

Diversified Trend Following

Quantitative investment strategies

February 13, 2014

This paper was originally published at Barclays on 13 February 2014 and authored by Kartik Ghia, Arne Staal and Charles Fattouche.

On August 24, 2016, Bloomberg acquired the Barclays Risk Analytics and Index Solutions Ltd. (BRAIS) business. The transaction includes the Barclays fixed income benchmark indices, BRAIS strategy indices and the intellectual property of the POINT portfolio analytics platform.

For more information regarding the acquisition, please access the press release:
[bloomberg.com/company/announcements/
bloomberg-acquisition-barclays-brais/](http://bloomberg.com/company/announcements/bloomberg-acquisition-barclays-brais/)

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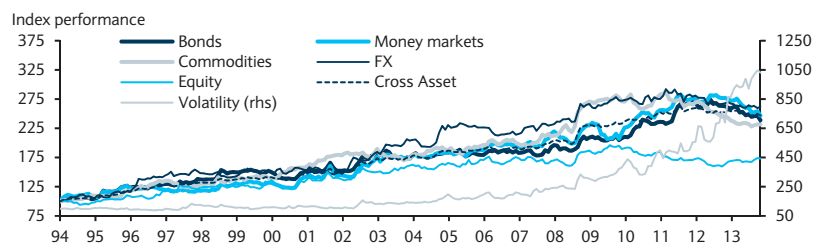
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Overview

Trend following, a classic investment strategy, is one of the few systematic trading approaches that perform well during periods of severe market distress. However, many investors are wary of a perceived ‘black box’ approach and lack of intuition with respect to the underlying performance drivers. In our view, trend following provides a disciplined and transparent systematic investment approach that applies across asset classes and instruments. We discuss the drivers and properties of the returns on diversified portfolios of trend strategies, illustrate how relatively simple strategies provide access to the ‘CTA factor’ and discuss the role of diversified trend portfolios in asset allocation.

- Trend-following strategies across asset classes and instruments lead to consistent performance profiles: less tail risk, more positive skew, lower volatility, and somewhat higher risk-adjusted returns than the long-only analogue. The main effect of trend following is to reshape payoff profiles by conditioning on persistent regimes.
- However, on individual instruments, performance improvements from trend following tend to be modest. Diversification is a key driver of portfolio performance. The natural long-only benchmark for trend strategies and CTA funds is a risk-weighted portfolio of the underlying instruments.
- We use the Barclays Cross Asset Trend (BCAT) Index Family to illustrate the commonality in trend following returns across active managers. These indices systematically identify and capitalize on medium-term price trends in liquid markets using a simple and robust approach. They provide building blocks for cross-asset trend investment solutions and can be used to benchmark actively managed trend strategies.
- Trend-following strategies are attractive overlay strategies for long balanced institutional portfolios. They display low correlation with broad asset classes, have limited draw-downs relative to equivalent long-only positions, and are characterised by attractive risk-diversification characteristics. Diversified trend-following can be an interesting complement and alternative to (long-only) risk parity investments.
- Finally, we provide some thoughts on lacklustre performance of trend strategies in recent years in the context of longer term performance and an unusual economic environment. We believe the strategy is best viewed as a diversifier over the long run, arguing that trend might have temporarily ‘broken’ but should start benefitting again from more stable market regimes and increased diversification potential.

FIGURE 1
Trend across asset classes (1994 – 2014)



Source: Barclays Research

Introduction to trend following

Trend following strategies are often associated with complex black-box statistical trading systems that are devoid of economic rationale. While the quantitative nature of trend following can result in complex trading systems, the intuition and principles underlying this approach are more easily understood. This paper explains the main characteristics of trend following strategies and attempts to provide economic intuition regarding the investment style. In our analysis, we construct trend following strategies with minimal parameterisation to highlight the consistency of strategy characteristics.

What is a trend?

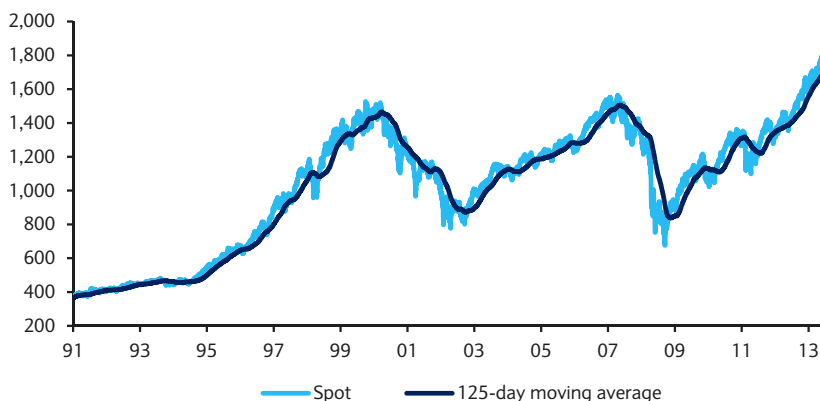
There is no commonly accepted definition of trend; to a high-frequency trader, it is a sequence of higher highs or lower lows in the span of minutes or even seconds, while to an economist, it can mean changes in macro variables over years or decades. In essence, all trend following investment strategies try to capture persistence in performance of financial instruments and asset classes over various time horizons. In this paper, we restrict ourselves to investing according to medium-term trends. Directional positions are expected to be held over weeks or months, rather than hours or days. The trends we condition on are best thought of as risk on/off market regimes: periods of price behaviour characterized by similar expected returns, volatility, and tail risk.

Statistically, a trend can be defined as a non-random movement in prices that represents systematic price variation. Trend following decomposes price variation into a component that is smooth and persistent, i.e., the trend, and one that represents random short-term variation around this component:

$$Price = trend + noise$$

Trend following in its most basic form consists of two steps: extracting the trend from historical prices and determining the direction of the trend and taking positions accordingly. While many would argue trend following attempts to predict future prices, we really only need to be able to recognize regimes in price behaviour and enter and exit accordingly with a minimal lag (in other words, 'condition,' rather than predict). The methods for accomplishing this range from simple look-back windows to highly complex statistical techniques based on different theories of signal extraction and filtering. Figure 2 illustrates the basic intuition of trend following with a simple moving average decomposition for the S&P 500.

FIGURE 2
Moving average trend on the S&P 500 (1991-2014)



Source: Barclays Research

Why might trends exist?

The profitability of trend following strategies is puzzling to many investors. After all, basic finance theory states that past performance does not provide information about future performance. Increasingly, academic studies refute this assumption, and the existence of cycles and trends in financial returns has become widely accepted. Unsurprisingly, attempts to explain the existence of consistently profitable trend following strategies abound in the academic literature. Explanations fall into three camps: returns are driven by exposure to sources of systematic risk, trend following captures one or more behavioural phenomena, and trends are caused by market structures. We review and synthesise some of the common arguments.

Risk sharing: Trend following captures time-varying risk premia

Risk premia will vary in response to changes in the economic environment and investor sentiment. Changes in the macroeconomic environment are accompanied by changes in the underlying factors driving asset prices. For example, as economic growth sputters, demand for commodities decreases; as central banks target inflation measures, market rates will adapt to policy regimes, when growth picks up, corporate earnings increase.

Behavioural phenomena

A second common explanation for the profitability of momentum is that of market inefficiency and investor irrationality. Several behavioural explanations for trend following have been proposed based on different aspects of investor psychology.

The most cited is the concept of under-reaction to news. Investors receive, interpret and process information over different horizons. Trends are generated by the slow, stepwise reaction of some investors to new information. A separate but related argument is based on what behavioural economists call the *disposition effect*. The preference of investors to realize gains and avoid losses makes them prone to hold on to losing positions for too long in an attempt to break even and to sell winning positions too early to lock in the upside. Once again, this means information is gradually incorporated into prices. Another aspect of investor psychology can lead to an amplification effect of trending behaviour. Investments that performed well in the recent past often seem more attractive than underperforming ones, leading to a *bandwagon effect* that causes investors to favour past winners and shun past losers.

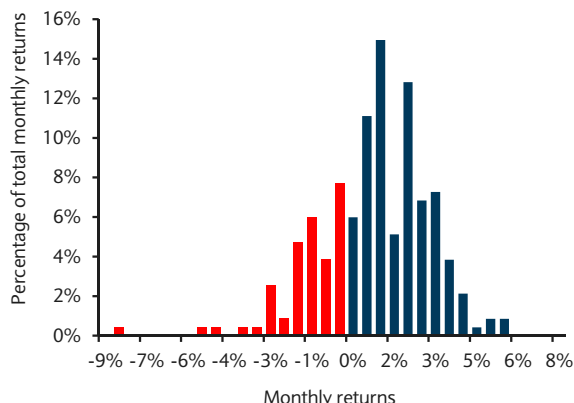
Market structure: Non-profit-seeking market participants and rigidities

Finally, the presence of market participants with non-profit objectives can lead to trending prices. In commodity and currency markets, many participants are driven by hedging demands dictated by the need to guarantee price levels, rather than maximise profit on that particular trade (i.e., a non-financial business exposure). This can have a noticeable effect on price setting in these markets. For example, growth in emerging markets can lead to persistent hedging requirements for commodities and currencies from western companies with local business interests. Another example is central banks which operate in rates and currency markets to achieve outcomes related to broader macroeconomic goals. Stable and predictable central bank policies can lead to trends in short-term interest rates. In more recent history, quantitative easing by central banks might have contributed to upward trends in equities. Market segmentation can contribute to trends as well; investors with different objectives and mandates can lead to persistent supply and demand imbalances.

Two pillars of trend performance: Regime adaption and diversification

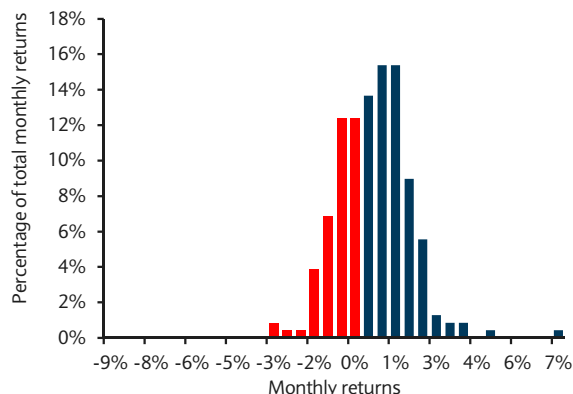
The results of trend following on individual instruments tend to be modest and lead to improvements in mean returns that are (over long periods and across asset classes) only marginally higher than the long-only equivalent investments. However, improvements in risk properties are substantial (volatility, skew, and tail risk) across asset classes and instruments. The improvements in return and risk properties on individual assets can be attributed to the ability of trend following to adapt to regimes in asset prices.

FIGURE 3
Distribution of monthly returns: Diversified long-only



Source: Barclays Research

FIGURE 4
Distribution of monthly returns: Diversified trend-following



Source: Barclays Research

The second pillar of trend following performance is diversification. Managed futures strategies tend to trade a large number of instruments simultaneously, often explicitly seeking risk diversification. This leads to more stable risk profiles and improved long-term risk-adjusted returns. Not only does applying the trend signal to individual instruments improve the risk-return properties of the individual instruments' return distributions, but it also breaks the correlations between and within asset classes – improving the diversification potential. As Figures 3 and 4 highlight¹, this diversification property allows the portfolio to have more attractive risk properties than an equally diversified long-only portfolio. Reshaping the return distribution by limiting the left tail (negative returns), strengthening the right tail and lowering volatility. We use a risk-diversified² long-only portfolio as a benchmark for our trend following portfolio.

In what follows, we analyse simple trend following approaches on liquid instruments across asset classes. We illustrate the properties of trend following using transparent strategies with minimal parameterization over a long history. We discuss improvements to this simple approach and use the Barclays family of trend indices to examine the commonality across trend strategies. We also discuss the role of trend strategies in asset allocation.

Trend methodology

Trend following can in principle be applied to any liquid instrument across asset classes. Using futures, forwards and swaps, we construct portfolios within and across asset classes. We first illustrate the power and characteristics of trend following using a trivial approach on data from 1972. We refine our methodology and provide fully tradable analysis when we discuss a family of Barclays trend indices.

The basics of a trend following strategy

All trend following strategies consist of a few basic building blocks:

- Trend detection
- Entry/exit rules: Decide when to take a position on a particular underlying and determine stop loss rules

¹ The histograms are based on models discussed in later sections.
² Volatility weighted asset class exposures

-
- Positioning/sizing: Decide how to size a position and maximum position sizing/leverage constraints
 - Portfolio construction/diversification: Decide how to combine individual positions

In the interest of brevity, we do not pursue a detailed discussion of implementation-related issues such as the optimal trade-off between trading frequency, transaction costs, margining, and market impact effects.

We start our analysis using a trivial trend following approach: a single look-back window comparing prices one day before rebalancing and three months ago. We enter a long (short) position if prices increased (decreased). We use a point-to-point change in the total return price index over a 3-month period to provide the long-run directional signal, but the analysis is remarkably robust to other look-back windows up to 12 months that capture monthly variations.

We then combine individual positions at the instrument level to ultimately construct a cross-asset class portfolio. A large part of the appeal of trend strategies is the diversification benefit provided by the cross-asset class exposure; we make this an explicit part of our strategy by first risk-weighting instruments within each asset class and then risk-weighting the asset class exposures relative to each other for the overall portfolio. Since all the instruments we use are unfunded, we scale our overall positions to achieve a volatility of 10% at the asset class levels. Since we do not target volatility at the cross-asset level, the realised volatility of the cross-asset portfolio is less than 10%.

Data

While trend following can be implemented on any liquid financial instruments, it is typically used to invest in futures contracts because of the relatively high liquidity, low transaction costs, and leverage potential. In our initial analysis, we use a combination of rolling futures, forwards and swap positions depending on the asset class (we consider rates, currencies (FX), commodities, and equities). The data are sourced from Barclays and Bloomberg. We begin our historical analysis in 1973. All our returns account for both rebalancing costs and roll costs incurred when investing in futures. We assume monthly rebalancing with a one-day lag between allocation decisions and trading. All returns are US dollar denominated. Note that in later sections, we introduce volatility, emerging market and money market instruments. Their omission in this section is due to limited data histories.

The detailed list of instruments for our historical analysis (1973-2013) is as follows:

- Currencies: Nine G10 currencies versus the US dollar
- Fixed income: Australia (10y); Canada (2, 5 and 10y); Germany (2, 5 and 10y); UK (2, 5 and 10y); Japan (2, 5 and 10y); US (2, 5 and 10y)
- Equity indices: Australia, Canada, Switzerland, Germany, Japan, Sweden, UK, Norway, US
- Commodities: individual instruments in five subsectors – agriculture, energy, livestock, industrial metals and gold

In everything that follows, we apply the exact same algorithm, with the same window choices, to all instruments and asset classes. While it is tempting to calibrate trend detection to specific instruments, the danger of over-fitting tends to outweigh the benefits of potentially capturing different economic mechanisms in different markets.

A first look: Diversified trend following since 1973

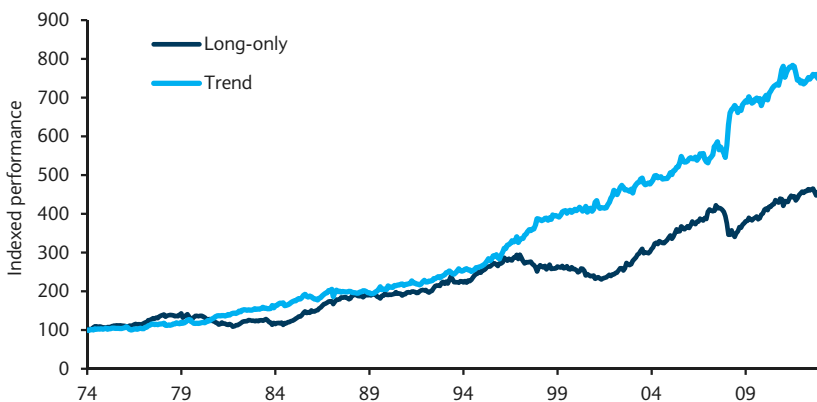
We analyse the performance of simple trend strategies from 1973 to 2013. This gives us the opportunity to gauge performance over multiple business cycles and economic crises. Significant episodes include the oil shock and high rates in the late 1970s/early 1980s, the equity boom-and-bust in the 1980s, the Asian crisis in the late 1990s, the tech bubble in 2000 and the credit crisis in 2008.

Empirical results: Long-only versus trend strategies

We compare and contrast diversified trend strategies with equivalent long-only portfolios (with the exception of volatility, which has a default short-only position³) at both the asset class and cross asset levels. The latter use the same risk-diversified portfolio construction approach, but do not attempt to adapt positioning in individual instruments to different environments through trend following. This allows us to separate the investment effects of diversification and trend following.

As we will see from Figures 5-11, relative to these long-only diversified portfolios, the trend signal increases average returns, lowers volatility, improves Sharpe ratios, reduces draw-downs, increases the likelihood of positive returns (except for currencies), and reduces time underwater.

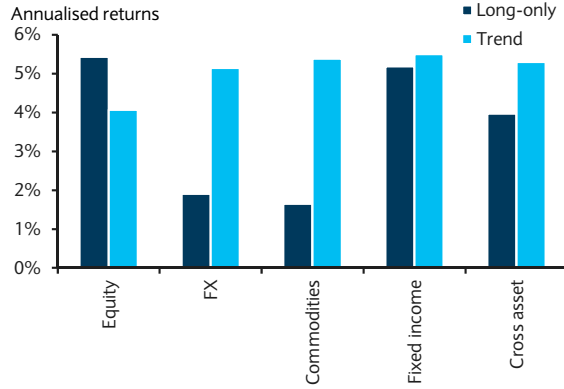
FIGURE 5
Indexed performance: Diversified long-only versus trend portfolio



Source: Barclays Research

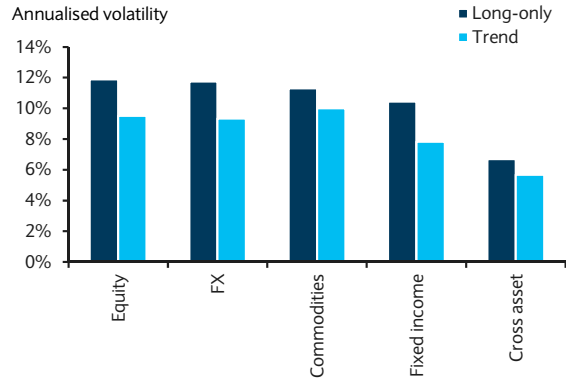
³ The default position for investors tends to be short volatility, given the accrual from the roll-down in futures.

FIGURE 6
Annualised returns by asset class: Long-only versus trend (1973-2013)



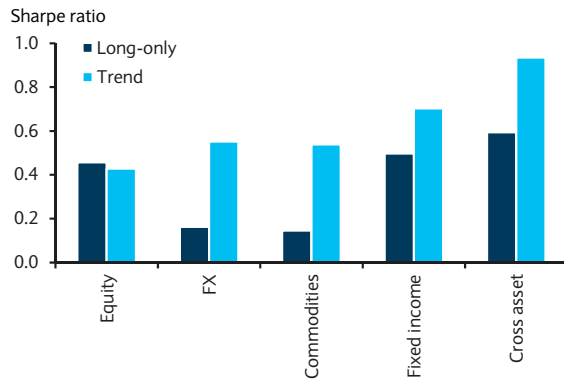
Source: Barclays Research

FIGURE 7
Volatility by asset class: Long-only versus trend (1973-2013)



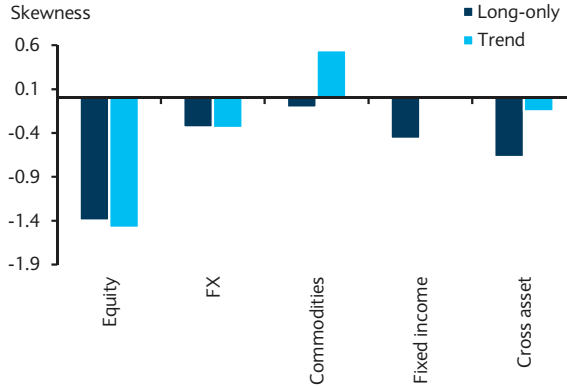
Source: Barclays Research

FIGURE 8
Sharpe ratios by asset class: Long-only versus trend (1973-2013)



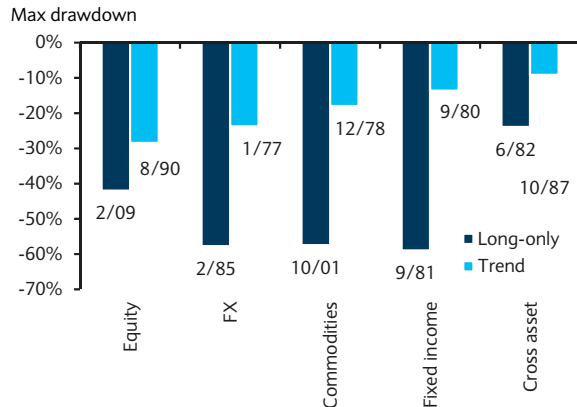
Source: Barclays Research

FIGURE 9
Portfolio skewness by asset class: Long-only versus trend (1973-2013)



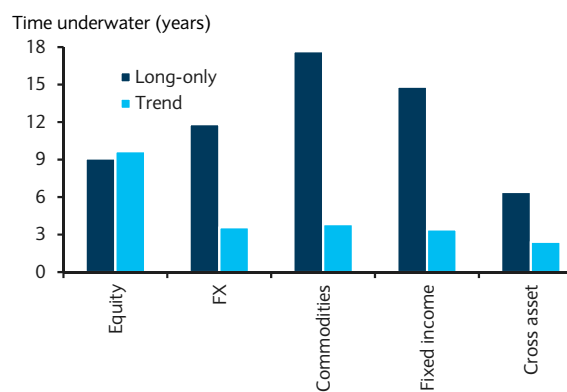
Source: Barclays Research

FIGURE 10
Draw-down comparison by asset class: Long-only versus trend (1973-2013)



Source: Barclays Research

FIGURE 11
Time underwater by asset class: Long-only versus trend (1973-2013)



Source: Barclays Research

Next we examine performance within sub-periods. The risk-adjusted performance for long-only portfolios (Figure 12) varies more significantly over the sample period than their trend-following equivalents. The pronounced differences in asset class returns over the four decades highlight the effect of the macroeconomic environment. The 1970s and early 1980s saw a strong pickup in inflation and a corresponding negative effect on fixed income returns relative to equity and commodities. This was reversed during the 1980s with the equity boom-and-bust, along with the recession in the early 1990s. The latter part of the 1990s and early 2000s saw the emerging market crises and dotcom bubble bursting, which led to fixed income outperforming once again. Cross-asset Sharpe ratios vary between 0.33 and 0.96, with annualised returns of 2.4-6.2%. While the cross-asset diversification does serve to smooth returns, draw-downs are still -23.9%, with a strong negative skewness (-0.67).

FIGURE 12
Performance statistics: Long-only portfolios

	Equity	FX	Commodities	Fixed income	Cross asset
Full period (1973-2013)					
Annualised returns	5.4%	1.9%	1.6%	5.2%	4.0%
Volatility	11.9%	11.7%	11.3%	10.4%	6.7%
Sharpe ratios	0.46	0.16	0.15	0.50	0.59
Skewness	-1.40	-0.34	-0.11	-0.47	-0.67
Drawdown	-42.0%	-57.7%	-57.5%	-59.0%	-23.9%
Time underwater	9.08	11.83	17.67	14.83	6.42
1973-1983					
Annualised returns	7.8%	-0.2%	1.9%	-1.2%	2.4%
Volatility	10.9%	12.8%	10.0%	12.5%	7.4%
Sharpe ratios	0.72	-0.01	0.19	-0.10	0.33
1984-1993					
Annualised returns	4.5%	5.0%	4.9%	8.5%	6.2%
Volatility	13.4%	11.6%	11.4%	10.0%	6.5%
Sharpe ratios	0.34	0.44	0.43	0.85	0.96
1994-2003					
Annualised returns	3.8%	0.6%	-2.6%	6.7%	2.6%
Volatility	12.2%	11.8%	12.4%	10.0%	6.7%
Sharpe ratios	0.32	0.05	-0.21	0.67	0.38
2004-2013					
Annualised returns	5.8%	2.0%	2.6%	6.5%	4.6%
Volatility	11.0%	10.8%	11.2%	9.0%	6.3%
Sharpe ratios	0.53	0.18	0.23	0.72	0.73

Source: Barclays Research

In contrast, and as illustrated in Figure 13, the trend portfolio displays more consistency in performance for individual asset classes and the composite portfolio. Risk-adjusted performance is steady across the four decades and ranges from 0.79 to 1.22. Annualised returns vary from a low of 4.7% during the most recent time (when markets have

experienced periods of range-bound returns accompanied by high volatility and significant levels of policy intervention) to a high of 6.6%. Volatility oscillates in a narrow band between 5.2% and 6.2%.

FIGURE 13

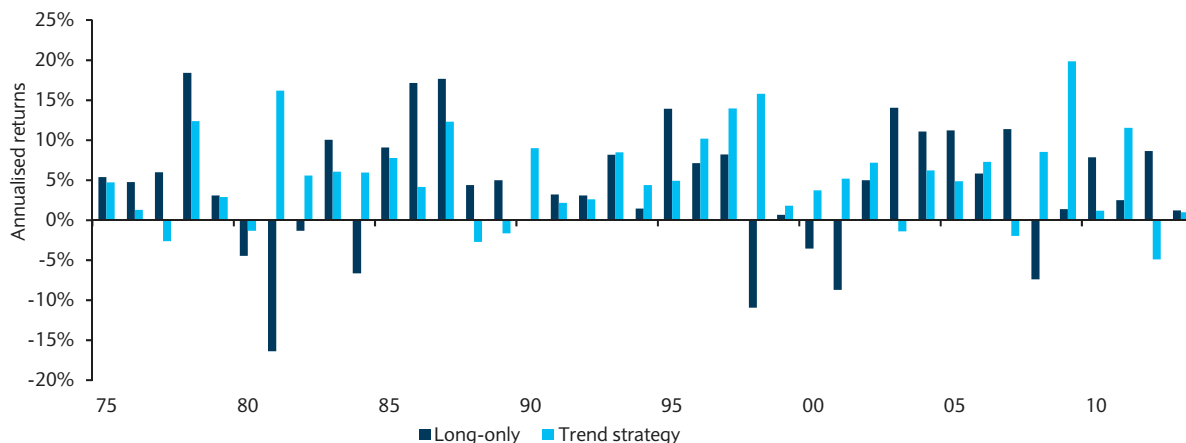
Performance statistics: Trend-following portfolios

	Equity	FX	Commodities	Fixed income	Cross asset
Full period (1973-2013)					
Annualised returns	4.1%	5.1%	5.4%	5.5%	5.3%
Volatility	9.5%	9.3%	10.0%	7.8%	5.7%
Sharpe ratios	0.43	0.55	0.54	0.70	0.93
Skewness	-1.48	-0.34	0.54	0.03	-0.15
Drawdown	-28.5%	-23.7%	-18.0%	-13.6%	-9.1%
Time underwater	9.67	3.58	3.83	3.42	2.42
1973-1983					
Annualised returns	3.2%	5.5%	3.9%	5.9%	4.9%
Volatility	7.1%	11.2%	8.5%	8.2%	5.2%
Sharpe ratios	0.45	0.49	0.46	0.72	0.94
1984-1993					
Annualised returns	1.6%	6.9%	6.3%	3.8%	4.9%
Volatility	11.4%	9.6%	10.1%	8.0%	6.2%
Sharpe ratios	0.14	0.72	0.62	0.47	0.79
1994-2003					
Annualised returns	5.3%	5.4%	7.7%	6.9%	6.6%
Volatility	9.7%	8.9%	12.0%	7.7%	5.4%
Sharpe ratios	0.54	0.61	0.64	0.89	1.22
2004-2013					
Annualised returns	6.3%	2.8%	3.6%	5.4%	4.7%
Volatility	9.3%	7.6%	8.9%	7.3%	5.8%
Sharpe ratios	0.68	0.37	0.41	0.74	0.82

Source: Barclays Research

Figure 14 compares annual long-only returns with trend strategy returns, highlighting the relative stability introduced by the directional signal. The trend returns display some cyclicity, but are significantly dampened compared with the long-only. Returns during the major global economic crises were largely unaffected, with the exception of the global recession in the early 1980s (when the strategy gained and lost in equal measure). The index was unaffected during the equity crash of 1987 and made a positive return during the Asian crisis of 1997 and credit crisis of 2008.

FIGURE 14
Annual returns: Long-only versus trend portfolio



Source: Barclays Research

As shown in Figures 15 and 16, both portfolios display low asset class correlations. Correlations between the asset class series and the cross-asset basket range from 0.43 to 0.69 for the long-only portfolios. The corresponding range for the trend strategy is narrower, spanning 0.55 to 0.68. The narrow range of the asset class correlations versus the cross asset portfolio confirms that no asset class dominates the combined portfolio.

FIGURE 15
Correlation analysis: Long-only asset class returns

	Equity	FX	Commodities	Fixed income	Cross asset
Equity	1	0.07	0.20	0.02	0.57
FX		1	0.39	0.14	0.69
Commodities			1	-0.08	0.65
Fixed income				1	0.43
Cross asset					1

Source: Barclays Research

FIGURE 16
Correlation analysis: Trend strategy returns

	Equity	FX	Commodities	Fixed income	Cross asset
Equity	1	0.16	0.22	0.27	0.68
FX		1	0.18	0.10	0.59
Commodities			1	0.11	0.64
Fixed income				1	0.55
Cross asset					1

Source: Barclays Research

Low correlation between long-only and trend returns for each of the corresponding asset classes (Figure 17) suggests the two portfolios are complementary.

FIGURE 17

Correlation analysis: Long-only versus trend returns

	Equity	FX	Commodities	Fixed income	Cross asset
Equity long-only	0.19	-0.08	-0.09	-0.07	-0.02
FX long-only	-0.07	0.08	-0.11	-0.05	-0.06
Commodities long-only	0.04	-0.01	-0.05	-0.03	-0.02
Fixed income long-only	0.08	-0.05	0.01	0.15	0.07
Cross asset long-only	0.10	-0.02	-0.11	-0.01	-0.02

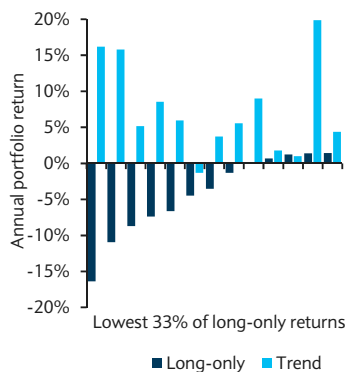
Source: Barclays Research

Sorting annual returns by long-only performance, Figures 18-20 show the attractive conditional performance by trend-following strategies; when long-only positions realize their largest losses, trend-following equivalents perform well (for illustration purposes, trend strategy returns are statically scaled to approximate the full-sample volatility of the relevant long-only benchmark).

The trend strategy behaves like a tail-hedge when the long-only portfolio suffers draw-downs, while participating in the upside when markets are bullish. Correlations tend to be more muted – albeit positive – during the periods of moderate long-only returns. The conditional correlation between the diversified long-only and trend portfolios subject to poor, moderate and strong returns for the long-only portfolio (Figures 18-20) are -0.38, -0.06 and 0.19.

FIGURE 18

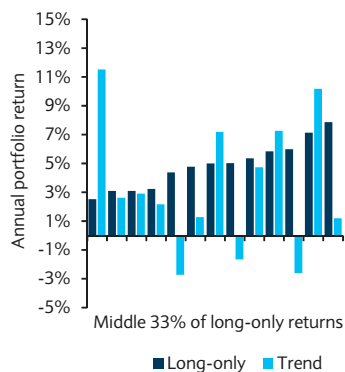
Acting as a tail hedge



Source: Barclays Research

FIGURE 19

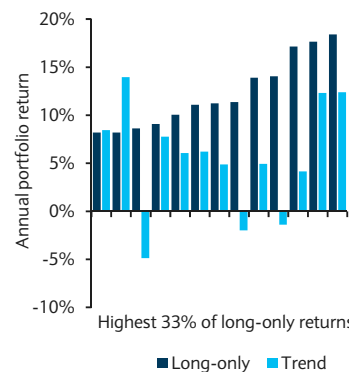
Mixed performance in the middle



Source: Barclays Research

FIGURE 20

Participating in the upside



Source: Barclays Research

Barclays trend indices

Having illustrated the desirable investment properties of diversified trend following relative to diversified long-only investing, even when using only the most trivial of methodologies, we touch upon robust improvements that can be incorporated into a more sophisticated approach. The family of tradable Barclays trend strategies is built upon these insights.

Enhancement to the trend algorithm

Over-fitting is a common pitfall in designing systematic trading strategies. We analyzed a large number of trend approaches using data from 1973 to 2013 and found that several features can robustly be implemented to enhance basic trend approaches. We introduce two additional signals to our original trend measure, both with a very intuitive rationale. Our approach now

consists of three steps: as before, the first signal determines the direction of trend, we introduce a second to detect turning points, while a third assesses the quality of the trend. The algorithm attempts to extract a trend from price movements with minimal assumptions about the statistical behaviour of the price series. If all three signals indicate a bullish (bearish) trend, we position long (short) in the individual instrument, else we remain un-invested for the forthcoming investment period. As before, in everything that follows, we apply the exact same algorithm, with the same parameter choices, to all instruments and asset classes.

Enhancements to portfolio construction and instrument universe

Unconstrained by the need for long historical evidence, we focus on a liquid universe of instruments that is broader than the one used in our analysis in the previous section. For example, we add equity volatility, money market and emerging market equity futures along with emerging market currency forwards to our tradable universe. To provide results (and tradable access) at the asset class level, the full universe of individual instruments is divided into six asset buckets and corresponding indices: equities, G10 and EM FX⁴, commodities, bonds, rates and volatility. All exposures are through futures-based instruments with the exception of currencies – for which we use one-month forwards.

We also adjust the portfolio construction methodology to ensure tradable strategy results for large positions. As before, we use two levels of risk weighting and simultaneously target exposures at the instrument and asset class levels. Since all the instruments we use are unfunded, overall positions are scaled to achieve a volatility of 10% at the asset class levels. This results in volatility of less than 10% at the diversified cross-asset level. Given varying instrument liquidity, leverage caps are applied on an instrument-by-instrument basis. In the event the net leverage level exceeds the leverage cap, we simply truncate the leverage at the cap.

Performance analysis (1994-2013)

Figures 21-31 show that our previous conclusions still hold over the shorter period with the more sophisticated implementation; risk-adjusted returns are improved relative to the comparable long-only portfolios. Long-term Sharpe ratios are comparable (0.89 for the long-only versus 1.03 for the trend strategy) but with significantly improved downside risk for the trend-following approach (as evidenced by the more attractive Calmar ratio),

Time spent in a drawdown ('time underwater') is a critical risk metric, especially for long term buy-and-hold investors. As shown in Figure 26, with the exception of bonds, trend strategies display a significant improvement versus long-only indices.

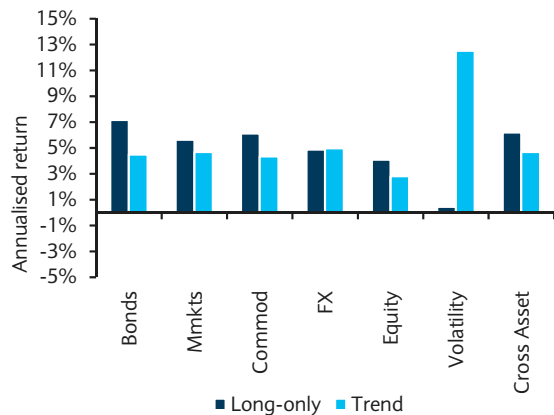
Correlations with the long-only benchmark indices highlight the attraction of trend strategies as a portfolio diversifier. The aggregate long-only portfolio displays strong absolute correlations with fixed income, equity, currency and commodities benchmarks (with the absolute values of 0.41-0.65). The corresponding trend strategy displays low levels of correlations with the same benchmarks, with absolute values of 0.03-0.27.

As can be seen in Figure 25 the non-overlapping drawdown periods for asset class trend and long-only strategies provide attractive diversification for investors.

⁴ Prior to 2002, the only EM currency was USD/MXN. From 2002 onwards, we include a basket of 15 global EM currencies versus the US dollar.

FIGURE 21

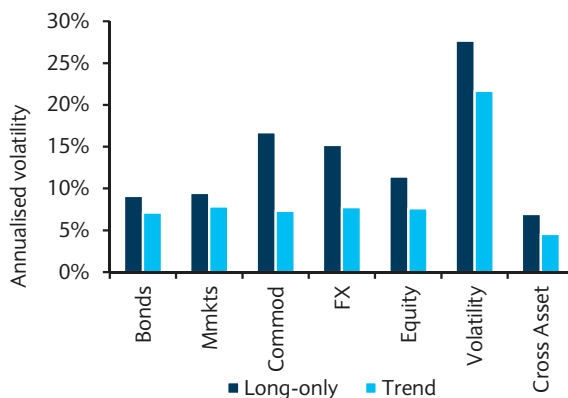
Annualised returns: Long-only versus trend



Source: Barclays Research

FIGURE 22

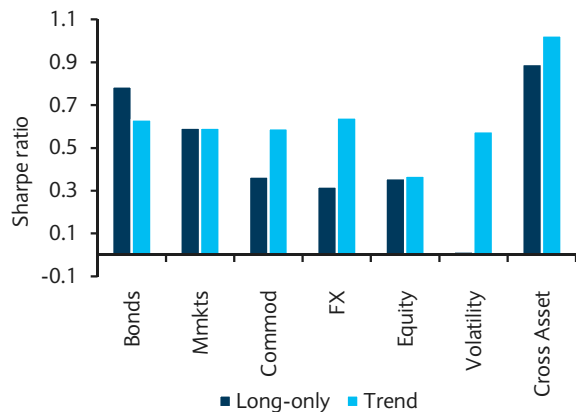
Volatility: Long-only versus trend



Source: Barclays Research

FIGURE 23

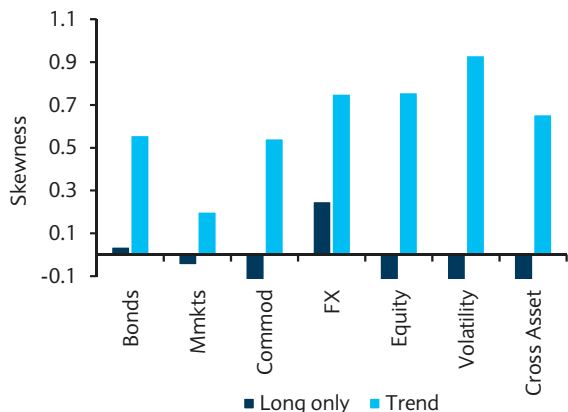
Sharpe ratios: Long-only versus trend



Source: Barclays Research

FIGURE 24

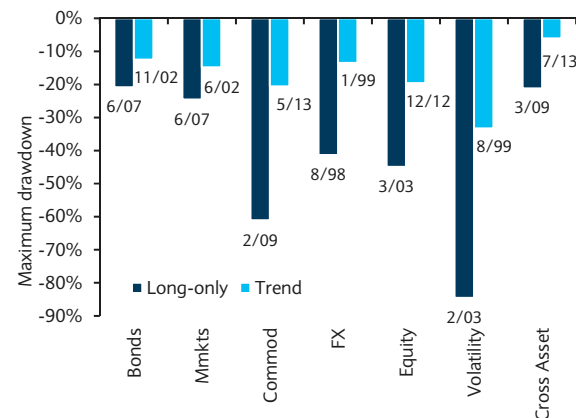
Portfolio skewness: Long-only versus trend



Source: Barclays Research

FIGURE 25

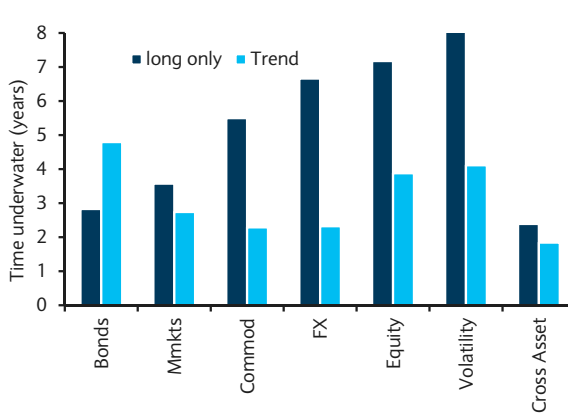
Draw-down comparison: Long-only versus trend



Source: Barclays Research

FIGURE 26

Time underwater: Long-only versus trend



Note: * Long-only volatility time underwater is 18 years (truncated for illustration purposes). Source: Barclays Research

FIGURE 27

Performance statistics: Long-only portfolios

	Bonds	Money markets	Commodities	FX	Equity	Volatility	Cross Asset
Full sample (1994-2013)							
Ann return	7.2%	5.6%	6.1%	4.9%	4.1%	0.4%	6.2%
Volatility	9.1%	9.5%	16.7%	15.2%	11.4%	27.7%	6.9%
Sharpe ratio	0.79	0.59	0.37	0.32	0.36	0.02	0.89
Calmar ratio	0.34	0.23	0.10	0.12	0.09	0.01	0.29
Max drawdown	-21%	-25%	-61%	-41%	-45%	-85%	-21%
Skewness	0.04	-0.05	-0.61	0.25	-0.75	-0.50	-0.67
Max time underwater	2.83	3.57	5.74	6.66	7.18	18.70	2.39
1st half (1994 - 2003)							
Ann return	8.4%	5.4%	4.3%	7.7%	3.2%	-11.0%	5.9%
Volatility	9.4%	10.1%	12.4%	17.3%	13.1%	23.4%	6.5%
Sharpe ratio	0.89	0.54	0.35	0.44	0.24	-0.47	0.91
2nd half (2004-2013)							
Ann return	6.0%	5.8%	7.9%	2.2%	5.0%	13.1%	6.4%
Volatility	8.8%	8.8%	20.1%	12.9%	9.6%	30.9%	7.5%
Sharpe ratio	0.68	0.66	0.39	0.17	0.52	0.42	0.86
Credit Crisis (2008-2013)							
Ann return	9.4%	10.1%	-1.9%	-3.4%	1.1%	14.3%	4.6%
Volatility	9.0%	8.6%	21.8%	13.8%	10.2%	35.2%	8.2%
Sharpe ratio	1.05	1.17	-0.09	-0.25	0.10	0.41	0.56
Asset class correlations							
Bonds	1.00	0.90	-0.15	-0.01	-0.25	-0.31	0.30
Money Markets		1.00	-0.13	0.03	-0.23	-0.23	0.35
Commodities			1.00	0.35	0.30	0.34	0.67
FX				1.00	0.22	0.23	0.69
Equity					1.00	0.64	0.50
Volatility						1.00	0.46
Cross Asset							1.00
Benchmark correlations							
MSCI	-0.29	-0.24	0.41	0.41	0.85	0.67	0.58
Global Agg	0.56	0.55	0.25	0.50	0.00	0.03	0.62
VIX	0.26	0.20	-0.29	-0.21	-0.64	-0.71	-0.41
GSCI	-0.14	-0.10	0.93	0.34	0.32	0.34	0.65
DXY	-0.04	-0.10	-0.42	-0.62	-0.06	-0.17	-0.53

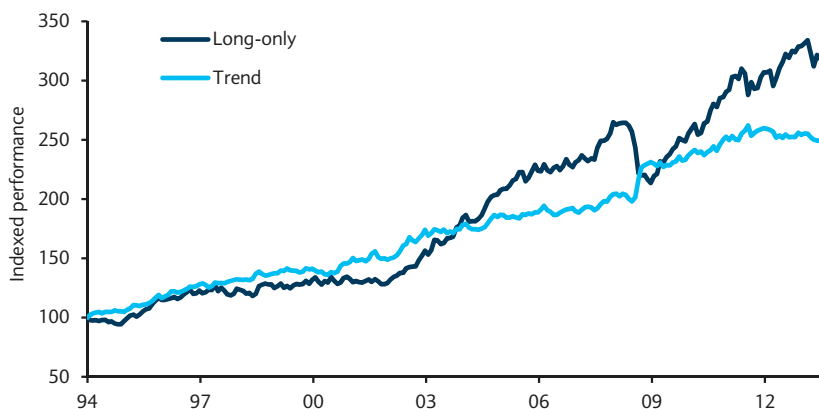
FIGURE 28

Performance statistics: Trend portfolios

	Bonds	Money markets	Commodities	FX	Equity	Volatility	Cross Asset
Full sample (1994-2013)							
Ann return	4.5%	4.7%	4.3%	5.0%	2.8%	12.5%	4.7%
Volatility	7.1%	7.8%	7.3%	7.8%	7.6%	21.7%	4.6%
Sharpe ratio	0.63	0.59	0.59	0.64	0.37	0.58	1.03
Calmar ratio	0.36	0.31	0.21	0.37	0.14	0.38	0.77
Max drawdown	-12%	-15%	-21%	-13%	-20%	-33%	-6%
Skewness	0.56	0.20	0.54	0.75	0.76	0.93	0.66
Max time underwater	4.79	2.74	2.81	2.80	4.40	4.11	2.36
1st half (1994 - 2003)							
Ann return	5.9%	5.8%	5.7%	7.7%	4.9%	3.8%	5.9%
Volatility	7.4%	8.5%	7.5%	8.3%	8.5%	18.8%	4.5%
Sharpe ratio	0.79	0.69	0.76	0.92	0.58	0.20	1.30
2nd half (2004-2013)							
Ann return	3.2%	3.5%	3.0%	2.4%	0.8%	21.8%	3.5%
Volatility	6.7%	7.2%	7.1%	7.2%	6.6%	24.0%	4.6%
Sharpe ratio	0.47	0.49	0.42	0.34	0.12	0.91	0.76
Credit Crisis (2008-2013)							
Ann return	4.4%	2.9%	1.2%	2.2%	0.8%	28.2%	3.8%
Volatility	7.5%	7.9%	7.7%	6.8%	6.4%	26.3%	5.2%
Sharpe ratio	0.59	0.38	0.16	0.33	0.13	1.07	0.72
Asset class correlations							
Bonds	1.00	0.81	-0.01	0.05	0.23	0.08	0.65
Money Markets		1.00	0.01	0.03	0.19	0.10	0.64
Commodities			1.00	0.22	0.23	0.12	0.48
FX				1.00	0.18	0.11	0.51
Equity					1.00	0.34	0.63
Volatility						1.00	0.44
Cross Asset							1.00
Benchmark correlations							
MSCI	-0.27	-0.24	-0.17	-0.04	-0.06	-0.05	-0.24
Global Agg	0.32	0.19	-0.05	0.03	0.01	-0.01	0.15
VIX	0.22	0.16	0.18	0.07	0.20	0.06	0.27
GSCI	-0.06	-0.02	0.01	-0.02	-0.04	0.01	-0.04
DXY	-0.01	-0.02	0.03	-0.05	0.08	0.06	0.03

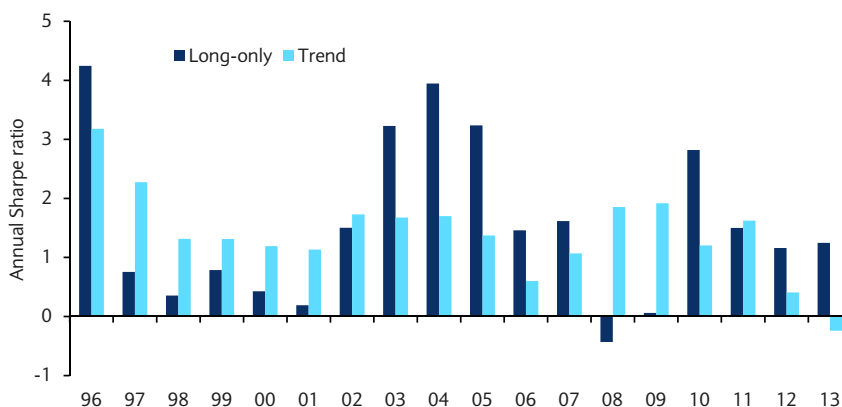
Source: Barclays Research

FIGURE 29
Indexed performance: Cross-asset long-only versus diversified trend portfolios



Source: Barclays Research

FIGURE 30
Sharpe ratios: Smoothing annual performance



Source: Barclays Research

As seen from Figure 31, the correlation between the long-only and trend indices is low, with the exception of money markets and bonds. For the latter, the trend has been largely one-directional for the past few decades.

FIGURE 31
Correlations between diversified trend portfolios and their long-only equivalents

	Bonds	Money markets	Commodities	FX	Equity	Volatility	Cross Asset
Bonds	0.59	0.40	-0.04	-0.03	0.14	0.07	0.34
Money markets	0.50	0.42	-0.06	-0.03	0.13	0.11	0.32
Commodities	-0.05	-0.02	0.05	0.03	-0.03	0.01	-0.01
FX	-0.01	-0.02	0.00	0.13	-0.02	-0.03	0.02
Equity	-0.21	-0.18	-0.18	-0.02	0.08	0.02	-0.14
Volatility	-0.32	-0.20	-0.13	-0.03	-0.05	0.10	-0.20
Cross Asset	0.15	0.12	-0.06	0.05	0.09	0.08	0.13

Note: Rows contain long-only returns. Source: Barclays Research

Barclays trend indices

The Barclays family of investible cross-asset trend indices provides access to trend-following returns in the major asset classes, based on the methodologies outlined above. The Barclays Cross Asset Trend index (Bloomberg ticker BXIXTAP) provides risk-diversified access across six asset classes. The single asset class indices in money markets (BXIXTMP), bonds (BXIXTBP), equity (BXIXTEP), G10 currencies (BXIXTDP), EM currencies (BXIXTYP), commodities (BXIXTCP) and volatility (BXIXTVP) allow investors to construct bespoke portfolios with respect to asset class exposures and weights. The individual asset class indices went live in December 2012, with the cross asset index launch in April 2013. An expanded cross asset trend index includes global credit instruments (via CDX contracts) and European equity volatility (tickers are BXIXTKP and BXIXTEV, respectively).

Providing access to the 'CTA factor'

We see our trend indices as the building blocks for CTA-style investments and compare the fully tradable history of our strategies (after all costs) to established CTA benchmarks and the largest individual funds.

Benchmarking diversified trend returns

The trend strategy outlined above is compared with standard CTA-style benchmarks and typical hedge fund benchmarks. The former comprise systematic funds, with each of the two benchmarks aggregating returns for a pool of funds. The hedge-fund benchmarks are two HFRX indices: the first an aggregate representing the overall (style) composition of the hedge fund universe and the second referencing funds following one-of-eight absolute return investing styles. We adjust the benchmark returns by using the overnight fed funds rate to calculate excess return versions. Figure 32 provides a detailed performance breakdown versus the benchmarks.

FIGURE 32
Performance relative to style benchmarks

	Barclays Cross Asset Trend	CTA benchmark Newedge CTA	HFRX benchmarks Global FoF*	Absolute Return**
Full sample (2001-2013)				
Ann return	4.6%	5.5%	0.1%	-1.9%
Volatility	4.9%	14.9%	5.9%	3.3%
Sharpe ratio	0.94	0.37	0.02	-0.59
Calmar ratio	0.75	0.30	NA	NA
Max drawdown	-6%	-19%	-29%	-23%
Skewness	0.78	0.12	-2.11	-1.73
1st half (2001 - 2007)				
Ann return	5.1%	8.2%	2.8%	0.6%
Volatility	4.6%	17.4%	4.4%	2.8%
Sharpe ratio	1.09	0.47	0.63	0.21
2nd half (2008-2013)				
Ann return	4.0%	2.4%	-1.9%	-3.4%
Volatility	5.2%	11.2%	6.9%	3.5%
Sharpe ratio	0.77	0.21	-0.28	-0.96
Asset class correlations				
Equity (MSCI)	-0.31	-0.11	0.80	0.54
Fixed income (Global Agg)	0.18	0.28	0.26	0.08
Volatility (VIX)	0.32	0.14	-0.60	-0.38
Commodities (GSCI)	-0.07	0.20	0.64	0.54

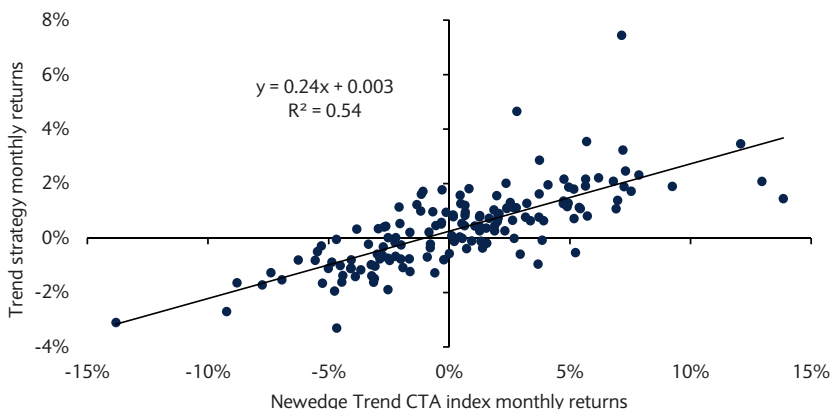
Note: *start date March 2003, ** start date July 2004

Source: Barclays Research

The CTA-style benchmark performs consistently over the two sub-periods, with low-to-moderate positive risk-adjusted returns and a draw-down of -19%. The HFRX indices perform noticeably worse, with flat-to-negative full period Sharpe ratios and draw-downs ranging from -23% to -29%. In contrast to the trend strategy and the CTA benchmarks, the HFRX indices perform very differently over the two sub-periods and imply a positive correlation with risky assets. The trend strategy and CTA-benchmark display similar characteristics: a mild negative/positive correlation with equity/volatility and being uncorrelated to fixed income and commodities. The HFRX indices, on the other hand, display moderate to high correlation with equity and commodities and negative correlation with volatility.

To investigate whether the Barclays trend indices provide access to the trend-following theme that investors seek when accessing CTA funds we look at a regression of monthly returns versus the Newedge CTA benchmark. The R-squared is approximately 0.54 and suggests that the simple CTA strategy captures the broad dynamics of CTA funds.

FIGURE 33
Correlation with the benchmark: Regressing monthly returns



Source: Barclays Research

Commonality in Trend Exposure

How much commonality is there in the performance of trend following strategies? We compare the performance of the Barclays cross-asset trend strategy with the six largest CTA funds known for trend following over 1999-2013. There are two key takeaway points from Figures 34 and 35. First, based on their live track records, trend following funds deliver attractive risk adjusted returns. Second, monthly returns are highly correlated both between these funds and between the funds and the Barclays cross-asset trend portfolio. This suggests a high degree of commonality across these investments. The characteristic positive skewness of CTA strategies is evident for all funds.

FIGURE 34

Benchmarking to CTA funds (1999-2013)

	Fund 1	Fund 2	Fund 3	Fund 4*	Fund 5	Fund 6**	Trend strategy
Full sample (1998-2013)							
Ann return	5.1%	6.7%	8.2%	8.4%	5.3%	8.7%	4%
Volatility	16.0%	11.2%	16.3%	20.8%	33.2%	18.1%	5%
Sharpe ratio	0.32	0.60	0.51	0.40	0.16	0.48	0.86
Calmar ratio	0.23	0.44	0.31	0.21	0.08	0.25	0.67
Max drawdown	-23%	-15%	-26%	-39%	-66%	-35%	-6%
Skewness	0.19	0.30	0.36	0.66	0.29	0.81	0.80
1st half (1998-2003)							
Ann return	11.8%	9.7%	9.1%	25.0%	7.6%	18.9%	5.2%
Volatility	18.6%	11.7%	22.8%	19.7%	38.6%	19.6%	5.0%
Sharpe ratio	0.63	0.83	0.40	1.27	0.20	0.96	1.02
2nd half (2004-2013)							
Ann return	2.0%	5.2%	7.8%	4.7%	4.1%	6.3%	3.5%
Volatility	14.6%	11.0%	12.1%	21.1%	30.2%	17.7%	4.6%
Sharpe ratio	0.14	0.48	0.64	0.23	0.14	0.36	0.76

Note: * Start date July 2001, ** start date June 2001.

Source: Barclays research, Bloomberg

FIGURE 35

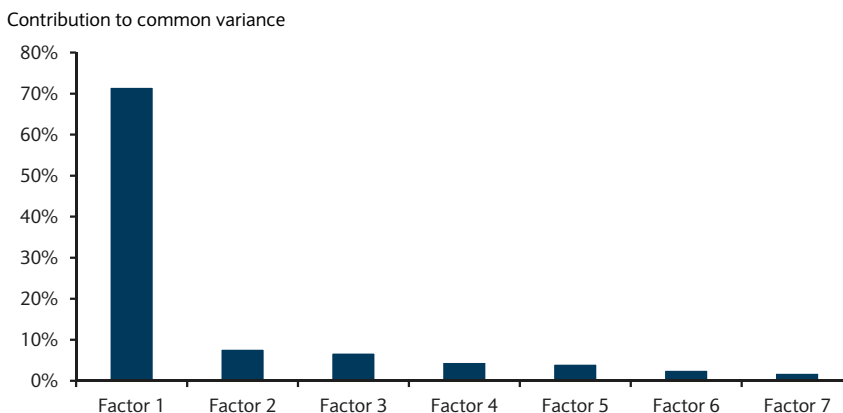
Correlation among CTA funds (1999-2013)

	Fund 1	Fund 2	Fund 3	Fund 4*	Fund 5	Fund 6**	Trend strategy
Fund 1	1.00	0.77	0.80	0.70	0.72	0.72	0.72
Fund 2		1.00	0.64	0.67	0.63	0.64	0.63
Fund 3			1.00	0.58	0.62	0.55	0.60
Fund 4*				1.00	0.56	0.66	0.60
Fund 5					1.00	0.67	0.65
Fund 6**						1.00	0.80
Trend strategy							1.00

Note: * Start date July 2001, ** start date June 2001. Source: Barclays Research

One way to visualise the size of a common factor in returns is through a principal component analysis (PCA). Based on normalised monthly returns, we extract the relative size of the seven orthogonal drivers of returns. As shown in Figure 36, the first factor captures 70% of the common variance in monthly returns. Figure 37 shows the factor loadings on the first principal component, which are roughly equal for all the CTA funds,

FIGURE 36
PCA analysis: Factor contributions (2001-13)



Source: Barclays Research

FIGURE 37
PCA analysis: Factor loadings (2001-13)

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
Fund 1	0.41	-0.23	-0.07	0.05	-0.08	0.28	0.83
Fund 2	0.38	-0.22	0.33	-0.64	-0.49	-0.06	-0.21
Fund 3	0.37	-0.57	-0.26	0.52	-0.14	0.03	-0.42
Fund 4	0.36	0.01	0.74	0.26	0.47	-0.20	-0.02
Fund 5	0.37	-0.05	-0.47	-0.45	0.64	-0.14	-0.10
Fund 6	0.38	0.57	-0.02	0.07	-0.04	0.67	-0.27
Trend strategy	0.38	0.50	-0.22	0.20	-0.33	-0.63	0.11

Source: Barclays Research

Full-period risk-adjusted returns and risk properties of the Barclays cross-asset trend strategy compare favourably with large trend-following funds. While it is of course unfair to compare simulated results with live track records, the experience since launching our indices suggests similar performance for a diversified CTA fund portfolio and our cross-asset trend index.

Asset allocation with a diversified trend portfolio

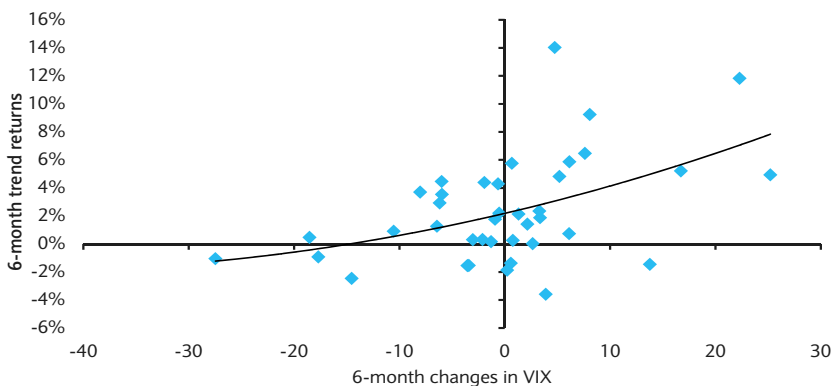
Diversified trend strategies have grown in popularity because they are seen as providing a stream of returns that is uncorrelated to the major asset class returns (portfolio diversification) and have historically provided positive returns when risky assets such as equity and commodities have experienced sharp declines (tail-hedging).

Trend has option-like characteristics

A feature of trend-following strategies that investors with risky asset exposure find attractive is the tail-hedging properties they display in a portfolio context. Based on a 20-year study using the 6-month changes in the level of VIX versus the corresponding trend strategy performance, we find trend returns are positively correlated to volatility, with the

slope an increasing function of level changes.⁵ This tends to re-affirm the performance drag trend strategies have experienced during the last two years given declining asset class volatilities (discussed in the final section).

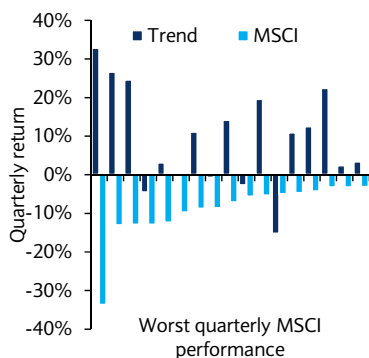
FIGURE 38
Trend returns versus changes in the VIX



Source: Barclays Research

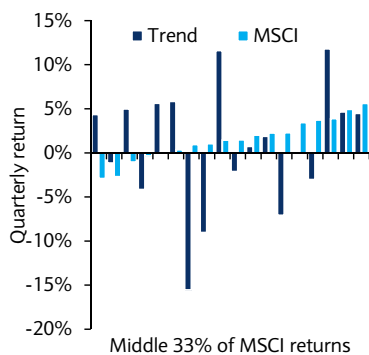
Trend strategies are especially attractive to long-only equity and commodity investors because of the conditional correlation to risky asset classes clearly visible in bullish and bearish markets. If we rank-order quarterly MSCI and GSCI returns and divide the sample into three buckets, we see a pattern which resembles the conditional correlations in the case of the long-only cross asset portfolio (in the previous section). For the purposes of analytic simplicity, in this study the trend strategy returns are statically scaled to approximate the full-sample volatility of the MSCI and GSCI respectively. During periods of equity and commodities market stress, trend portfolios display a negative correlation (thus capping downside returns) whilst participating in equity and commodity market rallies. In both cases, the three worst quarterly performances are offset by trend strategy returns. The middle third of the quarterly returns do not display any meaningful relationship. In fact the largest losses for the trend strategy are incurred during this period for both the GSCI and MSCI cases and do act as a drag on the GSCI and MSCI portfolios. Figures 39 to 44 illustrate the conditional relationships.

FIGURE 39
MSCI: Acting as a tail hedge



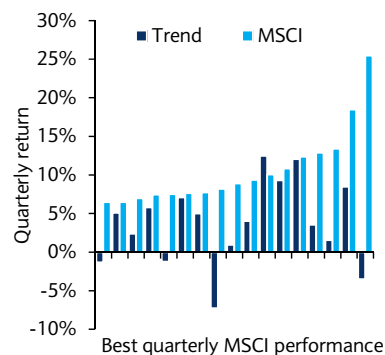
Source: Barclays Research, Bloomberg

FIGURE 40
MSCI: Mixed benefits



Source: Barclays Research, Bloomberg

FIGURE 41
MSCI: Participating in the upside



Source: Barclays Research, Bloomberg

⁵ In the past a sizeable number of trend strategy proponents have discussed the 'straddle-like' properties of trend versus asset class returns and investment style indices – i.e. that trend strategies tend to display positive returns when volatility is both rising or falling at the extremes. We find this is only partially borne out by this analysis.

FIGURE 42

GSCI: Acting as a tail hedge

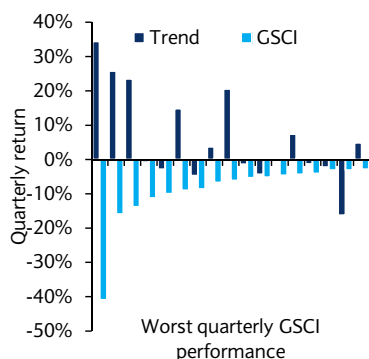


FIGURE 43

GSCI: Mixed benefits

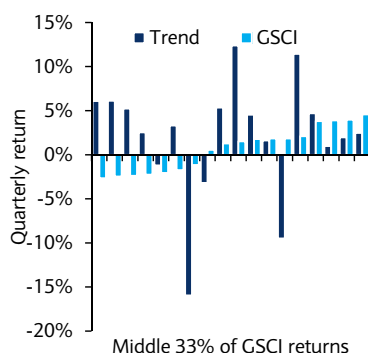
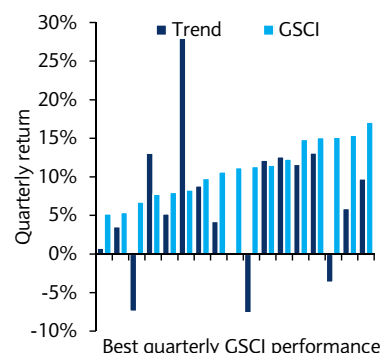


FIGURE 44

GSCI: Participating in the upside



Source: Barclays Research, Bloomberg

Source: Barclays Research, Bloomberg

Source: Barclays Research, Bloomberg

To further quantify this conditional correlation we segment the correlation analysis by negative and positive MSCI and GSCI returns. For the MSCI index, full-sample quarterly correlations are -0.36 which rise (in absolute terms) to -0.46 when MSCI returns are negative. The same holds for the GSCI, which has a full-sample correlation of -0.24, rising to -0.71 conditional on negative returns. Correlations tend to be less pronounced when underlying equity and commodity returns are positive; correlations with the MSCI and GSCI indices are 0.19 and 0.23 respectively. The tendency to provide downside protection in periods of stress while participating in some of the upside when markets rally is a key reason for the investment style's popularity.

Trend versus Risk Parity

We now turn our attention to the role of diversified trend following versus risk parity type portfolios. Without loss of generality, we use the standard cross-asset long-only volatility targeted portfolio constructed in the prior sections. The average bi-weekly returns correlation between the long-only and trend strategies is 0.22. This, however, does not tell the full story. A time series of the rolling 1-year correlation (Figure 45) indicates its changeable nature: for the bulk of the period, the correlation is between 0.0 and 0.4, moving on occasion to lows and highs of -0.50 and 0.79, respectively. Correlations tend to be flat or negative during periods of market stress (Asian crisis, bursting of the dotcom bubble and the credit crisis) and are weak to moderately positive during other periods.

This suggests a combined portfolio could offer an attractive return profile via the diversification of returns during periods of stable or positive market sentiment and tail-hedging during periods of market stress. In particular, the conditional correlation between the two portfolios suggests an investment in a long-only portfolio is attractive when market sentiment is risk-seeking, while rotation into a trend portfolio is useful when risk aversion is rising.

We construct two portfolios that allocate between the cross-asset long-only and trend portfolios. The first is an inverse-volatility weighted basket (risk-weighted) that rebalances monthly based on a rolling one-year historical volatility, while the second is a dynamic allocation strategy (signal-based) that also rebalances once per month based on the relative level of the VIX index. The risk-weighted basket displays an improvement in risk-adjusted performance versus the standalone strategies (absolute level as well as consistency over the two sub-periods), whilst displaying a significant improvement in skewness relative to the long-only strategy.

FIGURE 45
Rolling correlation between long-only and trend returns



Source: Barclays research

FIGURE 46
Timing exposure (1996 - 2013)

	Individual strategies		Portfolios	
	Long-only	Trend	Risk-based: Volatility weights	Signal-based: VIX indicator
Full sample (1996-2013)				
Ann return	6.7%	4.7%	6.0%	7.0%
Volatility	7.0%	4.6%	5.1%	5.6%
Sharpe ratio	0.95	1.01	1.17	1.26
Calmar ratio	0.35	0.80	0.44	1.09
Drawdown	-19%	-6%	-14%	-6%
Skewness	-0.72	0.67	0.12	0.21
1st half (1996-2002)				
Ann return	5.6%	6.1%	5.8%	6.1%
Volatility	6.4%	4.5%	4.6%	5.0%
Sharpe ratio	0.88	1.35	1.25	1.21
2nd half (2003-2013)				
Ann return	7.5%	3.6%	6.2%	7.7%
Volatility	7.5%	4.7%	5.5%	6.0%
Sharpe ratio	1.00	0.77	1.12	1.29

Source: Barclays research

The signal-based portfolio uses changes in the relative level of equity implied volatility (VIX index) to allocation between the long-only and trend portfolios. From our default 100% allocation to the long-only index, we construct a simple risk aversion indicator to vary the exposure to trend. The intuition behind this is that while the long-only portfolio accrues attractive returns over the long-run, it is adversely affected by worsening market sentiment. Relative levels of implied volatility are often used to gauge market sentiment, with rising levels suggesting increasing risk aversion and falling levels implying a shift into higher yielding investments. We use US equity implied volatility levels as a lead indicator of market sentiment, constructing an aggregate signal to allocate between the long-only and trend portfolios.

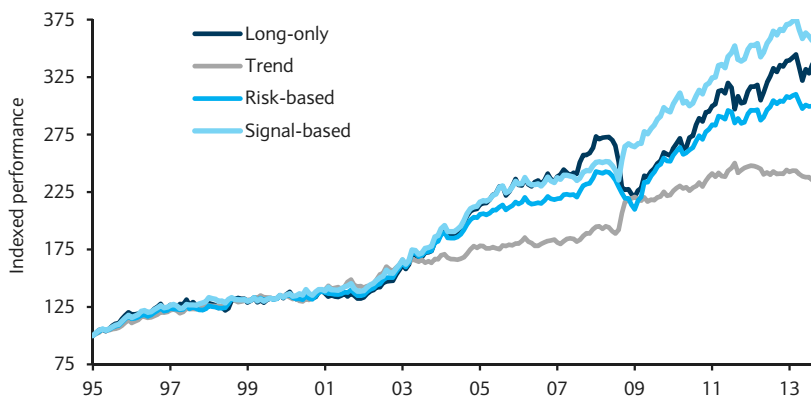
Based on a one-year rolling window, we calculate the z-score of the VIX index and assign thresholds as set-out in Figure 47 (corresponding to statistical convention) for weight allocations. The monthly allocation rotates between the two portfolios depending on the relative level of implied volatility.

FIGURE 47
Thresholding for portfolio allocation

Z-score threshold	Long-only exposure	Trend exposure
-2	100%	0%
-1	75%	25%
0	50%	50%
1	25%	75%
2	0%	100%

Source: Barclays Research

FIGURE 48
Indexed performance: Blending trend with long-only



Source: Barclays research

The signal-based portfolio displays enhanced risk-adjusted returns and downside statistics relative to the volatility-weighted portfolio (Figure 46). The full period Sharpe ratio is slightly higher at 1.26 while the maximum drawdown declines from -14% to -6%. The percentage exposure to the long-only strategy varies with time, but the average over the full period is 57%.

“The report of my death was an exaggeration.”⁶

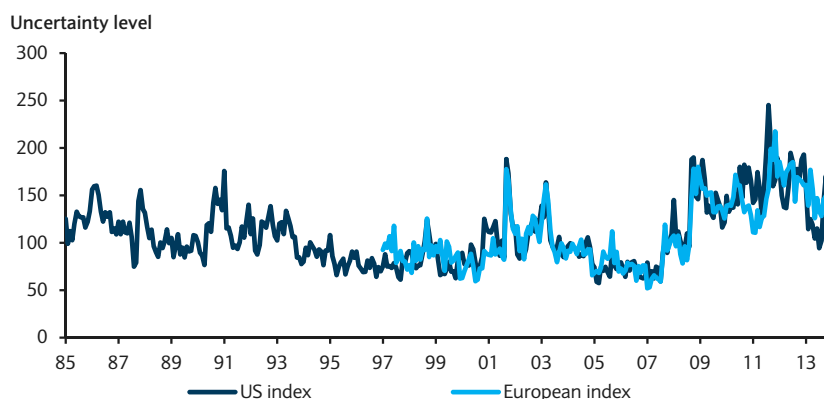
After a decade of stellar performance, CTA funds have (on average) struggled over the past two years. With lacklustre if not downright poor returns, there has been growing scepticism about the future of trend-following strategies. In our opinion, these fears are largely unfounded. A longer term historical perspective indicates that trend returns are cyclical in nature, with extended periods of weak performance. Market conditions during the past two years have certainly not been favourable to trend following. In the aftermath of the credit crisis, government rhetoric and intervention has⁷ made it difficult for systematic trend detection signals to identify persistent regimes in price patterns. As the global economy continues to recover and policy actions normalise, trends should once again become more apparent.

⁶ Mark Twain

⁷ This is often due to a combination of extraordinary policy action by authorities and the anticipation of market participants.

We can illustrate the decreasing level of uncertainty in the economy with the Baker-Bloom-Davis uncertainty index⁸, which uses news coverage, tax provisions, and dispersion in economic forecasts to construct an aggregate uncertainty index. The indicators used in the US version of the index are the number of newspaper articles relating to policy uncertainty, the dollar amount of federal tax provisions set to expire, and the dispersion of forecasts in the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. Index levels above and below 100 indicate average-and-below long-term levels of uncertainty. The European index uses analogous data from five major European countries⁹. Figure 49 shows historical levels for developed markets using data from the US and Europe as a proxy measure. The most striking observation is the common behaviour of the indices over the sample period. Following a relatively long period of a low level of uncertainty between 1993 and 2007 (punctuated by a two-year period of rising uncertainty around the dotcom bubble and the short recession in 2001), there was a sustained, sharp rise in the aftermath of the credit crisis until the end of 2012. Thereafter, there has been a sharp decline, especially in the recent past. Currently, levels are back near their long-run average. A similar analysis for emerging markets using data from India and China confirms this recent decline in uncertainty from historical highs.

FIGURE 49
Tracking policy uncertainty in developed markets



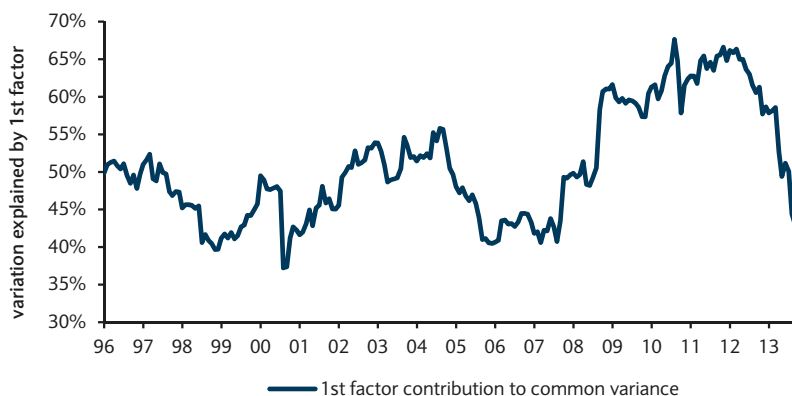
Source: Economic Policy Uncertainty

In addition, the last few years were characterised by high correlation between instruments and asset classes. This has effectively reduced the number of independent trends available, sharply reducing the benefits of diversification. As long-only asset class correlations begin to return to the long-run average and asset class movements decouple, the benefits of diversification should once again become apparent. Using a six-month rolling window and weekly returns, we find intra-asset class correlations have begun to move lower for equities, FX and commodities starting in Q3 2013. Another route to illustrate the normalisation of cross asset correlations is through principal component analysis (PCA). Based on 24-month rolling returns, Figure 50 is a time series representation of the percentage of common variation in returns across asset classes explained by the first factor (typically identified as 'risk-on/off'). The percentage of common variance explained by the first factor has varied cyclically since 1996 with an average contribution of 50%. Having reached recent highs during the aftermath of the credit crisis, the level of contribution by the first factor retraced sharply during 2013 and is now back to 2006/07 levels.

⁸ *Measuring Economic Policy Uncertainty*, Baker, Bloom and Davis, 2013.

⁹ Germany, United Kingdom, France, Italy and Spain.

FIGURE 50
Mapping the importance of 'risk-on/off'

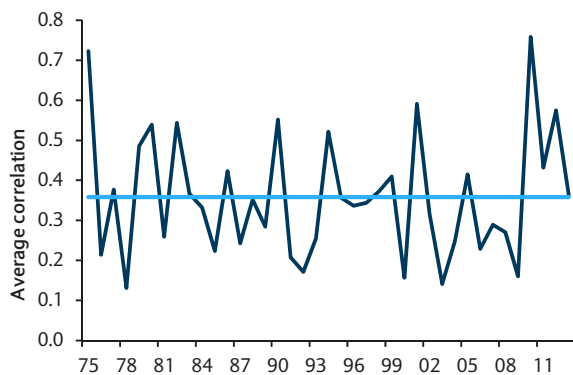


Source: Barclays Research

We highlight the relationship between trend strategy performance and asset class correlations using equity, commodity, and fixed income returns during 1975-2013. To avoid any confusion, we use monthly returns divided into non-overlapping calendar years. The measure of correlation used is the average absolute pair-wise correlation¹⁰. As Figure 51 highlights, annual correlations that were elevated since 2010 have now reverted to the long-run average. Rank-ordering annual trend strategy returns into quartiles based on the level of correlations, we see from Figure 52 the existence of an inverse relationship between the level of annual returns and correlations. The reversion of correlations to lower levels is supportive of improved trend strategy returns in the future.

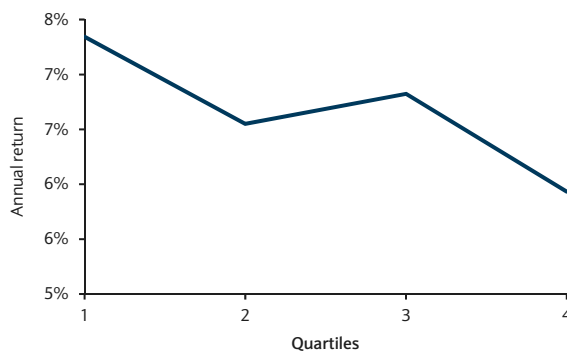
Looking at performance over a longer horizon, a two- to three-year underperformance relative to other styles is not unusual; the amount of premium available from most individual risk premia strategies is cyclical. Two recent examples are from the past 20 years: during the mid-1990s, performance was muted over a multiple-year span; and in 2006-07, when market volatility was low and option-selling strategies were profitable, CTA funds

FIGURE 51
Annual cross-asset correlation: 1975-2013



Source: Barclays Research

FIGURE 52
Trend returns versus correlations: 1975-2013



Source: Barclays Research

¹⁰ Absolute values account for negative correlations since our focus is on the levels and not sign of correlation. The average correlation is simply the average of the individual pair-wise correlations.

underperformed long-only risky assets. Trend strategies are inherently long-volatility strategies, with CTA funds benefiting from amplified price movements if they catch trends early enough. However, since the credit crisis, implied volatility levels have continued their decline across asset classes¹¹.

Conclusion

We provide evidence that diversified trend following on liquid assets provides improved risk-adjusted returns relative to an appropriate long-only benchmark. Our analysis highlights that a rules-based approach applied across asset classes can produce a comparable return profile to a CTA benchmark and individual CTA funds. While CTA-style strategies have performed poorly over the last few years, there is no reason to believe there has been a fundamental change in the performance drivers; Following the credit crisis, positioning to take advantage of trend has been made difficult by more choppy price action (tends to have an adverse effect on the quality of the signal) and higher absolute correlations between long-only asset class returns (commonly referred to as 'risk-on/risk-off'). Correlations and volatilities have begun to revert to long-run averages, effectively allowing for better diversification across trends in instruments and asset classes. As monetary policy begins to normalise and central banks start to signal policy moves with more regularity, trends are likely to become more stable and easier to identify.

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¹¹ With the exception of bonds, which had a brief, albeit sharp, rebound in mid-2013.

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