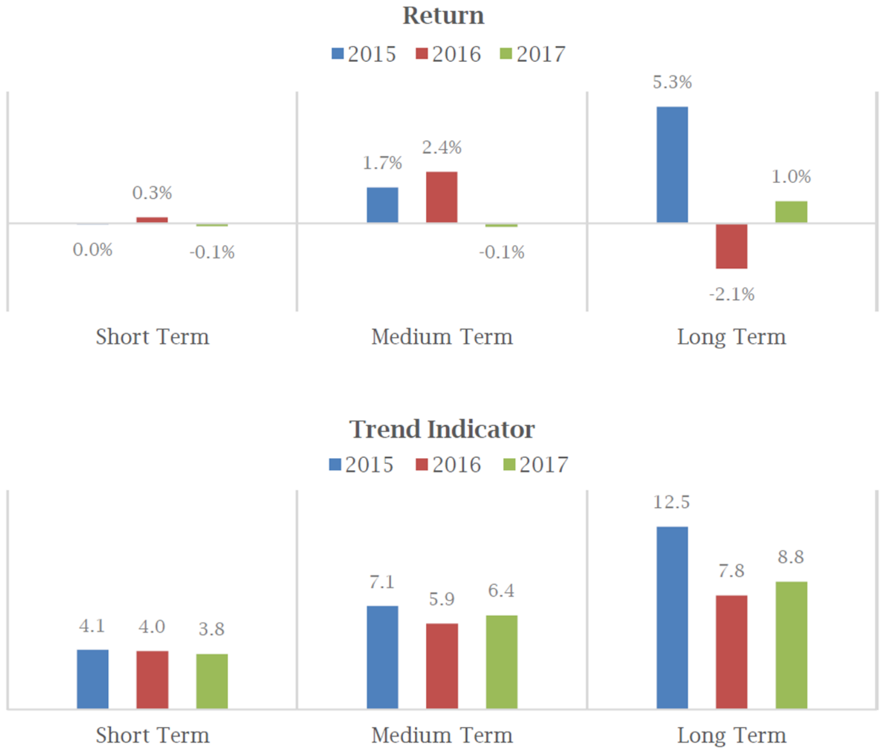
indicator is large for strong and stable trends and small for weak and variable trends. By design, the trend indicator does not distinguish between positive or negative trends.

The Versor Trend portfolio deliberately allocates more risk to assets, asset classes, and signals with stronger trend indicators. If this allocation process is successful, larger trend indicators are associated with larger return contributions. We now show that this has been the case, thereby mitigating the impact of less reliable trends.

Looking over time for a particular contract, a comparison of the panels in figure 3 shows that a given contract generally made larger return contributions during periods of stronger trends. Similarly, looking across contracts in a given period, the figure shows that the portfolio generally derived larger return contributions from contracts with stronger trends. This is evidence that the Versor process identifies trends and shifts risk allocations to contracts with stronger trends.

Figure 4 shows that same deliberate risk allocation also has been effective across asset classes. Similar to the previous figure, figure 4 graphs return contributions by asset class for each calendar year and the matching trend indicators. As the figure shows, the portfolio has been successful in earning larger return contributions from asset classes with stronger and more stable trends.

Figure 5: Effectiveness of Trend Signal Durations



The top panel of the figure shows returns, net of transaction costs, for simulated trend-following portfolios focused on signals with short, medium, and long durations, respectively. Short-term signals range from 1 to 3 months. Medium-term signals range from 3 to 6 months. Long-term signals range from 9 to 12 months. The bars show returns by calendar year. The returns for 2017 are up to April 30, 2017.

The bottom panel shows trend indicators for the same signal durations. The trend indicator measures the strength of the trend, regardless of sign, divided by the variability of the trend. The trend indicator for each duration is an average of multiple trend indicators for all of the futures contracts in the Versor Trend investable universe.

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While it is tempting to conclude that faster trend signals would be more productive in an environment with short trend durations, figure 5 demonstrates that this has not been the case. The returns, net of transaction costs, in the top panel show that short-term signals have been consistently ineffective over the last two and a half years. The top panel in figure 5 shows returns, not return contributions, because the netting of signals with different durations makes such attribution ambiguous. Moreover, short-term signals have generated such low net returns in all 3 years that we want to make it clear that low contributions are not driven by low exposures to short-term signals.

The bottom panel of figure 5 confirms that short-term signals had the weakest and most volatile trends, as measured by the trend indicator.

Although trends have been shorter over the last few years, these short trends also have been weak, so that the returns from faster signals were largely offset by the higher transaction costs associated with more frequent trading.

3. A Complement to Hedge Funds

Given the strong returns for the Versor Trend strategies in a challenging environment, investors should consider including Versor Trend in their portfolios. While investors have traditionally built trend-following exposures via CTA hedge funds, this has not worked as well recently. The SG Trend index — which consists of the largest CTA funds in the world — has materially underperformed Versor Trend alternative risk premia.

In addition to differentiated investment process and returns, two attractive features distinguish Versor Trend from CTA hedge funds. Due to the liquidity of Versor Trend, investors can scale up exposures when investors think the strategy will perform relatively well and scale them down when investors think the strategy will perform relatively poorly. Moreover, the absence of performance fees means that Versor Trend products are much cheaper than hedge funds during periods of high strategy returns, when investors would like to have larger exposures. For example, when trend following returns are 20% before fees, a 2/20 hedge fund leaves 14.4% return net of fees to the investor. At a 0.75% fixed fee, Versor Trend would return 19.25% to the investor, an additional 485 basis points!

4. Conclusion

The realized returns for Versor Trend strategy have confirmed one of our investment theses: a sophisticated alternative risk premia product can outperform a portfolio of high-quality hedge funds. Since inception, Versor Trend 1x has outperformed the SG Trend index by more than 4% annualized on a risk-adjusted basis. Versor Trend 2x has outperformed the SG Trend index by nearly 10% annualized on a risk-adjusted basis. Versor Trend has generated this large outperformance with a realized correlation of 0.9 with SG Trend returns.

Since the SG Trend index consists of the largest CTA hedge funds, this experience confirms that fund size is not a reliable indicator of excellent future performance.

We show that sophisticated trend-following signals and dynamic risk allocations have aligned the Versor Trend portfolio with trends in different assets and asset classes, even though such trends have recently been less stable. There is reason to believe that trends in futures prices will continue to exist but that they may continue to shift more quickly in the patterns exhibited over the last few years. In such an environment, successful trend-following strategies will require sophisticated signals and dynamic risk allocations. As a result, we are optimistic about the prospects for Versor Trend going forward, even if the recent trend following environment turns out to be the new normal and not an unusual episode. If the overall environment should turn out to be more favorable, these skills should add alpha to a higher baseline strategy return.

5. References

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Gurnani, Deepak and Ludger Hentschel, 2010, *Demystifying Hedge Funds: An Analysis of Trades and Alpha.* Investcorp. New York, NY.

Section 2

Unboxing Merger Arbitrage

4. Merger Arbitrage and ESG Impact Investing

Deepak Gurnani   Ludger Hentschel   Neetu Jhamb

October 2022

Contents

Executive Summary

A merger arbitrage portfolio can be structured to encourage large increases in ESG characteristics that are associated with particular mergers. Such a portfolio can generate attractive returns from investing in mergers that increase ESG scores by 50 percent, or more, over the life of the merger.

Compared to a naive implementation of merger arbitrage, a sophisticated implementation is associated with noticeably larger ESG improvements. The difference in average ESG improvements is nearly 20 percentage points. Moreover, the sophisticated merger arbitrage strategy also generates higher returns than the naive implementation.

These large improvements in ESG scores should make such a merger arbitrage strategy appealing to investors who seek to have positive ESG impact in addition to earning attractive, diversifying investment returns.

The large and quick ESG improvements of a sophisticated merger arbitrage strategy contrast sharply with the uncertain, small, and slow benefits of investing in firms that already have attractive ESG scores. It remains unclear whether these more common ESG investment strategies will generate attractive investment returns or improve ESG scores in the future. In long-term equilibrium, if investors value higher ESG scores they should be willing to accept lower returns. For merger arbitrage, however, we find no evidence that larger expected ESG improvements are associated with lower returns.

1. Introduction

Corporate mergers represent exceptional transformations for the participating firms. We show that one transformation is a large increase in the environmental, social, and governance (ESG) scores of the target firms. This represents an opportunity for merger investors to encourage large, quick increases in ESG scores.

We show that a portfolio of merger deals has experienced a 57% increase in ESG scores, on average. We are not aware of other investment strategies with similar demonstrated ESG impacts. We also show that a sophisticated merger arbitrage strategy can generate even higher ESG improvements of 63%. The ESG improvements associated with this sophisticated strategy are materially larger than the 46% ESG gains from a simpler merger arbitrage strategy that weights mergers according to deal size.

We first outline systematic merger arbitrage strategies and the main aspects of ESG investing. The core of the paper then documents the ESG impacts of merger arbitrage. We briefly discuss some regulatory implications before concluding.

2. Merger Arbitrage

Merger arbitrage, also known as risk arbitrage, focuses on purchasing the publicly traded shares of merger target companies, generally at a discount relative to the consideration offered by the acquirer. If the merger completes, the trade earns the spread between the value of the offer and the purchase price of the shares. For offers involving acquirer shares, sophisticated merger arbitrage trades generally short the acquirer shares offered for each target share. In the event the merger completes, this eliminates uncertainty about future acquirer share prices.

The principal risk of such trades stems from uncertainty about whether the merger will complete at the currently offered terms, terminate, or receive a higher offer. Historically, about 90% of mergers complete successfully. About 75% complete under the original terms and about 15% complete with improved offers. Only about 10% of mergers terminate. Most mergers complete or terminate in less than 6 months.

For our empirical analysis of merger arbitrage, we use the results of simulated merger arbitrage strategies that invest in nearly all liquid announced mergers in North America and Europe. The mergers have to be $500 million or larger. The offers may involve cash or stock in any combination. The simulated strategies hedge out the acquirer stock risk by shorting an appropriate number of acquirer shares for each target share. We investigate two systematic strategies: A "sophisticated" merger arbitrage strategy and a "naive" merger arbitrage strategy. The sophisticated strategy weights deals according to statistically sophisticated predictions about deal returns and deal risks. The predictions apply machine-learning methods to observable deal characteristics. The naive strategy weights deals in proportion to their size.

3. ESG Investing

Investors are increasingly interested in the environmental, social, and governance (ESG) consequences of their investments. The mainstream approach to this is to compare the ESG scores of a portfolio to the ESG scores of a benchmark portfolio. An alternative approach explicitly targets improvements in the ESG scores of the portfolio companies.

3.1 ESG Scores

Recently, public companies have begun to report a range of ESG information. One example of environmental information now reported by many firms is carbon emissions. For firms that don't yet report such facts, third-party data vendors like Refinitiv, MSCI, or CDP provide estimates. Third-party data firms also rate companies on a variety of ESG criteria not reported by any firm. Berg, Kölbel, Pavlova, and Rigobon (2021) point out that the ESG scores from different data vendors can vary materially.

Standards for aggregating this information from the firm level to the portfolio level are also still evolving.[1] But using a reasonable weighted average across portfolio positions yields a portfolio-level ESG score.

Some investors pursue an objective to hold portfolios with ESG scores that are better than comparable scores for a benchmark portfolio. For example, an investor may aim to hold a portfolio with lower carbon intensity than the market portfolio. Such investors direct their capital to firms with better ESG scores and away from firms with worse ESG scores. Avramov, Cheng, Lioui, and Tarelli (2021) and Pedersen, Fitzgibbons, and Pomorski (2021) describe portfolio construction methods that simultaneously pursue ESG objectives and investment return objectives.

Unfortunately, it is unclear whether such allocations provide firms with incentives to improve their ESG practices or improve investment returns.

Pastor, Stambaugh, and Taylor (2021) and Berk and van Binsbergen (2021) argue that a large shift in investments towards ESG-friendly firms eventually results in a higher cost of capital for the remaining firms, thereby providing financial incentives for ESG improvements. However, Berk and van Binsbergen (2021) argue that the current level of ESG investment is (still) too small to produce meaningful financial incentives. The empirical analysis by Heath, Macciocchi, Michaeli, and Ringgenberg (2022) finds no impact of ESG investing on corporate behavior.

The evidence on the investment performance of ESG-tilted portfolios is also mixed. Partly this may be due to the relatively short sample periods induced by the short history of ESG scores. Friede, Busch, and Bassen (2015) find that investment returns for ESG stocks have been above average. In contrast, Hong and Kacperczyk (2009) and Bolton and Kacperczyk (2021) find that investment returns for ESG stocks have been below average. However, both positive and negative results in this area tend to be statistically insignificant.

The theoretical equilibrium framework of Pastor, Stambaugh, and Taylor (2021) potentially can explain these conflicting or weak findings. Pastor, Stambaugh, and Taylor (2021) derive a model in which investors are willing to accept lower average returns for firms with better ESG scores. Such a tradeoff seems inevitable for investors who have portfolio objectives in addition to investment returns. Even though firms and portfolios with higher ESG scores should earn lower long-term average returns, they may temporarily outperform when investor preferences for ESG firms increase.

An interesting aspect of such an equilibrium framework is that investors with ESG preferences shift capital away from firms with poor ESG scores. This lowers the share prices of these firms and creates more attractive future returns for investors who pay less attention to ESG criteria. The result is that these investors increase their holdings of firms with poor ESG scores. This substitution reduces and possibly eliminates the effects of "divesting" from firms with poor ESG scores.

These theoretical and statistical challenges in detecting effects of ESG investing on corporate behavior

[1] Standards for carbon reporting may be the most advanced. For example, TCFD (2021) is a prominent standards proposal.

and portfolio returns raise questions about the efficacy of investment strategies that overweight firms or portfolios with attractive ESG scores.

3.2 ESG Impact

One way of overcoming the challenges associated with portfolios focused on current ESG scores is to consider investment strategies that deliver a positive short-term impact on ESG scores.

An investment strategy that pursues positive ESG impact should be interested in measuring ESG scores before the strategy enters positions and after the strategy exits positions. If ESG scores improve over the investment period, it seems fair to say that the strategy is associated with a positive ESG impact.

4. ESG Impact of Merger Arbitrage

Using a simulated, systematic implementation of merger arbitrage, we now show that such a portfolio is associated with large improvements in the ESG scores of the merger target firms.

4.1 ESG Data

In this study, we use ESG data from Refinitiv. The ESG data includes values self-reported by the firms and Refinitiv estimates for some firms that did not report. Even with those estimates, however, we do not have full historical ESG data for the mergers in our database. We have information about the characteristics of roughly 4,000 mergers in North America and Europe, including the United Kingdom. The mergers were announced between 2003 and 2022. While we have essentially complete information about merger outcomes and returns, for example, the availability of ESG data materially increases over time. We have relatively little ESG information for the earlier years of our merger sample.

The top-level ESG scores from Refinitiv are aggregated scores of underlying constituent scores. The top-level scores are calibrated so they range from 0 (worst) to 1 (best). On this scale, an increase in a firm's ESG score represents an improvement.

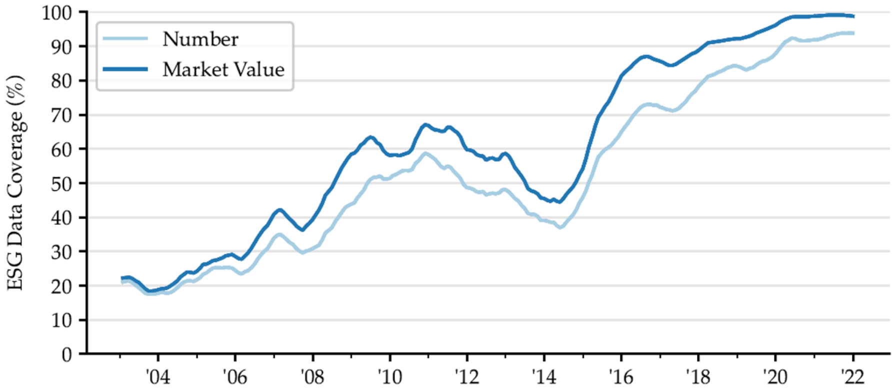
Figure 1 shows that the data coverage for ESG scores has improved over time. Although our merger data start in 2003, the ESG coverage during the early years is fairly low. In more recent years, we have ESG scores for 90% of mergers, or more.

4.2 Systematic Merger Arbitrage

In order to analyze the ESG impact associated with merger arbitrage, we simulate a systematic merger arbitrage strategy. The strategy buys all announced merger deals over $500 million in the United States, Canada, and Europe between 2003 and 2022. The strategy holds these positions until the mergers complete or terminate. More than 90% of announced mergers complete. On average, deals take about 5 months to complete. The portfolio operates with variable leverage. Leverage is higher when there are more mergers and lower when there are fewer merges. For offers that contain a stock component, the strategy shorts the appropriate number of acquirer shares in order to eliminate uncertainty about future prices of these shares. The short exposures rise when there are more stock offers and fall when there are fewer stock offers.

We compare two variations of this strategy. The first is a merger arbitrage strategy that uses sophisticated machine learning methods to make forecasts for different deal outcomes. Based on these forecasts, the strategy overweights attractive deals and underweights less attractive deals. The strategy's primary

Figure 1: ESG Data Coverage over Time



The graph shows the fraction of mergers for which we have ESG scores from Refinitiv. The light blue line shows coverage as a fraction of the number of outstanding mergers. The dark blue line shows coverage as a fraction of outstanding merger values.

Over the full sample period, the coverage averages 55% of the number of mergers and 63% of merger values. As the figure shows, coverage has increased markedly over time.

The merger sample includes the targets and acquirers from 1,991 announced mergers with market values over $500 million between January 2003 and May 2022.

Source: ESG Data received from Refinitiv. Internally prepared by Versor Investments.

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focus is on attractive portfolio returns but it also considers the ESG characteristics of the positions.[2] The second is a naive merger arbitrage strategy that holds positions that are directly proportional to the size of each merger. The naive strategy makes no forecasts for deal outcomes and pays no explicit attention to the ESG improvements associated with the mergers.

4.3 Measuring ESG Impact

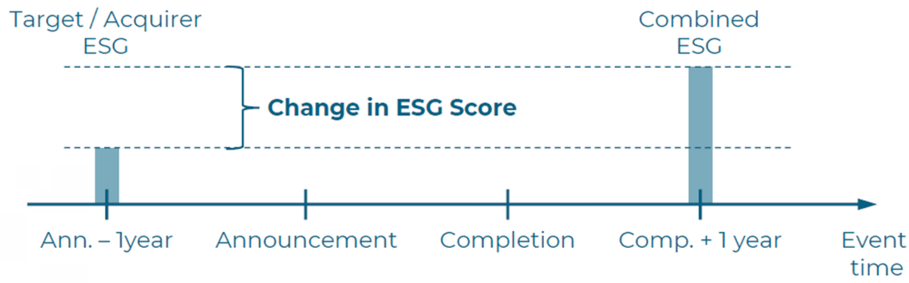
For the deals in these systematic merger arbitrage portfolios, we measure the changes in ESG scores over the period from 1 year prior to each merger's announcement to 1 year following each merger's completion. Figure 2 illustrates the timeline for this measurement in event time relative to merger announcements. We measure the changes for merger targets, a matched portfolio of their sector peers, merger acquirers, and a matched portfolio of their sector peers. We focus on successful mergers since they constitute more than 90% of all announced mergers.

Table 1 shows that the merger targets in this investable universe increased their ESG scores by an average of 57%! This increase vastly outstrips the contemporaneous increases for a portfolio of matched sector peers. The ESG scores of the sector peers rose by 10%, on average. The difference between these ESG improvements is highly statistically significant, with a Student t-statistic of nearly 19. The ESG scores for the acquirers in these transactions rose by 13%, also more than for their matching sector peers. Once again, we comfortably reject the hypothesis that acquirer and peer ESG scores increase by the same amount, with a Student t-statistic of nearly 5.

Table 1 shows results for overall ESG scores. Separately, we have investigated similar changes for the environmental, social, and governance scores and carbon emission intensities. All of these show similarly dramatic improvements.

[2] Versor offers a similar portfolio to clients.

Figure 2: Measuring ESG Changes for Mergers



The figure illustrates the event time line for ESG changes associated with mergers. We measure the changes over an interval that starts one year prior to merger announcement and ends one year after merger completion.

Although ESG scores overall have drifted up during this period, merger targets and acquirers have strongly outperformed their sector peers. Especially for merger targets, this difference is very large and unlikely to be matched by investment strategies that overweight firms with above-average ESG scores. For such strategies, there simply are not enough corporate events that have a chance to produce large ESG changes. By contrast, a merger is likely one of the largest corporate events in a firm's lifetime. In this sense, merger arbitrage can have an exceptional ESG impact. The data show that merger arbitrage has a large positive ESG impact.

A part of these large improvements in ESG scores stems from the fact that merger targets often start with below-average ESG scores. After completion of the merger, these scores are materially higher. While the associated portfolio holdings start with below-average ESG scores, they result in exceptional ESG improvements. This should be appealing to investors with an interest in making investments with a positive impact.

4.4 Predicting ESG Impact

A sophisticated merger arbitrage portfolio can target mergers with especially large ESG improvements since we can predict these changes.

Table 2 shows results from regressions that predict ESG changes based on various characteristics of the merger. The table shows results for univariate regressions based on selected predictors and for a multivariate regression including several predictors.

The predictors are proprietary and we veil their exact construction. However, table 2 demonstrates that we can forecast the majority of ESG changes associated with mergers.

The R^2 statistics in table 2 show that all of the regressions deliver material predictive power. Several of the models achieve R^2 values of 70%, or more. Predictive models like this can meaningfully separate mergers with large expected ESG improvements from mergers with small expected ESG improvements.[3]

4.5 ESG Changes and Merger Returns

It is natural to ask whether a merger arbitrage portfolio that overweights mergers with large expected ESG improvements realizes higher or lower returns than a portfolio that ignores ESG changes.

[3] In practice, even more accurate forecasts may be achievable with additional predictors or machine learning methods. Table 2 shows relatively simple linear models for illustration.

Table 1: ESG Impact of Mergers

	Targets		Acquirers	
	Change in ESG (%)	*t*-Stat	Change in ESG (%)	*t*-Stat
Merger	56.8	(22.7)	12.9	(20.4)
Sector Benchmark	9.5	(41.0)	9.6	(40.2)
Difference	47.2	(18.8)	3.2	(4.8)

The table compares the changes in average ESG scores for acquirers and targets participating in mergers and matched sector peers from 2 different merger strategies. Changes are expressed in percent. To the right of the estimates, the table shows the associated *t*-statistics in parentheses.

The sample includes 1,991 announced mergers with market values over $500 million between January 2003 and May 2022. There are 685 targets and 1,368 acquirers with available ESG scores.

Source: ESG data received from Refinitiv. Internally prepared by Versor Investments.

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Table 3 shows results of regressions

$$r_{i,t+1} - r_{f,t+1} = a + b\, E_t[\Delta s_{i,t+1}] + \epsilon_{i,t+1}, \tag{1}$$

where $r_{i,t+1} - r_{f,t+1}$ is the annualized, hedged return on merger i in excess of the contemporaneous risk-free return, $E_t[\Delta s_{i,t+1}]$ is the predicted change in the ESG score $s_{i,t+1}$ for the target firm in merger *i*, and $\epsilon_{i,t+1}$ are unexplained residual returns.[4]

The table shows that realized merger arbitrage deal returns do not have a strong association with expected ESG changes. Although deals with larger expected ESG improvements tend to have higher returns, this association is not statistically significant. While overweighting deals with larger expected ESG improvements may not reliably increase portfolio returns, there is no evidence that doing so reduces portfolio returns. This allows sophisticated portfolio construction for merger arbitrage to take advantage of especially large expected ESG improvements without a reduction in portfolio returns.

As we discussed in section 3, equilibrium analysis suggests that many ESG investment strategies should earn lower long-term investment returns. In table 3, we show that there is no evidence that such a tradeoff is required in merger arbitrage.

4.6 ESG Impact of Different Merger Arbitrage Strategies

We have shown that mergers in general have resulted in improved ESG scores and that we can predict these improvements. We now show that not all merger arbitrage strategies have the same ESG impact. We compare the ESG effects of two merger arbitrage strategies: the sophisticated merger arbitrage strategy we introduced above, which actively selects deals, and a naive strategy that simply holds deals in proportion to their market capitalization.

[4] Astute readers may be concerned that the estimate of *b* is likely to be downward biased if we wish to investigate the correlation between merger returns and actual changes in ESG scores. Since the actual changes in ESG scores will not be known until after the merger completes, we cannot use them as investment criteria. As a result, we care about the correlation between merger returns and expected changes in ESG scores. For this purpose, the estimate of b is unbiased.

Table 2: Predicting ESG Changes for Mergers

	(1)	(2)	(3)	(4)
Predictor 1	0.01			0.01
	(17.18)			(1.82)
Predictor 2		1.05		0.38
		(42.82)		(4.44)
Predictor 3			0.99	0.62
			(45.06)	(7.51)
N	685	685	685	685
R^2 (%)	30.18	73.86	75.83	76.59

The table shows results for regressions that try to predict the ESG changes for merger targets.

In all regressions, the dependent variable is the change in the target ESG score from one year before the merger announcement to one year after the merger completion.

The regression models use one or more explanatory variables. We label the explanatory variables predictor 1, predictor 2, and predictor 3, respectively. The precise nature of these predictors is proprietary.

All regressions include an intercept. The table shows the slope coefficients with their *t*-statistics in parentheses, the number of included observations, and the R^2 from the regression.

The sample includes announced mergers with market values over $500 million between January 2003 and May 2022 and available ESG scores.

Source: Data received from Refinitiv. Internally prepared by Versor Investments.

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As previously described, the sophisticated merger arbitrage strategy systematically invests in announced mergers in North America and Europe, including the United Kingdom. The strategy uses sophisticated machine learning methods to make forecasts for different deal outcomes. Based on these forecasts, the strategy overweights attractive deals and underweights less attractive deals. The strategy's primary focus is on attractive portfolio returns but it also considers the ESG characteristics of the positions.

In contrast, the naive strategy establishes positions that are directly proportional to the size of each merger and pays no attention to the ESG improvements associated with the mergers.

Each of these strategies takes positions in mergers when they are announced. The portfolio weights vary over time, as other mergers complete or come to the market. These fluctuating weights make it cumbersome to form weighted averages across the ultimate ESG outcomes of these mergers. We approximate these strategy weights using a slightly simpler, constant weight for each deal.

We approximate the target weights each strategy assigns to the deals by pooling all deals announced during a 6-month period. We pretend that the portfolio entered into all of these deals at the same time. This allows us to compute fixed target weights for each deal under each strategy. We then measure the weighted average ESG change for the merger targets. Finally, we repeat this process for subsequent 6-month periods. We choose 6 months, because a typical merger lasts about that length of time.

For each merger strategy, this creates a time series of weighted average ESG changes for the merger

Table 3: Merger Returns and Expected ESG Changes

	(1)	(2)	(3)	(4)
Predictor 1	-0.08			
	(-0.42)			
Predictor 2		0.19		
		(1.50)		
Predictor 3			0.14	
			(1.17)	
All				0.15
				(1.28)
N	685	685	685	685
R^2 (%)	0.02	0.03	0.02	0.02

The table shows results for regressions that link merger arbitrage returns to expected ESG changes for merger targets,

$r_{i,t+1} - r_{f,t+1} = a + b\, E_t\,[\Delta s_{i,t+1}] + \epsilon_{i,t+1}.$

In all regressions, the dependent variable is the hedged merger return in excess of the contemporaneous risk-free rate. Returns are expressed in annualized percentage points.

The explanatory variables are the predicted changes in target ESG scores using the different prediction models outlined in table 2.

All regressions include an intercept. The table shows the slope coefficients with their t-statistics in parentheses, the number of included observations, and the R^2 from the regression.

The sample includes announced mergers with market values over $500 million between January 2003 and May 2022 and available ESG scores.

Source: Data received from Refinitiv. Internally prepared by Versor Investments.

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targets. Since the number of deals with available ESG data materially increases over time, we take a weighted average of these time-series observations. The time-series weights are proportional to the number of deals with available ESG data in each period.[5] Importantly, these time-series weights are the same for both merger arbitrage strategies. Only the cross-sectional portfolio weights differ across the strategies.

Table 4 compares the ESG impact of these two strategies. The table shows that the sophisticated strategy delivers ESG improvements that are nearly 18 percentage points higher, on average. This difference in the average ESG improvements is statistically significant with a Student *t*-statistic of 4.8. Clearly, not all merger arbitrage strategies produce similar ESG improvements.

Importantly, the sophisticated merger arbitrage strategy also earns more attractive investment returns than the naive implementation. Since our focus here is on the ESG impact of merger arbitrage, however, we do not discuss performance details of these strategies.

[5] This is a generalized least squares estimate of the average ESG change when the periodic average changes have different variances due to the different numbers of data points in the cross-sections.

Table 4: ESG Impact of Different Merger Arbitrage Strategies

	Sophisticated		Naive		Difference	
	Change in ESG (%)	*t*-Stat	Change in ESG (%)	*t*-Stat	Change in ESG (%)	*t*-Stat
Merger	63.4	(22.1)	45.7	(19.6)	17.7	(4.8)
Sector	6.9	(21.8)	7.0	(21.0)	-0.1	(-0.2)
Difference	56.5	(19.6)	38.8	(16.5)	17.7	(4.8)

The table compares the weighted average changes in ESG scores for merger targets and sector peers across two different merger arbitrage strategies. Values in parentheses are *t*-statistics.

The "sophisticated" strategy systematically weights mergers based on a comprehensive set of forecasts for returns and risks, including ESG characteristics. (See text for additional details.) The "naive" strategy systematically weights mergers in proportion to the size of each merger.

To track ESG improvements for these strategies we pool all announced mergers in the investable universe over a six-month period. We then measure the change in the ESG scores for the merger targets from 1 year prior to the merger announcement to 1 year after the deal completion. The portfolio weights differ across the sophisticated and naive strategies.

This creates a time-series of weighted average ESG improvements. We use this time-series to compute the grand mean ESG improvement for each strategy. Since the number of mergers with ESG data increases over time, we weight the time-series observations by the number of available data points in each 6-month period. The time-series weights are the same for both merger strategies.

The sample includes announced mergers with market values over $500 million between January 2003 and May 2022 with available ESG scores. There are 685 merger targets with available ESG data. The portfolios take positions in 519 of these mergers.

Source: Data received from Refinitiv. Internally prepared by Versor Investments.

5. Regulatory Implications

The regulation of ESG disclosures and ESG-focused investment strategies is evolving rapidly.

Almost all of the regulatory focus has been on the reporting of current ESG characteristics for firms and investment portfolios. Such characteristics are clearly important to many investors and regulation should establish ground rules for transparent and consistent reporting of current ESG characteristics.[6]

As we show above, however, there is an important place for measuring ESG improvements over time. We think that this is a central focus for many investors. However, current ESG scores say essentially nothing about future ESG improvements. As we mentioned previously, merger targets tend to have below-average ESG scores but achieve very large ESG improvements.

While consistent ESG reports permit monitoring of improvements at the firm level, such measurements are more challenging for portfolios. Portfolio holdings are not constant over time. As a result, an improvement in portfolio ESG scores could stem from an improvement at the underlying firms, or simply from a portfolio shift to firms with higher ESG scores. The latter, of course, does not reflect a true economic improvement and is likely to be less important to investors.

[6] For a discussion of investor-relevant carbon reporting for portfolios, see Gurnani and Hentschel (2022).

We urge investors and regulators to establish additional standards for measuring the ESG impact of investment portfolios. We believe that ESG-focused investors care about the ESG impact of their investments at least as much as they care about the current ESG characteristics of their portfolios. This remains a neglected aspect of ESG reporting and regulation and should be addressed thoughtfully.

6. Summary

We show that a sophisticated merger arbitrage strategy is associated with large increases in ESG scores for the merger targets. On average, the ESG scores for merger targets rise by about 57% from one year before the merger to one year after completion of the merger. The improvements are similar for the overall ESG scores, the environmental scores, the social scores, and the governance scores.

A sophisticated merger arbitrage strategy can further increase these ESG improvements to 63%, on average. A simple merger arbitrage strategy that weights deal by deal size is associated with materially smaller ESG improvements of 46%. Moreover, the sophisticated merger arbitrage strategy also generates higher returns than the naive implementation.

These large and rapid ESG improvements associated with sophisticated merger arbitrage should be appealing to investors who wish to make investments with a positive ESG impact. Such improvements are possible because a merger is a dramatic and unusual event during the life of a firm.

We are not aware of other investment strategies that generate similarly large ESG improvements over similarly short time frames. Certainly, the large and rapid increases in ESG scores for merger arbitrage stand in stark contrast to the small, uncertain, and likely slow ESG benefits of investment strategies that overweight firms that already have attractive ESG scores.

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5. The Environment for Merger Arbitrage: 2021

Deepak Gurnani Ludger Hentschel

March 2021

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Executive Summary

Merger arbitrage capitalizes on the spread between a company's current share price and its final acquisition price.

After a tumultuous first half in 2020, the merger market has come back strongly with a large number of deals, low failure rates, many improved offers, and moderate times to completion. These and related characteristics of the merger markets should allow merger arbitrage strategies to build well diversified portfolios with relatively low risks of deal failure and attractive returns.

Fully exploiting the attractive environment requires a sophisticated investment strategy that can distinguish more attractive mergers from less attractive mergers and position the portfolio accordingly. Versor Investments has implemented an advanced systematic merger arbitrage strategy. The alpha forecast model for that strategy uses machine learning and a proprietary database covering more than 4,000 mergers to estimate the probability that a merger will close, determine downside risk, and perform competing bid analysis. The strategy invests in announced merger deals across the US, Canada, UK, and Europe.

1. Introduction

Merger arbitrage principally aims to earn the spread remaining between the target shares and the total value of the offer in announced mergers while minimizing the market exposures of the portfolio. For stock offers, this involves hedging the acquirer-specific risk by shorting an appropriate number of acquirer shares. While the risks of deal failures can be diversified across a portfolio with a large number of mergers, there is room to improve performance by reducing positions in riskier deals. When these trades are well executed, they earn attractive returns with close-to-zero correlations with equity markets.

Interestingly, the opportunity set for such merger arbitrage portfolios varies over time based on the number of mergers in the market and their characteristics. We describe several environment metrics and conclude that the current environment is attractive compared to historical norms.

2. The Merger Arbitrage Environment over Time

We now outline the most important aspects of the environment for merger arbitrage over time. Of course, we do so with an eye on how the current state of the environment compares to historical norms and the recent past.

2.1 Deal flow

A larger number of mergers increases the demand for merger arbitrage, elevates spreads, increases liquidity and capacity for merger arbitrage, permits more diversified portfolios and higher portfolio leverage. Merger deal flow varies over time. As a result, there are periods when merger portfolios are more or less attractive than is typical based on deal flow.

In early 2020, merger deal flow was materially reduced due to Covid-19. In March 2020, the global health crises triggered large market swings, which left potential acquirers uncertain about appropriate valuations. The associated uncertainty about economic growth also reduced deal flow. Finally, Covid-19 restrictions on travel and meetings made traditional merger negotiations impossible. As market volatility declined and many firms devised new operating modes, investment bankers adjusted to remote negotiations. The figures in this section show that deal flow overall has strongly recovered throughout the second half of 2020, after an understandably slow period during the first half of 2020

Number of mergers

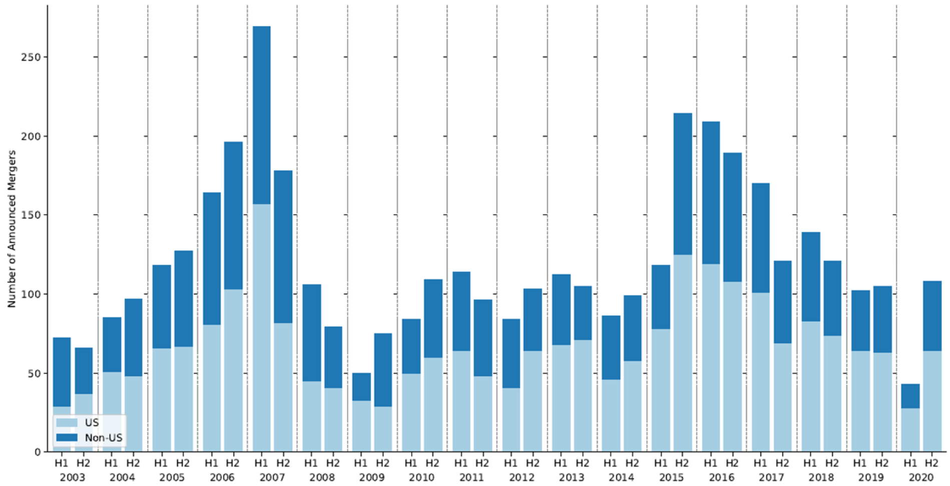
Figure 1 shows the number of mergers over time. The total numbers are divided into semi-annual periods, shown in pairs of bars for each calendar year. Moreover, the bars are subdivided into mergers with US and non-US targets.[1] The figure clearly shows that the last few years have produced an unusually high number of mergers, especially in the US. Although the number of mergers fell noticeably during the Covid-related market turmoil in the first half of 2020, deal flow has strongly recovered since then. In fact, the flow of new mergers continued to rise during the second half of 2020 and appears to continue at very high levels in early 2021.

Value of mergers

While more mergers are better for liquidity, spreads, diversification, and leverage, a large number of small mergers is less attractive than a similar number of large mergers. Small deals have less impact on market liquidity and overall spreads.

[1] A target stock is considered a US target if its primary equity listing is on a US stock exchange. Non-US mergers have target stocks with primary equity listings in Canada, Europe including the UK, Australia, and Japan.

Figure 1: Number of Announced Mergers



The figure shows the number of announced mergers by semi-annual calendar period. For each period, the total number is separated into US and non-US mergers, respectively. The bottom portion of each bar indicates the number of mergers with US targets; the top portion of each bar indicates the number of mergers with non-US targets. Non-US mergers constitute mergers with target stocks in Canada, Europe including the UK, Australia and Japan.

Source: Data received from Bloomberg. Internally prepared by Versor Investments.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

Figure 2 shows the dollar value of mergers over time. For each deal, the size is equal to the market value of the total offer. As for the number of mergers in figure 1, we subdivide the totals for each six-month period by US and non-US acquirers.

The figure shows that the dollar value of announced mergers strongly recovered during the second half of 2020, along with the number of deals. While the value of announced mergers in the first half of 2020 was below recent values, the second half was higher than the corresponding periods during 2017, 2018, or 2019, all of which had very strong merger activity. Like the number of mergers, the value of mergers continued to rise during the second half of 2020 and into early 2021

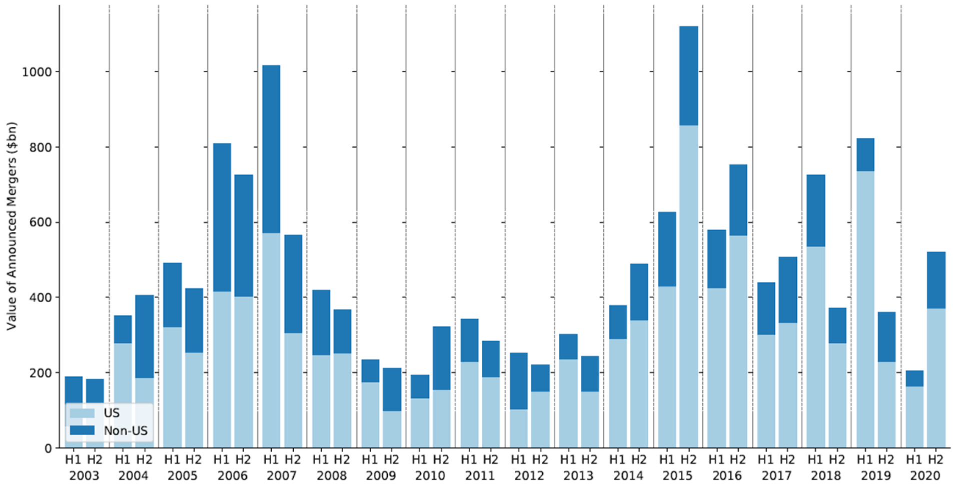
Cash available for future mergers

While it is difficult to make precise predictions about future deal flow, the cash on hand at both corporate and private equity acquirers gives some indication of possible future deal flow. Harford (1999) shows that cash-rich firms are more likely to attempt acquisitions. In part, this is true because potential acquirers with large amounts of available cash can make offers without accessing the debt markets. Of course, the cash can be used for either new mergers or competing offers on existing deals. Either one should benefit merger arbitrage portfolios.

Figure 3 shows the median cash to asset ratio for US large-cap and mid-cap firms. Clearly, many US firms have accumulated an unusual amount of cash during 2020. These firms may continue to hold some of that cash as a precaution against future operating cash demands. Most likely, however, they will also spend some of this cash on acquisitions, especially if the economy progresses on the road to recovery before large parts of the cash reserves are consumed for ongoing business reasons.

Figure 4 shows that private equity funds have also accumulated large amounts of cash, although this trend has built up over several years. Unlike corporations, private equity funds must spend their cash at some point. While PE funds may use some of the cash to support existing investments, a large

Figure 2: Value of Announced Mergers



The figure shows the dollar value of announced mergers by semi-annual calendar period. For each period, the total is separated into the value of US and non-US mergers, respectively. The bottom portion of each bar indicates the value of US mergers; the top portion of each bar indicates the value of non-US mergers. Non-US mergers constitute mergers in Canada, Europe including the UK, Australia and Japan.

Source: Data received from Bloomberg. Internally prepared by Versor Investments.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

fraction is likely to fund future acquisitions.

Some of the acquisition targets will be private companies in which merger arbitrage cannot take positions. However, many of the acquisition targets will be public companies that will become part of merger arbitrage portfolios.

As the figures show, cash at public and private potential acquirers is at exceptionally high levels. This should contribute to higher future merger activity.

Most recently, deal flow has been concentrated in the technology, industrial, and health care sectors. Figure 5 shows deal flow, in dollars, by sector during the second half of 2020. It is likely that high cash holdings (and high equity values) at some technology firms have contributed to mergers in that sector and will continue to do so.

2.2 Failures and competing bids

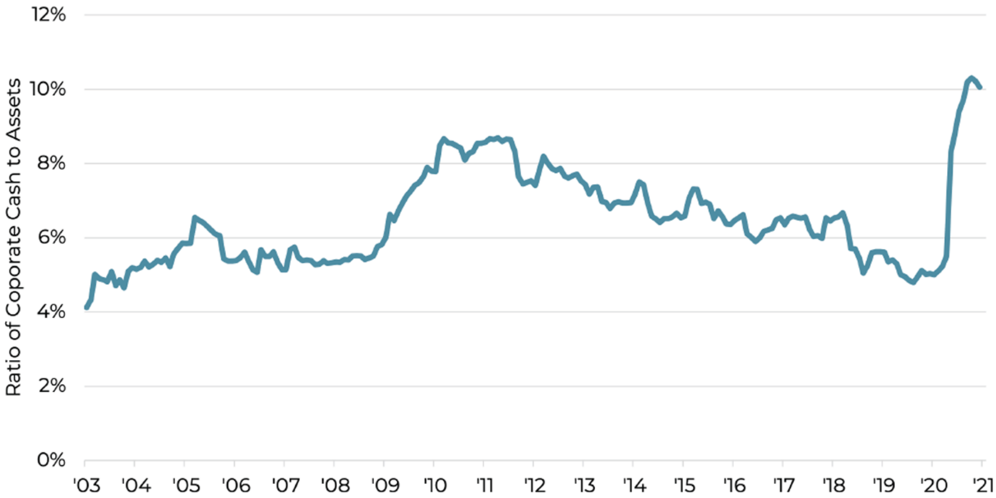
Most mergers complete based on the initial offer. This is a positive outcome for merger arbitrage. A few mergers fail, generally contributing negative returns to merger arbitrage. Interestingly, there is a third possible outcome, in which a merger receives an improved offer from the current bidder or a third party. This is the best possible outcome for merger arbitrage.

The frequency of failures

The failure of mergers is a key risk for merger arbitrage trading strategies. Although mergers fail infrequently, when they do they often contribute materially negative returns, even in well diversified portfolios. An environment with elevated deal failure rates is likely to detract from overall returns.

Figure 6 shows the evolution of merger termination rates over time. The figure shows that typical

Figure 3: Corporate Cash



The figure shows the cross-sectional median cash to assets ratio for US large-cap and mid-cap firms. The firms are the constituents of the large-cap and mid-cap components of the US S&P Broad Market Index.

Source: Data received from S&P and Worldscope. Internally prepared by Versor Investments.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

failure rates are just under 10%. But the rates vary over time. Despite the Covid-19 stresses on the economy and financial markets, recent failure rates have been very low. Although there were some Covid-related deal failures, the overall failure rate in 2020 remained low by historical norms.

The low termination rates in 2020 are strikingly different from those during the financial crisis of 2008/2009. During those years, merger termination rates reached twice their normal levels. Although early 2020 brought severe stress to financial markets and global economies, financial markets recovered fairly quickly and most mergers proceeded as planned. Part of this relatively high resilience in current mergers is likely to be structural. Over time, merger agreements, especially for definitive mergers, have become much stronger and more difficult to abandon.

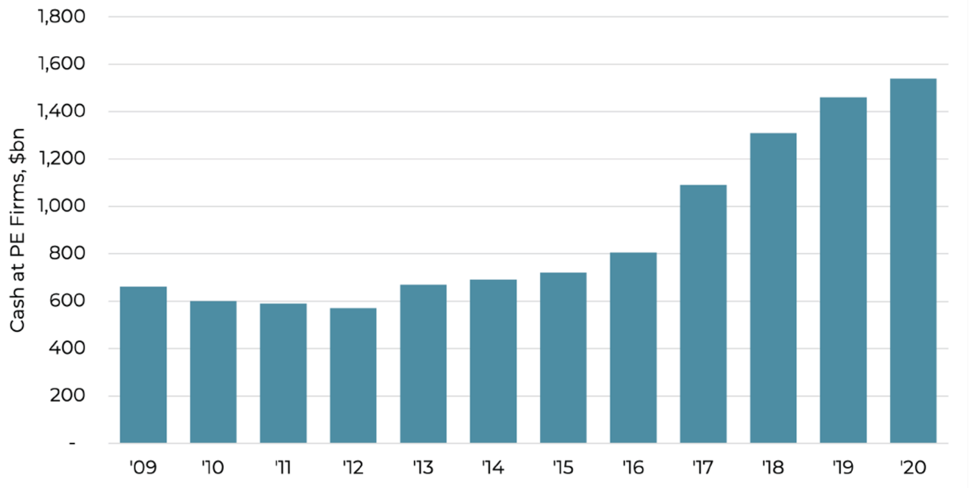
Barring a dramatic change in economic conditions, deal failure rates seem to have settled in a range that is highly advantageous for merger arbitrage going forward.

The frequency of competing bids

Long-term, improved offers occur about twice as frequently as deal failures. Most of the improved offers come from current bidders. Obviously, higher offers are good for merger arbitrage. In portfolios that successfully reduce positions in risky deals that might fail and increase positions in deals that might receive improved offers, the gains from improved offers can largely offset the losses from terminated deals. Of course, this positioning requires good forecasts of which deals may fail and which deals may receive an improved bid.

In late 2020 and at the beginning of 2021, mergers have received an unusual number of competing bids. Figure 7 shows the number of improved offers for each six-month period. As the figure shows, improved offers increased to unusually high levels in the second half of 2020. Many of these offers are amendments from the initial bidder, in part because market prices have continued to rise. A smaller

Figure 4: Dry Powder at PE Funds



The figure shows estimates of cash held by private equity funds. Values prior to 2020 are at year-end; the value for 2020 is for the end of March.

Source: Data received from Goldman Sachs. Internally prepared by Versor Investments.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

fraction of the improved offers are competing bids from a second potential acquirer. Although these competing bids have been relatively rare in the last few years, there was a notable increase in these offers most recently. Clearly, such increased competition is favorable to merger arbitrage.

2.3 Deal characteristics

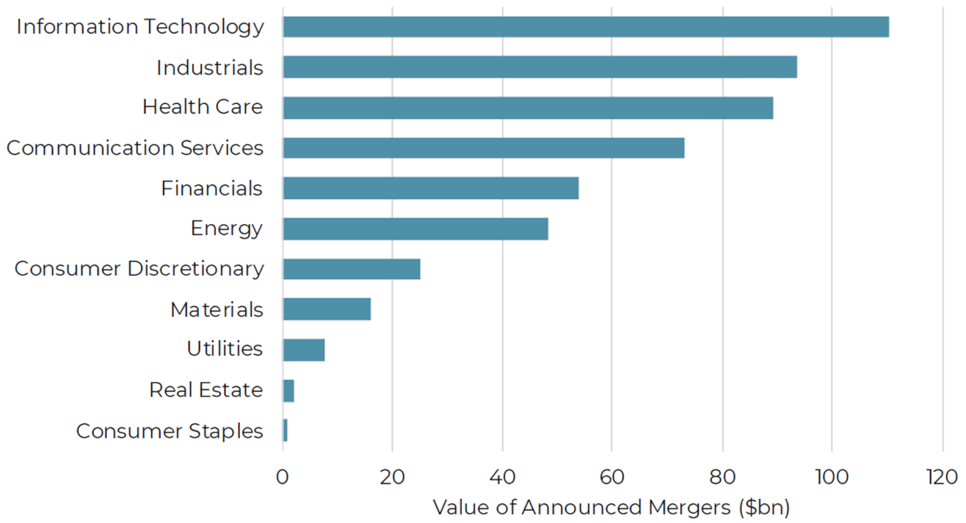
In addition to overall deal volume, merger arbitrage benefits from certain deal characteristics. All else equal, merger arbitrage performs better when mergers enter the market at wider spreads and close faster. While these characteristics always differ across deals, merger arbitrage benefits when more mergers have favorable characteristics. We present the average characteristics across outstanding mergers.

Friendly or hostile?

Whether both parties agree to the deal in a "friendly" merger or whether the target firm is resisting the offer in a "hostile" merger is a key indicator for the likely success or failure of the merger. Hostile mergers fail at roughly six times the rate of friendly mergers, 36% versus 6%. As a result, modest shifts in the proportion of friendly and hostile mergers can have material impact on the likely failure rates across deals.

Figure 8 graphs the fraction of friendly and hostile mergers over time. The figure shows that the current fraction of hostile mergers is unusually small. This should bode well for high rates of successful deal completion in the future.

Figure 5: Value of Announced Mergers by Sector



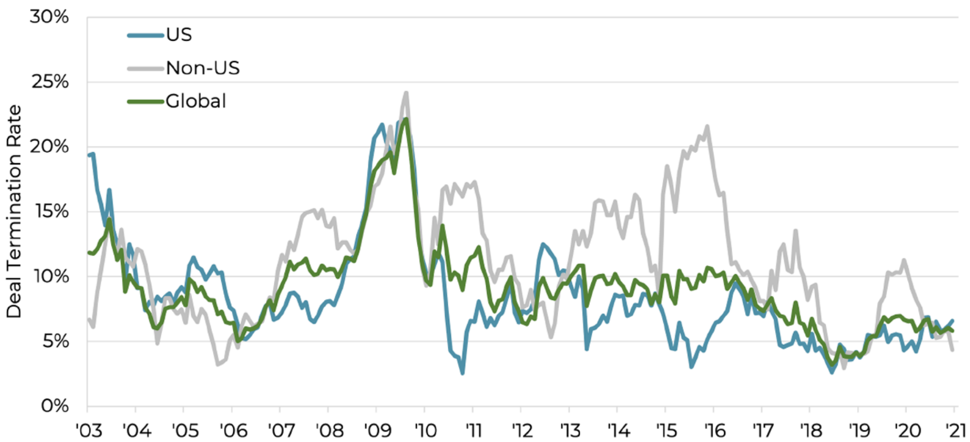
The figure shows the value of announced mergers by sector during the second half of 2020.

Source: Data received from Bloomberg. Internally prepared by Versor Investments.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

Recently, the relatively high fraction of friendly mergers likely has contributed to the lower failure rates we showed in figure 6. The anticipation of lower deal failure rates likely has contributed to tighter spreads as well.

Figure 6: Deal Terminations

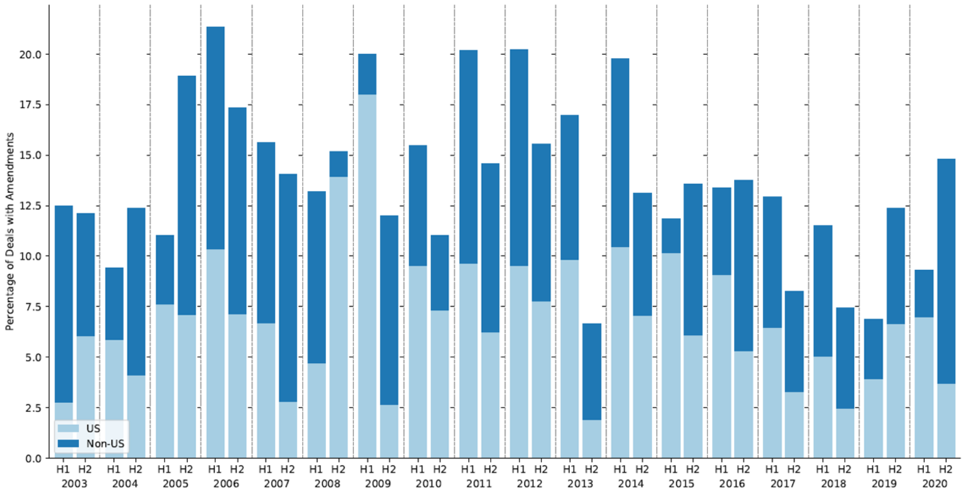


The figure shows the failure rate of mergers over time. The failure rate is the number of mergers that terminate divided by the sum of pending and terminating mergers.

Source: Data received from Bloomberg. Internally prepared by Versor Investments.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

Figure 7: Improved Offers



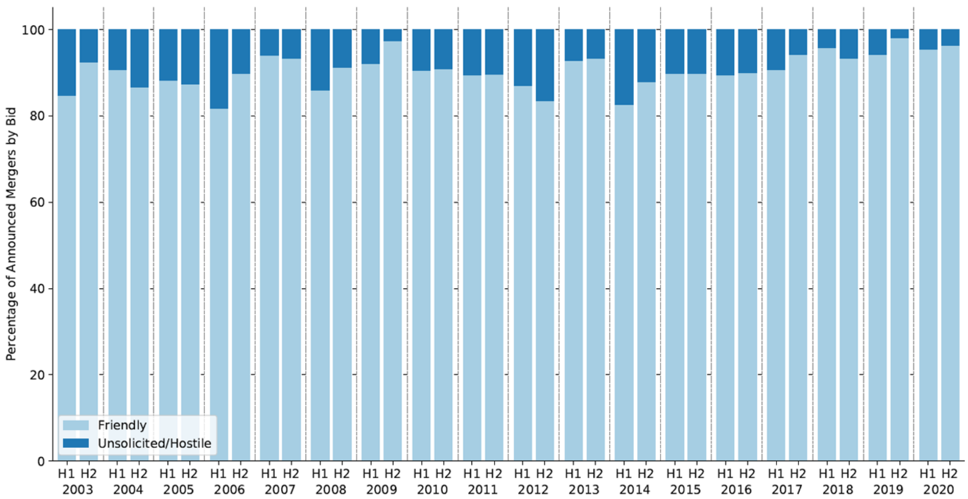
The figure shows the number of mergers that received an improved offer from the current bidder or a third party over time. The US and Non-US percentages are as a fraction of the global universe, so they correctly add up to the global fraction.

Source: Data received from Bloomberg. Internally prepared by Versor Investments.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

Of course, sophisticated merger arbitrage strategies attempt to gauge the failure probability for each deal as one input into determining position sizes. Naturally, however, when there are fewer hostile deals, it is easier to avoid deal failures.

Figure 8: Fraction of Friendly Mergers



The figure shows the fraction of announced mergers that are friendly or hostile, for successive six-month periods. A merger is "friendly" if both target and acquirer agree to merge at announcement. The bottom portion of each bar shows the fraction of friendly mergers; the top portion of each bar shows the fraction of hostile mergers.

Source: Data received from Bloomberg. Internally prepared by Versor Investments.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

Figure 9: Merger Spreads at Announcement

The figure shows the average merger spread at announcement in excess of the contemporaneous Treasury Bill yield, adjusted to the average deal duration. The spreads are not annualized and a merger arbitrage portfolio would expect to earn these spreads several times per year, depending on deal duration, amplify them with portfolio leverage, and add back the Treasury Bill yield.

Source: Data received from Bloomberg. Internally prepared by Versor Investments.

Merger spreads at announcement

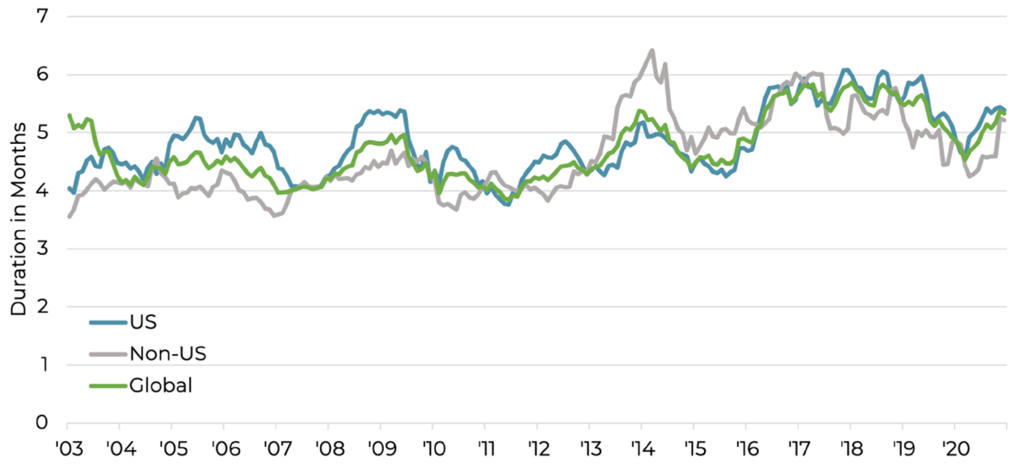
Since merger arbitrage attempts to earn the merger spreads, wider spreads offer better returns – all else equal. Merger spreads consist of two components: a risk-free interest rate and a risk premium for uncertainty about when, under what terms, and whether the merger will complete. If all mergers succeeded under the announced terms on known dates, merger spreads would be equal to the risk-free rate. The component of the spread over and above the risk-free rate of interest is an expected reward merger arbitrage earns in exchange for bearing the risk that the deal may not close on time, under the current terms. Of course, this return component remains uncertain until the deal actually closes.

In order to focus on the excess return component of the spread, figure 9 shows deal spreads at announcement minus the contemporaneous risk-free rate of interest. Since mergers are not expected to last a full year, we compound the risk-free rate to the expected deal duration.

Merger spreads are generally small. It is important to note that merger arbitrage attempts to earn these spreads several times per year since the average deal duration is materially less than one year. In addition, merger arbitrage portfolios can amplify these excess returns by applying leverage to the portfolio. Given current deal durations, which we discuss in the next section, we might expect to earn the spread 2 or 3 times per year. Given current deal flow, we might expect to double the spreads again via leverage. The final return might be about 5 times the excess spread plus the Treasury Bill yield, depending on deal durations, portfolio leverage, deal failures, and improved offers.

Figure 9 shows that current spreads are near, but slightly below, historic norms. As for individual deals, tight or negative merger spreads can be an indication that market participants discount the probability of failures or assign material probability to improved offers. As we showed in figures 6 and 7, both appear to be true at the moment.

Figure 10: Deal Durations



The figure shows the average deal duration for announced mergers over time. The duration is measured from announcement to successful completion or termination. US mergers have targets with primary equity listings in the US. Non-US mergers constitute mergers with target stocks in Canada, Europe including the UK, Australia and Japan.

Source: Data received from Bloomberg. Internally prepared by Versor Investments.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

Deal durations

All else equal, faster deal completion is better for merger arbitrage since it means that the portfolio earns the spreads sooner, which translates into a higher annual rate of return.

Generally, mergers complete over the course of a few months. Figure 10 shows that Covid restrictions on travel and meetings temporarily slowed deal completion in the first half of 2020. However, that increase started from a low base and deal durations remained at normal levels in the second half of 2020.

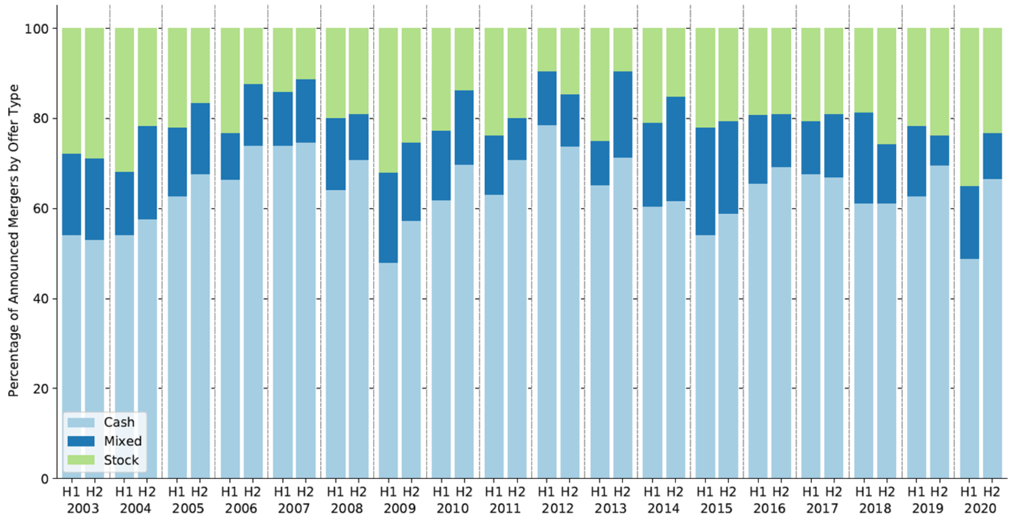
It appears that merger participants have found ways of coping with Covid restrictions and manage to complete mergers in fairly normal timeframes.

Forms of payment

Figure 11 shows the evolution of payment terms for mergers over time. Historically, cash has been the dominant payment form, either in pure cash offers or in combination with stock. In the first half of 2020, however, cash offers were far less prevalent as firms tried to conserve cash. We also saw this cash conservation in figure 3. A similar shift in payment terms occurred during the financial crisis in the first half of 2009. In addition to conserving cash, stock offers can be attractive in an environment of elevated uncertainty about market prices. In the event the value of the merger target falls materially as a result of an overall market decline, a stock offers automatically adjusts to changing market conditions.

As deal flow recovered in the second half, the fraction of cash offers returned to fairly normal levels.

Figure 11: Payment Types for Mergers



For semi-annual period, the figure shows the fraction of announced mergers by payment type: pure cash, pure stock, or a blend of the two. The bottom portion of each bar indicates the fraction of pure cash deals; the top portion of each bar indicates the fraction of pure stock deals; and the middle portion of each bar indicates the fraction of mergers with offers that include both cash and stock.

Source: Data received from Bloomberg. Internally prepared by Versor Investments.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

3. Summary

We provide a comprehensive review of the global environment for mergers and merger arbitrage investment strategies. Although Covid-19 brought material stresses to the market for mergers in the first half of 2020, the second half of 2020 produced an attractive environment. If anything, these improvements continued to accelerate towards the turn of the year and into 2021.

In the second half of 2020, deal flow was strong with large numbers and large values of mergers. This allows merger arbitrage strategies to build well diversified portfolios. Corporations and private equity funds have unusual amounts of cash on hand, which is likely to contribute to strong deal flow going forward. Not surprisingly, the early recovery in deal flow has been concentrated in sectors that have weathered Covid-19 relatively well, like technology and health care. In addition to continued strong deal flow in these sectors, we anticipate that there will also be a recovery of deal flow in sectors that have suffered under Covid-19, as stronger firms acquire weaker firms.

Despite the extraordinary economic stress from Covid-19, the vast majority of announced mergers completed. In fact the termination rates over the course of 2020 were below long-term average termination rates. Especially in the US, where new merger agreements will include even more stringent material adverse condition clauses, we expect termination rates to remain attractively low.

Similarly, the characteristics of mergers announced in the second half of 2020 indicate an attractive environment for merger arbitrage: spreads are near typical levels, deal durations are the same as they were over the last few years, and the mix of cash and stock offers is near historical norms.

Based on these considerations, we conclude that 2021 begins with a very attractive environment for merger arbitrage.

Fully exploiting the attractive environment requires a sophisticated investment strategy that can distinguish more attractive mergers from less attractive mergers and position the portfolio accordingly. Versor Investments has implemented an advanced systematic merger arbitrage strategy. The alpha forecast model for that strategy uses machine learning and a proprietary database covering more than 4,000 mergers to estimate the probability that a merger will close, determine downside risk, and perform competing bid analysis. The strategy invests in announced merger deals across the US, Canada, UK, and Europe.Based on these considerations, we conclude that 2021 begins with a very attractive environment for merger arbitrage.

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Section 3

The Evolution of Value

6. Value Returns in 2021: Mirage or Oasis

Deepak Gurnani Ludger Hentschel

April 2021

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Executive Summary

Value investment styles in single stocks have experienced unrelenting losses for several years, with especially large losses in 2020.

The negative returns to value investing strategies have made “cheap” stocks cheaper and “expensive” stocks more expensive. This has created extreme spreads in valuation measures between cheap and expensive stocks.

The last time valuation spreads reached similar levels was around 2000, at the end of the technology boom. When valuation spreads normalized over several years, value investment strategies earned strong returns.

For the first time in what feels like a long time, early 2021 has produced positive value returns. This may be a sign that the overwhelmingly negative sentiment toward value stocks is finally fading.

Importantly, the positive value returns in 2021, so far, have done little to shrink the extreme value spreads created by the previous negative returns. The case for positive value returns in stock selection strategies remains strong and the potential for future value returns remains undiminished.

It may finally be the beginning of a value recovery. For now, however, these positive returns to value strategies remain light spring showers after a long, hard drought.

1. Introduction

Value investment styles in equities have detracted from portfolio returns for several years. Simple approaches have led to losses since the financial crisis in 2008. Nearly all value styles suffered large losses in 2020. As a result, valuation spreads have widened to extreme levels.

At the beginning of 2021, value themes have shown positive returns for the first time in what feels like a long time. Following such dramatic and extended underperformance for value, there has to be concern that these early returns will turn out to be false hope. However, valuation spreads remain so wide that they will continue to exert upward pressure on value returns. When valuation spreads normalize, value strategies should see attractive returns.

Gurnani and Hentschel (2018) described poor returns to value investment strategies, wide valuation spreads, and a tendency for valuation spreads – and hence value investment returns – to mean revert. Of course, valuation spreads continued to widen for 2 more years, almost without interruption.

Early 2021 is the first period in several years where value investment strategies have earned positive returns. It may finally be the beginning of a value recovery. For now, however, these positive returns to value strategies remain relatively light spring showers after a long, hard drought.

2. Past Value Returns

The drawdown in value-based investment strategies in equities, especially in 2020, was so strong that the exact definition of "value" was not central to the overall outcome. Nearly any value-related approach would have lost money. This was true for US stocks and international stocks, for essentially all sectors, and for value metrics ranging from book-to-price ratios to earnings-to-price ratios, whether adjusted for growth expectations or not.

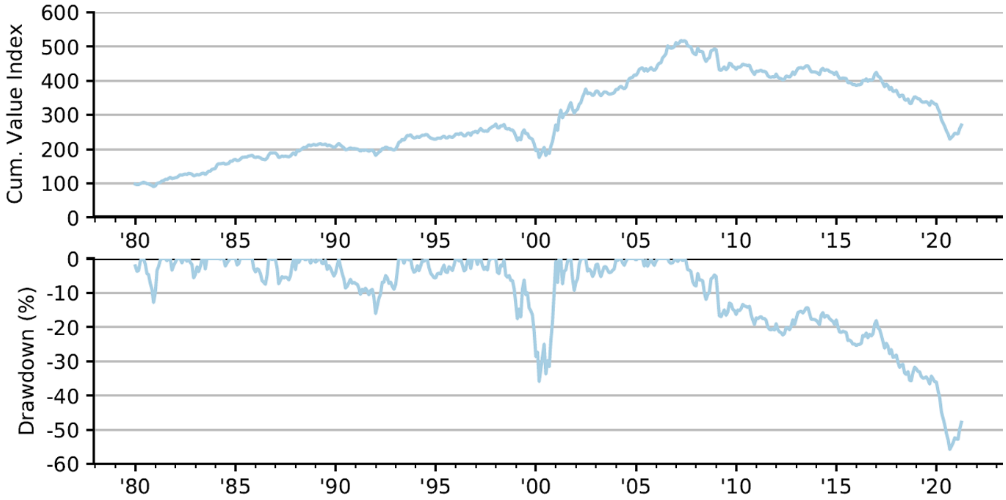
In Figure 1 we show the cumulative return spread for the Russell 1,000 Value index minus the Russell 1,000 Growth index. This is the return an investor would have generated by investing 100% in the Russell 1,000 Value index, shorting 100% of the Russell 1,000 Growth index and holding 100% in Treasury bills. As the graph shows, stocks in Russell's value universe have clearly lagged those in Russell's growth universe since the financial crisis. Yet, that underperformance appears to have accelerated further in 2017. Russell identifies value stocks based on book-to-price ratios and growth stocks based on IBES long-term growth forecasts and sales-per-share growth.[1] The value underperformance over the period January 2017 to December 2020 produced the largest drawdown in the value-minus-growth spread since the inception of the Russell style indexes in 1979. The return spread over the 2017 to 2020 period was roughly –39%. At the height of the technology boom, from January 1998 to June 2000, the cumulative value-minus-growth return for the Russell 1,000 index was –34%.

To highlight the recent underperformance of value, the bottom panel of figure 1 shows the drawdown associated with the returns in the top panel. As the figure shows, the simple Russell value-minus-growth strategy peaked before the financial crisis in 2008 and has not recovered since then. In fact, the speed and magnitude of the drawdown in 2020 was the worst since the peak of the technology boom in 1999.

One reason for the poor performance of the simple Russell 1,000 value-minus-growth strategy is that the underlying positions are persistently short stocks in the technology sector. Of course, the technology sector has outperformed the rest of the stock market over the last decade. While stocks in the sector may have appeared expensive relative to stocks in other sectors, they have not earned lower returns.

[1] See FTSE Russell (2021) for a detailed description of the Russell index methodology.

Figure 1: Russell Value Minus Growth Returns and Drawdowns



The top panel shows the cumulative return index for a hypothetical portfolio that invested 100% long in the Russell 1,000 Value index, 100% short in the Russell 1,000 Growth index, and 100% long in US Treasury bills.

The bottom panel shows the drawdowns relative to the trailing high-water mark for the returns in the top panel. Returns are monthly from December 1979 to March 2021, gross of all fees and transaction costs. Returns will be reduced by management fees and any other expenses incurred in the management of the strategy.

Source: Data received from FTSE Russell and Bloomberg. Internally prepared by Versor Investments.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

More generally, comparing a few simple valuation ratios across all stocks, regardless of sector or other firm characteristics, is a rather crude assessment of "value" and unlikely to earn reliable excess returns. Unfortunately, this fairly indiscriminate approach remains widely used in indexes, funds, and research publications.

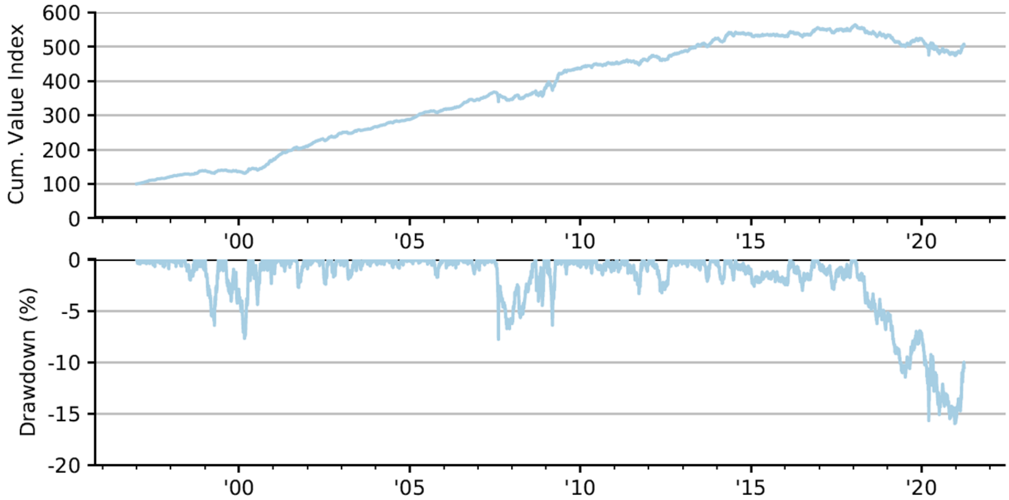
In Figure 2, we show that more sophisticated measures of value vastly outperformed the Russell value-minus-growth spread after the financial crisis. Not surprisingly, the more sophisticated value strategy has higher annual returns based on more advanced value signals, lower risk based on tighter risk management, and a materially higher Sharpe ratio. While the Russell value-minus-growth spread lost money nearly continuously following the financial crises, sophisticated measures of value continued to generate positive returns in many years.

However, as value sentiment turned ever more negative starting in 2017, even sophisticated measures of value were not able to overcome the massive negative sentiment towards value investment styles. As a result, there were large drawdowns over the last few years.

As before, the figure shows the return to a 100% long and 100% short portfolio. In this case, however, the long positions are stocks that were most attractive according to 4 valuation measures: book to price, forward earnings to price, cash-flow to price, and sales to price.[2] The short positions are stocks that were least attractive according to the same measures. The stocks are drawn from the most liquid US stocks, roughly equivalent to the Russell 1,000 constituents. However, the stocks are reassessed every week. Importantly, the stock valuations are measured relative to industry peers, so that the portfolio remains industry-neutral. The industry-neutral approach precludes losses that might have come from shorting technology stocks because they appeared expensive relative to utilities, for example. In

[2] We use these simple measures for presentation purposes. Actual Versor Investments portfolios use more than 20 different valuation characteristics to measure the value exposures of stocks.

Figure 2: Value Factor Returns and Drawdowns



The top panel shows the cumulative return index for a pure, market-neutral value factor in US large-cap stocks. The underlying portfolio is 100% long "cheap" stocks, 100% short "expensive" stocks, and 100% long in US Treasury bills. The value metric is a composite of 4 different value measures based on firms' balance sheets, income statements, and cash flow statements. The portfolios have no net exposures to the market overall, GICS industries, or about 20 other investment style composites, like momentum, for example.

The bottom panel shows the drawdowns relative to the trailing high-water mark for the returns in the top panel.

Returns are daily from January 3, 2000 to March 31, 2021, gross of all fees and transaction costs. Returns will be reduced by management fees and any other expenses incurred in the management of the strategy. Due to data availability, this sample period starts later than the one shown in figure 1.

Source: Data received from S&P Global and Refinitiv. Internally prepared by Versor Investments.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss. These results are based on simulated or hypothetical performance results that have certain inherent limitations. Unlike the results shown in an actual performance record, these results do not represent actual trading. An investment with Versor Investments is speculative and involves substantial risks; investors may lose their entire investment. No one should rely on any simulated performance in determining whether to invest with Versor Investments. Please see additional important disclosures in the back.

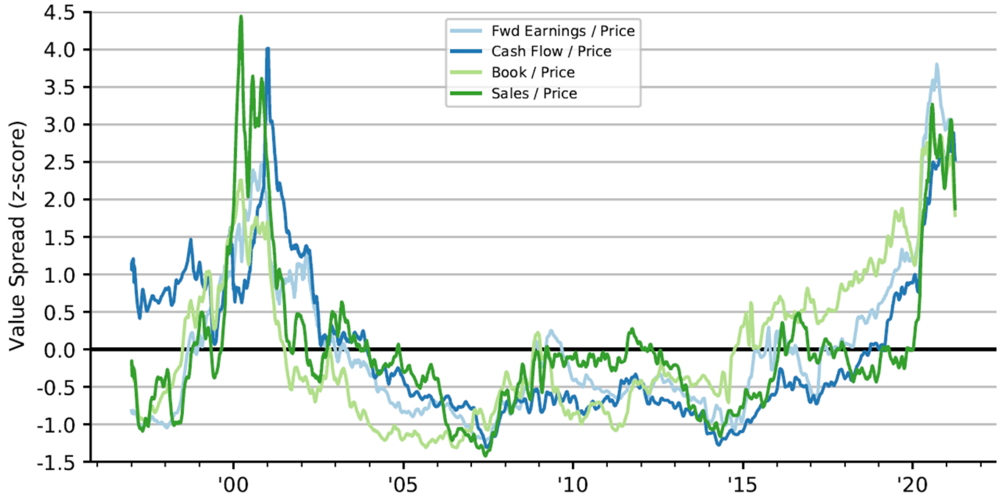
addition to industry exposures, the portfolios also eliminate exposures to a large number of other style factors that might have contributed returns or volatility.[3] In that sense, the portfolios are "pure" value style portfolios.

Due to limited data availability, the returns in figure 2 start significantly later than those in figure 1. As for the cruder Russell definitions of value, however, the returns were strongly negative over the last two years.

Interestingly, in both figures we can see a notable uptick in value returns for 2021. While these positive returns still pale in comparison to the preceding drawdown, they should give hope to investors who expect an eventual recovery in value returns.

[3] The excluded style factors include a large number of variations within themes like size, momentum, analyst sentiment, quality, and volatility.

Figure 3: Differences in Valuations



The figure shows US valuation spreads over time. Valuation spreads are the weighted average difference between the valuation ratios of stocks with attractive ratios and stocks with less attractive ratios.

In each US industrial sector and geographic region, we assign positive weights to stocks with attractive valuations and negative weights to stocks with unattractive valuations. The weights are larger for more attractive stocks. The positive weights sum to 1. The negative weights sum to −1. For earnings yields, the weighted sum of earnings yields is the average spread in earnings yields between attractive and unattractive firms on that date. We form a regional average of such spreads by taking a weighted average across all industrial sectors.

Each of the four lines uses a different valuation ratio: analyst forecasted earnings divided by current market prices, reported cash flows divided by market prices, reported book values divided by market prices, and reported sales divided by market prices. Value spreads are monthly data from January 1997 to February 2021. The data include approximately the largest 1,000 US stocks by liquidity and market cap.

Source: Data received from S&P Global and Refinitiv. Internally prepared by Versor Investments.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

3. Value Spreads

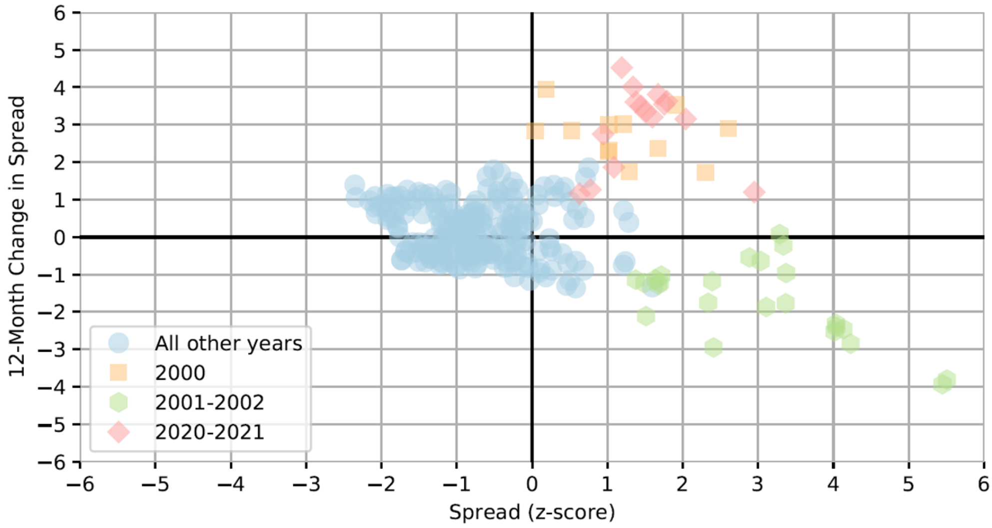
When value investment styles generate such large negative returns, cheap stocks become cheaper and expensive stocks become more expensive. We measure this notion by tracking the intra-sector differences in valuation ratios.

In order to focus on stock selection effects, we once again remove sector differences from our measures. In each sector, we assign positive weights to stocks with attractive earnings yields and negative weights
When value investment styles generate such large negative returns, cheap stocks become cheaper and expensive stocks become more expensive. We measure this notion by tracking the intra-sector differences in valuation ratios.

In order to focus on stock selection effects, we once again remove sector differences from our measures. In each sector, we assign positive weights to stocks with attractive earnings yields and negative weights to stocks with unattractive earnings yields. The weights are larger for more attractive stocks. The positive weights sum to 1. The negative weights sum to −1. On a given date, the thus-weighted sum of earnings yields measures the average spread in earnings yields between attractive and unattractive firms on that date within a given sector. We form an overall average of such spreads by taking a weighted average across all sectors.[4]

[4] The sector weights are proportional to the square root of the number of stocks in each sector. This is an approximation to the capital an investment strategy might deploy in each sector. See Gurnani and Hentschel (2018) for additional details about these value spreads.

Figure 4: Mean Reversion in Value Spreads



The figure graphs US values spreads on the horizontal axis and changes in US value spreads over the subsequent 12 months on the vertical axis. The association between large spreads and subsequent declines in the spreads indicates that spreads have a tendency to revert to "normal" values. Both spreads and changes in spreads are shown in z-score units.

The spreads are averages of multiple valuation spreads, like those shown in Figure 3. Spreads and spread changes are monthly data from January 1997 to March 2021. In order to measure the spread changes over the subsequent 12 months, the last recorded spread is for March 2020. The spreads are based on US large-cap and mid-cap stocks.

The color coding identifies the end dates for spread changes: orange squares for months in 2000, green hexagons for 2001-2002, red diamonds for 2020-2021, and blue circles for all other dates.

Source: Data received from S&P Global and Refinitiv. Internally prepared by Versor Investments.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

Figure 3 shows historical spreads based on 4 different valuation measures: book to price, forward earnings to price, cash flow to price, and sales to price. The figure shows z-scores for these measures, which remove the historical means and divide by the historical standard deviations. A score of zero indicates spreads at the historical mean. A score of 1 indicates value spreads 1 standard deviation above the historical mean.

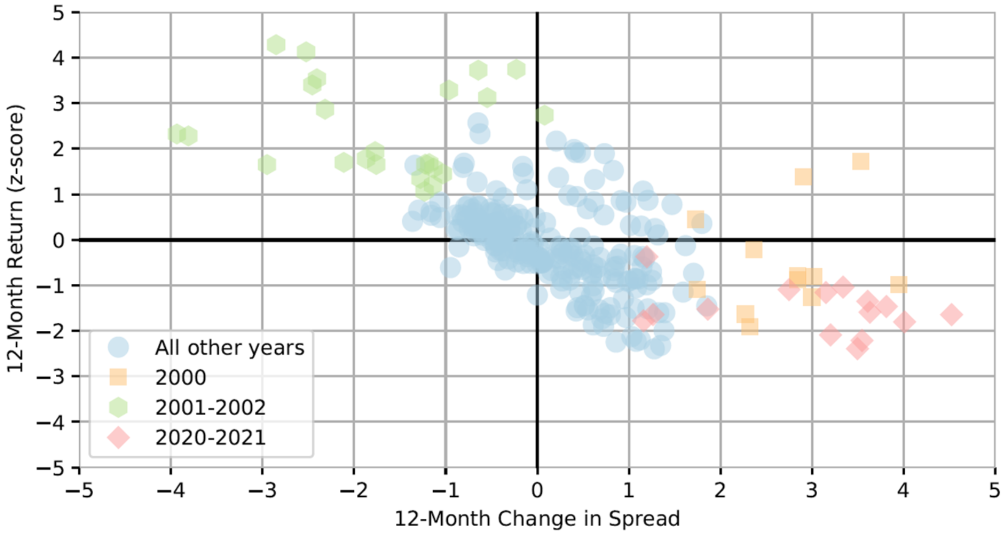
As the figure shows, several of these valuation spreads reached historical peaks near the end of 2020. These extremely unusual differences in stock valuations naturally give rise to predictions that these differences will normalize. However, the situation was similar at the end of 2019, when valuation spreads were already high. Of course, we now know that things got worse from there.

Although the positive value returns for early 2021 had a tendency to reduce the value spreads, that effect remains modest for now. There is still plenty of room for positive value returns before the spreads revert to historically more typical levels.

Figure 4 shows that wide value spreads are generally followed by a decline in those spreads. The figure shows historical spreads along the horizontal axis. Wide spreads are toward the right end. The vertical axis shows changes in spreads over the following 12 months. Negative changes correspond to compression in spreads, at the bottom of the vertical axis. As the figure shows, wide spreads historically have been followed by spread compression.

Notably, the association between spreads and subsequent 12-month spread changes was much weaker

Figure 5: Changes in Value Spreads and Value Returns



The figures graphs the annual change in US value spreads on the horizontal axis and the contemporaneous returns to US value portfolios on the vertical axis. Both spread changes and returns are shown in z-score units.

The spreads are averages of multiple valuation spreads, like those shown in Figure 3. The returns are for the corresponding average portfolios. Spread changes and returns are measured each month from January 1997 to March 2021. The spreads and returns are based on US large-cap and mid-cap stocks.

The color coding identifies the end dates for returns and spread changes: orange squares for months in 2000, green hexagons for 2001-2002, red diamonds for 2020-2021, and blue circles for all other dates.

Source: Data received from S&P Global and Refinitiv. Internally prepared by Versor Investments.

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during the peak of the technology boom. The 12-month spread changes ending in 2000, associated with spreads a year earlier, are marked by orange squares. A similarly unusual episode occurred over the last year. Spread changes ending in January 2020 to March 2021 are marked with red diamonds. During these two exceptional periods, wide value spreads were associated with further widening of those spreads. According to the figure, the behavior of value spreads during 2020 was roughly as unusual as during the peak of the technology boom. Importantly, however, the wide spreads created by the technology boom were strongly associated with subsequent spread normalization, marked with green hexagons.

Naturally, when value spreads compress value investment strategies earn positive returns. Figure 5 shows that this has happened historically. Value strategies are long "cheap" stocks and short "expensive" stocks. A rise in the price of the "cheap" long positions and decline in the price of the "expensive" short positions leads to value spread compression and positive value returns. Conversely, when value spreads expand, value strategies tend to suffer losses. As the figure shows, the association between 12-month spread changes and contemporaneous 12-month returns is more reliable than the association between spreads and subsequent 12-month spread changes in figure 4. Even during the technology boom and in 2020, marked by the orange squares and red diamonds, respectively, an increase in valuation spreads was accompanied by negative value returns.

Based on the historical experience documented in figure 5, we are confident that value investment strategies will earn strong returns when value spreads normalize from their recent extremes. Based on the historical experience documented in figure 4, we know that wide spreads are generally – but not always – followed by compression in value spreads. As figure 4 shows, there have been exceptional periods where already wide spreads expanded further: 2020 is a key example of this unusual behavior. The main question appears to be when value spreads will normalize.

4. Why Value Now?

The severe negative performance of value investment styles has coincided with very unusual economic circumstances: direct and sustained government support for financial markets. Given the rarity of this policy stance, it is difficult to prove that record-low interest rates and record-high stock prices caused poor value returns. However, record-low interest rates should produce lower long-term discount rates and increase the present value of far-away profits. To the extent this happened, it should have contributed to the underperformance of value investment styles that favor current assets and income over long-term, speculative growth prospects.

Covid relief programs have again produced a range of government support efforts. In early 2021, however, there were signs that the rapid increase in government debt required to fund these programs may finally stop interest rates from falling ever lower. Should interest rates inch higher, they may disappoint investors who priced stocks based on extremely low discount rates. A repricing of stocks based on higher interest rates should produce lower stock prices and favor value investments.

Even though higher interest rates may lead to lower equity returns, this does not have a direct effect on *market-neutral* value portfolios. On balance, however, environments with moderate or low equity market returns tend to be better for value investments. Especially investors concerned about higher interest rates and lower stock prices should find market-neutral value investments attractive.

Looking at the early 2000s, figure 3 shows that value spreads declined from a peak similar to current levels. Value spreads continued to fall over the next 5 years, well past 2005. Figures 1 and 2 show that value investment strategies had very strong returns during the 2000 to 2004 period: Going long the Russell 1,000 Value index and short the Russell 1,000 Growth index earned more than 100% cumulative returns; the simulated pure value strategy described in figure 2 earned similar returns but at lower risk. These returns accrued both during the initial overall market decline and the subsequent market recovery. Both simulated strategies use leverage of 100% long and 100% short, for illustration. Actual implementation often run at higher leverage, which amplifies returns. Although there surely are differences between 2001 and 2021, and there remains uncertainty about when value spreads will normalize, a material decline in value spreads should produce strong returns for value investment strategies.

5. Summary

For several years, there has been much discussion of value investment strategies for stocks. Simplistic approaches to value investing, in particular, have suffered nearly uninterrupted losses since the financial crisis. In 2020, however, basically all value investment styles for stocks suffered extreme losses. Regardless of the details of the value measures, using them for security selection produced large negative returns.

The negative returns to value investing strategies have made “cheap” stocks cheaper and “expensive” stocks more expensive. This has created extreme spreads in valuation measures between cheap and expensive stocks.

The last time valuation spreads reached similar levels was around 2000, at the end of the technology boom. When valuation spreads normalized over several years, value investment strategies earned strong returns. Even then, these returns were not based simply on betting against technology stocks. Valuations within sectors normalized as well, and led to strong returns for more sophisticated, industry-neutral value investment strategies.

For the first time in what feels like a long time, early 2021 has produced positive value returns. This may be a sign that the overwhelmingly negative sentiment toward value stocks is finally fading.

Importantly, the positive value returns in 2021, so far, have done little to shrink the extreme value spreads created by the previous negative returns. The case for positive value returns in stock selection strategies remains strong, the potential for future value returns remains undiminished – but also largely unrealized for now.

6. References

FTSE Russell, 2021, Russell U.S. equity indexes construction and methodology (v5.0), FTSE Russell, London, England.

Gurnani, Deepak, and Ludger Hentschel, 2018, Value factor performance in 2018, Versor, New York, NY.

7. Value Factor Performance in 2018

Deepak Gurnani Ludger Hentschel

October 2018

Contents

Executive Summary

Nearly all investors claim to pursue "value" strategies. There is compelling evidence that such strategies are attractive in the long term. However, value investing, especially as a stock selection strategy, has performed unusually poorly in the last 12 months.

The recent underperformance of value stock selection strategies can be seen across developed markets and in nearly all sectors. Globally, value strategies applied to stock selection have earned returns roughly 3.7 standard deviations below their historical means. In the context of normally distributed returns, such observations should be exceedingly rare.

While the poor performance of value strategies has been painful for value investors, it has created unusually attractive opportunities going forward. The valuation spreads between cheap and expensive stocks in the US are now in the top 5 percent of spreads since 2003. When these spreads revert to their historical norm, as they tend to do, value investors may earn large returns going forward.

Importantly, the value stock selection strategies we investigate are market neutral. They should have low correlations with equity or bond markets. This is borne out by historical correlations. As a result, the potential attractiveness of market-neutral value strategies is not contingent upon return expectations for stock or bond markets.

1. Introduction

Nearly all investors claim to pursue "value" strategies. There is compelling evidence that such strategies are attractive in the long term. However, value investing, especially as a stock selection strategy, has performed unusually poorly in 2018.

The recent underperformance of value stock selection strategies can be seen across developed markets and in nearly all sectors. Globally, value strategies applied to stock selection have earned returns more than 3.5 standard deviations below their historical means.[1]

While the poor performance of value strategies has been painful for value investors, it has created unusually attractive opportunities going forward. The valuation spreads between cheap and expensive stocks in the US are now 1.7 standard deviations above their historical norms. This puts the current spreads in the top 5% of US value spreads observed since 2003. When these spreads revert to their historical norm, as they tend to do, value investors who implement their strategies in a market-neutral fashion are likely to earn large returns.

A well-known, striking precursor for wide value spreads and subsequent high value returns is the period around the turn of the millennium. During the late 1990s, value stocks and strategies performed poorly and value spreads widened. During the early 2000s, value strategies strongly recovered even as stock markets overall experienced extended declines. While there may be similarities with the current environment, we intentionally exclude this period from our analysis because it may be historically extreme.

The stock selection value strategies we analyze are one of several alternative risk premia strategies we have investigated and implemented. Within value, we consider a broad range of value characteristics derived from firms' balance sheets, income statements, and cash flow statements. These factors are related to a well-established literature on systematic investment strategies, also known as "factors" or "anomalies". Possibly the most prominent paper in this literature is Fama and French (1992), who include the book-to-price ratio ("high minus low" or "HML") as a value factor in their analysis of US stock returns. Like the Fama and French (1992) value portfolios, our strategies are long-short, market-neutral portfolios. Nonetheless, there are other important differences in implementation, which we discuss next.

2. Value Factors in Stock Selection

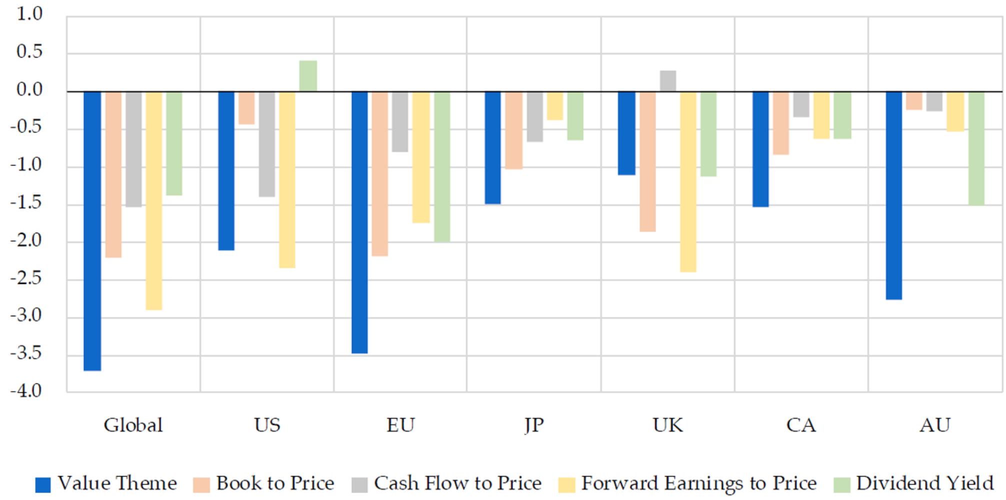
Value investors select stocks on the basis of value judgements, which are often rooted in the firms' income statement, cash flow statement, or balance sheet. We simulate such value strategies systematically by computing valuation ratios for stocks and then ranking stocks relative to their industry peers. Such comparisons intentionally ignore inter-industry differences in valuation ratios. We analyze value performance in the United States, Europe, Japan, UK, Canada, and Australia, but we only compare stocks to their local peers, never across regions. Such comparisons intentionally ignore inter-region differences in valuation ratios.

For this paper, we focus on earnings yields (the inverse of P/E ratios), cash-flow yields, dividend yields, sales-to-price ratios, and book-to-price ratios. These measures are widely used in analyzing company valuations. For each of these valuation ratios, at the time of calculation, we use the latest reported financial statements for the trailing 4 quarters and the prevailing market value of equity.

By design, the value strategy portfolios we analyze are market neutral. We rank stocks within regions

[1] If the returns to value follow a standard normal distribution, returns at or below the –3.5 standard deviation level should occur in only 0.02 percent of outcomes.

Figure 1: 2018 Value Returns by Country



The figures shows value returns for 2018 in different countries.

All returns are from January to August 2018. The returns are expressed in z-scores relative to a return history from 2003. The z-scores attempt to reduce the potential effects of data snooping by reducing the long-run average return by 33%. The adjusted historical returns are scaled so that they have a mean of zero and standard deviation of one. A z-score of zero represents an average return. Negative values are below the long-run average. Returns below -2 or above 2 are exceptional.

Simulated returns reflect estimated implementation costs.

Past performance is not indicative of future results. Performance reflects the reinvestment of income.

and industries based on valuation ratios and then build portfolios that are long stocks with the most attractive ratios and short stocks with the least attractive ratios. This is appealing because it isolates the performance of the value strategy from other influences like market, country, or industry contributions.

Our value portfolios use long and short weights that vary smoothly with the valuation ratio relative to industry peers in a region. The most attractive stocks receive the largest positive weight, the least attractive stocks receive the largest negative weights, and intermediate stocks receive intermediate weights.[2]

Finally, our value strategy portfolios also remove the influence of other potentially confounding stock characteristics, including firm size, liquidity, return volatility, price momentum, earnings quality, and analyst sentiment. We remove all of these effects by estimating value returns via Fama and MacBeth (1973) cross-sectional return regressions.

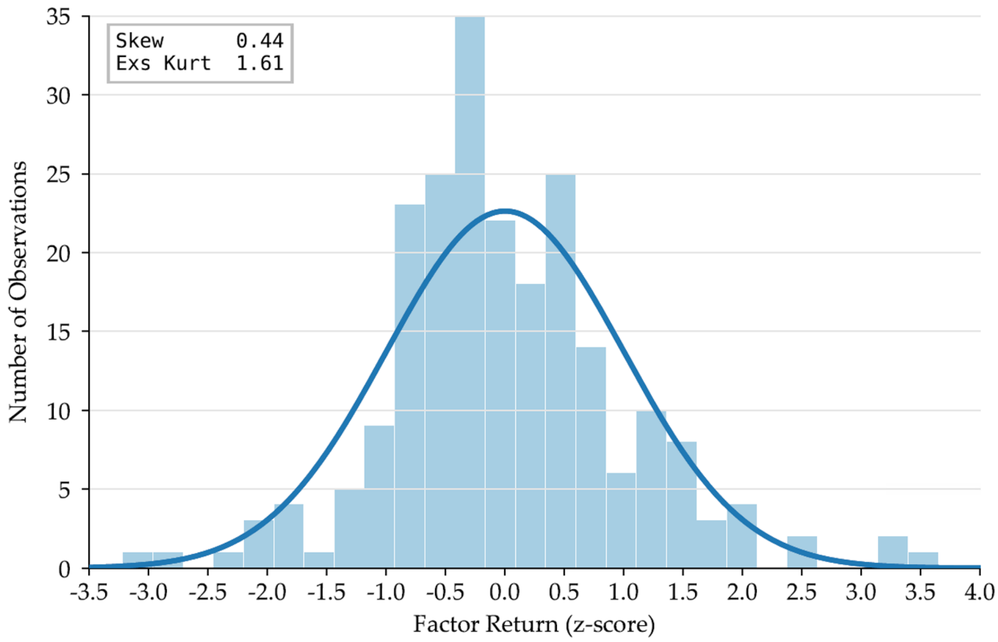
3. Recent Performance

Value factors have attractive long-term performance but their recent returns have been unusually poor. This poor performance is widespread. It was realized across many different value measures, sectors of the economy, and countries.

Figure 1 summarizes the returns to several value measures in z-score terms in six regional markets and for a global, overall average. A z-score of 0 represents the mean return for the value strategy

[2] A common alternative for constructing long-short value portfolios is to equally weight stocks in the extreme quantiles, for example quintiles or deciles. Such quantile spread portfolios quickly become unwieldy in multiple dimensions.

Figure 2: Historical Distribution of Value Returns



The figure shows the histogram of monthly global value returns in z-scored units. For comparison, the figure also shows a normal distribution with the same mean and standard deviation.

Returns are monthly from January 2003 to August 2018. The value returns are for a global average of value factors.

Past performance is not indicative of future results. Performance reflects the reinvestment of income.

in a given region over the sample period from January 2003 to August 2018. The global z-score of –3.7 means that value returns for 2018 (through the end of August) have been 3.7 standard deviations below the historical mean. In the context of normally distributed returns, such observations should be exceedingly rare.[3]

As the figure shows, the negative performance is not isolated to particular regions or individual valuation ratios. Nearly all valuation ratios are associated with poor performance in nearly all regions. Generally, the different regions and value styles offer diversification. The unusual alignment of negative performance during 2018 across many different value strategies gives rise to exceptionally negative global, overall value returns. The value portfolios associated with our value strategies are market neutral and can be levered to a broad range of risk levels. A strategy levered to 15 percent annual risk has risk levels similar to equity markets. At that risk level, a simulated global value strategy has delivered an historical average annual return just under 34 percent. For 2018, through August, the same portfolio has returned –23 percent.[4, 5]

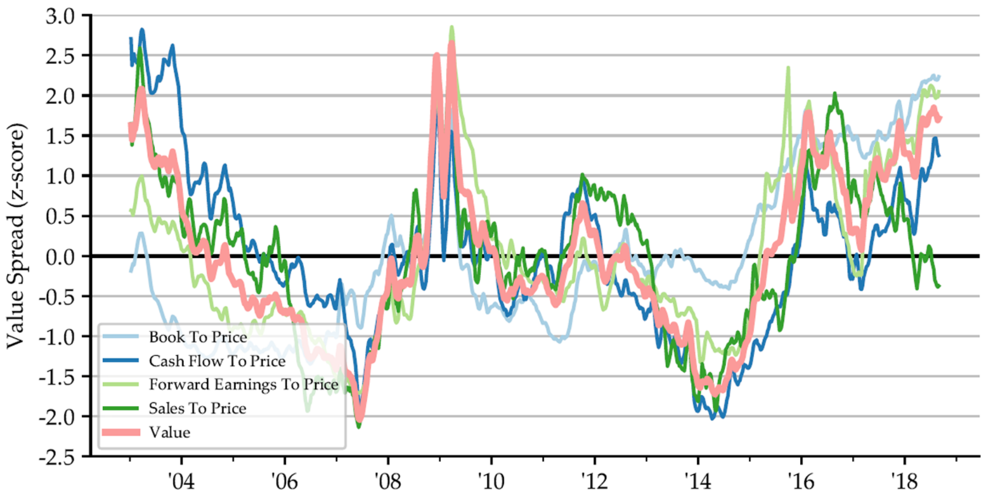
Unusual observations like this may raise concerns about infrequent but extreme negative value returns. Such concerns appear unfounded. Figure 2 shows a histogram of monthly global value returns that shows an approximately symmetric return distribution. In fact, daily, monthly, and quarterly value

[3] Many of the valuation ratios we use in forming our value strategies have been discussed in the academic literature. While we have made no direct attempt to select the value strategies with the best past performance, it seems likely that value strategies with exceptionally high past performance have attracted more attention. This phenomenon has been called "data snooping". In an attempt to address concerns that collective data snooping may have inflated past returns, we apply a "haircut" to the z-scores in Figure 1. We reduce the mean excess returns by 33 percent prior to computing z-scores.

[4] The portfolio simulations deduct estimated implementation costs.

[5] Past performance is not indicative of future results. Performance results reflect the reinvestment of income. The return estimates presented here are based on Versor's internal systems, have not been reconciled with an administrator and do not reflect the official books and records of any account.

Figure 3: Value Spreads



The figure shows US valuation spreads over time. Valuation spreads are the weighted average difference between the valuation ratios of stocks with attractive ratios and stocks with less attractive ratios.

In each US industrial sector and geographic region, we assign positive weights to stocks with attractive valuations and negative weights to stocks with unattractive valuations. The weights are larger for more attractive stocks. The positive weights sum to 1. The negative weights sum to –1. For earnings yields, the weighted sum of earnings yields is the average spread in earnings yields between attractive and unattractive firms on that date. We form a regional average of such spreads by taking a weighted average across all industrial sectors.

Each of the four panels uses a different valuation ratio. The top left uses analyst earnings forecasts from IBES divided by current equity market prices. The top right uses reported cash flows divided by market prices. The bottom left uses reported book values divided by market prices. The bottom right uses reported sales divided by market prices

Value spreads are monthly data from January 2003 to August 2018. The data cover US large-cap and mid-cap stocks.

Past performance is not indicative of future results. Performance reflects the reinvestment of income.

returns have slightly positive skewness. Also, based on the skewness and kurtosis of the quarterly simulated value returns, Jarque and Bera (1980) statistical tests cannot reject the hypothesis that the value returns follow a Gaussian/Normal distribution at the 99% confidence level.

Equity style index returns offer corroborating evidence that value strategies have performed unusually poorly in 2018. For example, a portfolio that goes long the Russell 1000 Value index and short the Russell 1000 Growth index is a very simple market-neutral value strategy. Such a strategy would have lost nearly 13 percent from January 1, 2018 to August 31, 2018.[6] Value strategies, like ours, that hedge out additional risk often are part of diversified portfolios that run more leverage than the 100% long and 100% short exposures of such a simple portfolio.

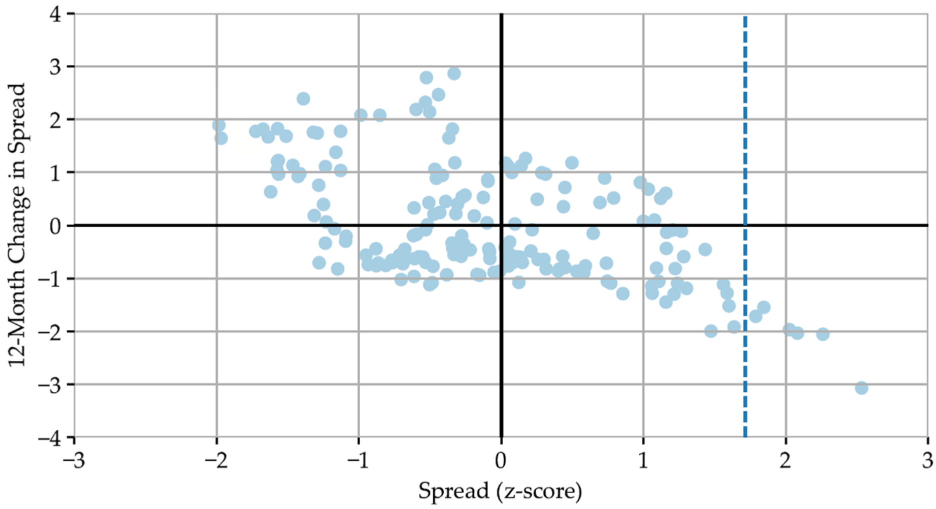
4. Value Spreads and Returns

As a direct result of the poor performance of value factors, “cheap” stocks have become even cheaper and “expensive” stocks have become even more “expensive”. We can measure this increase in valuation differences using value spreads. For example, we can compute earnings yields for all stocks and compute the difference in earnings yields for cheap and expensive stocks. We can compute similar spreads for other value metrics like cash-flow yields and book-to-price ratios.

In order to focus on stock selection effects, we once again remove geographical and sector differences

[6] The Russell 1000 Value index returned 3.71 percent and the Russell 1000 Growth index returned 16.44 percent, according to FTSE Russell at https://www.ftserussell.com/index-series/index-tools/russell-index-performance-calculator.

Figure 4: Mean Reversion in Value Spreads



The figure graphs US values spreads on the horizontal axis and changes in US value spreads over the subsequent 12 months on the vertical axis. The association between large spreads and subsequent declines in the spreads indicates that spreads have a tendency to revert to "normal" values,

The spreads are averages of multiple valuation spreads, like those shown in Figure 3. Spreads and spread changes are monthly data from January 2003 to August 2018. The spreads are based on US large-cap and mid-cap stocks.

The vertical dashed line marks the spread level at the end of August 2018.

Past performance is not indicative of future results. Performance reflects the reinvestment of income.

from our measures. In each industrial sector and geographic region, we assign positive weights to stocks with attractive earnings yields and negative weights to stocks with unattractive earnings yields. The weights are larger for more attractive stocks. The positive weights sum to 1. The negative weights sum to –1. On a given date, the thus-weighted sum of earnings yields is the average spread in earnings yields between attractive and unattractive firms on that date. We form a regional average of such spreads by taking a weighted average across all industrial sectors in the region.[7]

Figure 3 graphs US valuation spreads over time. The figure displays each of the spreads in z-score units with a long-term mean of zero and a time-series standard deviation of 1. The figure shows that the valuation spreads generally move together but are slightly different from each other. This is one reason we prefer to track several valuation metrics and diversify our value portfolios across these measure

At the end of August, 2018, the weighted average "Value" composite of the 4 component spreads in Figure 3 was at 1.7 standard deviations above its long-run mean.[8] That spread is in the top 5 percent of observed US value spreads since 2003.

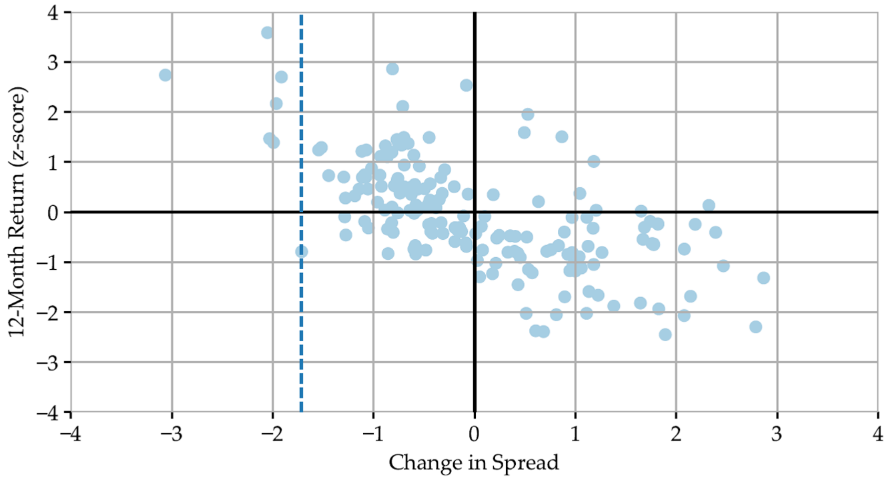
Current value spreads in other developed markets are less extreme than US value spreads but they are well above their historical norms. In Europe and Japan, spreads for value composites at the end of August were just outside the top 25 percent of value spreads since 2003.

Figure 3 clearly shows unusually large spreads in many US valuation ratios. If the spread is larger today than previously, a natural interpretation is that – relative to expensive stocks – cheap stocks are cheaper than usual.

[7]The weights are proportional to the square root of the number of stocks in each sector. This is an approximation to the capital the strategy deploys in each sector and is commonly referred to as the available breadth in the sector.

[8] We assign a weight of one third to earnings and cash flow yields and a weight of one sixth to sales to price and book to market, respectively.

Figure 5: Value Returns and Changes in Value Spreads



The figures graphs the annual change in US value spreads on the horizontal axis and the contemporaneous returns to US value portfolios on the vertical axis.

The spreads are averages of multiple valuation spreads, like those shown in Figure 3. The returns are for the corresponding average portfolios. Spread changes and returns are measured each month from January 2003 to August 2018. The spreads and returns are based on US large-cap and mid-cap stocks.

The dashed vertical line indicates the change in spread if the August 2018 spread level reverts back to normal (zero) over the course of 12 months.

Past performance is not indicative of future results. Performance reflects the reinvestment of income.

4.1 Mean reversion in spreads

Interestingly, unusually wide value spreads are often followed by a compression of the spreads back to more normal levels. We illustrate this in Figure 4. The figure displays US value spreads on a given date on the horizontal axis and the change in US spreads over the following 12 months on the vertical axis. For large spreads, on the right, subsequent spread changes are generally negative. That means that wide spreads tend to compress back toward more normal spread levels.[9] The figure indicates the current spread level with a dashed vertical line. We cannot place a marker for August 2018 on the graph since we don't yet know the value return over the next 12 months.

4.2 Performance during spread tightening

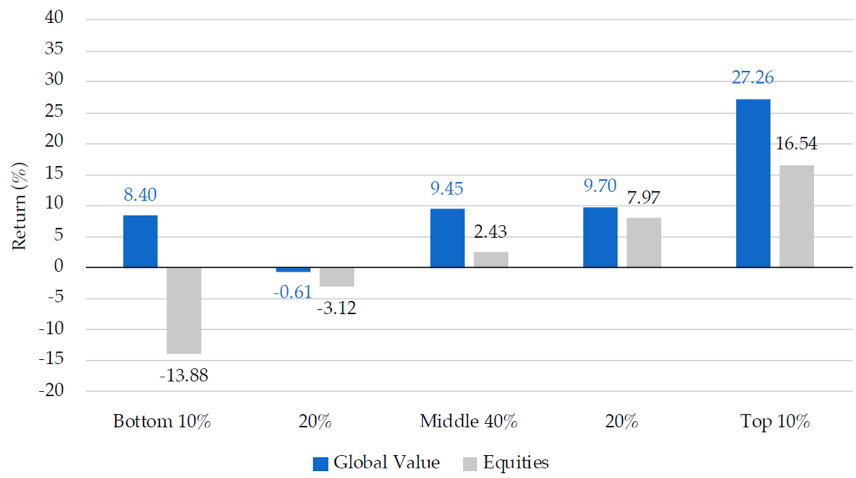
Naturally, as value spreads compress, the valuations of cheap stocks rise towards those of previously more expensive stocks. As this happens, value strategies generally earn positive returns. Figure 5 shows 12-month changes in value spreads and the contemporaneous returns to value factors. In the figure, value returns are generally higher during periods of tightening value spreads, on the left.

Moreover, for larger spread compression, on the far left, value returns tend to be especially large. If the current US value spreads were to revert back to normal levels with a z-score of 0 over the next 12 months, the change in spreads would be –1.7. The figure indicates this change with a dashed vertical line. The historical experience suggest that US value returns associated with such a change might be +1 or +2 standard deviations above their historical norm. That corresponds to a return of 26 percent or 43 percent for a US value portfolio levered to 15 percent risk.

Notably, however, there have also been periods where strong compression in value spreads has been accompanied by negative value returns. These episodes can occur when changes in fundamentals

[9] This mean reversion is also apparent for individual value styles shown in the time-series spread plots in Figure 3, which appear to fluctuate around and revert to "normal" levels. The figures correctly suggest that a full cycle may take longer than the 12 months we focus on for our analysis.

Figure 6: Value Returns in Different Equity Market Environments



The figure shows monthly average returns for a simulated global value portfolio and the equity market in different equity market environments.

The figure groups calendar months according to the returns of the MSCI World equity market index from January 2003 to August 2018. The value returns are for the matching calendar months.

The left-most group contains the 10% of months with the worst equity returns. The second group contains the next 20% of months by equity returns. The middle group contains the middle 40% of months by equity returns. The right-most group contains the 10% of months with the highest equity returns.

The value returns are for a long-short portfolio of large-cap and mid-cap stocks in the US, Canada, continental Europe, the UK, Japan, and Australia. The portfolio is long attractive stocks based on a broad range of value characteristics and short unattractive stocks based on the same value characteristics. The portfolio is levered to 15% annual volatility. The value returns are net of estimated implementation costs.

Past performance is not indicative of future results. Performance reflects the reinvestment of income.

rather than changes in prices drive the compression in valuation spreads.

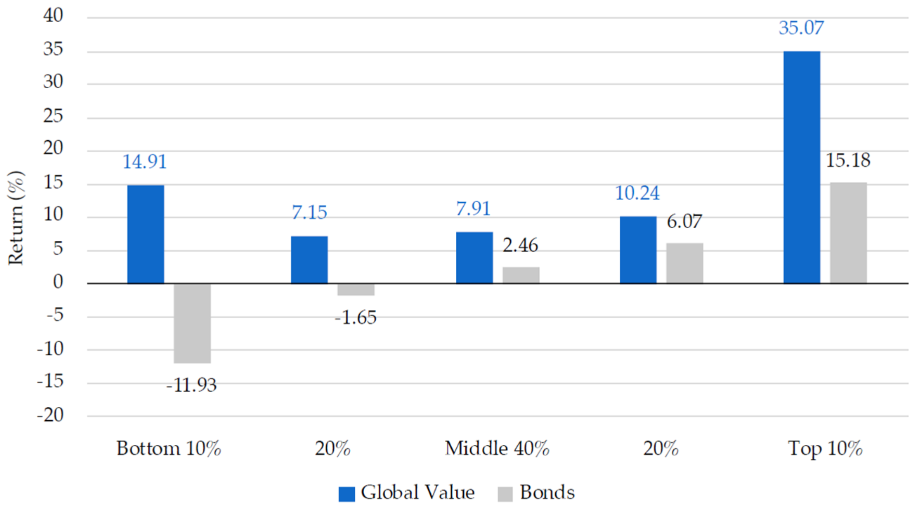
The above illustrates three facts: current valuation spreads are unusually wide, wide spreads tend to compress, and compression in valuation spreads is associated with high returns for value strategies. We infer that the current wide value spreads indicate an attractive environment for value strategies going forward.

5. Value in Different Market Environments

There are at least two reasons why even investors who agree that value spreads are currently wide may be concerned that this does not represent an attractive opportunity. First, overall equity market valuations are not low and value returns may be negatively affected by declining stock markets. Second, value returns may be negatively affected by global interest rates, which may continue to rise after an extended period of record-low yields. We show that this is not the case.

The value portfolios that allow us to measure value returns and spreads are structurally market neutral. The portfolios are long and short equal dollar amounts with zero net exposure to the market, industrial sectors, and predicted market betas. There is reason to believe that such portfolios have low or no correlation with equity market returns. Figure 6 illustrates empirically that this has been borne out. The Figure shows the average equity market returns and average value factor returns in 5 different equity market environments. The bars on the far left correspond to the 10% of the worst

Figure 7: Value Returns in Different Bond Market Environments



The figure shows monthly average returns for a simulated global value portfolio and the bond market in different bond market environments.

The figure groups calendar months according to the returns of the Bloomberg/Barclays U.S. Long Treasury bond market index from January 2003 to August 2018. The value returns are for the matching calendar months.

The left-most group contains the 10% of months with the worst bond returns. The second group contains the next 20% of months by bond returns. The middle group contains the middle 40% of months by bond returns. The right-most group contains the 10% of months with the highest bond returns.

The value returns are for a long-short portfolio of large-cap and mid-cap stocks in the US, Canada, continental Europe, the UK, Japan, and Australia. The portfolio is long attractive stocks based on a broad range of value characteristics and short unattractive stocks based on the same value characteristics. The portfolio is levered to 15% annual volatility. The value returns are net of estimated implementation costs.

Past performance is not indicative of future results. Performance reflects the reinvestment of income.

equity market returns; the next group corresponds to equity markets in the next 20% of equity market returns; followed by the middle 40%, next 20%, and top 10% of equity market returns. Clearly, value factors have performed well on average even when equity markets have done poorly. From January 2003 to August 2018, the rank correlation between simulated, monthly, global, pure value returns and equity market returns measured with the MSCI World index has been 0.16.

Similarly, Figure 7 shows the performance of global value factors in a simulated stock selection strategy during different environments for bond markets. Since the value portfolios only trade stocks, not bonds, there is no simple logic that the returns on value portfolios would have material association with bond market returns. Once again, the empirical evidence shows this to be true historically. From January 2003 to August 2018, the rank correlation between monthly simulated pure value returns and bond market returns measured with the Bloomberg/Barclays Long-Duration Bond index has been 0.25.

6. Summary

We demonstrate that "value" strategies in stock selection have performed unusually poorly in 2018, through August. As a direct result of this performance, "cheap" stocks have become even cheaper relative to "expensive" stocks. We show that such valuation spreads are now exceptionally wide, especially in the US. We furthermore show that wide spreads tend to shrink back towards more normal levels and that such spread compression tends to be associated with high value returns. We conclude that the current wide value spreads indicate an attractive environment for value investment strategies in stock selection.

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Section 4

Alternative Risk Premia - Efficient and Uncorrelated

8. The Case for Alternative Risk Premia, Part 1

Deepak Gurnani Ludger Hentschel

Februrary 2016

Contents

Executive Summary

Alternative risk premia factors (“alternative factors”) are emerging as attractive investment opportunities. They have demonstrated four attractive properties:

1. Alternative factors have exhibited persistently low correlations among alternative factors and with traditional risk premia factors (“traditional factors”).

2. Alternative factors have generated positive returns during periods of negative returns for traditional factors.

3. Alternative factors have generated superior risk adjusted returns compared to traditional factors.

4. Portfolios with allocations to alternative factors have enjoyed higher returns and lower risk than portfolios dominated by traditional factors.

These return characteristics imply that institutional investors and their portfolios can derive material benefits from investing in alternative factors. Furthermore, alternative factors have significant capacity, which makes them meaningful even for the largest institutional investors. They also offer high transparency, attractive liquidity, and relatively low fees. Interestingly, investors likely have some exposures already to alternative factors through “alpha” managers, who may be charging much higher fees.

1. Introduction: Risk Premia as Return Components

We use figure 1 to define alternative risk premia. The figure graphically decomposes the total return of a portfolio into returns from the risk-free rate, traditional risk premia, alternative risk premia, and idiosyncratic alpha.

Of these, alternative risk premia are the least familiar. We define alternative risk premia factors as systematic implementations of active trading strategies offered at low, generally fixed fees. Examples of alternative risk premia factors include stock selection factors (momentum, valuation, quality), trend following, event investing, and systematic macro factors (momentum, carry, valuation). The two features that distinguish alternative risk premia from traditional risk premia are that

1. alternative risk premia do not have market exposures.
2. alternative risk premia require active trading.

The requirement that alternative risk premia do not have market exposures, at least on average, implies that they generally contain long and short positions in the underlying securities.

Alternative risk premia factor portfolio

For the purpose of our empirical analysis, we construct an alternative risk premia factor portfolio with 25% risk weight to each of four factors: stock selection; trend following; systematic macro, and equity event. The portfolio is rebalanced annually at the beginning of each calendar year and is scaled to an annualized volatility of 8%. The underlying factor portfolios are sourced from Versor Investments internal research and publicly available factor returns on Bloomberg. The factor portfolio returns are based on simulated performance of systematic investment rules. They assume the reinvestment of dividends and other income. They are net of fees, expenses, and estimated transaction costs.

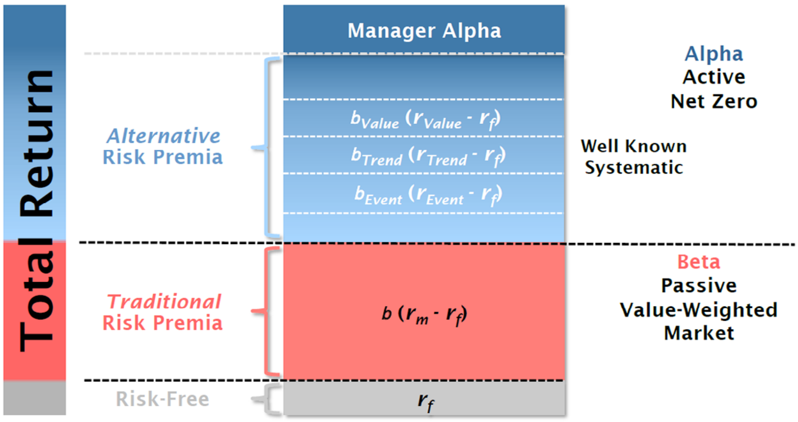
The stock selection portfolio systematically invests in individual global equities based on their characteristics. The portfolio invests in developed markets and is market neutral by holding equal long and short exposures. Long positions tend to have attractive valuations, high earnings quality, positive analyst sentiment, positive momentum, and attractive accounting measures of financial stability. Short positions tend to score poorly on the same characteristics.

The trend following portfolio invests in 70 liquid futures contracts using trend-following signals to determine long and short positions. In addition, the portfolio uses sophisticated risk management to ensure proper diversification across signals and asset classes.

The systematic macro portfolio also invests in liquid futures contracts but determines positions based on cross-sectional carry, value, and momentum signals.

The equity event portfolio invests in North American and European corporate events: announced mergers and Dutch auction share repurchases. The positions are determined by the announced deal characteristics and sized based on a proprietary risk model for mergers.

Figure 1: Return Components



For illustrative purposes only. Actual Implementation may differ.

Traditional risk premia factor portfolio

We refer to common market segments (or asset classes) like global equities, global fixed income, and commodities as traditional risk premia factors. Long exposures to traditional factors like these dominate most institutional portfolios.

For illustration, we construct a traditional factor portfolio as a risk-weighted portfolio with risk weights as follows: global equities: 37.5%; government / investment-grade bonds: 30%; high yield credit: 7.5%; commodities: 25%. We interpret this as a simple implementation of a risk parity portfolio. The portfolio is rebalanced annually at the beginning of each calendar year and is levered to a nominal total weight of 150% on each rebalance day. Returns assume the reinvestment of dividends and other income.

For the purpose of our empirical analysis, we use the MSCI World (net) total return index for global equities. Similarly, we use the Barclays Global Aggregate (un-hedged) bond index for government and investment grade bonds; the Barclays Global High Yield (un-hedged) index for high yield credit; and the S&P GSCI total return index for commodities. The returns for all underlying indices are sourced from Bloomberg, MSCI, and Barclays.

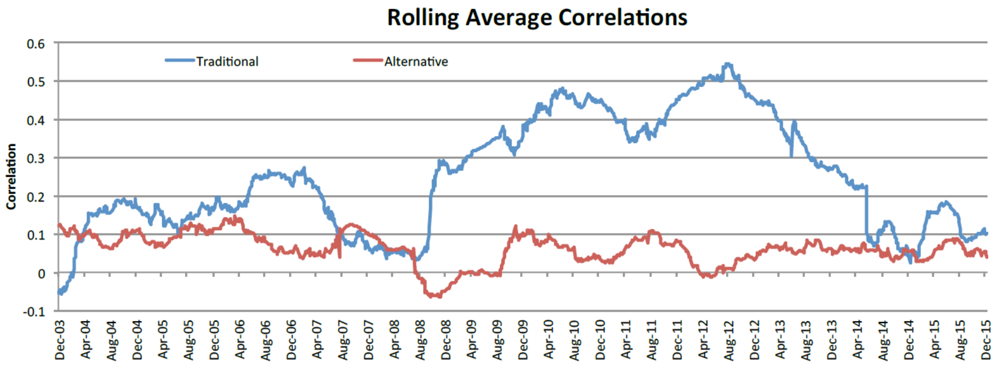
2. Low Correlations

Diversification is the most powerful tool for portfolio construction and risk management. Diversification is most effective with investments that have low and stable correlations with each other. Alternative risk premia possess both of these properties.

Figure 2 compares average correlations among traditional factors with the average correlation among alternative factors. We compute pair-wise, one-year rolling correlations between traditional factors, represented by global equities, global fixed income, and global commodities. On each day, we average the three pair-wise rolling correlations generated to compute the average correlation across traditional factors. The blue line in figure 2 plots these correlations.

Similarly, the red line plots the average pair-wise, one-year rolling correlations among alternative factors represented by stock selection, trend following, systematic macro and equity events risk premia.

Figure 2: Return Components



Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

The graph shows that Alternative factors exhibited persistently low correlations over the period. The analysis covers the period January 2003 to December 2015.

3. Attractive Returns During Periods of Market Stress

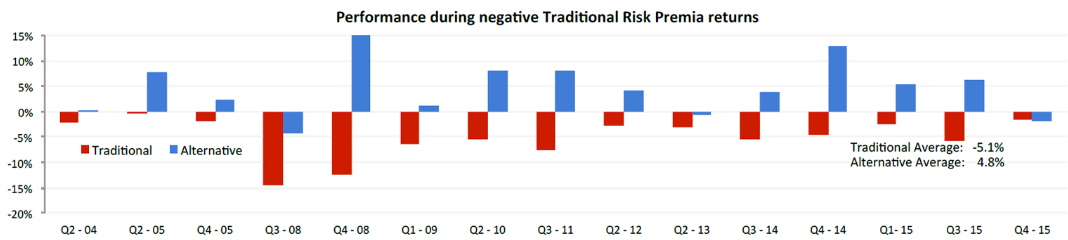
Figure 3 presents the performance of our simulated alternative portfolio during quarters with negative returns for the traditional portfolio.

The analysis covers the period January 2003 to December 2015 and includes 15 quarters with negative returns for the traditional portfolio. Over these 15 quarters, the alternative portfolio returned +4.8%, on average, while the Traditional portfolio returned -5.1%.

Figure 4 repeats this analysis for quarters with negative returns to global equities, represented by the MSCI World index. The analysis covers the period January 2003 to December 2015 and includes 15 quarters with negative returns to global equity markets. Over these 15 quarters, global equity markets returned -7.5%, on average. By contrast, the alternative portfolio returned +5.5%, on average, over the same 15 quarters.

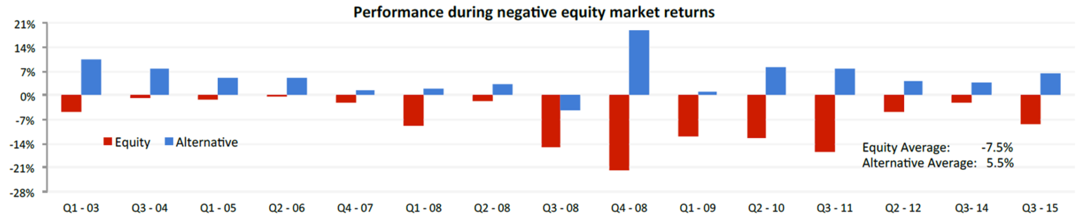
It is well known that equity risk dominates most institutional portfolios. Investments that perform well when equities are down, offer such portfolios excellent opportunities for diversification.

Figure 3: Returns During Periods of Market Stress



Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

Figure 4: Returns During Periods of Equity Market Stress



Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

4. Superior Risk-Adjusted Returns

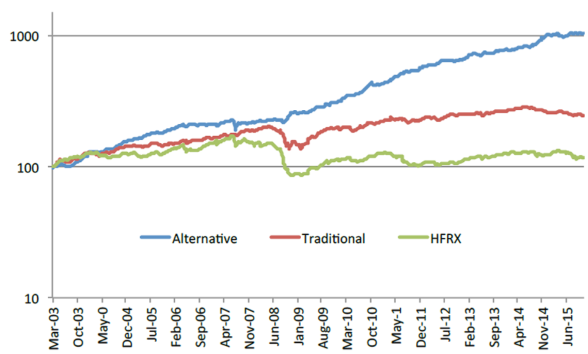
Figure 5 compares the cumulative returns of a simulated alternative risk premia portfolio to returns on the traditional risk premia portfolio and the HFRX Global Hedge Fund index returns. We include the HFRX index because some hedge funds may have exposures to alternative risk premia factors.

The blue line traces the cumulative simulated returns of the Alternative portfolio; the red line traces the cumulative returns of the Traditional portfolio and the green line traces the cumulative returns of the HFRX Global Hedge Fund index. The graph compounds daily returns from January 2003 to December 2015.

The table on the right shows summary statistics for the returns of these portfolios. The mean, median, and risk statistics are annualized.

The analysis shows that the alternative portfolio exhibited the highest Sharpe ratio among the three portfolios. Moreover, the alternative portfolio has also exhibited low beta and high alpha with respect to global equities and sovereign debt. The beta with respect to the HFRX Global Hedge Fund index is higher, but the alpha remains similarly high.

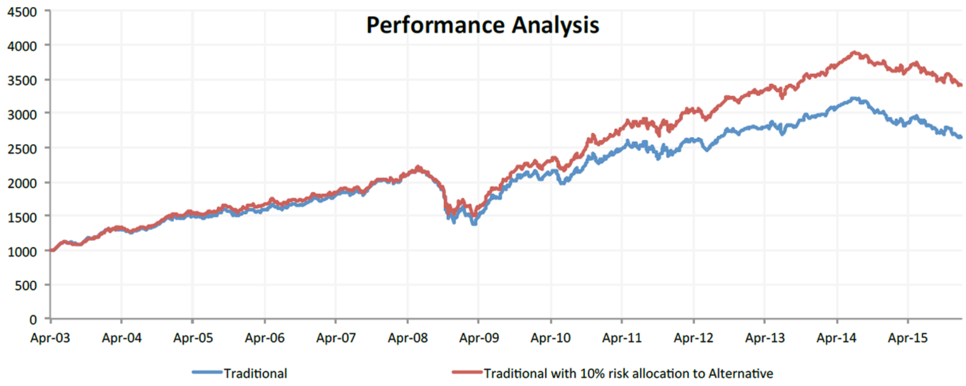
Figure 5: Historical Performance Comparison



	Alternative	Traditional	HFRX
Arithmetic Mean	18.7%	8.3%	1.4%
Geometric Mean	20.0%	7.9%	1.2%
Median	19.9%	12.1%	4.4%
Risk	8.1%	11.6%	5.6%
Sharpe Ratio	2.25	0.56	-0.01
Max Drawdown	-4.7%	-34.4%	-25.3%
Percent Positive	75.8%	60.8%	59.5%
Equity α	16.2%	3.0%	-1.4%
Equity β	0.07	0.43	0.16
Sov. Debt α	15.8%	3.8%	0.0%
Sov. Debt β	0.36	1.05	0.00
HFRX α	16.7%	6.5%	-
HFRX β	0.70	1.34	-
Equity + Sov. Debt + HFRX α	16.5%	1.1%	-
Equity β	-0.12	0.35	-
Sov. Debt β	0.39	0.95	-
HFRX β	1.07	0.29	-

The alphas and betas with respect to equity returns, sovereign debt and HFRX Global Hedge Fund index are based on regression estimates for the full sample period. We proxy equity returns with the MSCI World index and sovereign debt returns with the Barclays Global Aggregate index. The regressions use returns in excess of the 3-month Treasury Bill return.

Figure 6: Cumulative Returns



Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

5. Enhanced Portfolio Performance

Figure 6 compares the cumulative returns of a simulated traditional portfolio and the returns of a simulated traditional portfolio augmented with a 10% risk allocation to alternative factors (for illustration only). The blue line traces the cumulative returns of the traditional portfolio. The red line traces the cumulative returns of traditional portfolio with the 10% risk allocation to alternative factors. The graph compounds daily returns up to December 31st, 2015. The analysis shows that overall portfolio performance is enhanced by allocation to Alternative factors.

Live experience

Early live experience with alternative factor portfolios, especially during recent periods such as the third quarter of 2015 and January 2016, has confirmed the main findings presented earlier. Alternative factor portfolios have exhibited positive returns during both of these periods. At a factor level, strong performance in Trend-Following and Stock Selection was partially offset by a small loss in Equity Events.

6. High Capacity

Alternative factor portfolios have high capacity because they are highly diversified, systematic strategies that invest in highly liquid instruments. For example, limiting trading in futures and equities to a maximum of 5% of average daily volume translates into capacity for an individual firm to manage tens of billions of dollars in assets under management.

7. Conclusion

Alternative factor portfolios have significant capacity available to make them interesting for institutional investors. In addition to the attractive fees, alternative risk premia factor portfolios offer enhanced liquidity and transparency versus hedge funds. There now exist several competing alternative risk premia products with more sure to enter the market in the near future. When comparing these products, we can also show that hedge fund experience, risk management in particular, is an important ingredient in successful alternative factor products. Yet, alternative factor products offered by hedge funds create an internal conflict between the high-fee hedge fund and the low-fee alternative factor products. A natural way to avoid this conflict is to choose alternative factor products from asset managers without competing hedge fund products but with hedge fund experience.

9. The Case for Alternative Risk Premia, Part 2

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January 2017

Contents

Executive Summary

Previously, in "The Case for Alternative Risk Premia: Part 1", we demonstrated that alternative risk premia factors have attractive average return characteristics due to their controlled risk and strong returns. As a follow-up, we show that alternative risk premia perform well across different market environments. We analyze alternative risk premia performance in different return environments for equities, credit, Treasuries, and TIPS. Naturally, we are especially interested in performance during the most challenging market environments for these asset classes.

We group more than 50 alternative risk premia factors into 4 categories: Stock Selection, Trend Following, Global Macro, and Equity Event.

The analysis shows that the low correlation between alternative risk premia and market factors produces attractive returns for alternative risk premia during challenging market environments. However, particular alternative risk premia are especially resilient during challenging times for the different asset classes. Using historical data, we show that, during periods of stress in the equity and credit markets, Stock Selection and Trend Following factors perform especially well. During periods of stress for Treasuries, Macro and Equity Event factors perform especially well. Finally, during periods of stress for TIPS, Stock Selection and Equity Event factors perform especially well.

The performance heterogeneity of alternative risk premia during stress periods in the different asset classes show that investors generally should hold a diversified portfolio of alternative risk premia. Since investors likely are especially concerned about portfolio performance during periods of stress in equity or credit markets, a slightly smaller allocation to Equity Events will provide better diversification during these episodes.

In contrast to many hedge fund portfolios, well-constructed alternative risk premia portfolios have consistently low correlations with the major asset classes. As a result, diversified alternative risk premia portfolios outperform hedge fund portfolios during periods of market stress.

We conclude that alternative risk premia are valuable components of institutional portfolios due to their attractive return characteristics, excellent diversification during periods of market stress, scalability, and low fees.

1. Investment Objectives

Construct a risk premia factor portfolio:

- superior risk-adjusted returns.
- uncorrelated to equities and bonds.
- liquid and scalable.
- fair level of fees and expenses.

Factors to be included in the portfolio to be evaluated for scalability, cash efficiency, and trading costs.

2. Market Indices

Evaluate the performance of risk premia factors in different market environments.

Four market indices used:

Table 1

Asset Class	Index	Data Source	Data Start Date
Equity	MSCI ACWI	Bloomberg	Jan-1990
Sovereign Debt	Barclays Global Treasury	Barclays	Jan-1990
High Yield Credit	Barclays Global High Yield	Barclays	Jan-1990
Inflation Protected Debt	Barclays World Government Inflation-Linked	Barclays	Jan-1997

3. Alternative Risk Premia Factors

50+ alternative risk premia factors from Versor's risk premia factor library of investible factors.

Table 2

Factor Category	Factor Library	Investible Universe
Stock Selection	By factor class: value, momentum, quality By region: US, Europe, Japan, UK, Canada and Australia	6000+ stocks in US, Canada, UK, Europe, Japan, and Australia
Systematic Macro	By factor class: carry, value, momentum By asset class: commodities, equities, fixed income and currencies	70+ Exchange Traded Futures: Commodities, Equities, Fixed Income, Currencies
Trend Following	By asset class: commodities, equities, fixed income and currencies By signal duration: short-, medium-, and long-term	70+ Exchange Traded Futures: Commodities, Equities, Fixed Income, Currencies
Equity Events	By region: US, non-US Event type: mergers, equity events	Announced mergers and equity events in US, Canada, UK, and Europe

4. Analysis Methodology

Using statistical techniques, we have systematically analyzed the performance of the various risk premia factors during different market environments.

Using equity markets as an example we divide the entire data into 5 states of the world (bins) based on equity market performance.

- Less than 10th percentile (worst performing),
- 10-30th percentile, 30-70th percentile, 70-90th percentile, and
- Greater than 90th percentile (best performing)

We systematically analyze performance of each risk premia factor during the 5 states, with particular focus on performance during the 10% worst performing periods.

- Statistics presented are estimated using quarterly data.
- Only those quarters are considered for which the data is available for both Versor factor and market index.
- Data for each quarter is categorized into 5 bins, based on the mean and the standard deviation of market index.

Similarly, we create scenarios for each of the other market indices and analyze risk premia performance.

This analysis is repeated for each of the 50+ alternative risk premia factors.

Important Information Regarding Versor Investment's Hypothetical Performance Information

The following results setting forth Versor Investment's "implementation" of different strategies are simulated. These results have been generated by applying Versor Investment's systems to historical pricing data for the publicly-traded instruments (including securities and futures) in which the Versor Investment's accounts will trade. Because these results are simulated, they are subject to all of the material inherent limitations of back-tested data. Due to these limitations (among others), the U.S. Commodity Futures Trading Commission requires that the following disclaimer accompany such information:

THESE RESULTS ARE BASED ON SIMULATED OR HYPOTHETICAL PERFORMANCE RESULTS THAT HAVE CERTAIN INHERENT LIMITATIONS. UNLIKE THE RESULTS SHOWN IN AN ACTUAL PERFORMANCE RECORD, THESE RESULTS DO NOT REPRESENT ACTUAL TRADING. ALSO, BECAUSE THESE TRADES HAVE NOT ACTUALLY BEEN EXECUTED, THESE RESULTS MAY HAVE UNDER-OR OVER-COMPENSATED FOR THE IMPACT, IF ANY, OF CERTAIN MARKET FACTORS, SUCH AS LACK OF LIQUIDITY. SIMULATED OR HYPOTHETICAL TRADING PROGRAMS IN GENERAL ARE ALSO SUBJECT TO THE FACT THAT THEY ARE DESIGNED WITH THE BENEFIT OF HINDSIGHT. SPECIFICALLY, VERSOR CONTINUOUSLY SEEKS TO ENHANCE ITS METHODOLOGIES AND THEREFORE A SURVIVORSHIP BIAS IS PRESENT AS THESE HYPOTHETICAL PERFORMANCE RESULTS ARE CONTINUOUSLY UPDATED TO APPLY WHAT VERSOR BELIEVES TO BE THE MOST OPTIMAL APPROACH AT THAT POINT IN TIME. NO REPRESENTATION IS BEING MADE THAT ANY ACCOUNT WILL OR IS LIKELY TO ACHIEVE PROFITS OR LOSSES SIMILAR TO THESE BEING SHOWN.

An investment with Versor Investment's is speculative and involves substantial risks; investors may lose their entire investment. No one should rely on any simulated performance in determining whether to invest with Versor Investment's.

5. Factor Performance Summary

Table 3: Equity

Negative equity returns (Bottom 10%)	Positive equity returns (Top 10%)
Outperform: • Stock: value, quality, momentum • Macro: value • Trend following	Outperform: • Stock: value • Macro: carry • Trend Following • Equity Event
Underperform: • Macro: carry, momentum • Equity Event	Underperform: • Stock: quality, momentum • Macro: momentum

Table 4: High Yield

Negative credit returns (Bottom 10%)	Positive credit returns (Top 10%)
Outperform: • Stock: value, quality, momentum • Macro: value • Trend following	Outperform: • Stock: value • Macro: carry, value • Equity Event
Underperform: • Macro: carry, momentum • Equity Event	Underperform: • Stock: quality, momentum • Macro: momentum

Table 5: Sovereign Debt

Negative treasury returns (Bottom 10%)	Positive treasury returns (Top 10%)
Outperform: • Stock: value, quality • Macro: value • Equity Event	Outperform: • Stock: value, equity • Macro: value, carry, momentum • Trend Following • Equity Event
Underperform: • Macro: momentum • Trend Following	Underperform:

Table 6: TIPS

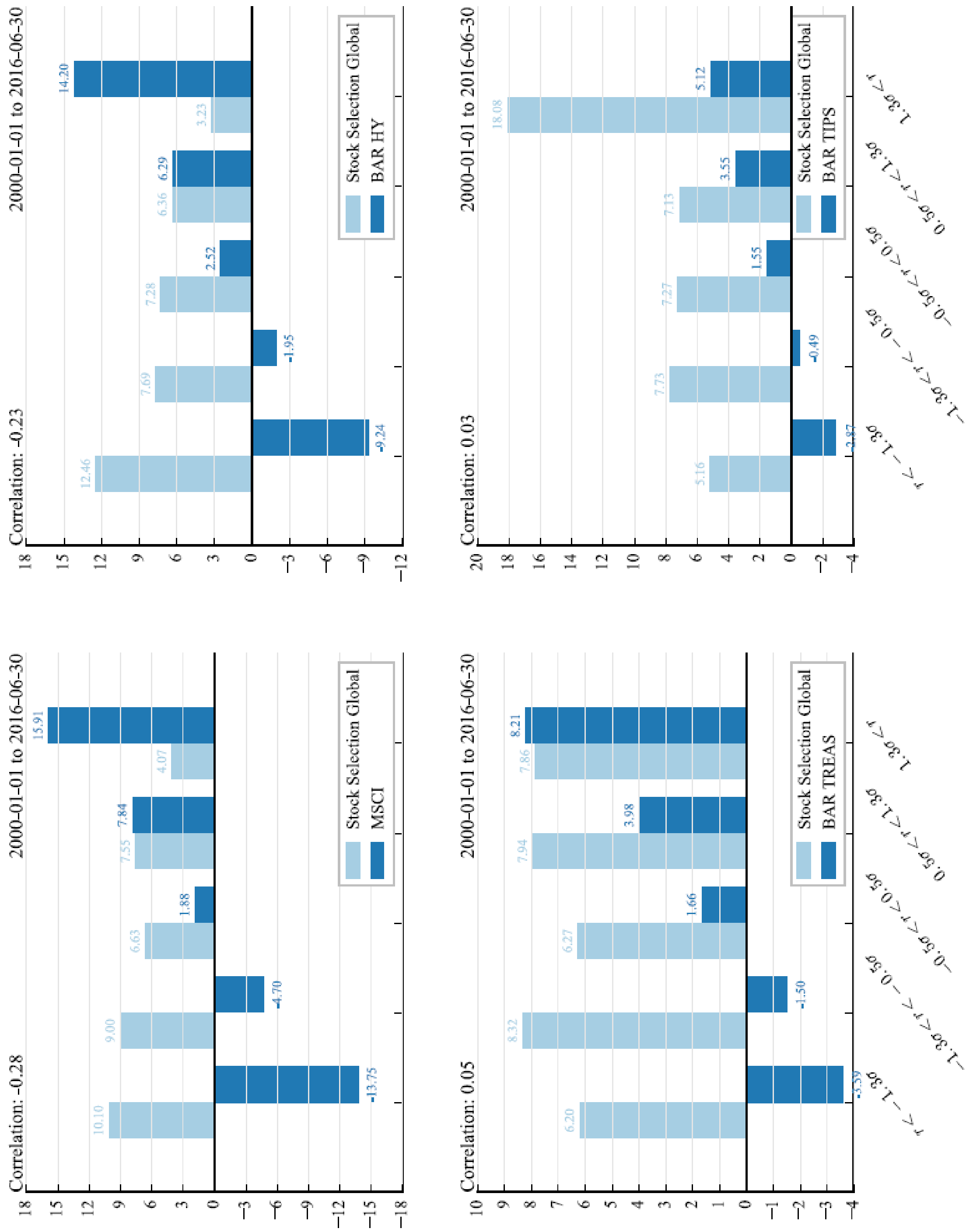
Negative TIPS returns (Bottom 10%)	Positive TIPS returns (Top 10%)
Outperform: • Stock: value, quality • Macro: value • Equity Event	Outperform: • Stock: value, equity • Macro: value, carry, momentum • Trend Following • Equity Event
Underperform: • Macro: carry momentum • Trend Following	Underperform:

6. Factor: Stock Selection Global

Table 7

Brief Description	Performance Ratings (1-10)
Stock selection invests in individual equities to construct a global market-neutral long-short portfolio. The individual positions are systematically chosen based on a large number of the characteristics for each stock. The characteristics can be grouped into theme: Value, Earnings Quality, Profitability, Momentum, and Analyst Sentiment. The portfolio minimizes net exposers to the overall market, countries, and sectors in order to focus on individual stocks.	Overall: 10 Negative Returns — Equity: 10; Credit: 10; Treasury: 10; TIPS: 10 Others — Scalability: 9; Cash Efficiency: 8; Trading Costs: 8
Economic Rationale	**Correlations**
The systematic process employs core investment themes that also guide many discretionary investment processes. The strategy employs several signals in each theme in order to reduce the effects of forecasting errors from any one signal. The strategy employs signals from 5 theme with relatively low correlation in order to increase diversification.	Stock: 1.00; Macro: 0.05; Trend: 0.11; Events: 0.05

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.



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7. Factor: Trend Following

Table 8

Brief Description

Trend following trades liquid futures and forward contracts in all of the major asset classes: commodities, fixed income, equities, and currencies. For individual contracts, the strategy holds long positions when the contract has fallen in value. The strategies uses a range of lookback periods to measure changes in value. The strategy balances risk across contracts and asset classes. At a point in time, the strategy may be long or short many different contracts in an asset class. Over extended periods, however, the strategy has long and short exposures to most asset classes.

Performance Ratings (1-10)

Overall	Negative Returns			
	Equity	Credit	Treasury	TIPS
7	10	10	8	6

Others

Scalability	Cash Efficiency	Trading Costs
10	10	9

Economic Rationale

Future experience periods of persistent price increases or declines. The trend following strategy tries to identify these trends as they evolve and establish positions to take advantage of them. There is extensive academic evidence that trend strategies in futures markets have generated attractive returns.

Correlations

Stock	Macro	Trend	Events
0.11	0.32	1.0	-0.06

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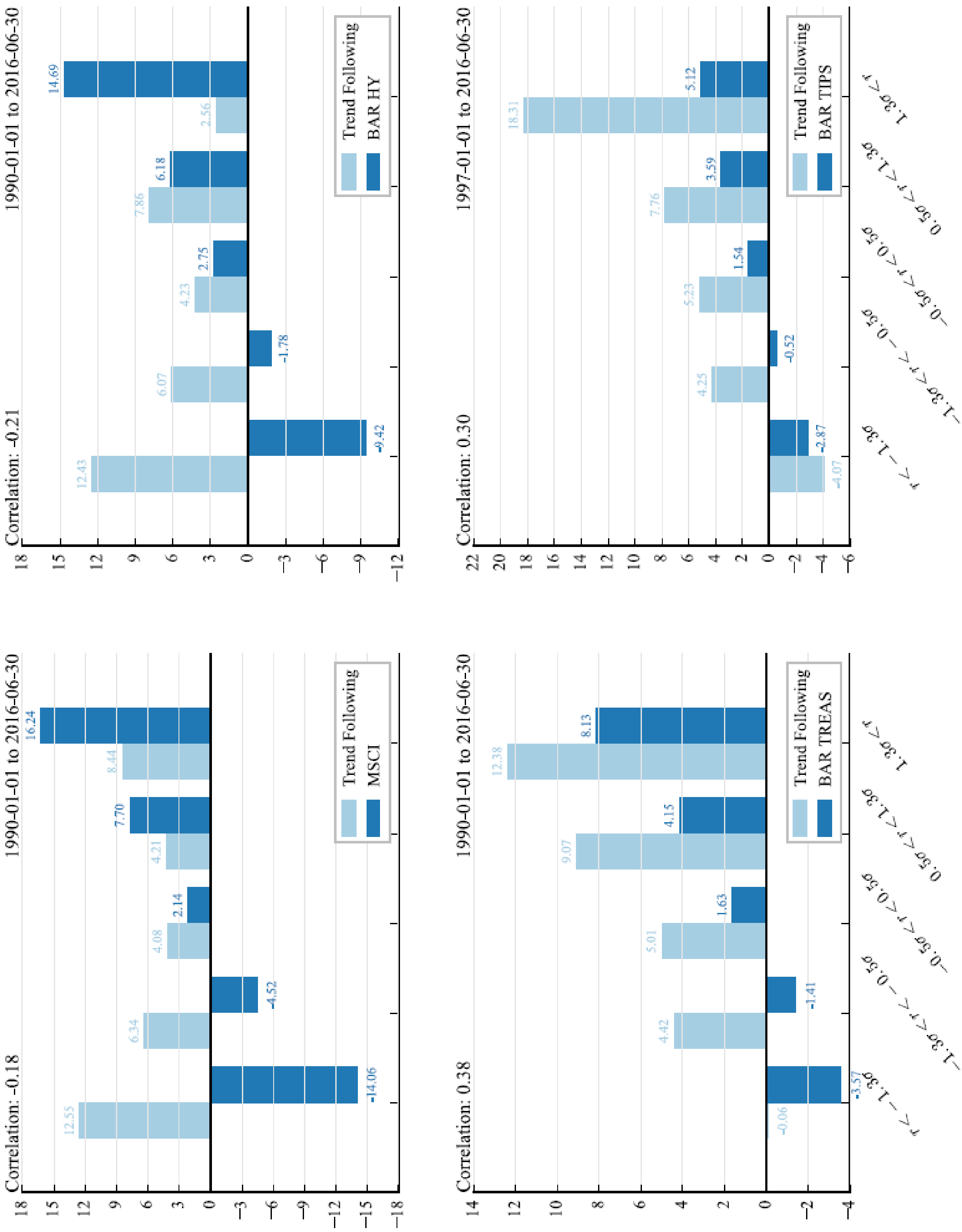

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8. Factor: Macro Global

Table 9

Brief Description	Performance Ratings (1-10)				
	Overall	Negative Returns			
		Equity	Credit	Treasury	TIPS
The Systematic Macro strategy trades futures and forwards in the major asset classes: commodities, fixed income, equities, and currencies. In each asset class, the strategy holds long and short positions to minimize net exposers to the asset class. Long and short positions are chosen based on 3 major themes: Value, Momentum, and Carry.	8	9	7	10	6
	Others				
	Scalability	Cash Efficiency	Trading Costs		
	10	10	9		
Economic Rationale	**Correlations**				
	Stock	Macro	Trend	Events	
The strategy collects a diverse set of trades from 3 themes with relatively low correlation. There is extensive academic evidence that trades based on the systematic macro theme have generated attractive returns.	0.05	1.0	0.32	-0.02	

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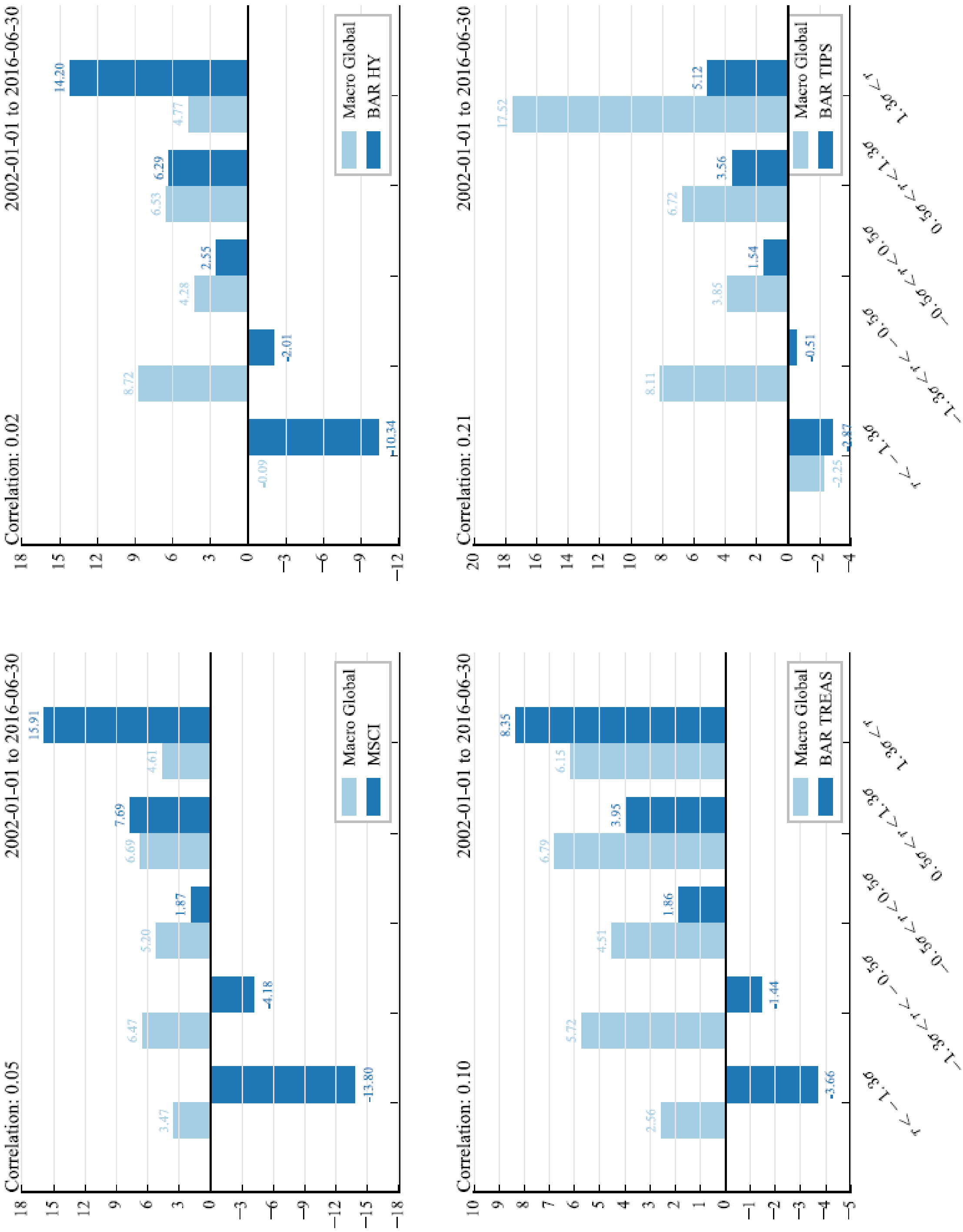

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9. Factor: Equity Events

Table 10

Brief Description	Performance Ratings (1-10)				
	Overall	Negative Returns			
		Equity	Credit	Treasury	TIPS
The Equity Events trades stocks around announced corporate actions like mergers and spinoffs. For mergers, the strategy buy shares in the takeover target and shorts and appropriate number of shares in the acquiring firm. The hedge ratio is chosen so there is no market risk if the merger succeeds.	7	7	6	10	10
	Others				
	Scalability	Cash Efficiency	Trading Costs		
	5	8	9		
Economic Rationale	Correlations				
	Stock	Macro	Trend	Events	
Corporate actions often trigger selling by the previous owners of the shares because the original reason for holdings the shares has been disrupted by the corporate action. At the same time, equity event trades try to purchase these stocks at a slight discount relative to their ultimate value. There is extensive academic evidence that equity event trades have generated attractive returns.	0.05	-0.02	-0.06	1.0	

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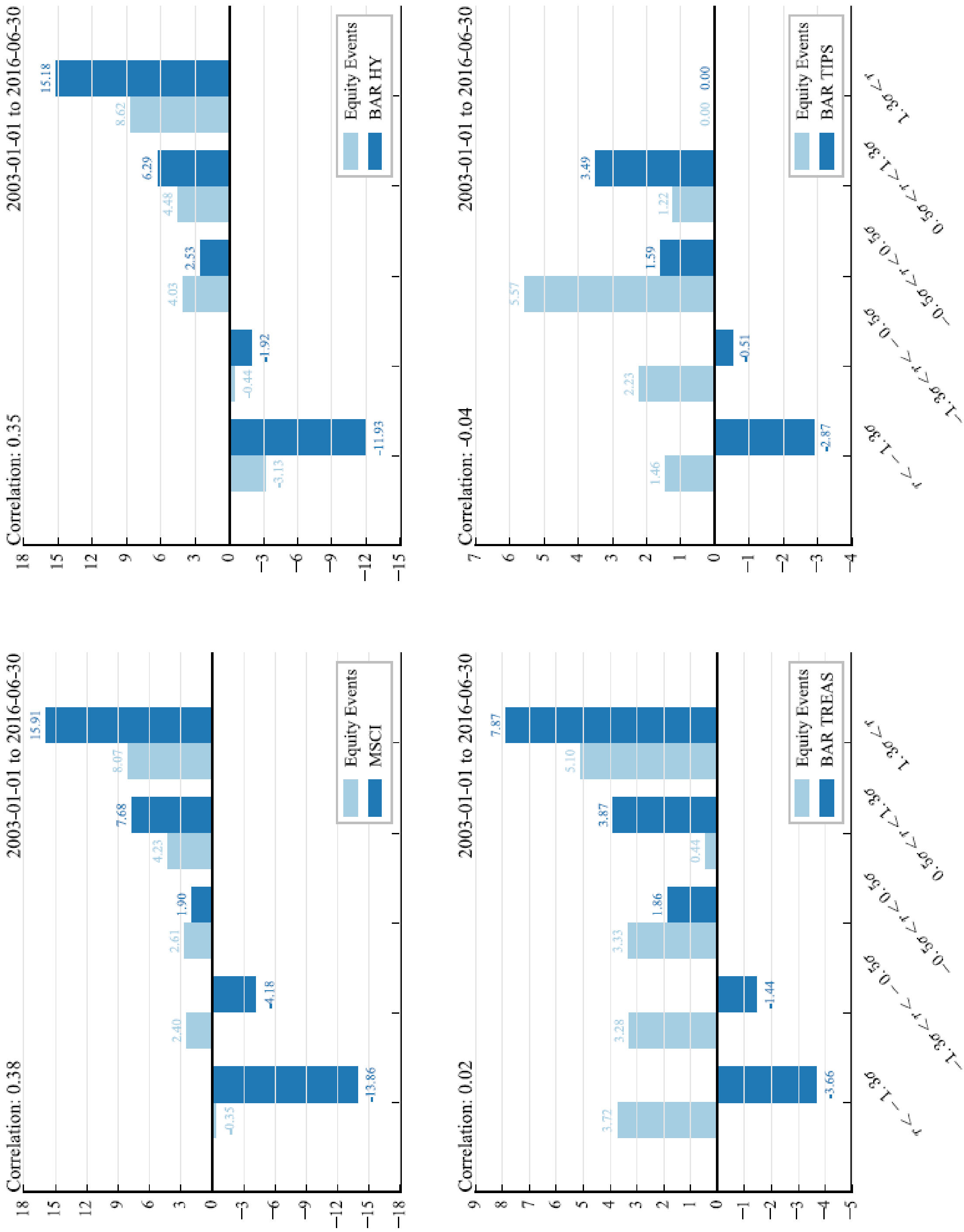

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10. Proposed Risk Premia Portfolio

Factor Category	Factors Included	Target Risk [1] (Average)	Tactical Factor Allocation models
Stock Selection	• factor class: value, momentum, quality region: US, Europe, Japan, UK, Canada and Australia	30%	• forecasted returns to value, momentum, quality • var-covariance matrix of factor returns
Systematic Macro	• factor class: carry, value, momentum • asset class: commodities, equities, fixed income and currencies	30%	• forecasted returns to carry, value, momentum
Trend Following	• asset class: commodities, equities, fixed income and currencies • signal duration: short-, medium- and long-term	30%	• strength of the trend signals • market volatility and correlations (signal to noise ratio)
Equity Events	• region: US, non-US • event type: mergers, other equity events	10%	• merger environment – deal risk, deal spreads, volatility of merger deal spreads

Performance Notes

The returns for the Versor Investment's implementation are based on simulated performance of systematic investment rules. They are net of simulated transaction, financing and stock borrowing costs, and 0.75% annual management fees and assume the reinvestment of dividends and other income. The fee structure is for Founder Share class as outlined in "Key Terms". Certain investors may have higher management and performance fees, depending on the applicable share class. Please see important disclosures at the end of the presentation.

Versor Alternative Risk Premia factor allocates to the Stock Selection - Global, Trend Following – Global, Equity Event – Global and Systematic Macro – Global factors.

The Trend Following – Global and Stock Selection - Global factor simulated returns start in 2000; the Systematic Macro – Global simulated returns start in 2002; the Equity Event – Global factor returns simulated start in 2003.

Simulated returns for respective strategies are used until the start of live trading and live returns from that point forward. Live trading data for Stock Selection – Global starts on May 8th, 2014; for Trend Following – Global on December 19th, 2014; for Equity Event – Global on February 9th, 2015. Systematic Macro – Global strategy has not commenced live trading.

Versor is seeking to offer the Alternative Risk Premia Portfolio, which combines different factors, to its clients. Clients may also choose to invest in one of the standalone factors: Stock Selection, Equity Event, Systematic Macro and/or Trend-following. The allocations to each of the component risk premia is done based on the historical volatility of returns and correlations between the strategies, so as to target desired risk contribution from each of the components. The components are rebalanced quarterly and the total allocation is scaled up to achieve 8-10% volatility on every rebalance.

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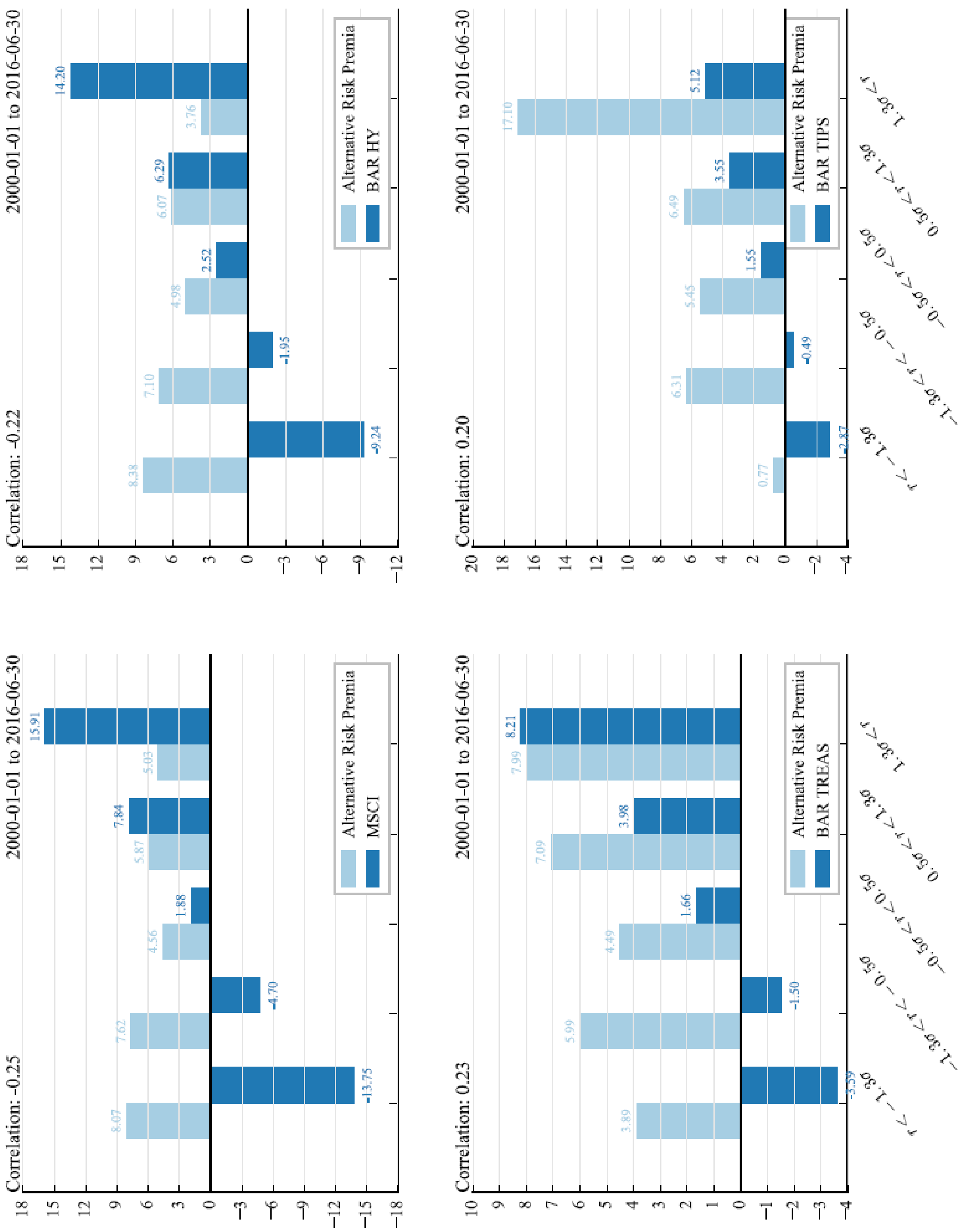
[1] Target risk contribution (average over time) with variation around target based on tactical factor allocation models. Overall Portfolio risk target is 8-10% annualized standard deviation.



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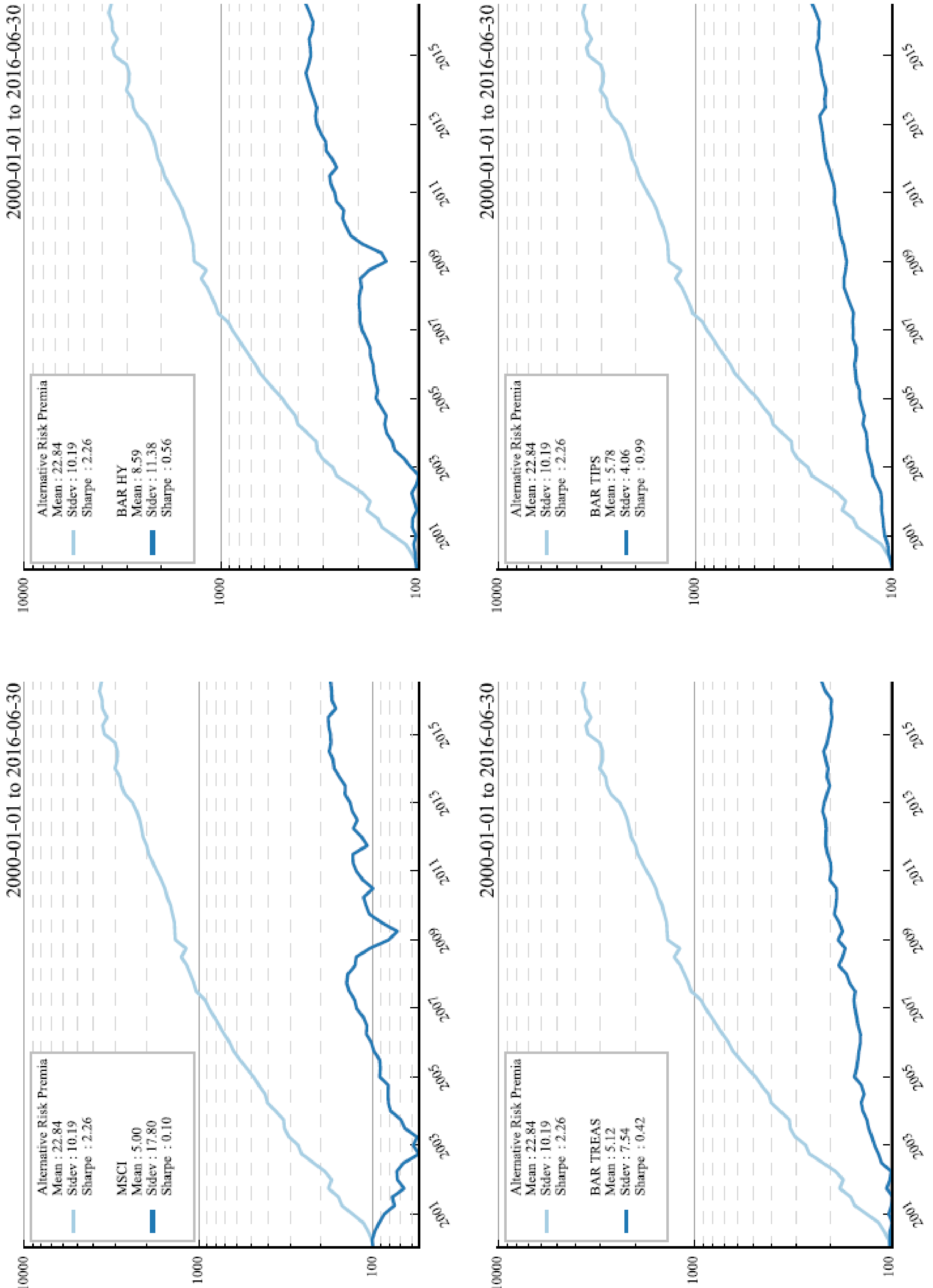

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11. Conclusion

Alternative risk premia are attractive portfolio components for institutional investors

- Superior risk-adjusted returns
- Uncorrelated with equities and bonds
- Scalable
- Outperform well-designed portfolio of hedge funds

Performance achieved historically through:

- balanced allocations to factors
- emphasis on factors that have historically performed well, even during difficult markets
- value added through ("bottom up") tactical factor shifts

Versor Investments has a differentiated product offering

- Pioneers in alternative risk premia investing
- Superior investment process
- Alignment of interest

Asset Allocation Analysis Disclosures

The information contained in this material is based on benchmark and/or generic data and should be used for illustrative, educational and reference purposes only, and should not be relied upon for any other purpose, including without limitation for making any investment or risk decisions. This does not constitute a recommendation to adopt any potential asset allocation. The investor and its risk and investment consultants and advisors should independently evaluate the information herein and make any decisions regarding risk and investment requirements based on whatever information and sources that such consultants and advisors deem appropriate.

Certain of the risk management techniques and concepts discussed herein are based on the prior performance of, and historical observations regarding, various indices and markets, which performance in the future may be materially different. Thus, there could be no assurance that the techniques and concepts discussed herein would be effective in the event such indices and markets perform differently than anticipated based on historical observations.

Alpha and tracking error assumptions reflect ARP's internal estimates. Expected return models apply statistical methods and a series of fixed assumptions to derive estimates of hypothetical average asset class performance. The appropriate statistical model and fixed assumptions is subjective and may vary. These models have limitations, as the assumptions may not be consensus views, or the model may not be updated to reflect current economic or market conditions. These models should not be relied upon to make predictions of actual future performance. ARP has no obligation to provide updates or changes to such data. There can be no assurance that these returns can be achieved. Actual returns are likely to vary. Past performance does not guarantee future results, which may vary.

Strategic long-term assumptions are subject to high levels of uncertainty regarding future economic and market factors that may affect future performance. They are hypothetical indications of a broad range of possible returns. The returns do not reflect the deduction of investment advisory fees, which will reduce returns.

References to indices, benchmarks or other measures of relative market performance over a specified period of time are provided for your information only and do not imply that the portfolio will achieve similar results. The index composition may not reflect the manner in which a portfolio is constructed. While an adviser seeks to design a portfolio which reflects appropriate risk and return features, portfolio characteristics may deviate from those of the benchmark.

The index returns are provided for purposes of comparison and include dividends and/or interest income and, unlike the returns presented for the various strategies, do not reflect fees or expenses. Unlike the various strategies presented which are actively managed and periodically may maintain cash positions, an index is unmanaged and fully invested. The comparison of the performance of the various strategies presented to these indices may be inappropriate because the various strategies are not as diversified as the indices, may be more or less volatile than the indices, and may include securities which are substantially different than the securities in the indices. Although information and analysis contained herein has been obtained from sources the Adviser believes to be reliable, its accuracy and completeness cannot be guaranteed.

Investors cannot invest directly in indices. The indices referenced herein have been selected because they are well known, easily recognized by investors, and reflect those indices that the adviser believes, in part based on industry practice, provide a suitable benchmark against which to evaluate the investment or broader market described herein. The exclusion of "failed" or closed hedge funds may mean that each index overstates the performance of hedge funds generally.

10. Alternative Risk Premia in CTA–Trend Following

Deepak Gurnani Ludger Hentschel

January 2016

Contents

Executive Summary

The recent coincidence of high volatility in returns among CTA hedge funds and the arrival of Trend Following alternative risk premia products has provided an excellent early test for these alternative risk premia products. Although still relatively brief, the actual experience has borne out the main predictions of alternative risk premia providers: due to the absence of performance fees, the products can outperform hedge funds during periods of high strategy returns; with excellent risk management, the products can outperform the strategy on average. Hence, when implemented carefully, the products can provide the gross strategy returns at lower fees than hedge funds, leading to net-of-fee outperformance.

When selecting alternative risk premia products, choosing a provider with significant hedge fund experience but without conflicting hedge fund products may be the best way to obtain the strategy insight and risk management essential to successful alternative risk premia products.

Due to the strategy insights and risk management of the Versor team, the Versor Trend Following factor has delivered CTA strategy returns and outperformed the benchmarks at material fee savings during a period with large positive and negative CTA strategy returns.

1. Introduction

Using the example of Trend Following, we show that the early experience with alternative risk premia products has been positive. Since the CTA strategy has experienced large positive and negative returns recently, the CTA example is a good test of the claim that alternative risk premia are an attractive alternative way to capture hedge fund strategy returns, despite the relatively short live history of alternative risk premia products. Our trend following risk premia product has clearly matched the CTA strategy returns and outperformed the benchmarks.

For many years, we have researched the existence of alternative risk premia factor exposures in hedge fund portfolios. For example, see Gurnani and Hentschel (2010).[1] Recently, several firms – ours among them – have launched alternative risk premia products that allow investors to benefit from these insights directly.

We define alternative risk premia products as systematic implementations of trading strategies offered at low, generally fixed fees. There currently are several competing alternative risk premia products with more to enter the market in the near future. When comparing these products, we show that hedge fund experience, risk management in particular, is an important ingredient in successful alternative risk premia products. Yet, alternative risk premia products offered by hedge funds create an internal conflict between the high-fee hedge fund and the low-fee alternative risk premia products. A natural way to avoid this conflict is to choose alternative risk premia products from asset managers without competing hedge fund products but with hedge fund experience.

2. Trend Following and CTA Returns

We define the Trend Following factor, at its core, as a collection of trend-following signals applied to a large set of diverse, liquid futures contracts, using careful risk management in order to ensure diversification across contracts, asset classes, and signals.

The Versor Trend Following process invests in more than 60 liquid futures contracts across the four major asset classes: commodities, equities, fixed income, and exchange rates. The trades for each contract are driven by a collection of 7 trend-following signals. These signals indicate long positions when recent prices are higher than previous prices and short positions when recent prices are lower than previous prices.[2] The signals consider prices at different points in time with comparison periods ranging from 1 month to 1 year. In addition, the signals use different measures of price increases, including direct comparisons of adjusted prices (time series momentum) and comparisons of average prices (moving average cross-overs).

The Versor Trend Following process sizes these long and short positions with a collection of risk management techniques that consider the volatility of signals, contracts, and asset classes, as well as their correlations. The goal is to avoid portfolio concentration on any one signal or contract.

Recent Performance

We launched the Versor Trend Following factor on December 19, 2014. Table 1 shows performance statistics from inception until Dec 31, 2015, a period slightly more than a year. The table also includes information for the HFRX Systematic Diversified CTA index and the Newedge Trend Indicator. The HFRX index measures returns for CTA hedge funds net of fees and transactions costs. In contrast, the Newedge Trend Indicator is a frequently cited simulated systematic implementation of a trend

[1] Fung and Hsieh (2001), Moskowitz, Ooi, and Pedersen (2012), and Hurst, Ooi, and Pedersen (2013) describe similar ideas for CTA-trend following strategies.

[2] Due to the expiration of individual futures contracts, we adjust futures prices before comparing them across expiration dates.

Table 1: Realized Performance from 12/19/2 014 to 12/31/2015

	Versor Trend	HFRX CTA	Newedge
Panel A: Summary Statistics			
Return	4.38	0.44	-6.34
Risk	9.99	8.74	15.59
Sharpe Ratio	0.44	0.05	-0.41
Panel B: Relative Performance			
Versor Alpha (% pa)		4.10	7.63
Versor Beta vs index		0.95	0.51
Panel C: Correlation			
Versor correlation vs index		0.79	0.84

The table shows summary statistics based on realized daily returns for the Versor Trend Following factor from December 19, 2014 to December 31, 2015. For comparison, the table shows summary statistics for two separate benchmarks: the HFRX Systematic Diversified CTA index and the Newedge Trend Indicator.

Panel A shows realized annualized returns, annualized risk, and annualized Sharpe ratios. The Versor and HFRX returns are net of fees and transaction costs.

Panel B shows the annualized realized alpha of the Versor Trend Following factor relative to the beta-adjusted benchmark returns. The panel also shows the betas.

Panel C shows the realized correlation of the Versor Trend Following factor with the 2 benchmark series, based on daily returns.

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

Reported actual returns are unaudited preliminary estimates, subject to revision and net of 0.75% per annum management fees. Returns for the factor are estimated by applying a notional capital allocation (and applicable expenses) to the P/L associated with the portion of the Versor Alternative Risk Premia Master Fund Ltd allocated to the Trend Following factor. Performance results reflect the reinvestment of income. Please note that the returns could be materially different from those stated above in case the Trend Following factor was managed in a dedicated standalone fund. The fee structure is for Day 1 Investor Share Class as outlined in "Key Terms" of the fund documents. Certain investors may have higher management and performance fees depending on applicable share class. Please see important disclosures at the end.

following strategy. Returns on the Newedge Trend Indicator do not account for fees.

Overall, the live Versor Trend Following factor has generated strong returns and outpaced the indexes over this period.

The live Versor Trend Following factor returns have realized a beta very close to 1 with respect to the HFRX index. This is the result of a realized correlation of 0.79 between the two return series and a slightly higher risk for the Versor factor. These realized values for correlation and risk are very close to the long-term values for the simulated backtest.

Relative to the beta-adjusted benchmark returns, the Versor Trend Following factor has generated annualized alpha of 4.10% and 7.63% with respect to HFRX index and Newedge Trend Indicator respectively.

To approximate the higher risk level of a typical CTA hedge fund instead of the Versor Trend Following factor, we also show pro forma results for a levered version of the factor (Versor Trend 2x). The portfolio is levered by a factor of 2. As table 2 shows, the returns and risk from the levered factor were approximately twice those shown in table 1. This leaves Sharpe ratios and correlations nearly unchanged. As a consequence of the additional leverage, however, the betas with respect to the reference returns double, producing a beta close to 1 with respect to the Newedge Trend Indicator. Due

Table 2: High-Vol Pro Forma Performance from 12/19/2014 to 12/31/2015

	Versor Trend 2x	HFRX CTA	Newedge
Panel A: Summary			
Return	8.61	0.44	-6.34
Risk	19.98	8.74	15.59
Sharpe Ratio	0.43	0.05	-0.41
Panel B: Relative			
Versor Alpha (% pa)		8.76	15.82
Versor Beta vs index		1.90	1.03
Panel C: Correlation			
Versor correlation vs index		0.79	0.84

The table shows summary statistics based on levered daily returns for the Versor Trend 2x factor from December 19, 2014 to December 31, 2015. For comparison, the table shows summary statistics for two separate benchmarks: the HFRX Systematic Diversified CTA index and the Newedge Trend Indicator.

Panel A shows annualized returns, annualized risk, and annualized Sharpe ratios. The Versor and HFRX returns are net of fees and transaction costs.

Panel B shows the annualized realized alpha of the Versor Trend 2x factor relative to the beta-adjusted benchmark returns. The panel also shows the betas.

Panel C shows the realized correlation of the Versor Trend 2x factor with the 2 benchmark series, based on daily returns.

Certain hedge fund managers run the CTA strategy at 16-20% annualized volatility (approximately twice the volatility of the Versor Trend Following factor). Versor has generated pro forma results for running the Trend Following factor at 16-20% annualized volatility. There are no assurances however that the actual performance from running the Trend Following factor at higher volatility levels will be in line with the pro forma results shown above. In fact, the actual returns could be much lower than those shown above. Versor does not manage any capital using the Versor Trend 2x factor. Please see important disclosures at the end of the presentation.

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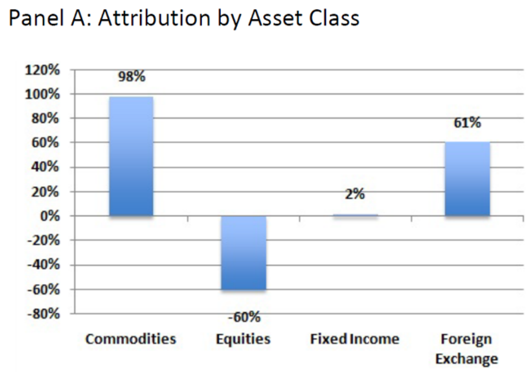
The pro forma results for the Versor Trend 2x Strategy are estimated from the live performance of the Trend Following factor, using the process described below. The target volatility of the Versor Trend 2x Strategy is 16- 20% annualized (twice that of the Trend Following factor). Each month the excess returns for the Trend Following factor are calculated by subtracting the 1-month US T-Bill return from the monthly total return. The excess strategy return for the month is then multiplied by 2 (the ratio of the volatilities of the two strategies) to arrive at the excess return for the Versor Trend 2x factor. The pro forma returns for the Versor Trend 2x factor are computed by adding the 1-month US T-Bill return to the excess returns for the month. This process is repeated for each month and has the net effect of increasing the profits in profitable months for the Trend Following factor and conversely increasing the losses during periods where Trend Following factor suffers losses. Pro forma returns are net of 1.50% per annum in management fees and reflect the reinvestment of income.

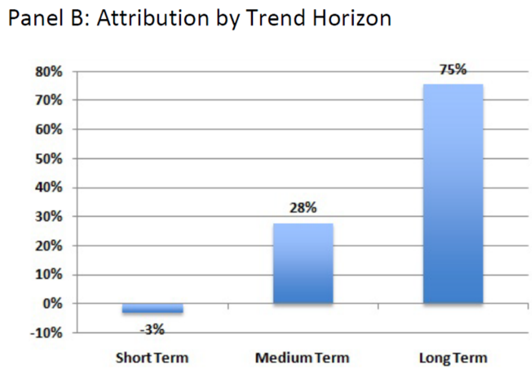
to the higher returns, the annualized alphas are higher, 8.76% and 15.82% with respect to HFRX index and Newedge Trend Indicator respectively for the levered version of the Trend Following factor.

Figure 1 shows performance attribution for the Versor Trend Following factor from January 2015 to December 2015. Panel A shows performance attribution by four major asset classes. Commodities positions contributed 98% of the factor return in 2015, benefiting from fall in energy, base metal and precious metals during the year. Exchange rates also contributed positively, benefiting from strength of the dollar versus both developed and emerging currencies. Equities detracted from performance and contributed negatively during 2015.

Panel B shows performance attribution by trend horizon. Interestingly, long-term signals (six months to one year) contributed 75% of the factor return in 2015. Short-term signal contributions were modestly negative due to losses in Q2 and Q4 on sharp market reversals.

Figure 1: Performance Attribution from 1/1/2015 to 12/31/2015





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The figure shows performance attribution for the Versor Trend Following factor from January 2015 to December 2015. Panel A shows performance attribution by four major asset classes: commodities, equities, fixed income, and exchange rates. Panel B shows performance attribution by trend horizon: short-term, medium-term and long-term. Returns used for performance attribution are gross of transaction cost, expenses and fees.

As mentioned earlier, the Versor Trend Following process uses risk management techniques to avoid portfolio concentration on any one signal or asset class or contract.

Simulated Historical Performance

Our longer-term simulated backtests confirm that our trend following process clearly captures the main characteristics of the hedge fund strategy returns measured by CTA hedge fund indexes. For the longer history, we use the Barclay CTA index before the HFRX daily returns became available. Both indexes are widely followed averages of CTA hedge fund returns but are not directly investable. Importantly, the index returns are net of the hedge fund fees charged by the constituent funds. Unfortunately, we do not know exactly what those fees were.

Table 3 shows summary statistics for the simulated historical returns to our systematic implementation of the Trend Following factor and compares these returns to a benchmark return series. The benchmark returns start with the Barclay CTA index and switch to the HFRX Systematic Diversified CTA index in January 2009, when daily HFRX returns become available. In the backtest, the Versor Trend Following factor returned 13.4% per annum net of estimated transaction costs and 75bps in fees, compared with realized returns of 4.9% for the benchmark net of transaction costs and fees. The strategy achieved this return at a risk level of 9.7%, compared to 8.4% for the benchmark. In order to generate the strategy gross returns, an alternative risk premia factor should operate at slightly higher risk than a strategy index net of performance fees.

Panel B in Table 3 illustrates the relation between the Versor Trend Following returns and the benchmark CTA index returns. The Versor Trend Following has a beta of 0.79 with respect to the benchmark index. Net of the beta-adjusted benchmark CTA index return, the Versor Trend Following have generated an annualized alpha of 9.5%. Part of this alpha clearly stems from the fee advantage of the alternative risk premia product relative to hedge funds. At a list price of 2/20, hedge funds with a gross return of 8.25%, would have charged 3.25% in fees and returned 5% net of fees. This fee represents 43% of the average spread between the simulated Versor Trend Following returns and the benchmark CTA index returns.

Table 3: Simulated Performance

	Versor CTA	Benchmark
Panel A: Summary Statistics		
Arithmetic Mean	13.40	4.90
Geometric Mean	13.70	4.60
Median	14.30	2.40
Risk	9.70	8.40
Sharpe Ratio	1.06	0.17
Max Drawdown	11.30	16.70
Panel B: Relative Performance		
Versor Alpha (% pa)		9.50
Versor Beta vs index		0.79

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

The table shows summary statistics based on simulated monthly returns for the Versor Trend Following factor from January 1990 to 18th December 2014. For comparison, the table shows summary statistics for a benchmark that consists of the Barclay CTA index from January 1990 to December 2008 and the HFRX Systematic Diversified CTA index from January 2009 to December 2014. All statistics except for drawdowns and betas are annualized. Returns for the simulated Versor Trend Following factor are net of estimated transaction costs and 75bps in annual management fees.

Hypothetical performance results have many inherent limitations, some of which are described below. No representation is being made that any account will or is likely to achieve profits or losses similar to those shown. In fact, there are frequently sharp differences between hypothetical performance results and the actual results subsequently achieved by any particular trading program.

One of the limitations of hypothetical performance results is that they are generally prepared with the benefit of hindsight. In addition, hypothetical trading does not involve financial risk, and no hypothetical trading record can completely account for the impact of financial risk in actual trading. For example, the ability to withstand losses or adhere to a particular trading program in spite of trading losses are material points which can also adversely affect actual trading results. There are numerous other factors related to the markets in general or to the implementation of any specific trading program which cannot be fully accounted for in the preparation of hypothetical performance results and all of which can adversely affect trading results.

Table 4 shows correlations between the Versor Trend Following factor returns and several common benchmarks, starting in January 2005 when all 3 of the benchmark returns become available. As the table shows, the correlation between the Versor Trend Following factor returns and any of the benchmarks is very similar to the correlations between the benchmarks. In that sense, the Versor Trend Following factor captures the CTA strategy returns. In part because there is no consensus strategy index, we

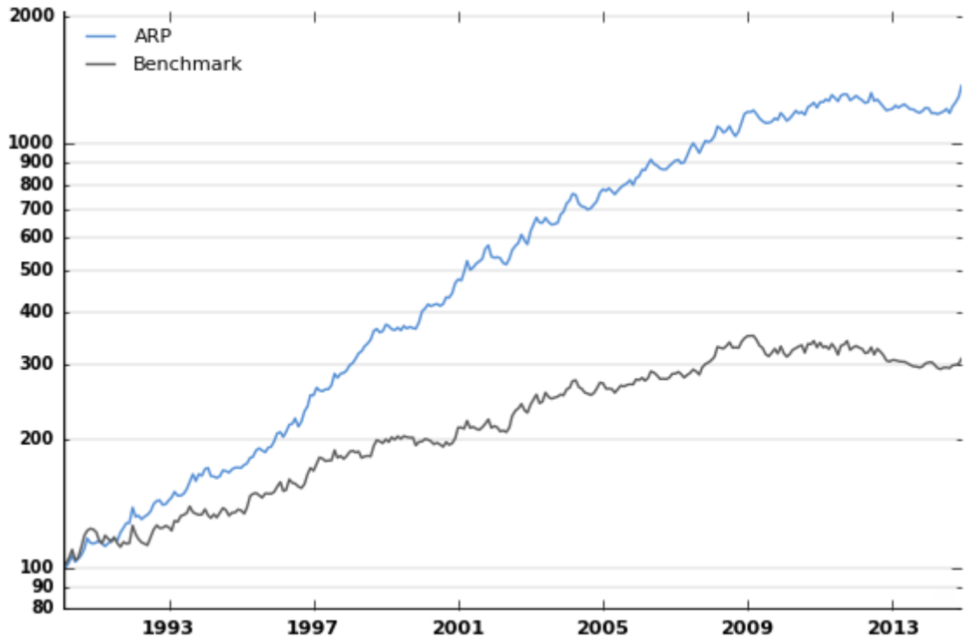
Table 4: Return Correlations

	Versor CTA	Barclay	HFRX	Newedge
Versor CTA	1.00	0.79	0.82	0.79
Barclay	0.79	1.00	0.83	0.73
HRFX	0.82	0.83	1.00	0.69
Newedge	0.79	0.73	0.69	1.00

Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

The table shows the correlation matrix for the monthly returns of the simulated the Versor Trend Following factor, the Barclay CTA index, the HFRX Systematic Diversified CTA index, and the Newedge Trend Indicator. The returns cover the period from January 2005 to December 2014, when all four series are available.

Figure 2: Simulated Performance



Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

The figure shows cumulative performance for the simulated Versor Trend Following factor and a benchmark. The benchmark consists of the Barclay CTA index from January 1990 to December 2008 and the HFRX Systematic Diversified CTA index from January 2009 to December 2014. The latter index is not available for earlier periods. Returns for the simulated Versor Trend Following factor are net of estimated transaction costs and 75bps in annual management fees.

Hypothetical performance results have many inherent limitations, some of which are described below. No representation is being made that any account will or is likely to achieve profits or losses similar to those shown. In fact, there are frequently sharp differences between hypothetical performance results and the actual results subsequently achieved by any particular trading program.

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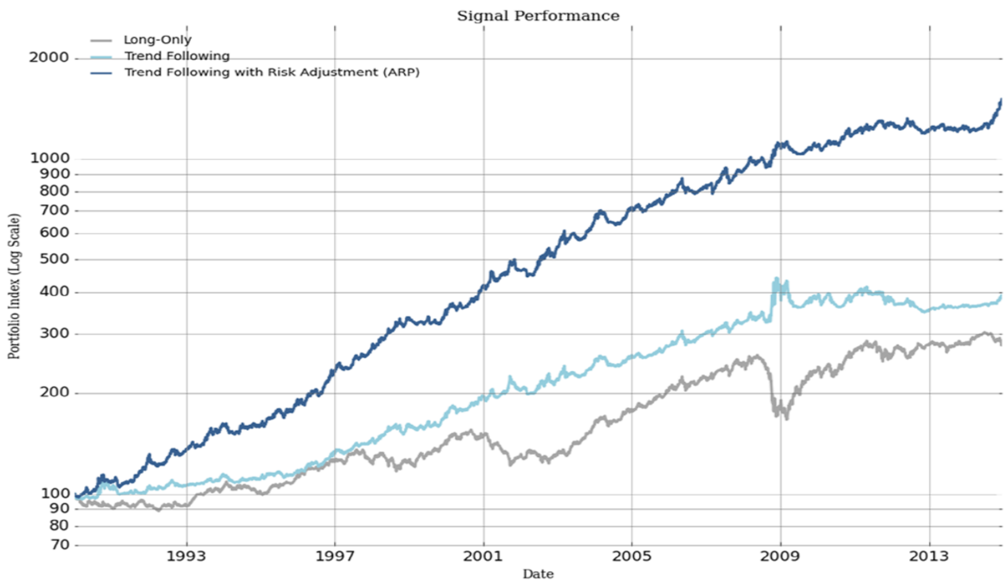
make no explicit attempt to maximize correlation or minimize tracking error with a benchmark index. The high correlation presumably is a result of capturing the basic CTA trading style with our trend-following signals and risk management techniques.

Figure 2 compares simulated cumulative returns for the Versor Trend Following factor and the benchmark index. The graph illustrates the outperformance of the systematic implementation in the backtest. To simplify the graphical comparison, we levered our strategy returns to have the same realized risk as the index returns.

Figure 3: The Value of Risk Management (Simulated Performance)



Past performance is not indicative of future results. Performance results reflect the reinvestment of income. Commodity interest trading involves substantial risk of loss.

The figure shows cumulative performance for simulated investment strategies in 71 liquid futures contracts. The contracts are rolled systematically, prior to expiration. The grey line is based on long-only investments with equal weights to sectors, equal weights to subsectors within sectors, and equal weights to contracts within subsectors. The light-blue line represents equal-weighted long or short investments in the same futures contracts based on a collection of trend-following signals. The dark-blue line represents risk-managed positions in the same futures contracts, based on the same trend-following signals. For comparison, all 3 return series have been levered up or down to a common risk level of 8%. All of the returns are gross of transaction costs and fees.

Hypothetical performance results have many inherent limitations, some of which are described below. No representation is being made that any account will or is likely to achieve profits or losses similar to those shown. In fact, there are frequently sharp differences between hypothetical performance results and the actual results subsequently achieved by any particular trading program.

One of the limitations of hypothetical performance results is that they are generally prepared with the benefit of hindsight. In addition, hypothetical trading does not involve financial risk, and no hypothetical trading record can completely account for the impact of financial risk in actual trading. For example, the ability to withstand losses or adhere to a particular trading program in spite of trading losses are material points which can also adversely affect actual trading results. There are numerous other factors related to the markets in general or to the implementation of any specific trading program which cannot be fully accounted for in the preparation of hypothetical performance results and all of which can adversely affect trading results.

Risk Management Adds Value

An important finding is that risk management is a crucial feature of a successful implementation of the Trend Following factor.

Figure 3 compares cumulative returns (in simulated backtests) from 3 different investment processes using the same investable universe of 71 liquid futures contracts. The grey line at the bottom shows the cumulative returns from investments in 71 futures contracts with equal dollar allocations to sectors, equal dollar allocations to subsectors within sectors, and finally equal dollar allocations to contracts within subsectors. For brevity, we refer to this as “equal dollar” allocations. These allocations ensure a basic level of diversification. All of the positions are long. The light blue line in the middle shows the cumulative returns from similar equal dollar investments in all 71 futures contracts based on the trend-following signals. Depending on the signal, however, these positions can be long or short. Finally, the dark blue line at the top of the chart shows the cumulative returns from risk-managed investments in all 71 futures contracts based on the same trend following signals. These trades have the same direction as those generating the light blue line, but they differ in size depending on the riskiness of the trades.

The effect of risk management is twofold. First, it reduces overall risk, allowing the portfolio to run with higher leverage in order to enhance returns. Second, risk management directly adds to returns. The combination of the two results in the dramatic performance increase shown in figure 3. To fully appreciate the magnitude of this improvement, it is important to recognize that the vertical axis uses a logarithmic scale to make the lines fit on the same chart.

3. A Complement to Hedge Funds

Given these results from the early live performance and the simulated backtest, many investors should ask themselves why they should pay the "2/20" list price for CTA hedge funds. The answer to this question depends crucially on whether the investor has found an exceptional CTA manager. Truly exceptional CTA managers deserve high fees. Yet, finding such managers and developing conviction that they will remain exceptional CTA managers is quite difficult.

For many investors, especially those with large CTA hedge fund allocations, it seems sensible to consider core strategy investments via low-cost alternative risk premia products. Almost by definition, a strategy allocation spread across several managers earns close to the strategy return – a return that can be earned at lower fees via alternative risk premia products.

These core allocations can be scaled up when the investor thinks the strategy will perform relatively well and scaled down when the investor thinks the strategy will perform relatively poorly. The liquidity of alternative risk premia products facilitates such tactical asset allocation. Moreover, the absence of performance fees means that alternative risk premia products are much cheaper than hedge funds during periods of high strategy returns. For example, when strategy returns are 22% before fees, a 2/20 fund leaves 16% return net of fees to the investor. At a 1% fixed fee, an alternative risk premia product would return 21% to the investor, an additional 5 percentage points!

Of course, core allocations to risk premia products can be complemented with allocations to exceptional managers when investors find them. Interestingly, however, there have been media stories that even the largest, brand-name CTA managers did not outperform the CTA indexes during the live performance period we analyze.

To allow investors to make these types of asset allocation decisions across strategies, Versor offers individual factors. For investors who prefer to invest in a fully diversified portfolio of factors with managed allocations, Versor offers a customized multi-factor portfolio.

4. Conclusion

Early experience with Trend Following alternative risk premia has confirmed the main findings from backtests: a well-managed alternative risk premia product can match or outperform CTA strategy returns. While the alternative risk premia match the main characteristics of the returns during positive and negative periods, the large fee savings during periods of strong strategy returns have produced higher average returns net of fees for investors.

In addition to the attractive fees, alternative risk premia offer enhanced liquidity and transparency.

When evaluating alternative risk premia products, it seems especially important to consider the risk management built into the product. As for hedge funds, such risk management should minimize incidental, undesired exposures other than those directly associated with the alternative risk premia. Generally speaking, it would be very difficult for the investor to implement such risk management outside of the product.

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Key Personnel

Deepak Gurnani

Founder and Managing Partner

Deepak Gurnani is the Founder and Managing Partner of Versor. Deepak is the former CIO of Investcorp's Hedge Fund Group and was one of the founding members in 1996. He was also a member of the Management Committee there. Deepak retired from Investcorp in March 2013. Prior to Investcorp, Deepak Gurnani spent six years with Citicorp.

Deepak has conducted extensive research over the last 20+ years into various aspects of hedge fund investing – analyzing risk and return of hedge funds, quantifying alternative risk premia inherent in hedge fund returns, using tactical asset allocation to enhance hedge fund portfolio returns, integrating hedge funds into institutional asset allocation and using separate accounts for risk management. Deepak holds a BTech from the Indian Institute of Technology, Delhi, and an MBA from the Indian Institute of Management, Ahmedabad.

Ludger Hentschel

Founding Partner, Investments

Ludger Hentschel joined Versor as a Founding Partner and is based in New York. Ludger has over 20 years of experience in quantitative research and investing. Prior to joining Versor, he was Managing Director of Analytical Research at MSCI for leading research in global multi-asset class risk models. This included alternative investments, asset allocation and macroeconomic risk and liquidity risk. Before joining MSCI, Ludger was Head of Quantitative Research and Asset Allocation for the Hedge Fund Group at Investcorp. Previously, he was the Director of Equity Research at New York Life Investment Management, was an Associate Professor of Finance at the University of Rochester and served as an Economist for the Board of Governors of the Federal Reserve System.

Ludger earned a BS in Mechanical Engineering from Yale and a PhD in Economics from Princeton. He has published articles in leading academic finance journals, served as an Associate Editor for the Journal of Financial Economics, and is a frequent speaker at financial seminars and conferences. He serves on the Board of Directors of the Lester B. Pearson College of the Pacific US Foundation.

Andrew Flynn

Founding Partner, Chief Operating Officer

Andrew Flynn has over 20 years of experience in hedge fund operational management and control. Prior to joining Versor, he spent 10 years at Tudor Investment Corporation and was Global Head of Operations, reporting to the COO. At Tudor, Andrew was extensively involved in the setup of Tudor's quantitative trading business, regulatory compliance, legal negotiations, enterprise risk management, and matters of industry best practice. He was co-chair of Tudor's Brokerage Committee, and a member of the Credit Committee and Global Risk Forum.

Previously, Andrew held operations management positions at Citco Fund Services, Maximus Capital, and Moore Capital. Andrew received a BBA in Finance from the IONA College Hagan School of Business in New Rochelle, New York.

DeWayne Louis

Founding Partner

DeWayne Louis joined Versor as a Founding Partner and is based in New York. DeWayne has 20 years of experience in quantitative investment strategies, investment banking, private equity and hedge funds. Prior to Versor, DeWayne joined Investcorp's Hedge Fund Group at the inception of the North America and Europe branches. He remained there for nearly a decade. Prior to Investcorp, DeWayne was an Associate Director in UBS' Private Equity Secondary Group, focusing on buying and selling private equity interests in the secondary market. Earlier in his career, DeWayne was an Associate in the Investment Banking Division of Credit Suisse where he focused on mergers, acquisitions and project finance transactions.

DeWayne was appointed by New York City Mayor, Eric Adams, to the board of the New York City Economic Development Corporation ("NYCEDC"). NYCEDC is the City's primary vehicle for promoting economic growth in each of the five boroughs. DeWayne holds a BS in Finance and International Business with a French minor from Georgetown University. There, he was a four-year varsity letterman on the football team.

Nirav Shah, CFA

Founding Partner

Nirav Shah has over 18 years of experience in quantitative research, asset allocation and developing scalable systems. Prior to Versor, Nirav was the founder of a consulting firm focused on quantitative research. Prior to that, Nirav was a Vice President at Investcorp in New York focused on asset allocation and quantitative research. Earlier in his career, Nirav worked as a Quantitative Researcher at Phoenix Global Capital Management, a CTA based in Chicago.

Nirav earned an MS in Finance from the Illinois Institute of Technology, Chicago and a BE in Computer Engineering from Mumbai University. Nirav is also a CFA charter holder.

Neetu Jhamb

Partner

Neetu Jhamb has more than 15 years of experience in merger arbitrage and special situations investing. Before Versor, she was the Event Driven Sector Specialist at JP Morgan analyzing mergers, spin offs, SPACs and other corporate reorganizations for the trading desk and advising clients. Prior to JP Morgan, she was an Event Driven Portfolio Manager at Severn River Capital where she invested in risk arbitrage and other special situations. Prior to joining Severn River, she was a Portfolio Manager in Proprietary Trading at JP Morgan where she invested in event driven equity, risk arbitrage and distressed debt. At P. Schoenfeld Asset Management, a New York City based hedge fund, she spent four years as a research analyst specializing in risk arbitrage and special situations analysis.

Neetu began her career in the Investment Banking Group at JP Morgan as an analyst in mergers and acquisitions. Neetu graduated from Barnard College, Columbia University.

Victoria Hart

Partner, Investor Relations

Victoria Hart is a Partner at Versor Investments. Originally from the Chicago area, she moved to New York to pursue a career in finance. There, in 2019, she became a Versor Analyst. In the Summer of 2021, she was promoted to Principal. Since December 2022, she's been a Partner at the Firm. She specializes in branding and building client relationships. Victoria holds a B.A. in Economics from the University of Illinois at Urbana-Champaign.

Nishant Gurnani

Partner, Investments

Nishant leads futures and FX research at Versor Investments working closely with the Investment Committee in driving the investment research agenda across all strategies. Based in New York, Nishant operates across the full spectrum of strategy development from alpha signal generation to portfolio construction. Additionally, he plays an integral role in the Firm's efforts in alternative data sourcing and the applications of machine learning.

Prior to joining Versor Investments, Nishant was the second hire on the data team at Brex, a San Francisco-based financial technology firm, working on a mix of data science, analytics and engineering projects focused on credit risk.

Nishant holds an A.B. in Mathematics from Princeton and an M.S. in Statistics from UC San Diego.

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The HFRX Global Hedge Fund Index includes managers and is designed to be representative of the overall composition of the hedge fund universe. It is comprised of all eligible hedge fund strategies; including but not limited to convertible arbitrage, distressed securities, equity hedge, equity market neutral, event driven, macro, merger arbitrage, and relative value arbitrage. The strategies are asset weighted based on the distribution of assets in the hedge fund industry.

The HFRX EH: Equity Market Neutral Index includes managers employing the Equity Market Neutral strategies. Equity Market Neutral managers typically employ sophisticated quantitative techniques of analyzing stock price and fundamental data to ascertain information about future price movement and relationships between securities, select securities for purchase and sale. These can include both Factor-based and Statistical Arbitrage/Trading strategies.

The SG Trend Index includes managers employing the Systematic Diversified CTA strategy. Systematic Diversified CTA managers typically employ an investment process designed to identify opportunities in markets exhibiting trending or momentum characteristics across individual instruments or asset classes. Strategies utilize quantitative processes which focus on statistically robust or technical patterns in the return series of the asset, and typically focus on highly liquid instruments.

The HFRX Macro: Systematic Diversified CTA Index includes managers employing the Systematic Diversified CTA strategy. CTA managers typically employ an investment process designed to identify opportunities in markets exhibiting trending or momentum characteristics across individual instruments or asset classes. Strategies utilize quantitative processes which focus on statistically robust or technical patterns in the return series of the asset, and typically focus on highly liquid instruments.

The Barclays CTA Index (BARCCTA Index)

provides a benchmark of representative performance of commodity trading advisors (CTAs). In order to qualify for inclusion in the Index, a CTA must have four years of prior performance history. Refer to www.barclayhedge.com for more details on index construction methodology.

A combination of HFRX Macro: Systematic Diversified CTA Index and BARCCTA Index is used as the benchmark index for the Trend Following risk premia strategy returns. BARCCTA Index (monthly) returns are used for the period January 1990 to December 2008. HFRX

Macro: Systematic Diversified CTA Index (daily) returns are used from January 2009 onwards. Combination index used due to availability of daily return data from HFRX Macro: Systematic Diversified CTA index (from January 2009 onwards).

The Barclays Global Aggregate Index provides a broad-based measure of the global investment-grade fixed income markets. The three major components of this index are the U.S. Aggregate, the Pan-European Aggregate, and the Asian-Pacific Aggregate Indices. The index also includes Eurodollar and Euro-Yen corporate bonds, Canadian government, agency and corporate securities, and USD investment grade 144A securities.

The Barclays Global Treasury Index tracks fixed-rate, local currency government debt of investment grade countries, including both developed and emerging markets. The index represents the treasury sector of the Global Aggregate Index and contains issues from 37 countries denominated in 24 currencies.

The Barclays Global High Yield Index represents the US High Yield Index, Pan-European High Yield Index, High Yield CMBS Index, and non-investment grade portion of the Barclays Global Emerging Markets Index.

The MSCI World Index represents a free float-adjusted market capitalization weighted index that is designed to measure the equity market performance of developed markets. As of February 2013, it includes 24 developed market country indices: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

The MSCI ACWI captures large and mid cap representation across

23 Developed Markets (DM) and 24 Emerging Markets (EM) countries. With 2,490 constituents, the index covers approximately 85% of the global investable equity opportunity set.

The S&P GSCI™ Total Return index measures a fully collateralized commodity futures investment that is rolled forward from the 5th to the 9th business day of each month. Currently the index includes 24 commodity nearby futures contracts. The Total Return is significantly different than the return from buying physical commodities.

The S&P 500 index covers the 500 largest companies that are in the United States. These companies can vary across various sectors. The S&P 500 is one of the most important indices in the world as it widely tracks how the United States stock market is performing.

The SG CTA Index calculates the net daily rate of return for a pool of CTAs selected from the largest managers open to new investment. It is equal-weighted and reconstituted annually.

The SG Macro Trading Index is a broad based performance measure for constituents that trade Global Macro strategies. The SG Macro Trading Index (Quantitative) is a sub-index of the SG Macro Trading Index covering quantitative Global Macro strategies. The SG Macro Trading Index (Discretionary) is a sub-index of the SG Macro Trading Index covering the discretionary strategies.

The Eurekahedge Multi-Factor Risk Premia Index is composed of multiple strategies managed by large global banks, and is designed to provide a broad measure of the performance of a diversified portfolio of systematic drivers of risk and return across asset classes.

The Bloomberg Barclays US Treasury: 20+ Year Total Return Index measures US dollar-denominated, fixed-rate, nominal debt issued by the US Treasury. Treasury bills are excluded by the maturity constraint.

The S&P U.S. Treasury Bill Index is a broad, comprehensive, market-value weighted index that seeks to measure the performance of the U.S. Treasury Bill market. U.S. Treasury Bill 0-3 Month Index is designed to measure the performance of U.S. Treasury bills maturing in 0 to 3 months.

The SG Multi Alternative Risk Premia Index calculates the daily rate of return for a group of the largest ten multi-asset, multi-alternative risk premia programs managed by investment managers. These managers often trade equity indices, fixed income, currencies, commodities, and single name equities. Managers aims to systematically capture a diversity of discrete risk premia, including value, carry, momentum, and equity style premia. The index is equally weighted, and reconstituted and rebalanced on an annual basis.

The Russell 1000 Value Index measures the performance of those Russell 1000 companies with lower price-to-book ratios and lower forecasted growth values. The index was developed with a base value of 200 as of August 31, 1992.

The Russell 2000 Value Index measures the performance of those Russell 2000 companies with lower price-to-book ratios and lower forecasted growth values.

The Russell 1000 Growth Index measures the performance of those Russell 1000 companies with higher price-to-book ratios and higher forecasted growth values. The index was developed with a base value of 200 as of August 31, 1992.

The Russell 2000 Growth Index measures the performance of those Russell 1000 companies with higher price-to-book ratios and higher forecasted growth values.

The HFR Bank Systematic Risk Premia Indices are a series of benchmarks designed to reflect the performance of the universe of managers that employ a portfolio allocation strategy based on targeting risk levels across the various components of an investment portfolio.

HFR Bank Systematic Risk Premia Commodity Index: A composite of all Bank Systematic Risk Premia Commodity styles.

HFR Bank Systematic Risk Premia Credit Index: A composite of all Bank Systematic Risk Premia Credit styles

HFR Bank Systematic Risk Premia Currency Index: A composite of all Bank Systematic Risk Premia Currency styles.

HFR Bank Systematic Risk Premia Equity Index: A composite of all Bank Systematic Risk Premia Equity styles.

HFR Bank Systematic Risk Premia Rates Index: A composite of all Bank Systematic Risk Premia Rates styles.

Refer to HFR, Societe Generale, Barclayshedge, MSCI, Barclays, Russell and S&P websites for more details on their respective index construction methodology.

VERSOR

Versor creates diversified sources of absolute returns across multiple asset classes. Within a scientific, hypothesis-driven framework, Versor leverages modern statistical methods and vast datasets to drive every step of the investment process. Alpha forecast models, portfolio construction, and the trading process rely on the ingenuity and mathematical expertise of 50+ investment professionals.

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