Part 1: Trend, My Friend, Is This the End?

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In Part 1 of 2 we explore the reduced performance of trend followers over the past decade but fail to find evidence that this is due to the commonly proffered reason of overcrowding of the strategy. Instead we find that the cause can be laid at the feet of the markets themselves – those markets commonly traded by trend followers have simply not trended as strongly in the past decade. In Part 2 we will turn our attention to the "trendiness" of a novel dataset of alternative commodity markets, selected based on a set of simple criteria. This will feature in a forthcoming edition of the GCARD.

Trend Followers

As is well known, classical trend following in liquid markets has struggled over most of the past decade since the global financial crisis (GFC), and stands in sharp relief to the performance of similar systems prior and during the crisis. As an example, taking March 2009 as the start of the post-GFC period,[1] we find that the Sharpe Ratio (SR) of the BarclayHedge Barclay CTA Index has been essentially zero (0.1 +/- 0.3 standard error) compared to a SR of 0.8 (+/-0.2 s.e.) before then. Via Opdyke (2007) the probability that the pre-GFC SR is positive is 99%, but it is only 60% for the post-GFC SR whilst the probability that the post-GFC SR is *less* than the pre-GFC period is 95%. Clearly, something has changed!

Why Has the Performance Declined?

Is it Overcrowding?

A common hypothesis is that the amount of capital deployed in trend-following strategies has reached the scale where competitive saturation is now a significant concern. This refers to the degradation in performance caused by increased competition for the same source of alpha. Indeed, recent reduced Commodity Trading Advisor (CTA) performance has been coincident with assets under management (AUM) in Managed Futures strategies at historic highs ($350Bn), and this growth has outstripped the increase in the size and number of futures markets, with the ratio of managed futures AUM to total average daily futures trading volume (in dollars) doubling from pre- to post-GFC periods (0.16 to 0.27).

But, correlation does not necessarily mean causation. We here attempt to measure any impact on CTA performance arising from a general crowding of the strategy. Direct observation is of course impossible, because one cannot evaluate market behavior on a counterfactual basis. We can however simulate the counterfactual: *what would have happened if one had traded behind everybody else?* This implementation lag refers to the negative impact on performance of the inevitable delay between sample time (when the model "sees" the price) and execution time (when the model "fills" its desired holdings.)

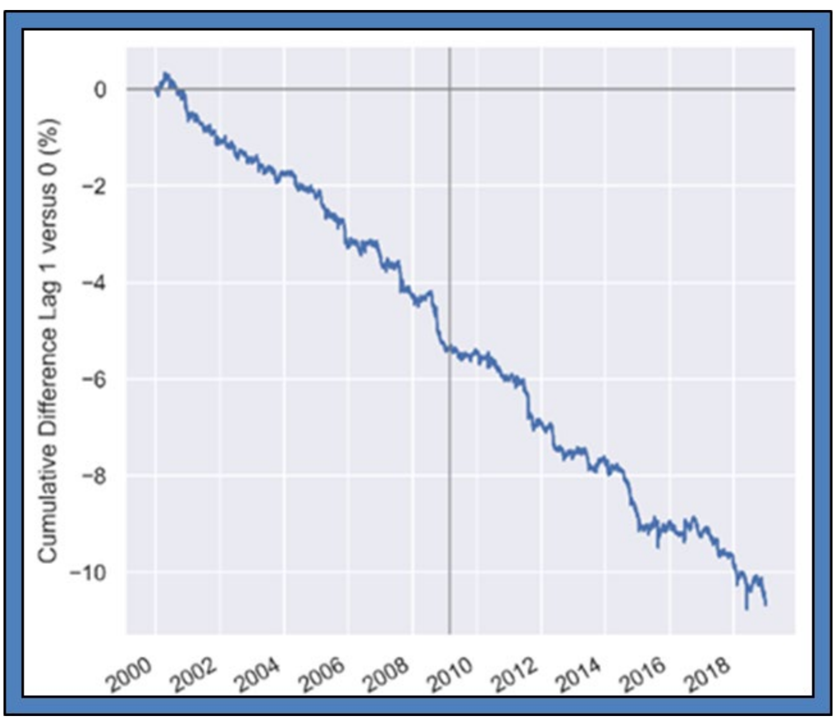
Quantifying Saturation via Alpha Decay

The crux of this analysis is that if the recent growth in assets and players is cannibalizing alpha, then we should see an increasingly negative cost to "trading late," because all those assets and players will have created a "footprint" in the market, and the late entrant will buy after the competition has bought, or sold after they have sold.

We backtest a trend-following simulation on a set of over one hundred *liquid* futures markets from 2000-2019 (across bonds, rates, currencies, equities and commodities), comparing the resulting performance when we either assume the theoretical – but unachievable – case of simultaneous sampling and execution (Lag 0) to the case where we trade a *full* 24 hours later (Lag 1). The Lag 0 SR before fees is 0.75, dropping to 0.7 for Lag 1. At 10% annualized volatility, 0.05 Sharpe points equates to 50bps annualized loss in performance, or about a cost of 8% of net alpha (for a Lag 0 after fees SR of 0.66.)

To address the possibility of crowding leading to increased alpha degradation, we need to know if this cost has been accelerating. This would manifest itself as an increasing performance differential over time. However, the cumulative differential between the Lag 0 and Lag 1 account curves has been stable over time (Figure 1), and there is no obvious acceleration over the recent past. Thus, we see no footprint of increased trend-follower AUM leading to competitive saturation and overcrowding.

Figure 1
Cumulative Lag 1 Underperformance versus Lag 0 Backtest, Showing the Consistent and Persistent Gradient



Sources: Gresham Investment Management (GIM), Bloomberg.

Why Haven't Assets Swallowed Alpha?

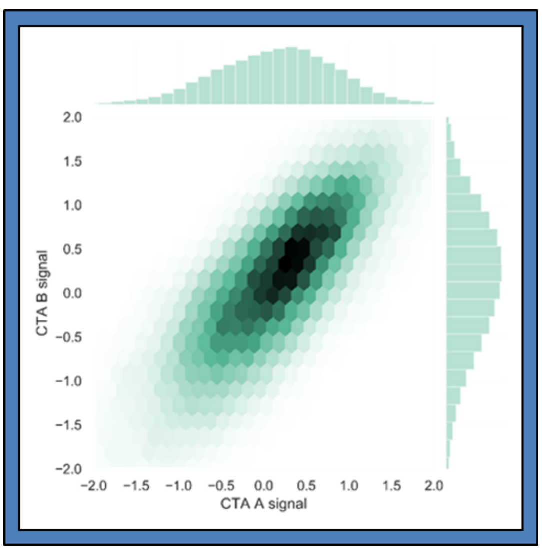
One explanation is "stock versus flow." The natural concern is that any individual CTA will overestimate available liquidity inasmuch as it fails to fully consider the combined assets of similar participants, who will also presumably be making their own assessment of available liquidity. However, this phrasing of the issue ignores a key differentiation between positions and trades – what we call the *stock* (the collective position across the space) and the *flow* (the incremental changes in that position by participant, for which the question of liquidity is highly relevant.) Indeed, even for two hypothetical CTA's with identical market allocations, they may have substantial differences in their respective parameterizations (e.g., speed) of their strategies.

Toy Model

Two similar trend-following strategies are run on each liquid futures market. Here trend following has been defined as being an exponentially weighted moving average crossover (EWMAC). The two strategies have similar effective speeds in terms of information window, defined as the number of days into the past that contain 50% of the EWMAC weight. For CTA A, a single medium speed EWMAC has been used. For CTA B, a mix of both a fast and slow EWMAC has been used. Both CTAs have an effective speed of around 45-50 days.

The mean signal correlation between CTA A and B across more than 100 such markets is 0.77 over the past decade, whilst for the changes in signal (Δsignal), the mean correlation is 0.58. Next, because signals are all normalized into the same units, we can aggregate all the data into a single relationship. This is displayed as a density plot in Figure 2 due to the large number of data points (260,000). For this super-sample, signal correlation is 0.79 and Δsignal correlation is 0.58 – very similar to the individual market analysis.

Figure 2
Signal Density for CTA A and B across Liquid Futures



Sources: GIM, Bloomberg.

Note that the Δsignal correlation is likely to represent an *upper* limit for the degree of overlapping trading behavior, because the only difference introduced was in terms of trend horizons and even then, they were "effective speed" matched – we will relax and test this hypothesis next.

A Step Closer to Realism

In the real world, different CTAs – even in the narrowly defined trend bucket – employ a wide range of different techniques to achieve their ends: there are different definitions of "trend" (EWMA oscillator and break-out, for example), different "splines" or response functions mapping raw signal to model conviction, different risk models for inverse-volatility scaling, different portfolio risk controls, different smoothing, buffering and trade/position limits … the list is as potentially as long as there are lines of code in the strategy codebase.

We attempt to construct a more realistic comparison between two (somewhat arbitrary) trend-following CTAs. For CTA A, we adopt a plain-vanilla 1-month realized volatility for inverse position sizing, for which we then simulate positions and trades. For CTA B, an approach more similar to our own strategies has been adopted, including our proprietary robust volatility model, signal and position buffering, and a signal spline incorporating endogenous awareness of forecast uncertainty and trend exhaustion.

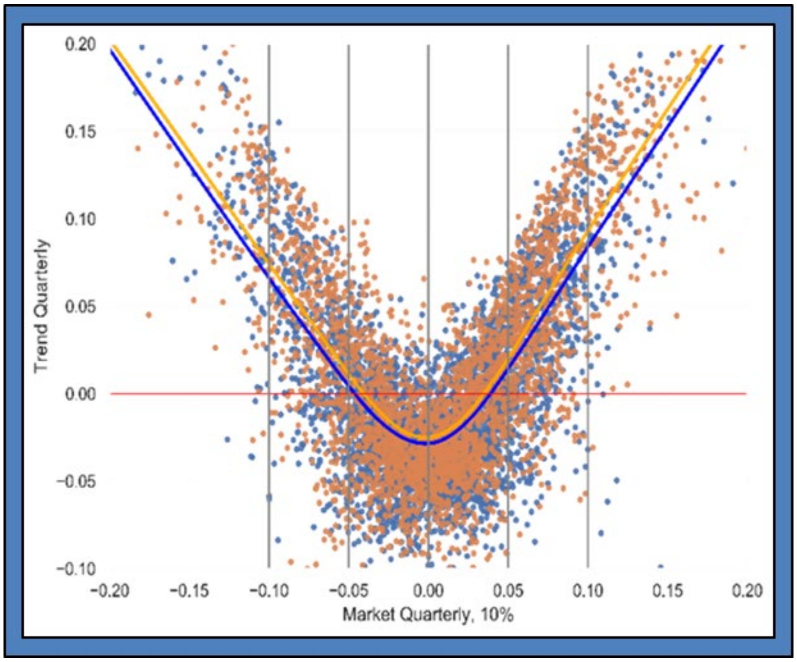
We cannot meaningfully aggregate positions across all futures markets (as notional positions are not normalized) but we can find the correlation for each market in turn, and the average correlation of each pairwise position was 0.74, and the average trade correlation was 0.30 – again, not high, and substantially lower for the "flow" than for the "stock." So, despite having very similar positions, two CTAs' trades can in fact be quite uncorrelated.

<u>Maybe It's the Signal?</u>

When we looked for evidence of overcrowding we failed to find its footprint in the lag-trading analysis. Furthermore, the notion that all trend followers' trading activity is similar was found to be less likely than is commonly believed. So, if we cannot convincingly blame overcrowding for poor trend performance post-GFC, perhaps we can instead blame the machinery of trend following itself. Maybe EWMACs and their ilk no longer efficiently capture trends in markets?

Using the same trend-following definition as used in Figure 1, we plot in Figure 3 the risk-adjusted quarterly returns[2] of futures markets[3] versus the resulting simulated quarterly return from trend following[4] on those individual markets, splitting the data into pre- and post-GFC. For both periods we overlay a Loess line of best fit. The resulting convex "CTA smile" is a well-known result and demonstrates how trend following is akin to a synthetic long straddle (e.g., Merton (1981), Fung and Hsieh (1997) and Dao *et al.* (2016).) It is perhaps remarkable that the pre- and post-GFC relationship is virtually identical. Crucially, therefore, the mechanism by which trend following translates market moves into trend returns has not altered.

Figure 3
Quarterly Return CTA Smile for Liquid Futures in Two Periods (orange = pre-GFC, blue = post-GFC). Loess Fits Indicated. Market Quarterly Returns are Risk-Adjusted to 10% Annualized Risk.



Sources: GIM, Bloomberg.

So What Changed?

If we look at the density of data in different regions of the observed CTA smile, we find that there is a difference between the two periods. Table 1 sets out the proportion of quarterly market returns that were "small" (absolute returns < 5%) and "large" (absolute returns > 10%). There has been a marked shift of occurrence away from *large* trends and into *small* trends.

Table 1
Occurrence Counts for Small and Large Risk-Adjusted Market Quarterly Returns

	Small Trend (|Mkt Retn| < 5%)	Large Trend (|Mkt Retn| > 10%)
pre-GFC	59% of quarters	10% of quarters
post-GFC	68% of quarters	5% of quarters

Given that trend following, viewed as a straddle, can be characterized as bearing an options cost when markets are not trending (the central region) and a pay-off when markets are trending (the tails), this observation explains the weak performance of trend following in the post-GFC period – markets spent more of their time in small weak trends and the occurrence of larger trends was almost halved. It is beyond the scope of this paper to proffer a reason as to why markets have trended less in the past decade but the fact that the cause lies with the markets rather than with trend following itself suggests that those same markets could exhibit larger trends again in the future, with a commensurate improvement in trend-following performance.

Concluding Remarks

We were unable to find evidence that the poor performance of mainstream trend followers over the past decade (post-GFC) was due to overcrowding and found that even similar trend-following approaches can result in lowly-correlated trading activity. Indeed, the "mechanical" transformation of market moves into resulting trend-following returns was shown to be the same pre-/post-GFC, implying that the act of trend following itself was not "broken." Rather, it appears that the cause lies with the behavior of the markets themselves, with a marked reduction in the occurrence of large (quarterly) moves in markets. Therein lies some hope for mainstream trend followers since the cause appears to be exogenous and one might expect that the behavior of markets could change again in the future. However, as we do not have a crystal ball we will instead look elsewhere for markets that have continued to exhibit larger trends – this will be covered in Part 2 in a forthcoming edition of the *GCARD*.

Endnotes

1 Exact date choice has minimal impact on conclusions.

2 Chosen to be similar in timeframe to the horizon of medium-speed trend followers.

3 Risk-adjusted to an annualized risk of 10%.

4 Again, targeting 10% annualized risk.

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Dr. Thomas Babbedge has over 10 years of experience building and assessing quantitative trading systems for the world's largest CTA. After obtaining a Ph.D. in Extragalactic Astrophysics from Imperial College London, he worked as a post-doctoral researcher at Imperial and a visiting researcher at Caltech. In 2007 Dr. Babbedge joined Winton Capital Management where he worked as a Senior Researcher, Head of Investment Analytics, and Personal Researcher for David Harding. In 2016 he joined GreshamQuant within Gresham Investment Management to develop Alternative Market strategies. Dr. Babbedge is an author/co-author of over 50 peer-reviewed scientific papers in international journals including *Nature*, with citations totaling to 6,000.

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