Revolution Capital Management

Alternative metrics for Portfolio construction

This page is intentionally left blank.

Version 13.1.1.0

Important Notices

By accessing this presentation herein, the reader hereby agrees to the following conditions:

- The reader will not disclose the information or data herein in any fashion (including but not limited to verbal, written or electronic means) to any outside party for any purpose whatsoever.
- The reader intends to use the data for internal research purposes only.
- The reader qualifies as a "Qualified Eligible Person" (QEP) as defined in CFTC Regulation 4.7.
- The reader acknowledges that the information contained herein abides by NFA Compliance Rule 2-29 regarding the use of hypothetical performance results.

This document is not a solicitation for investment. Such an investment is offered only on the basis of information and representations that are made in the appropriate offering documents. No representation is made that an investor will achieve similar results. Futures trading is speculative and involves substantial risk.

EXECUTIVE SUMMARY

- Mean-variance optimization is an insufficient tool for constructing managed futures portfolios. We explore the issue by examining a mix of trend-following and short-term programs.
- We find that there are numerous causes for this:
  - Time-scale-dependent skewness and kurtosis.
  - Time-dependent correlations to trend-following.
  - Limited degrees of freedom (i.e. independent return streams) available, mostly at short time scales.
  - Obscuring of true degrees of freedom by manager-specific idiosyncrasies ("idiosyncratic noise").
- Optimal portfolio construction must account for these issues.
- Stressor-response analysis is a viable alternative to mean-variance approaches for creating robust portfolios.
  - Robust systems arise naturally without explicitly optimizing for performance or drawdowns.
  - Portfolio designers need to work more closely with CTAs to successfully implement this approach.

Section 1

Data Sets

Data set details

- We use 8 trend followers from the Newedge CTA Index.
- We use 8 short-term programs from the Newedge Short-term Traders Index, including Mosaic Institutional.
- We add Revolution's Alpha program since it bridges the gap between the two styles.
- We analyze 69 months of data between March 2007 and November 2012 (inclusive).
- All data is actual except for Ion's between March 2007 and October 2007; this was obtained from their back-tested simulations.
- All data sets are normalized to 12% annualized volatility based on monthly returns.
- No attempt is made to do running adjustments to volatility migrations (e.g. Winton).

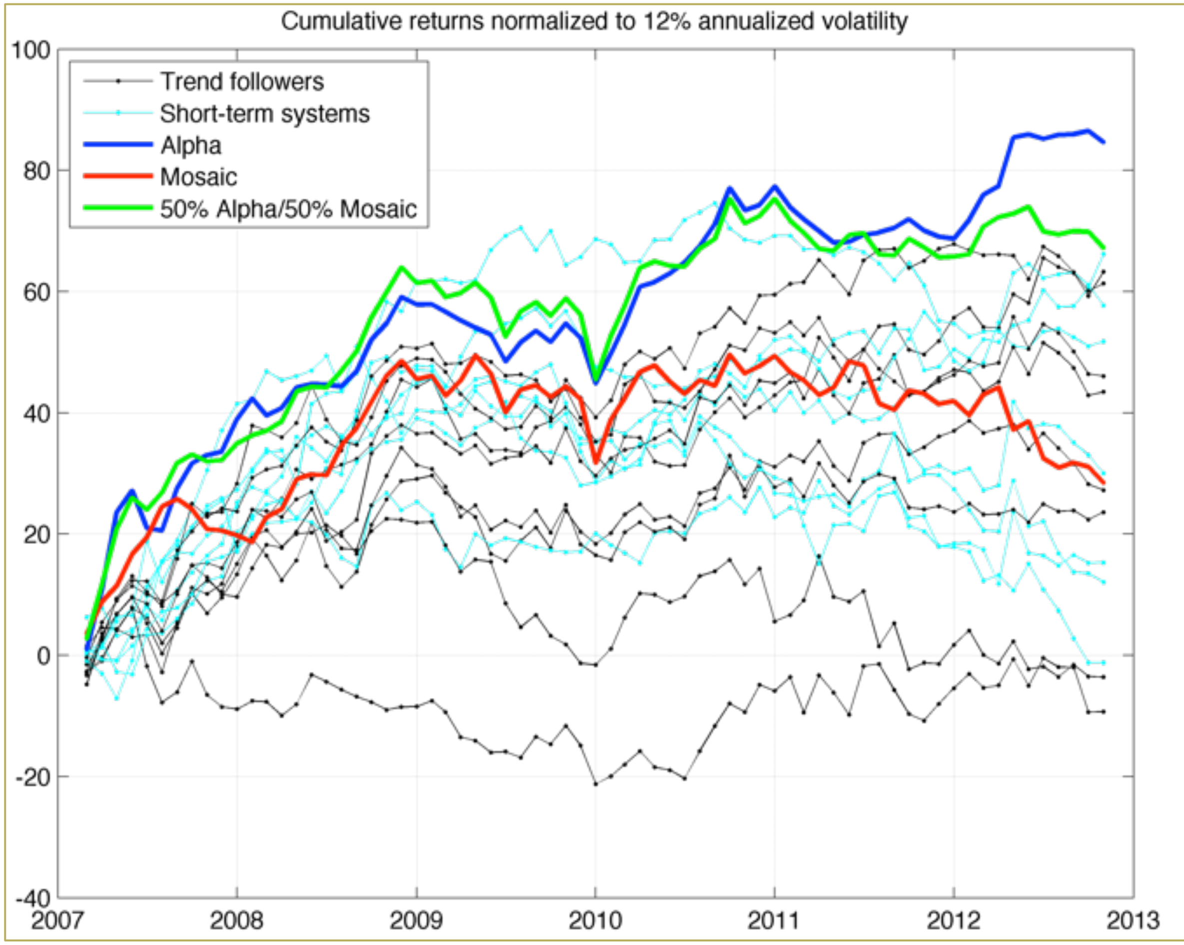
Trading programs

Trend followers	Short-term traders
MAN AHL	Boronia
Aspect	Conquest (Macro)
Campbell	Crabel (Multi-product)
Cantab (Aristarchus)	Ion
FX Concepts (Multi-strategy)	Kaiser
Lynx	QIM
Transtrend	Niederhoffer (Diversified)
Winton	Revolution (Mosaic Inst.)
	Revolution (Alpha)

All trend followers are in the Newedge CTA Index. All short-term traders are in the Newedge Short-term Traders Index except for the Revolution Alpha program.

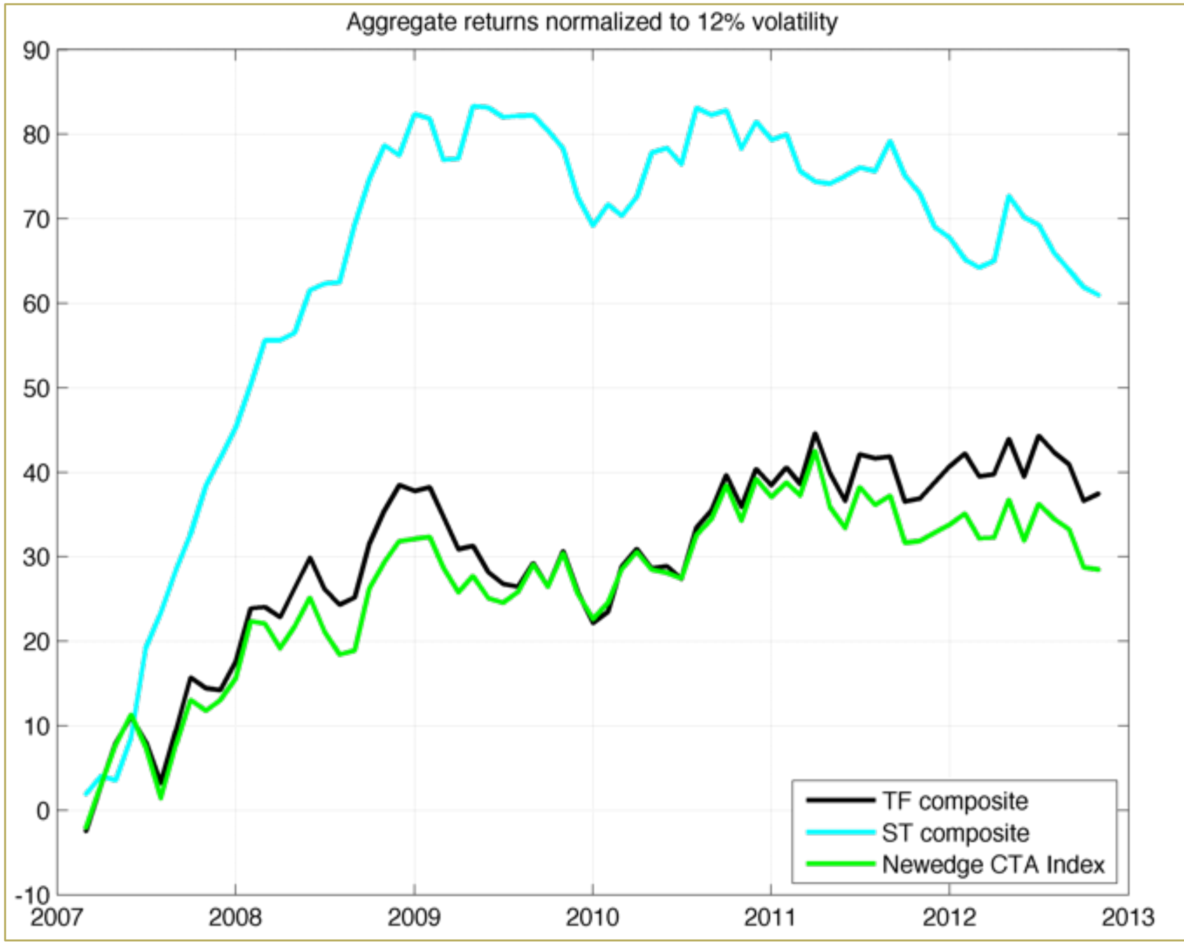
REVOLUTION Capital Management

Cumulative returns



- All returns are normalized to 12% annualized volatility.
- Trend followers are shown in black, short-term traders in cyan.
- Alpha, Mosaic, and a 50/50 mix are shown in blue, red, and green, respectively.
- Alpha has the best performance over the time period, while Mosaic is in the 50th percentile. The 50/50 mix is 2nd behind Alpha.
- The performance spread of trend followers and short-term programs is about equal.

Cumulative returns vs. style



- On a volatility-adjusted basis, short-term systems have outperformed trend following, largely due to strong 2007/2008 performance.
- The composite of our sampled TF programs is very similar to the Newedge CTA Index.
- Short-term systems have underperformed trend following since 2009.

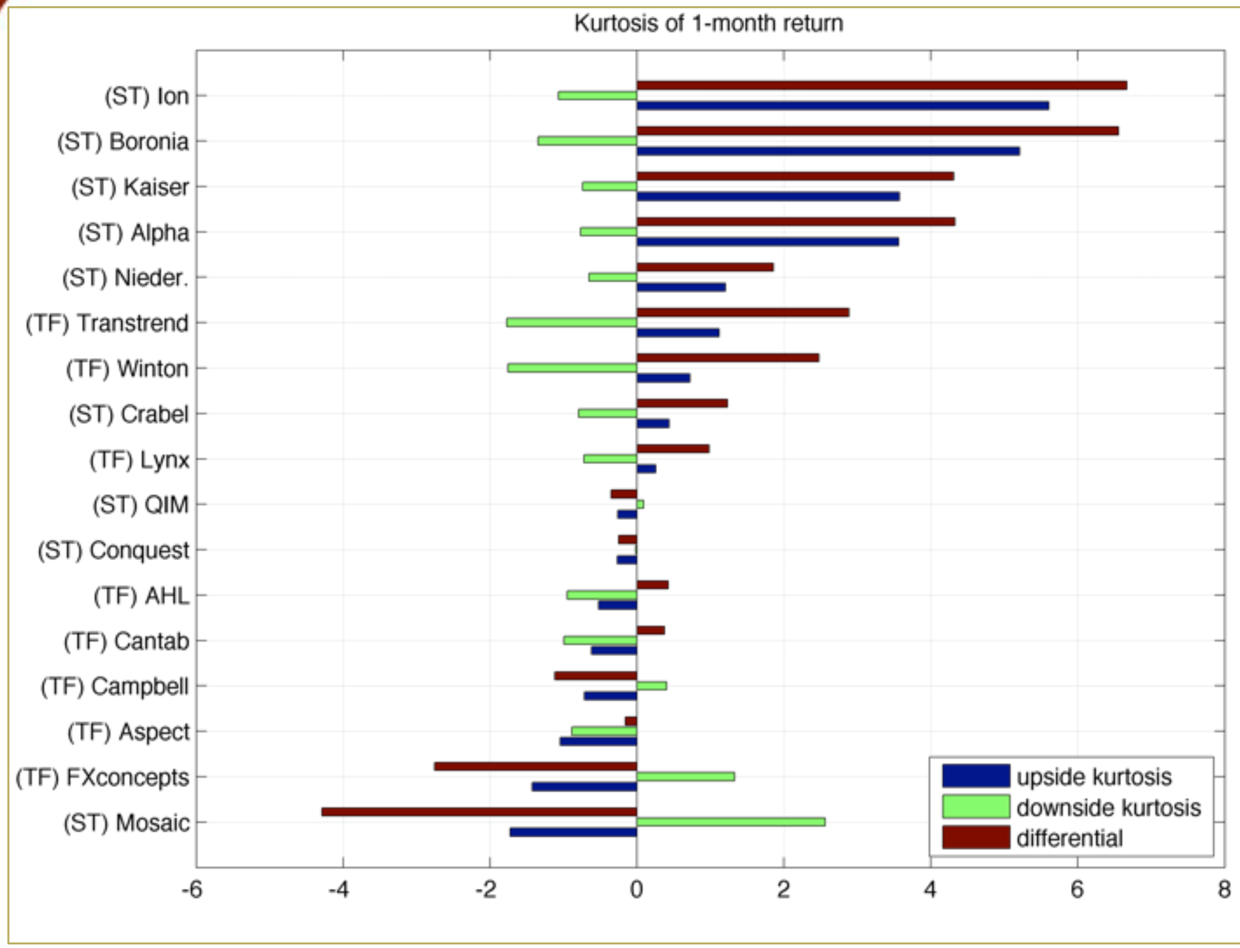
Section 2

Skewness and Kurtosis

Skewness and Kurtosis

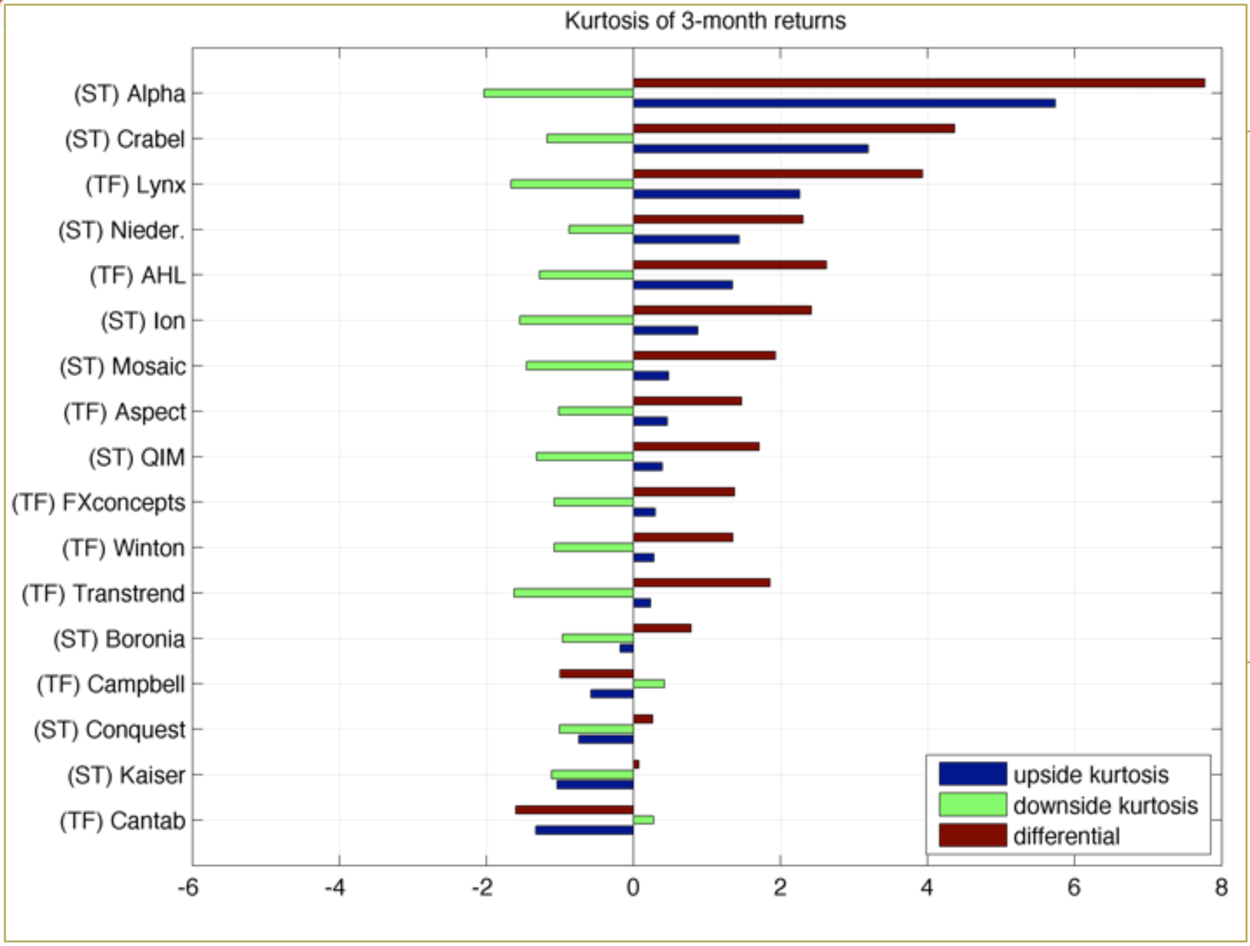
- Skewness and kurtosis are generally linked for futures returns (i.e. negative skew = fat downside tail and positive skew = fat upside tail).
- By separating out positive kurtosis and negative kurtosis, we can see a system's properties in greater detail.
- On 1-month time scales, most programs have positive excess upside kurtosis and negative excess downside kurtosis ("excess" means relative to Gaussian distribution).
- Short-term, trend-biased systems are most likely to have positive excess upside kurtosis.
- On 3-month time scales, the picture is dramatically different. Mosaic, which has negative excess upside kurtosis on 1-month scales, is fairly neutral on 3-month scales. This is a deliberate outcome of system construction.

Kurtosis of 1-month returns



- Long-term trend followers are fairly neutral.
- Short-term trend-biased systems tend to have positive excess upside kurtosis.
- Mosaic has negative excess upside kurtosis and positive excess downside kurtosis.
- [“Differential” = upside excess kurtosis – downside excess kurtosis].

Kurtosis of 3-month returns



- On 3-month time scales, the results are quite different.
- Nearly every system has negative excess downside kurtosis.
- Mosaic's statistical properties are now much like the others.
- Short-term, trend-biased systems now have 3 of the 5 lowest differentials.

Skewness and Kurtosis conclusions

- These statistical properties can be heavily time-scale-dependent, but there is generally an approach toward Gaussian distributions on longer time scales.
- System style affects how risk is accumulated or shed and thus drives short-term kurtosis.
  - Degree of momentum component(s) is critical factor.
  - This may be due to deliberate or inadvertent system design.
- Risk management and trading style are inextricably linked.
- Designers need to understand how and why the time-scale dependence exists for each program.
- Mean-variance optimization is naive and cannot effectively incorporate this information.
- Over-reliance on monthly-based skewness and kurtosis measures (often via the Sortino ratio) can lead to "inbreeding".

Section 3

Idiosyncratic noise, degrees of freedom, and the illusion of diversification

Definitions

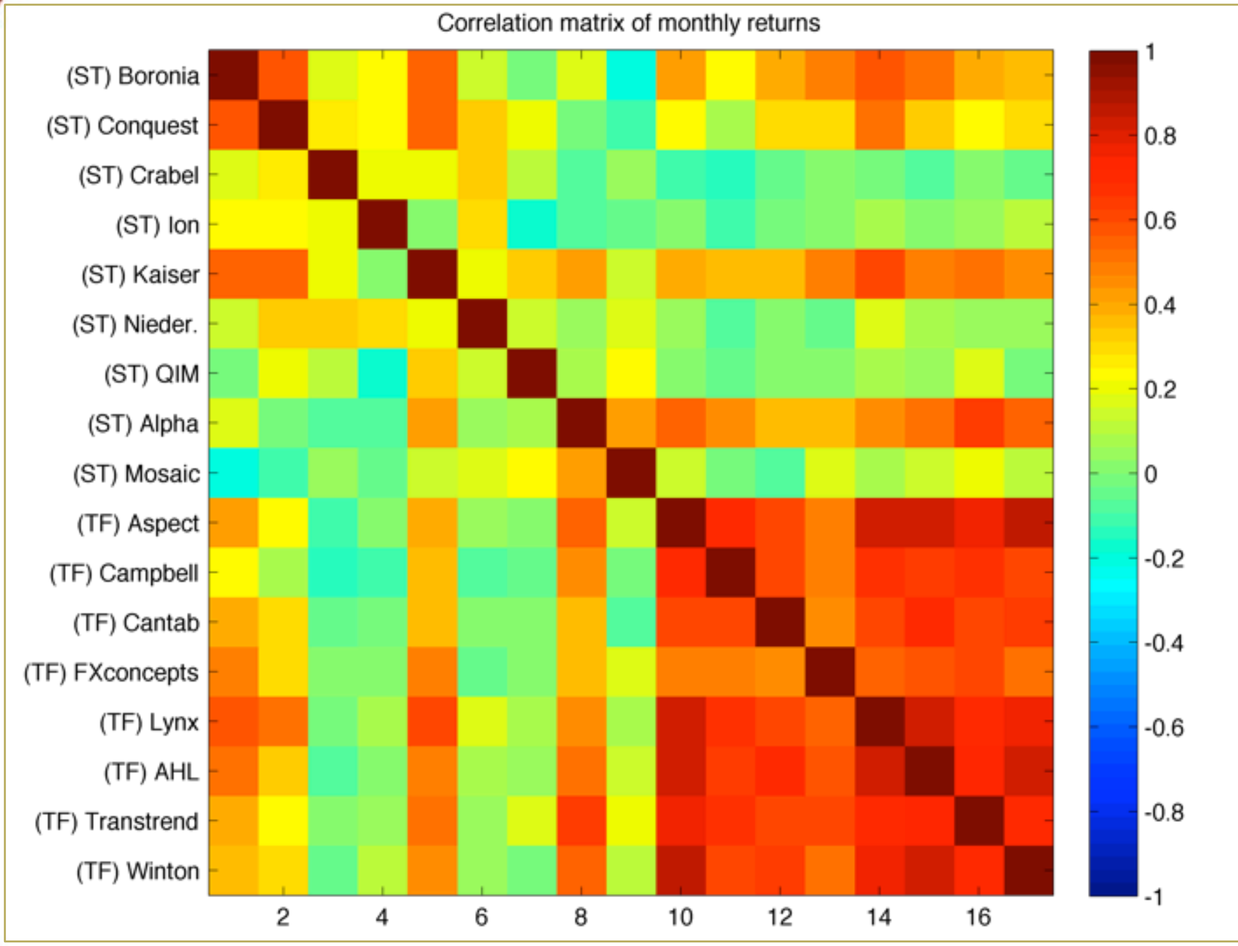
- ***Degree of freedom (DOF)***: a truly-independent return stream that is (by definition) structurally uncorrelated to other return streams.

- ***Idiosyncratic noise***: the return variability that arises between managers not due to true differences in trading strategy but rather due to differences in market or sector weightings, volatility estimation approaches, trade entry/exit nuances, and any other particulars of the system **implementation** (as opposed to the system **concept**).

How many DOF are there?

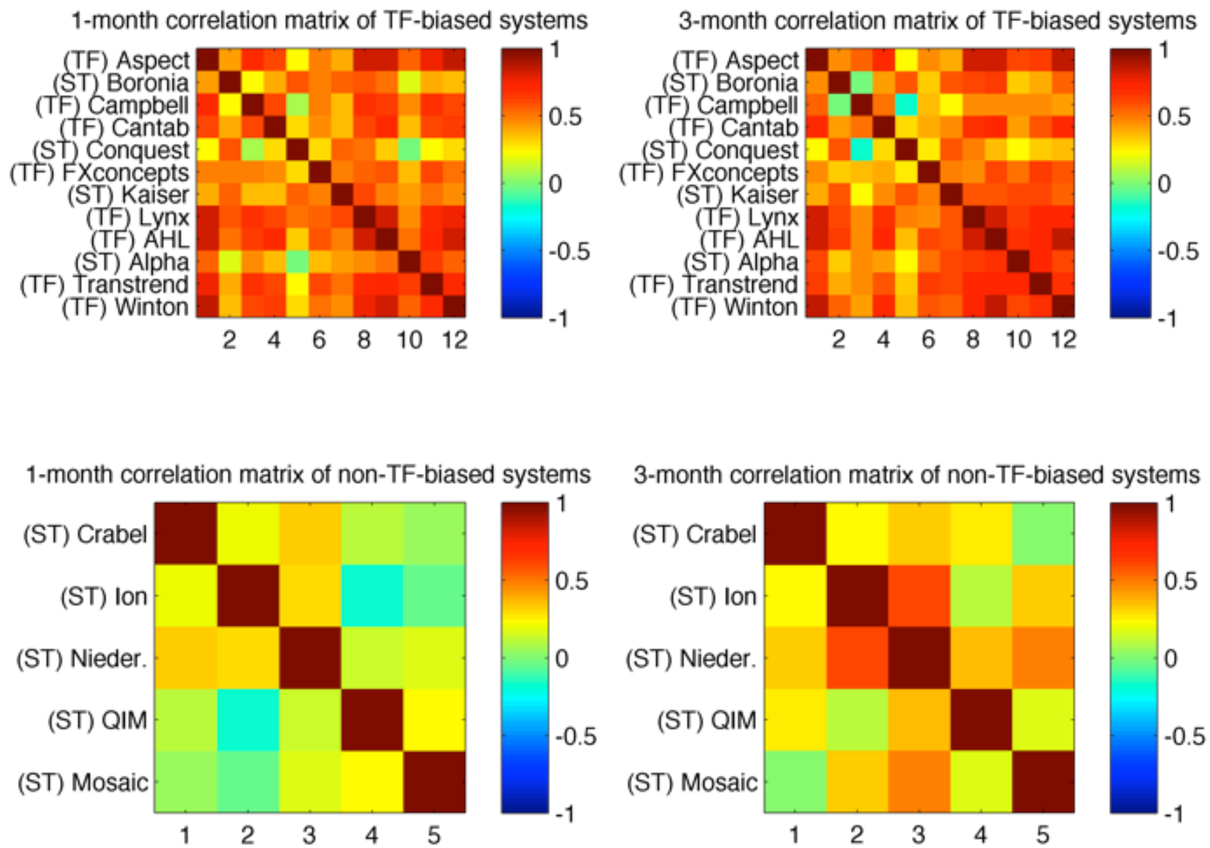
- In an ideal world, there are an infinite number of DOF available for portfolio construction (though perhaps not in equal numbers).
- In reality, three different methods lead us to the same estimate, which is both finite and relatively small.
- Approach #1: Time-scale cascade
  - Simple empirical observation is that a given model shows de-correlated returns when time scales are changed by a factor of 4.
  - If 100 days is a natural time scale at the long end, this implies a cascade towards shorter time scales as follows: 25 days, ~6 days, ~1.5 days, ~0.4 days.
  - We stop counting at 0.4 days due to capacity constraints.
  - Total DOF is thus about 5 if capacity is desired.
- Approach #2: Correlation-based estimation
  - Correlation matrix suggests considerable overlap, especially among trend followers.
  - Correlation-based DOF determination (procedure is described in detail in full document) suggests 4-6 total DOF.
- Approach #3: Principal component analysis
  - After 4th or 5th principal component, amplitudes decay similar to random noise.
  - Best estimate is again 4-6 total DOF.

Correlation matrix (1-month returns)



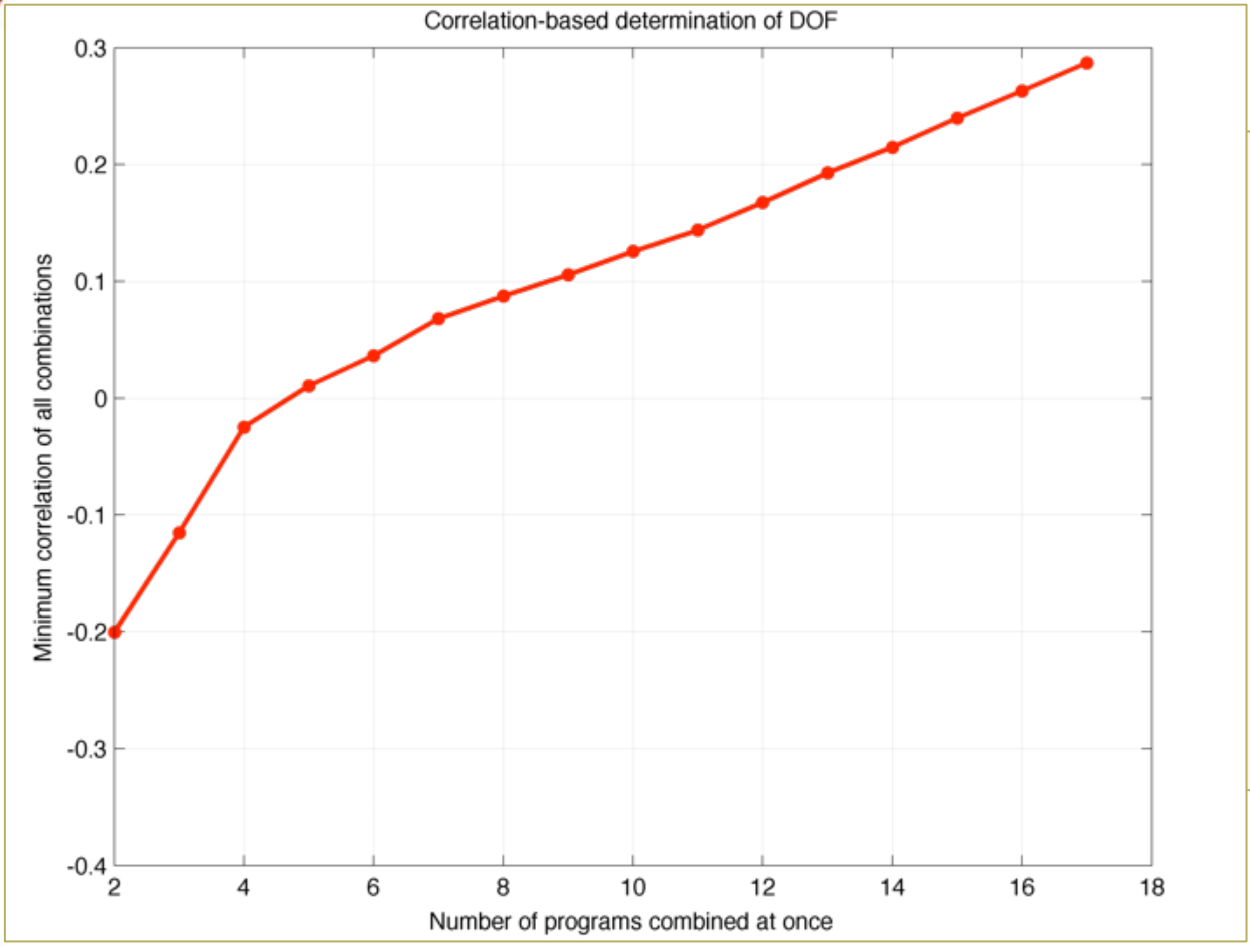
- Trend followers are highly correlated to each other.
- Short-term traders divide into two groups.
- First ST group is trend biased (Boronia, Conquest, Kaiser, Alpha).
- Second ST group is not trend biased (Crabel, Ion, Niederhoffer, QIM, Mosaic).

Correlation (broken out by style)



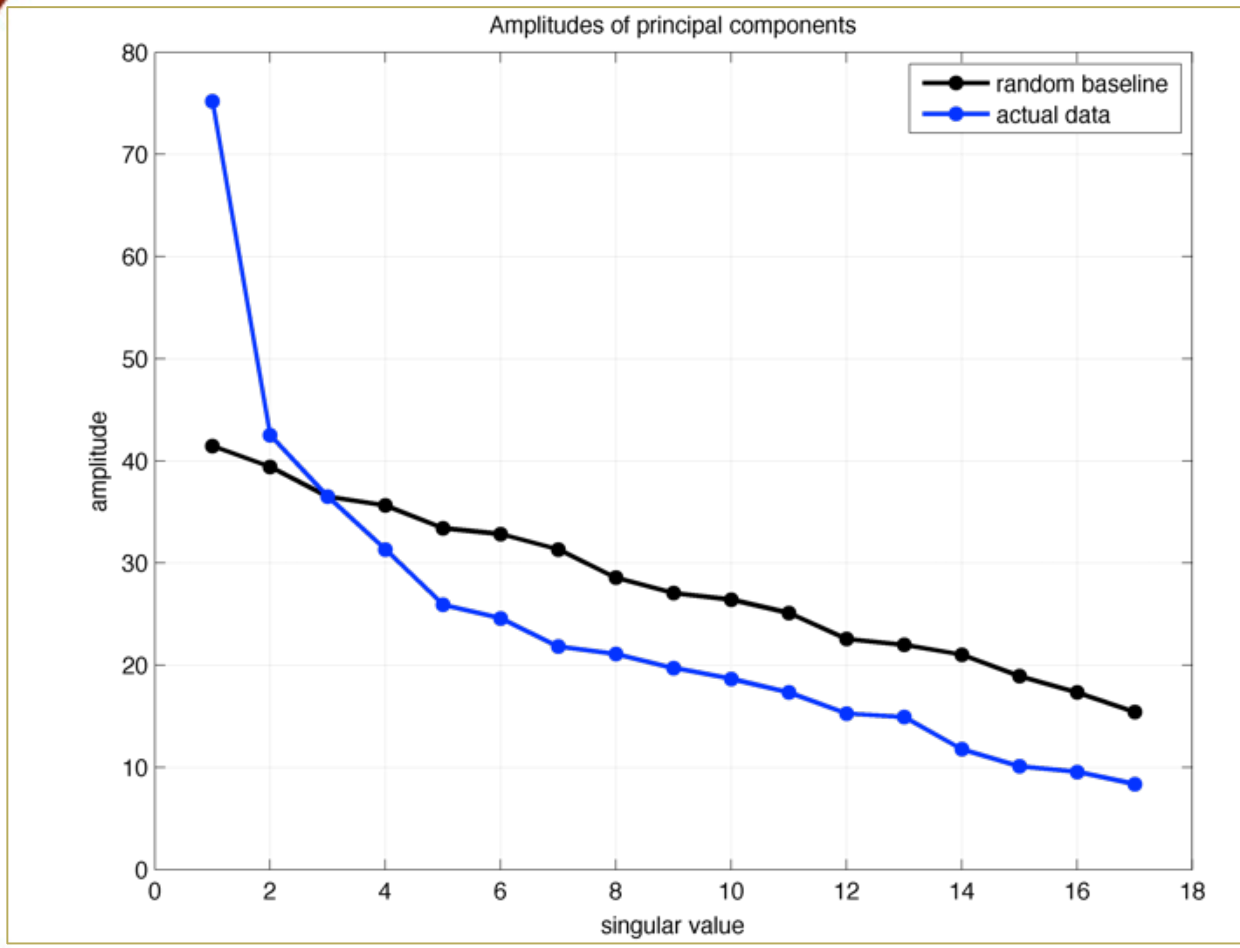
- Non-TF-biased systems show greater diversity.
- Diversity diminishes on 3-month time scales, suggesting an element of idiosyncratic noise.

Correlation-based DOF analysis



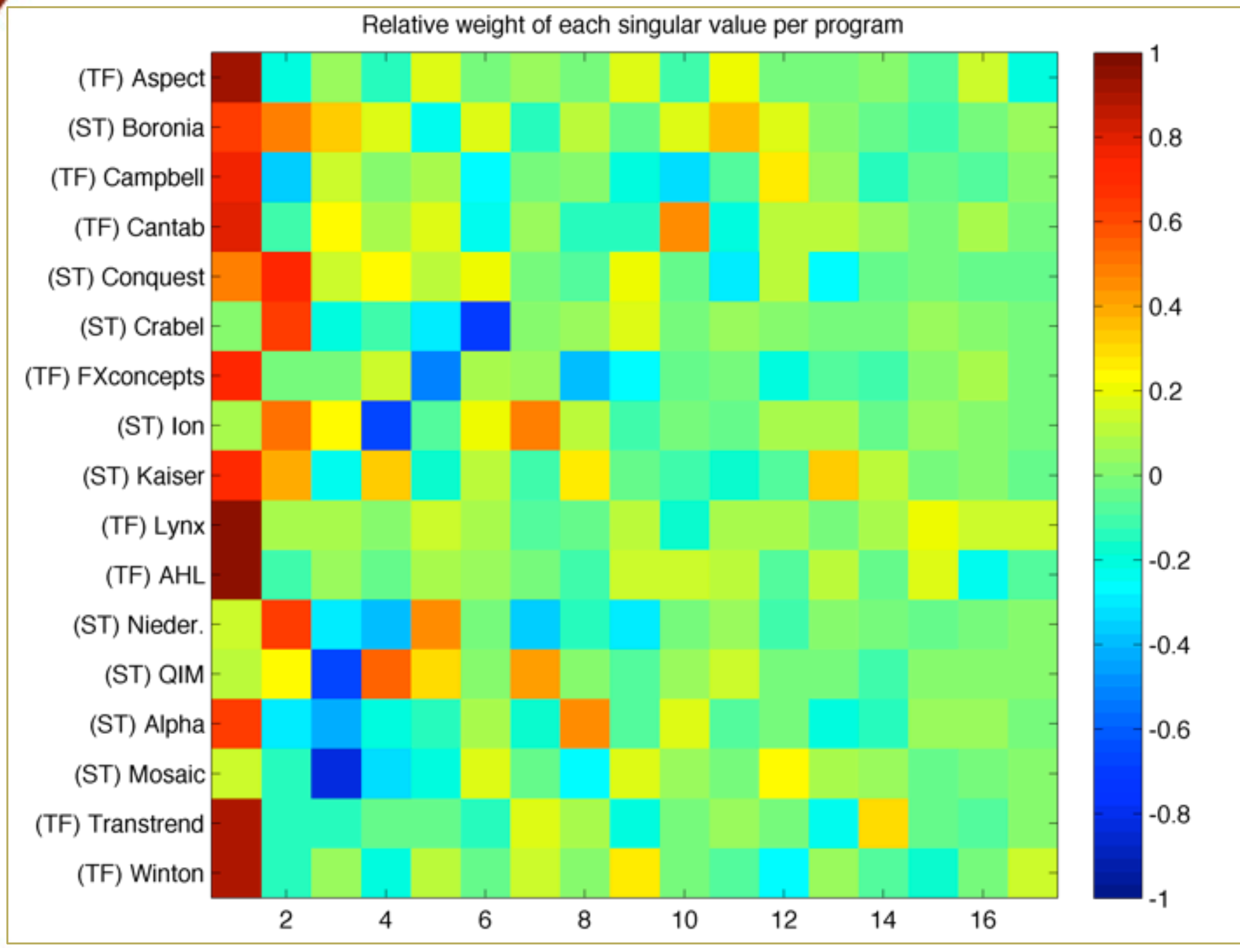
- Once 5 or more programs are combined together, we are unable to achieve non-positive pair-wise average correlation, thus suggesting that there are no more than 4-6 degrees of freedom embedded in these 17 programs.
- This procedure is only approximate and thus, while 5 DOF is our best estimate, the value is somewhat subject to noise.

Principal component amplitudes



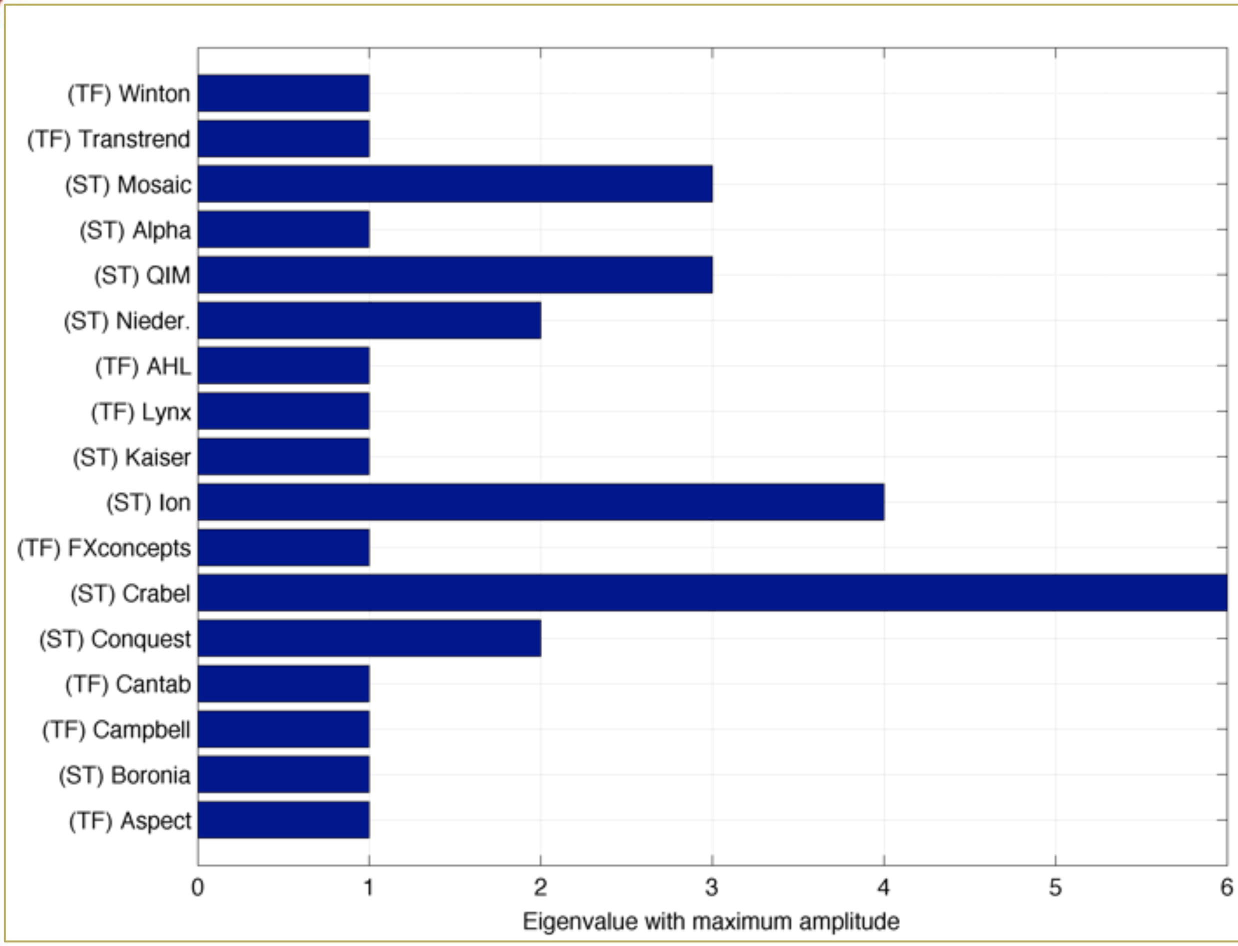
- Principal component amplitudes show decay in line with random noise roughly from 5th component onwards.

Principal component matrix



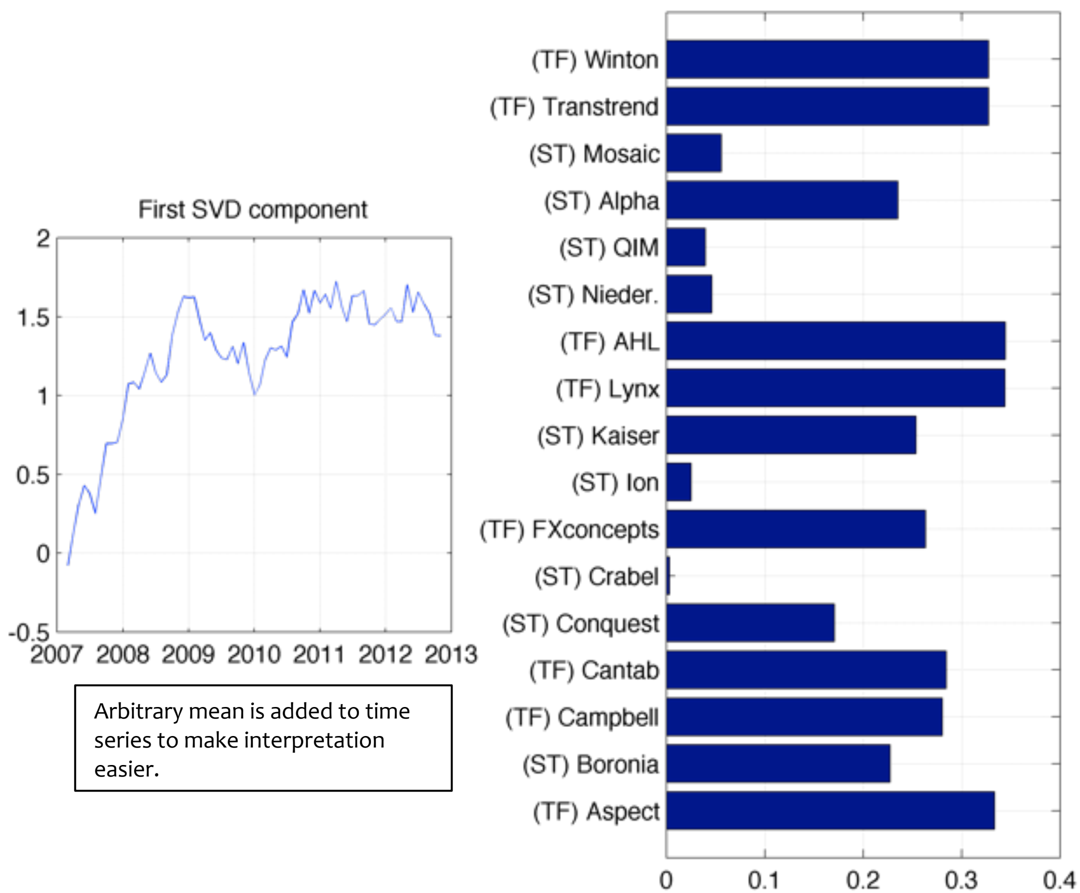
- Principal component 1 is dominant for long-term trend followers.
- Principal component 2 is dominant for short-term trend followers.
- Non-TF-biased systems show components 3, 4, or 6 (in Crabel's case) as the dominant mode.

Dominant principal component Indices



- Component with maximum similarity to a given program is either 1, 2, 3, 4, or 6.
- ALL TF programs have PC 1 as the dominant mode (as well as Alpha, Kaiser, and Boronia).
- Non-trend-biased ST programs have a wider range of dominant modes.
- The overall range suggests 5-6 DOF.

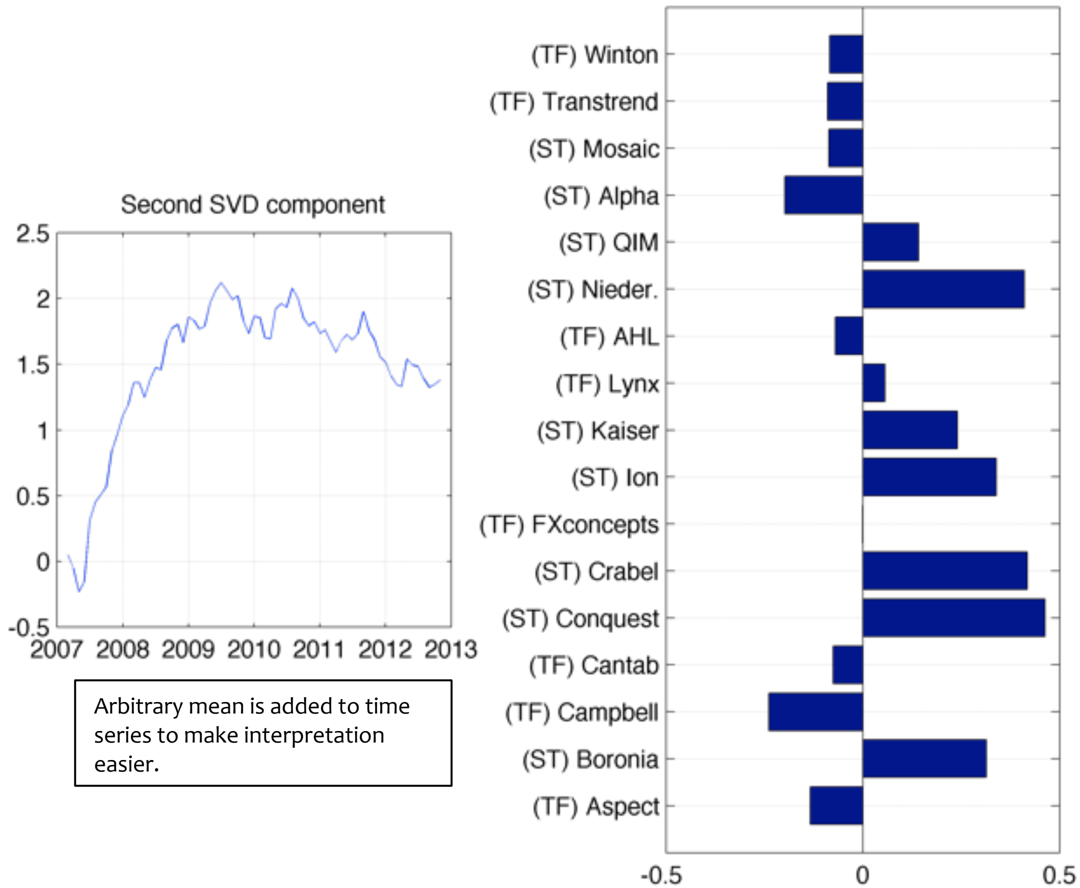
Principal component 1



Arbitrary mean is added to time series to make interpretation easier.

- High similarity to all TF programs.
- No program has a negative exposure to this component.
- The 5 previously-identified non-TF-biased programs have the lowest amplitudes.

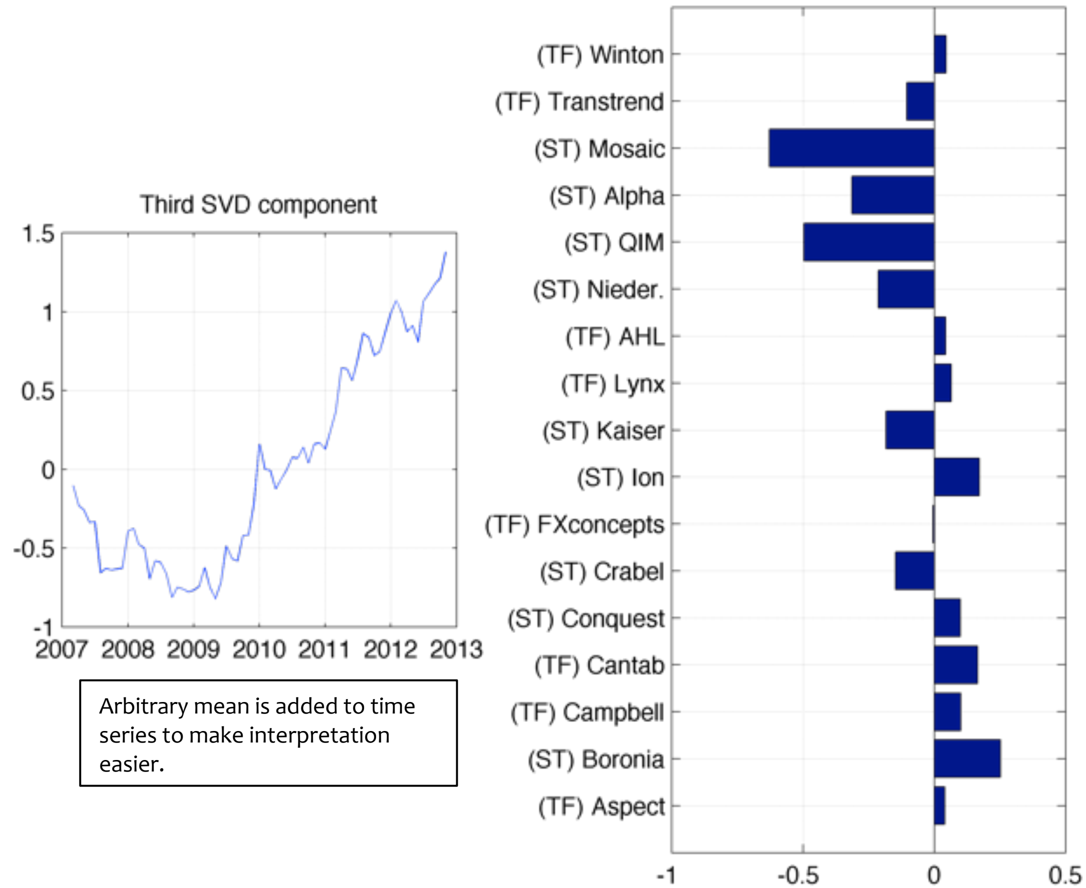
Principal component 2



Arbitrary mean is added to time series to make interpretation easier.

- Short-term systems show the greatest exposure to this mode.
- It is similar to our internal, short-term TF models, and it also closely resembles the overall STTI.

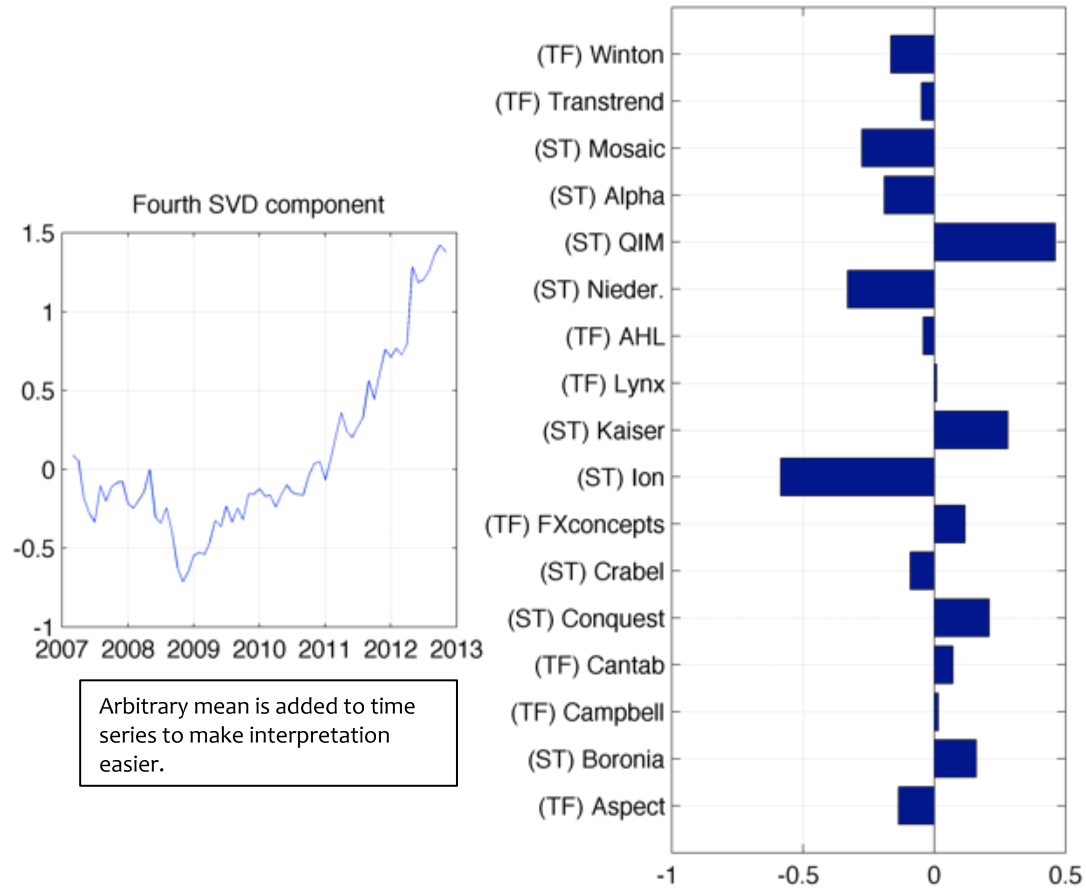
Principal component 3



Arbitrary mean is added to time series to make interpretation easier.

- Mosaic and QIM have the greatest exposure to this dynamic.
- Since they have negative amplitudes, it suggests opposing the dynamic shown in the left-hand plot.
- This is some sort of counter-trend mode.

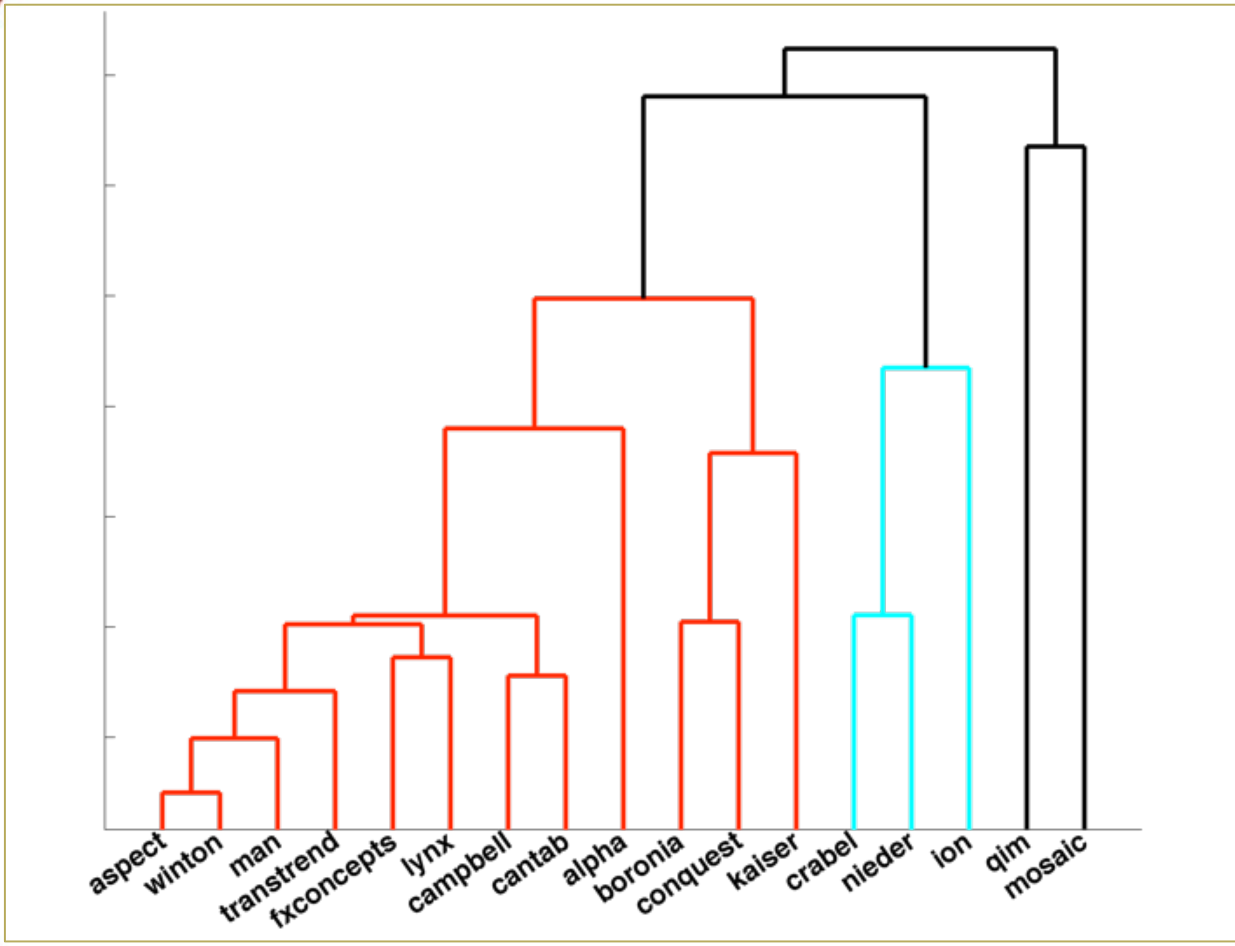
Principal component 4



Arbitrary mean is added to time series to make interpretation easier.

- In contrast to PC 3, Mosaic and QIM oppose each other with this mode.
- Niederhoffer and Ion (and Alpha, Winton, and Aspect to a smaller extent) share this mode with Mosaic. It is another type of counter-trend or mean-reversion mode.

PCA-based family tree



- Classification isbased on first four principal components.
- All 8 TF programs are on left side of tree.
- All 8 ST programs are on right side of tree.
- Mosaic is most closely related to QIM (historically).
- Alpha sits squarely between TF and ST programs.
- Short-term, TF-biased systems (Boronia, Conquest, Kaiser) naturally group together.
- Aspect, Winton, and Man group together (perhaps due to common ancestry).

DOF conclusions

- Three different methods suggest that there are only 4 to 6 true DOF available, with a best estimate of 5.
- Time-scale arguments suggest that most of these are at shorter time scales. This runs counter to most portfolios, which weight longer-time-scale strategies much more heavily (partially due to capacity reasons).
- Idiosyncratic noise, though not providing structural diversification, is still useful for maximizing efficiency of "alpha" extraction and for reducing manager risk.
- Principal component analysis can highlight similarities and differences across programs, allowing one to generate a family tree for a given set of trading strategies.
- The family tree conforms to *a priori* expectations, with Mosaic being mostly unique and disconnected to trend following, while Alpha bridges the gap between trend-followers and short-term systems.
- Recognizing the finite diversification potential is critical for constructing optimal portfolios.

Section 4

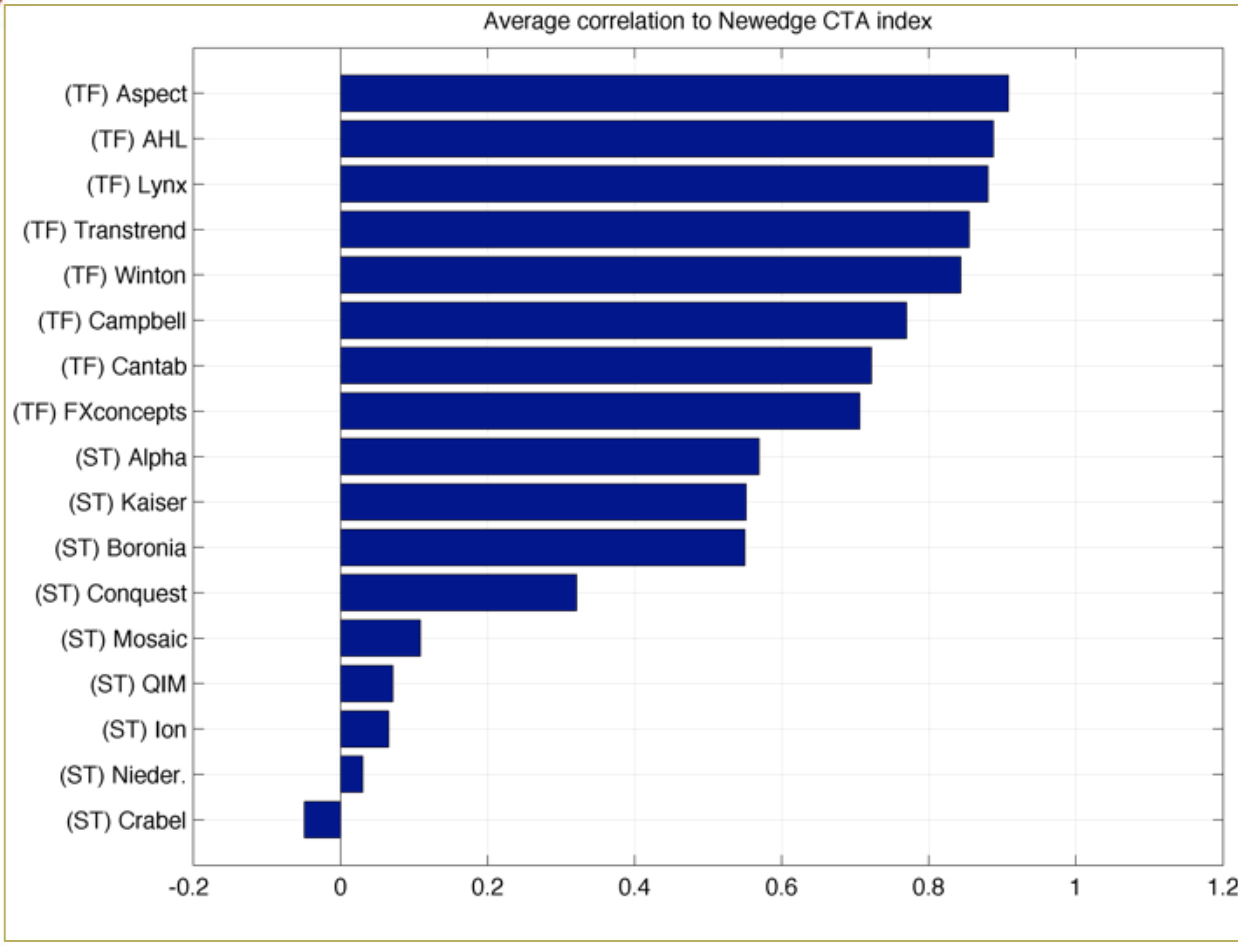
Correlation considerations

Correlation considerations

- Given a total diversity of 4-6 DOF, can we extract useful information from standard correlation analyses?*
- The answer is yes, especially if we look at conditional correlations and also the time-dependent variability of correlations.
- Conditional correlations break out correlation relative to times when trend-followers are either profiting or not.
- Running correlations reveal correlation variability and also show which short-term systems move in (or out of) phase with each other.

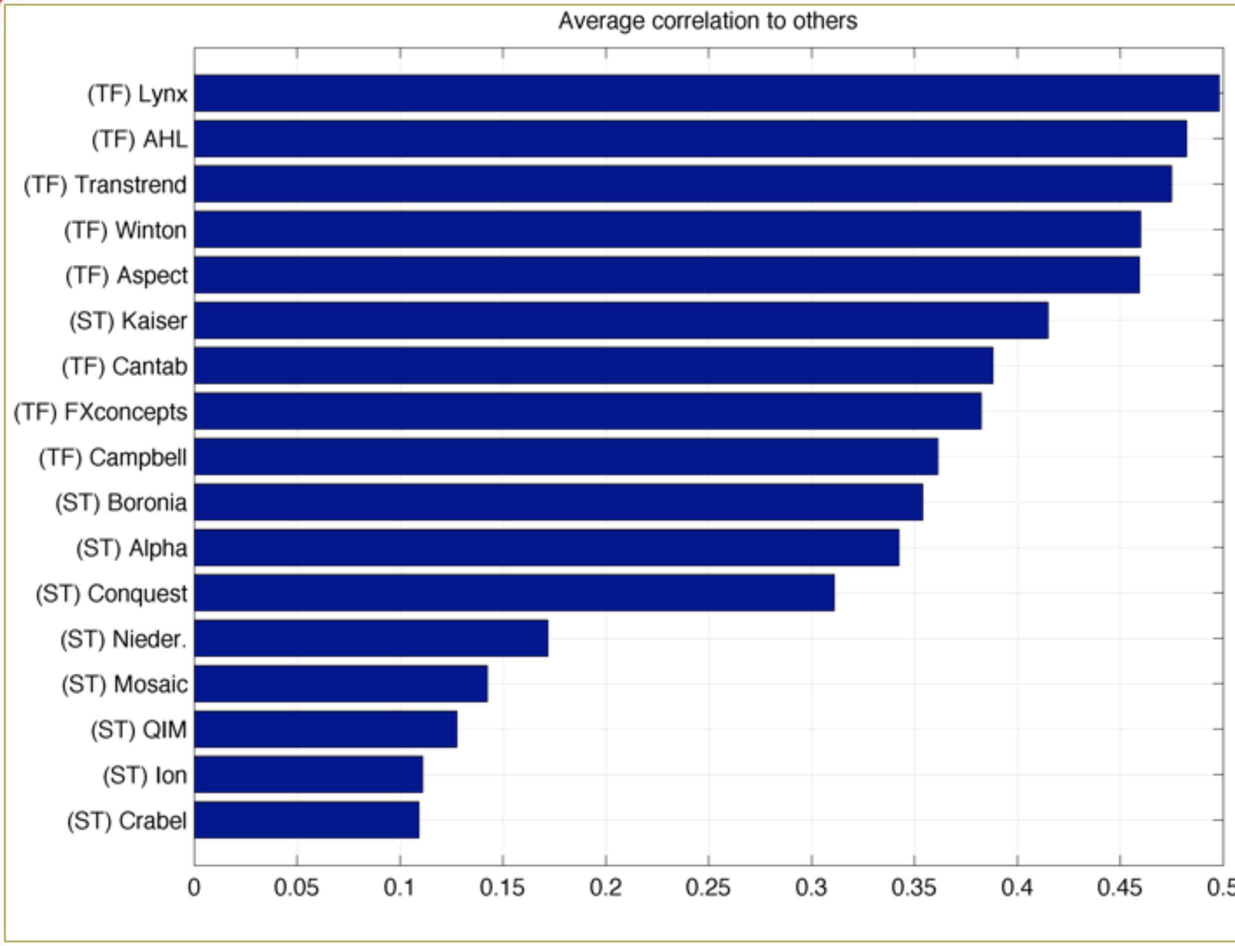
*As an aside, 25 (or 50 or 100 or …) strategies with pairwise correlations of 0.25 don't produce any more **true** diversification than 4 strategies with pairwise correlations of 0.

Average correlations to Newedge CTA index



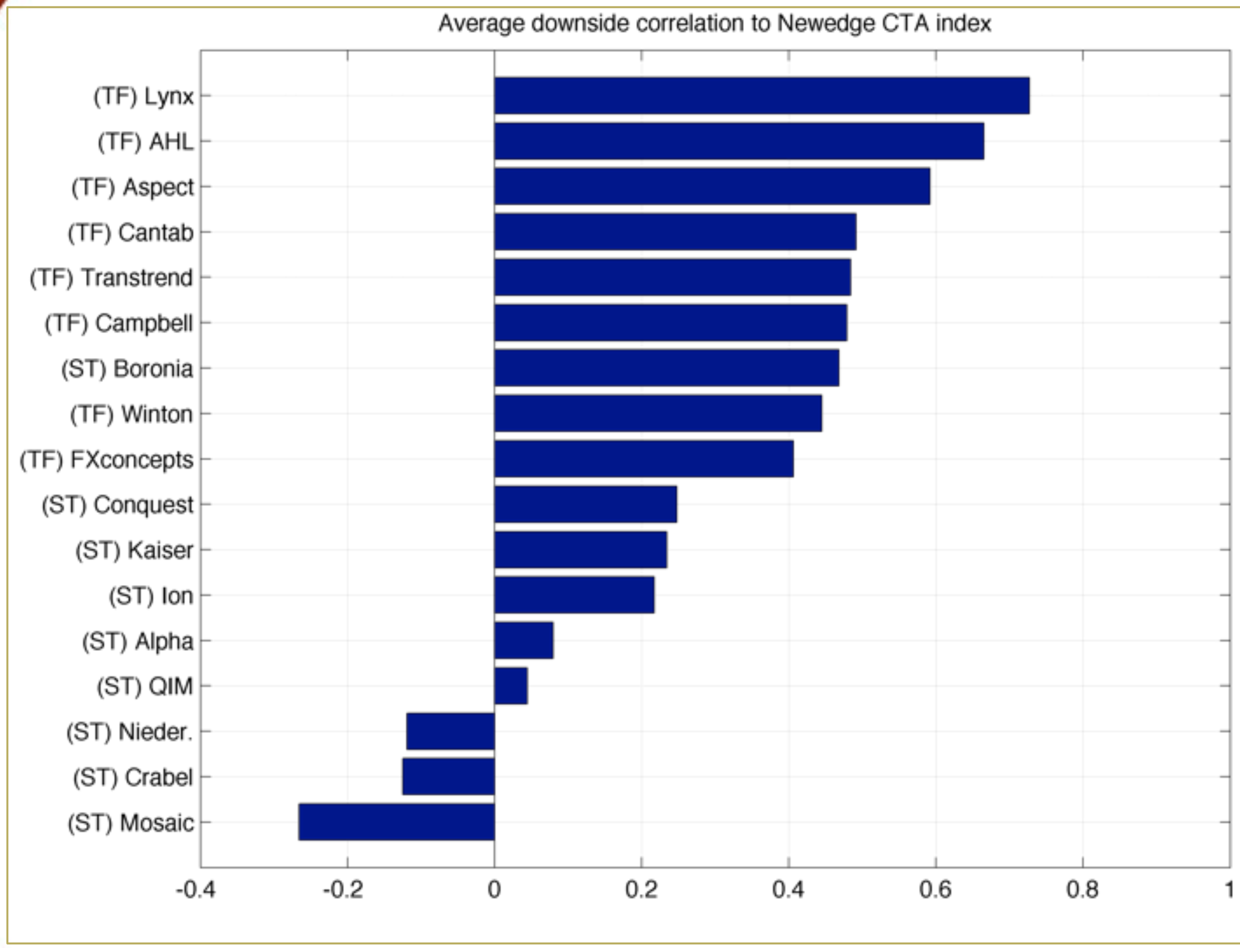
- All trend followers have uniformly-high monthly correlation to Newedge CTA Index.
- Alpha and TF-biased short-term programs have moderate correlations.
- The remaining 5 non-TF-biased systems, including Mosaic, exhibit low average correlations.

Average correlations to others



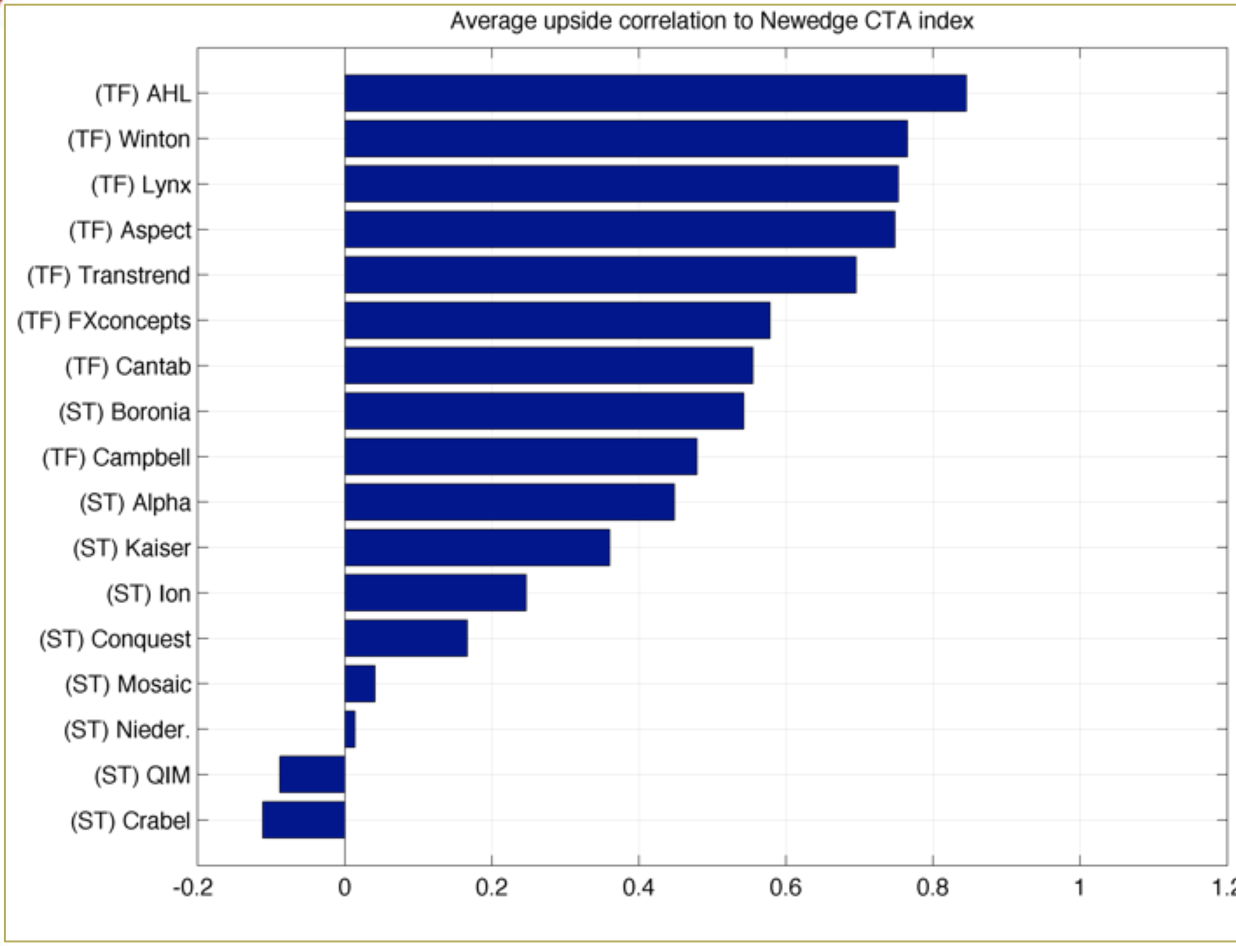
- All trend followers have uniformly-high monthly correlation to Newedge CTA Index.
- Alpha and TF-biased short-term programs have moderate correlations.
- The remaining 5 non-TF-biased systems, including Mosaic, exhibit low average correlations.

Average downside correlations to Newedge CTA index



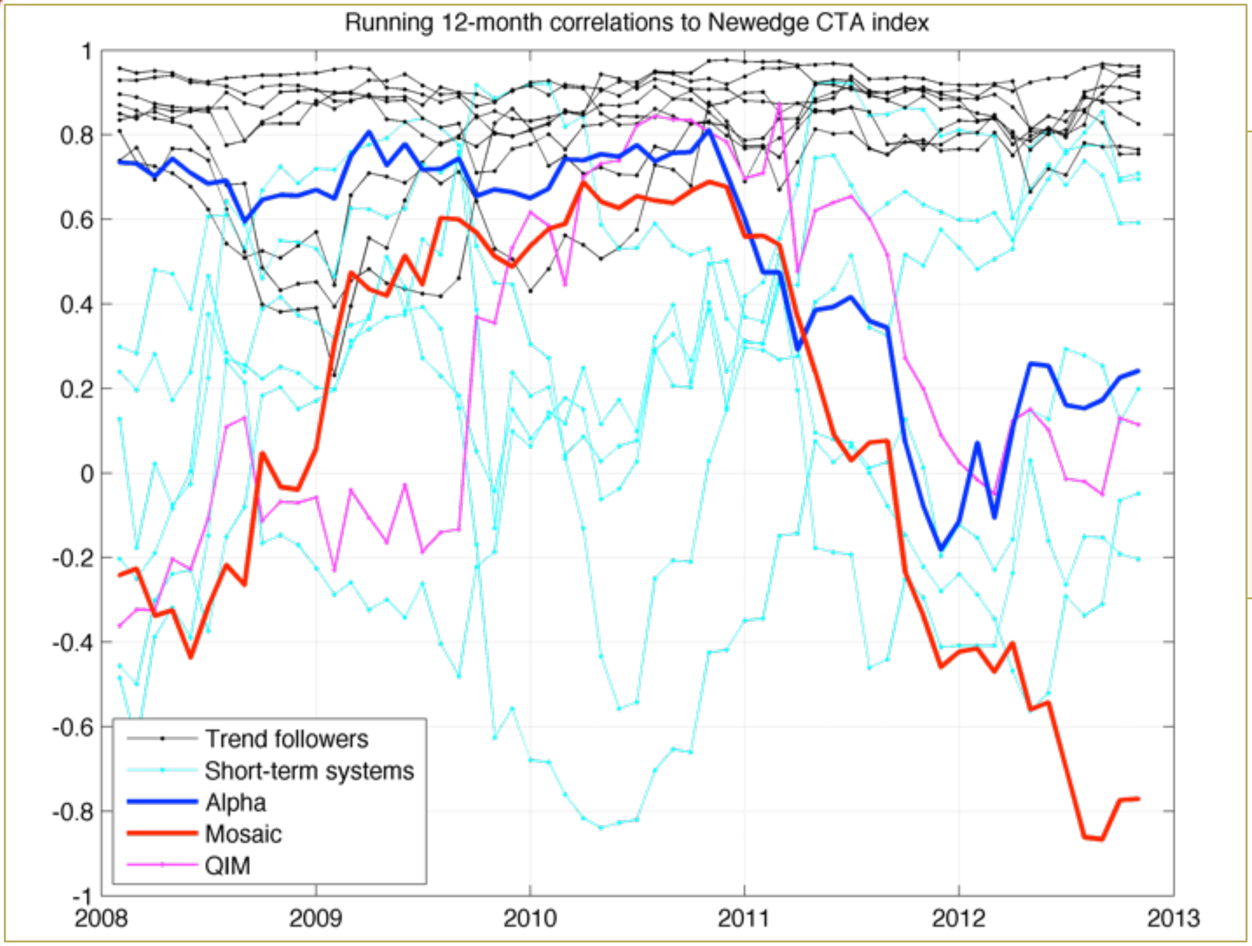
- All trend followers have uniformly-high monthly correlation to Newedge CTA Index.
- Alpha and TF-biased short-term programs have moderate correlations.
- The remaining 5 non-TF-biased systems, including Mosaic, exhibit low average correlations.

Average upside correlations to Newedge CTA index



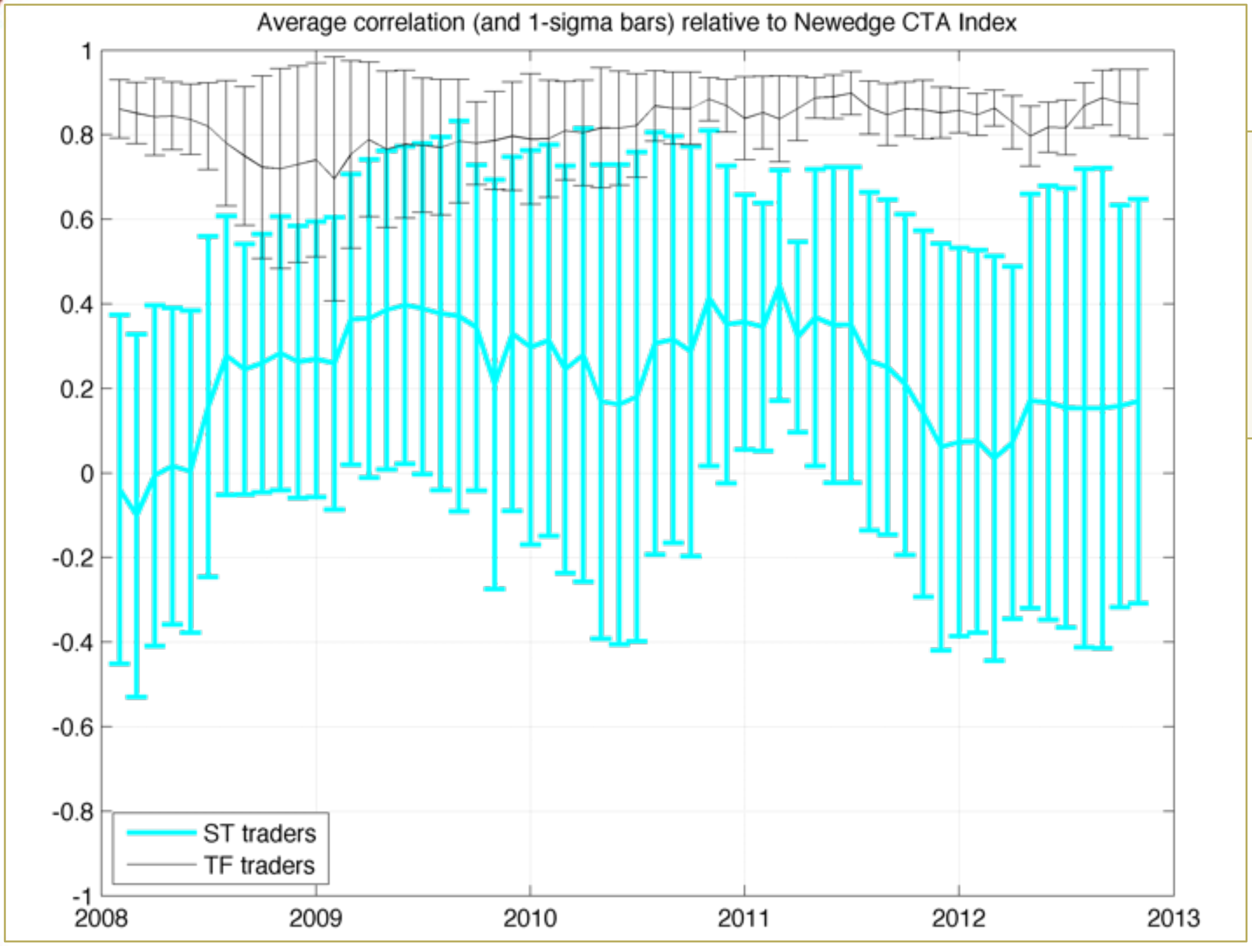
- All trend followers have uniformly-high monthly correlation to Newedge CTA Index.
- Alpha and TF-biased short-term programs have moderate correlations.
- The remaining 5 non-TF-biased systems, including Mosaic, exhibit low average correlations.

Correlation variability per program



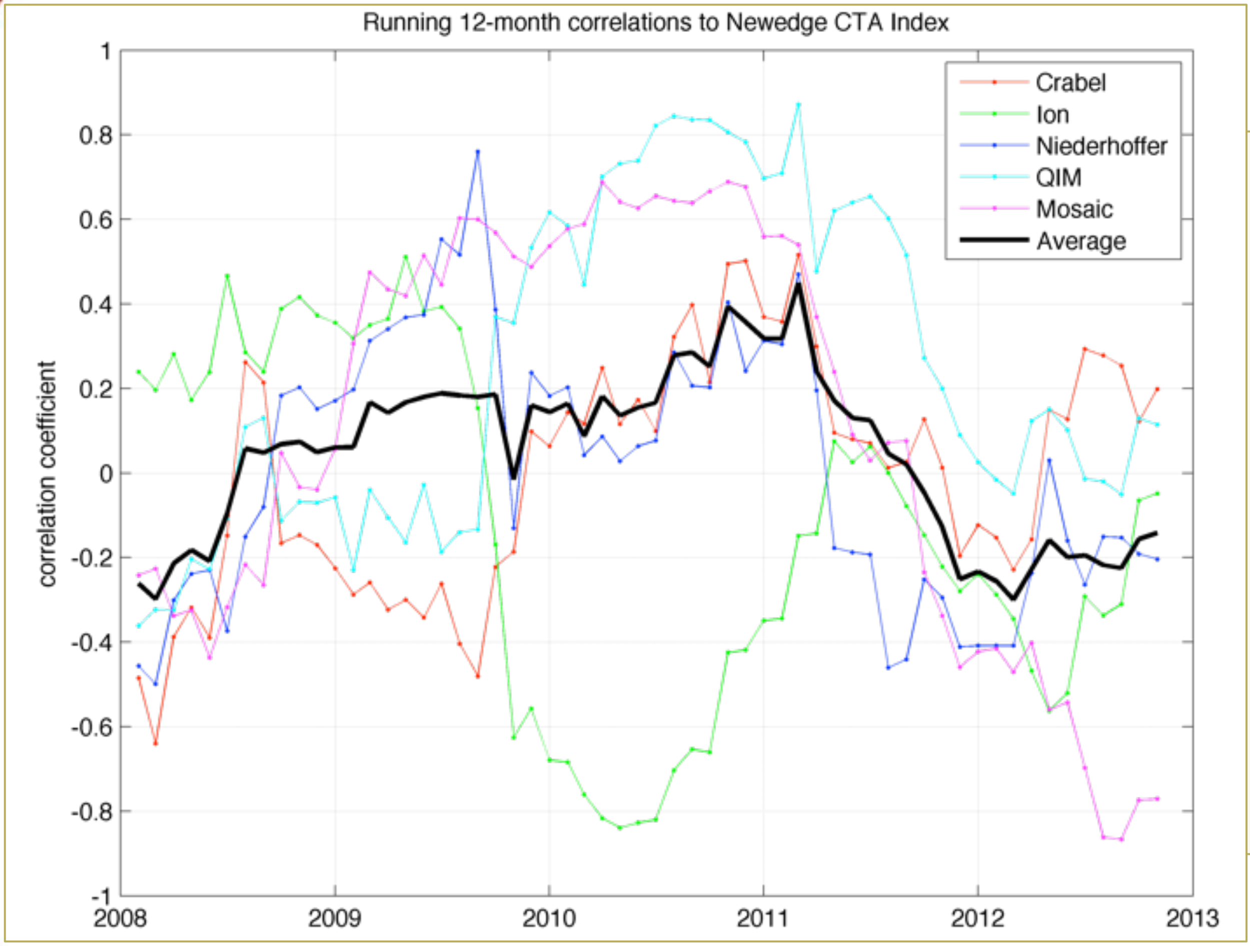
- All trend followers have uniformly-high monthly correlation to Newedge CTA Index.
- Short-term systems show much more variability.
- Mosaic has a large historical range of running correlation to the Newedge CTA Index.

Correlation variability per style



- In aggregate, trend followers show very little deviation from the index.
- Short-term traders show fairly-low correlation on average but much higher variability.

Correlations of non-trend-biased short-term traders



- All of the non-trend-biased ST programs have a large variability in TF correlation.
- The running correlations are themselves largely uncorrelated.
- This information can potentially be used to match up short-term traders to create overall profiles with less TF correlation variability (the average, for instance, shows good stability with an average correlation of ~0.

Correlation conclusions

- Standard correlation analyses are of limited value.
  - They are useful in identifying strongly-trend-biased systems.
  - Looking at cross-manager correlations are of some value in identifying systems with less average overlap to others.
- Improving on this concept, conditional correlation analysis can identify how systems may preferentially help or hurt in situations where TF returns are negative.
- In addition, running correlation analyses show that short-term systems exhibit high variability relative to TF returns.
  - This can be problematic because it's hard to guarantee that these systems can offset TF losses in any particular situation.
  - However, by looking at the "correlation of correlations", one can identify complementary short-term programs whose TF overlap occurs asynchronously, thus yielding a stable, uncorrelated short-term program suite.
- Stressor-response analysis (next section) alleviates many of the limitations of correlation-based techniques.

Section 5

Stress testing and stressor response analysis

Stressor response considerations

- Correlations focus on the output of systems but they don't reveal the *cause* of positive or negative returns.
- One promising alternative is to examine how different systems respond to specific **stressors**. These stressors can further be associated with different macro environments so that one can potentially minimize the sensitivity of a portfolio to a broad range of macro-economic conditions (or at least understand what to expect from a given portfolio).
- Five basic stressors were devised:
  1. Average cross market correlation.
  2. Volatility (based on VIX, the Volatility Index).
  3. Price divergence on 4-day to 8-day time scales. This is essentially a measure of how oscillatory price movements are on these time scales. Large values imply small trends and large mean reversion on the particular time scale.
  4. Price divergence on 16-day to 28-day time scales.
  5. Price divergence on 40-day to 50-day time scales.
- Then we created 5 more stressors based on the rates of change of these quantities, thus arriving at 10 total stress conditions.
  - e.g. rate of change of correlation indicates whether correlations are increasing, decreasing, or constant.
  - Rate of change of price divergence is not intuitive but these conditions correlate highly to the price divergence itself.

REVOLUTION Capital Management

Stressor response considerations

- Response tables segregate historical behavior into lowest quintile of the stressor, highest quintile, and the middle 3 quintiles. Lowest quintile for ROC stressors means that ROC is very negative.
- Results are shown for both end-of-day and intra-day models. Daily data is required, so external programs are not analyzed.

Stressor response findings

- For the correlation stressor, all EOD models prefer a low-correlation environment.
- Focusing on ID models, we can more clearly see trends vs. model type and time scale. Increasing the TF and CCT frequencies yields models that respond more favorably to high-correlation environments.
  - Note that model structure is unchanged; only time scales are altered.
  - This supports the theory of time-scale differentiation as a DOF generator.
- VIX response shows that high-volatility environments are preferred by TF but not our short-term EOD models.
- Correlation ROC stressor produces similar (but even worse) results compared to correlation stressor. CCT 16x model, however, outperforms when correlation ROC is large.
- VIX ROC stressor shows that nearly all models underperform in low VIX ROC environment (i.e. declining volatility).
- 40-50 day divergence stressor shows (unsurprisingly) that TF models underperform when prices oscillate on these time scales. Short-term models exhibit average performance.

Correlation response (EOD models)

Model	Low correlation environment		Average correlation environment		High correlation environment	
	Delta Sharpe	Delta mean, sigma	Delta Sharpe	Delta mean, sigma	Delta Sharpe	Delta mean, sigma
ID CCT 16x	-0.60	-47.4, -18.1	-0.09	-4.9, 2.2	0.86	62.1, 11.7
ID CT 16x	0.67	24.4, -31.5	0.03	10.5, -2.7	-0.75	-56.0, 39.8
Newedge CTA Index	0.24	30.0, -0.7	0.14	20.4, 0.9	-0.66	-91.3, -1.9
Internal TF	0.67	50.5, -9.0	0.19	19.9, -0.6	-1.20	-110.2, 10.8
Alpha	0.73	23.8, -14.1	0.33	21.3, -0.6	-1.72	-87.6, -15.9
Mosaic	0.88	21.8, -18.6	-0.05	-1.2, -1.7	-0.73	-18.2, -23.7

Values in tables are deltas that are relative to the overall average for each particular system.

Correlation response (ID models)

	Low correlation environment		Average correlation environment		High correlation environment	
Model	**Delta Sharpe**	**Delta mean, sigma**	**Delta Sharpe**	**Delta mean, sigma**	**Delta Sharpe**	**Delta mean, sigma**
TF 2x	1.45	95.3, -15.7	-0.04	2.1, -2.7	-1.32	-101.5, 23.8
TF 4x	0.39	28.9, -13.1	0.33	37.4, -2.5	-1.37	-141.2, 20.5
TF 8x	0.68	67.0, -8.7	0.17	22.6, -1.1	-1.18	-134.8, 12.1
TF 16x	0.44	60.8, -3.9	0.09	13.3, -1.8	-0.70	-100.7, 9.4
CT 2x	-0.37	-102.1, -23.7	-0.27	-83.1, -2.8	1.19	351.5, 32.2
CT 4x	0.23	-5.3, -17.0	-0.49	-67.6, -5.9	1.25	208.2, 34.9
CT 8x	1.45	57.7, -27.9	-0.28	-17.7, -8.2	-0.61	-4.5, 52.3
CT 16x	1.68	48.5, -38.7	-0.23	-1.5, 0.4	-1.00	-44.1, 37.4
CCT 2x	2.19	64.6, -20.1	0.06	9.5, -0.7	-2.38	-93.1, 22.1
CCT 4x	1.94	44.8, -23.2	0.13	12.7, -0.5	-2.33	-83.0, 24.7
CCT 8x	0.06	-19.7, -23.3	0.26	10.6, 0.6	-0.83	-12.0, 21.6
CCT 16x	-1.29	-77.2, -17.9	0.24	8.9, 0.2	0.57	50.4, 17.2

VIX response (EOD models)

	Low VIX environment		Average VIX environment		High VIX environment	
Model	**Delta Sharpe**	**Delta mean, sigma**	**Delta Sharpe**	**Delta mean, sigma**	**Delta Sharpe**	**Delta mean, sigma**
ID CCT 16x	0.37	25.2, 3.8	-0.13	-11.7, -4.4	0.02	10.0, 9.4
ID CT 16x	-0.05	-8.3, -3.8	0.09	8.2, -1.3	-0.22	-16.3, 7.6
Newedge CTA Index	1.13	116.5, -18.3	-0.59	-80.3, 1.3	0.65	124.5, 14.5
Internal TF	1.28	76.2, -18.2	-0.76	-75.0, -4.0	1.02	148.9, 30.1
Alpha	1.10	53.7, -4.2	-0.33	-18.2, -1.2	-0.13	1.0, 7.9
Mosaic	0.67	19.1, -11.7	-0.08	-3.4, -1.4	-0.43	-8.8, 16.0

Correlation ROC response (EOD models)

	Low correlation ROC environment		Average correlation ROC environment		High correlation ROC environment	
Model	**Delta Sharpe**	**Delta mean, sigma**	**Delta Sharpe**	**Delta mean, sigma**	**Delta Sharpe**	**Delta mean, sigma**
ID CCT 16x	-1.56	-96.1, -11.8	-0.89	-60.1, -1.6	4.22	276.4, 16.6
ID CT 16x	1.48	154.4, -18.4	1.11	144.8, -10.8	-4.81	-588.6, 50.9
Newedge CTA Index	0.14	20.3, -8.1	0.78	107.8, -2.8	-2.47	-343.6, 16.5
Internal TF	-0.09	-3.8, -7.2	0.9	80.8, -4.6	-2.59	-238.7, 21.1
Alpha	0.65	28.8, -13.0	1.38	81.7, -3.0	-4.78	-274.0, 21.9
Mosaic	0.10	4.7, -8.4	1.32	71.1, -3.4	-4.06	-218.1, 18.6

REVOLUTION Capital Management

VIX ROC response (EOD models)

	Low VIX ROC environment		Average VIX ROC environment		High VIX ROC environment	
Model	Delta Sharpe	Delta mean, sigma	Delta Sharpe	Delta mean, sigma	Delta Sharpe	Delta mean, sigma
ID CCT 16x	-1.96	-111.3, 0.1	0.35	14.9, -3.2	0.92	66.5, 9.5
ID CT 16x	-0.72	-55.6, 17.1	0.99	96.8, -9.6	-2.26	-234.7, 11.8
Newedge CTA Index	-2.42	-344.0, 7.3	0.84	105.9, -10.7	-0.10	26.4, 24.9
Internal TF	-3.91	-374.2, 11.0	0.99	69.5, -14.8	0.94	165.7, 33.5
Alpha	-1.94	-100.1, 6.9	0.87	39.8, -7.5	-0.65	-19.4, 15.6
Mosaic	-0.16	11.8, 16.6	0.43	10.5, -11.8	-1.11	-43.3, 18.9

VIX ROC response (ID models)

	Low VIX ROC environment		Average VIX ROC environment		High VIX ROC environment	
Model	Delta Sharpe	Delta mean, sigma	Delta Sharpe	Delta mean, sigma	Delta Sharpe	Delta mean, sigma
TF 2x	-3.43	-315.5, 14.6	0.7	46.5, -12.9	1.32	176.1, 24.1
TF 4x	-4.27	-501.5, 16.8	0.75	55.4, -17.6	2.03	335.4, 35.9
TF 8x	-4.75	-615.3, 11.7	0.54	33.8, -15.2	3.13	513.8, 33.8
TF 16x	-3.66	-667.2, 10.8	-0.17	-60.7, -13.2	4.17	849.2, 28.9
CT 2x	2.22	585.1, 20.2	0.03	-1.0, -17.8	-2.30	-582.1, 33.2
CT 4x	2.46	352.4, 21.6	0.19	7.3, -16.3	-3.04	-374.1, 27.3
CT 8x	0.66	96.7, 23.5	0.71	38.1, -13.6	-2.78	-211.1, 17.2
CT 16x	-0.77	-32.4, 17.8	1.18	80.0, -11.5	-2.78	-207.7, 16.9
CCT 2x	-1.58	-60.6, 10.8	0.74	22.9, -9.4	-0.62	-8.2, 17.5
CCT 4x	-3.11	-125.2, 12.6	1.11	37.9, -9.5	-0.22	11.6, 15.8
CCT 8x	-3.25	-116.7, 3.6	1	28.1, -7.5	0.25	32.4, 18.9
CCT 16x	-2.12	-118.9, 0.4	-0.05	-8.5, -3.5	2.27	144.3, 10.0

40-50 DAY DIVERGENCE RESPONSE (EOD MODELS)

	Low divergence environment		Average divergence environment		High divergence environment	
Model	**Delta Sharpe**	**Delta mean, sigma**	**Delta Sharpe**	**Delta mean, sigma**	**Delta Sharpe**	**Delta mean, sigma**
ID CCT 16x	-0.07	5.2, 7.1	-0.23	-16.4, -4.5	0.76	44.0, 6.3
ID CT 16x	0.12	16.5, 6.2	-0.23	-24.5, -3.2	0.57	56.9, 3.5
Newedge CTA Index	0.83	118.7, -5.9	0.15	26.7, 0.5	-1.29	-198.9, 4.3
Internal TF	0.43	48.3, -2.9	0.21	24.2, 1.0	-1.04	-120.9, -0.1
Alpha	1.20	90.8, -0.45	-0.48	-37.1, -0.1	0.24	20.4, 0.7
Mosaic	1.05	48.6, -4.7	-0.29	-22.1, -7.8	-0.19	17.6, 28.0

Stressor response conclusions

- Stressor response can be used as a primary optimization tool (weight models in order to minimize sensitivity to any one environment).
  - Trial studies show that this can produce portfolios with robust statistics and performance without optimizing for either metric explicitly.
- Potential for combining with specific stress-incident response (Gulf War, Lehman collapse, etc.)
- Synthetic data is a potentially-powerful extension of this concept.
  - Use T-distributed data with varying DOF (to alter fat-tailedness).
  - Apply preferred levels of volatility and correlation clustering.
  - Portfolio designer can supply CTAs with standardized, synthetic input data and then analyze outputs to gauge system responses.
  - By comparing results of all portfolio candidates, this allows for a solid gauge of portfolio robustness and provides a feedback mechanism if improvements are needed.
  - Requires deep level of coordinated effort between portfolio designers and CTAs.

Overall conclusions

- The commonly-used statistical metrics (monthly-based correlations, kurtosis, etc.) are insufficient for creating robust portfolios.
  - Conditional, time-varying, and time-scale-dependent measures are much more valuable.
  - Moreover, it is critical to understanding what can be improved via risk management versus what is endemic to the particular strategy.
  - Blind reliance on statistics can lead to inbreeding (i.e. overweighting of latently-similar strategies).
- The true number of degrees of freedom available appears to be finite and limited (4 to 6).
  - We theorize that time scales provide the primary means of diversification, which further implies that most DOF reside on time scales of 25 days or less.
  - Most systems contain a random mix of the available DOF, so appropriately mating managers can be difficult.
  - Idiosyncratic noise is still useful and can be exploited to smooth returns and efficiently extract underlying alpha.
- Stressor-response optimization is a viable alternative to mean-variance approaches.
  - Requires one to devise relevant stress conditions or synthetic data sets.
  - Robust systems naturally arise as outcome without explicitly optimizing for performance or statistical properties.
  - Requires high level of coordination between portfolio designer and CTA.