Diversification In The Managed Futures Universe

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Introduction & Motivation

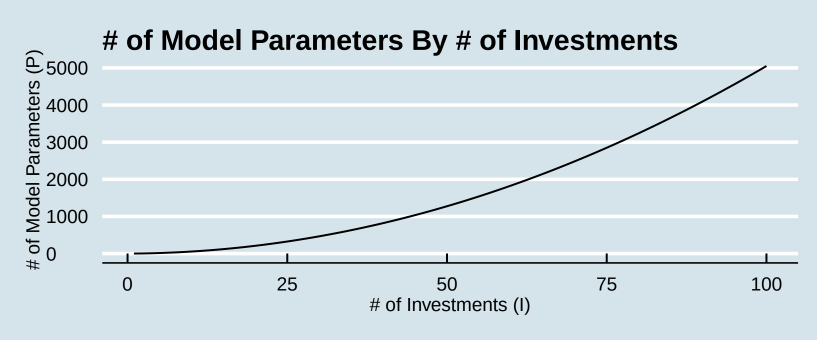
Objective

Maximize investors' future wealth by determining how to allocate capital among a set of available managed futures investments in such a way as to maximize *compound* growth subject to a set of constraints

- Reducing variability of returns has as much impact on total return as increasing magnitude of returns
- Portfolio return variability is a function of the co-variability of investment component returns
- Select sets of investments with *future* positive average returns and low co-variability

Problem: Too Many Moving Parts to Understand Intuitively!

As size of a portfolio increases, number of inter-relationships between components explodes



– Becomes increasingly difficult to understand drivers of portfolio return as number of components rises

– Too many moving parts (particularly during a crisis)

Solution

- Group investments that tend to move together
- Focus on trying to find groups that are independent
  - One common way to reduce dimension of portfolio allocation problem
- Can be accomplished through use of statistical *factor models*

Data

– Extracted data for all managed futures programs from the Altergis website (`http://www.managedfutures.com/`)

– Scraped managed futures program profiles are found here:

- `http://www.managedfutures.com/program_profiles.aspx`

Raw Data Extraction, Transformation, and Loading (ETL)

For each managed futures program we extract:

[1] Manager Info

- CTA Name / Address

[2] Program Info

- Program Name
- Investment Methodology
- Instruments/Sectors/Geographical Focus
- Holding Periods (Short/Medium/Long)
- Investment Terms and Info

[3] Performance Track Record

- Monthly Returns

Data Exploration

Systematic – 63.6% of the programs are 100% systematic, while 82.6% claim that the proportion of their operation that is systematic is 90% or above

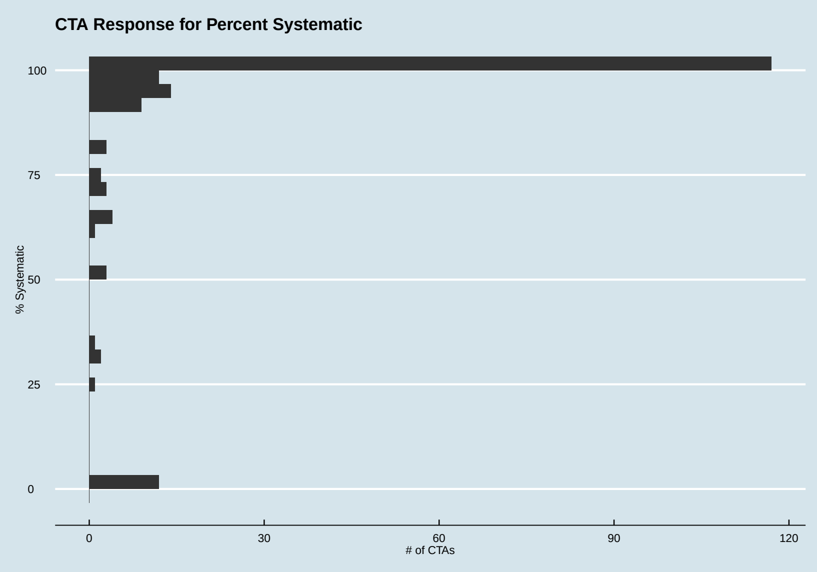
Region of Operations – Vast majority of programs are operated out of either the US or UK (81.55%)

- 71.84% US-Based
- 9.71% UK-Based
- 1.94% do not provide information about geographical location

Margin-to-Equity & Leverage – Typical program employes about 9x leverage (i.e., margin-to-equity of 11.11%)

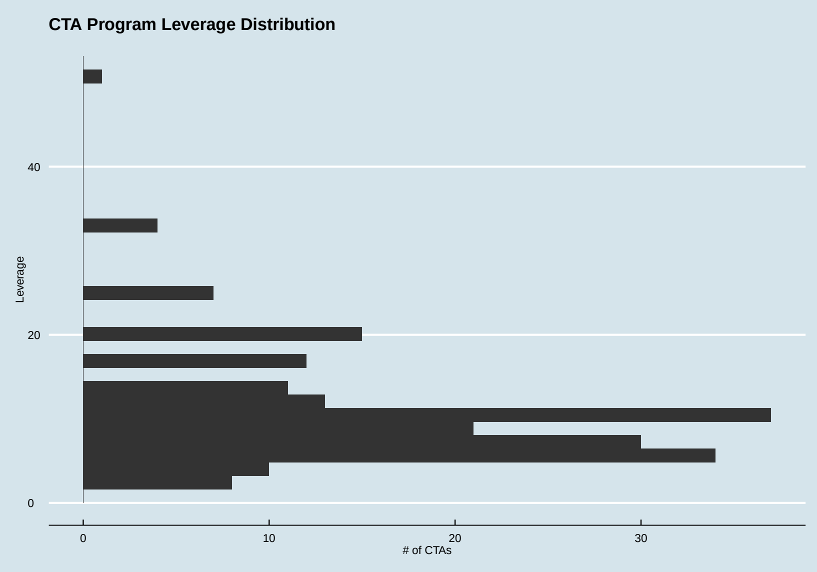
- Varies a lot across programs (1.7x to 50x)
- Concentrated around 7x and 12x

Systematic



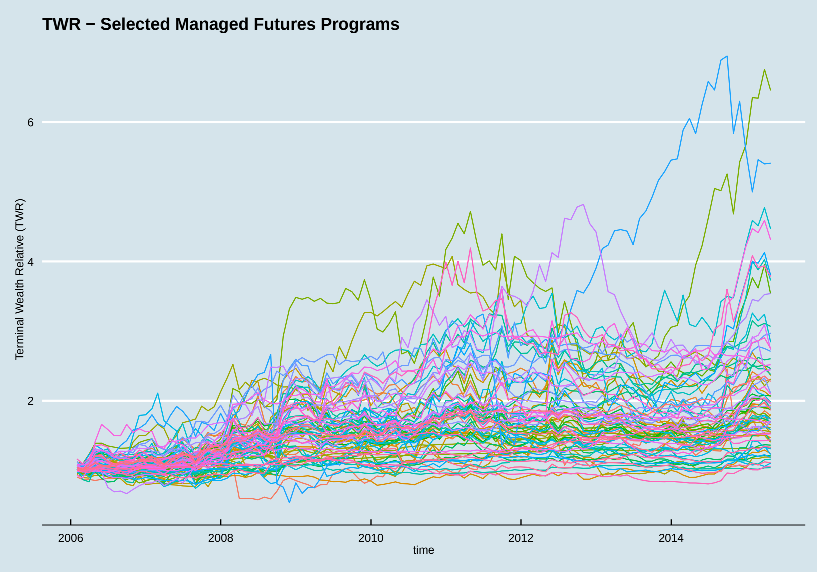
CTA Response for Percent Systematic
100
75
50
25
0
% Systematic
0
30
60
90
120
# of CTAs

Leverage



CTA Program Leverage Distribution
Leverage
40
20
0
0
10
20
30
# of CTAs

Monthly Returns



Data Cleaning

– Data cleaning of majority of collected data pertaining to manager and program information was beyond scope of this project

- Result: None of this data was used in the modeling sector of the paper

– manager and program information collected is somewhat unstructured and visual inspection of the managed futures website reveals many reporting inconsistencies across managers

-Quick exploratory analysis confirms that data is reported somewhat inconsistently by CTAs

– In particular, there appears to be very little validation of manager and program information submitted by CTAs

- Result: this part of the collected data set requires a lot of cleaning and standardization before it can be used effectively in our modeling

Data Preprocessing: Standardizing Returns

– Standardization rescales a variable while preserving its order

– Denote monthly return of i^{th} investment for m^{th} month as $r_{i,m}$ and define standardized return as:

$$\hat{r}_{i,m} = \frac{(r_{i,m} - \bar{r}_{i,M})}{\sigma(r_{i,M})}$$

- $\hat{r}_{i,m}$ = standardized return of i^{th} investment for m^{th} month using data over time interval 1 to M
- $r_{i,m}$ = observed return of i^{th} investment for m^{th} month
- $\bar{r}_{i,M} = \frac{1}{M}\sum_{m=1}^{M}(\hat{r}_m)$ = mean of return stream of i^{th} investment over time interval 1 to M
- $\sigma(r_{i,M})$ = standard deviation of returns for i^{th} investment over time interval 1 to M

Correlations

Represent standardized returns as an I x M matrix $\hat{R}$ with an empirical correlation matrix C defined as:

$$C = \frac{1}{M}\hat{R}\hat{R}^T$$

- T denotes the matrix transform

– Correlation matrix (C) of returns ($\hat{R}$) and covariance matrix ($\Sigma_{\hat{R}}$) of standardized returns ($\hat{R}$) are *identical*

Principal Component Analysis (PCA)

Objective: Find linear transformation Ω that maps a set of observed variables $\hat{R}$ into a set of uncorrelated variables F. Define I x M statistical factor matrix as:

$$F = \Omega \hat{R}$$

– Each row f_k $(k = 1, \dots, N)$ corresponds to a factor F of $\hat{R}$

– Transformation matrix Ω has elements $\omega_{k,i}$.

– First row of ω_1 (which contains first set of factor coefficients or 'loadings') chosen such that first factor (f_1) is aligned with direction of maximal variance in I-dimensional space defined by $\hat{R}$.

– Each subsequent factor (f_k) accounts for as much of remaining variance of $\hat{R}$ as possible (subject to constraint that ω_k are mutually orthogonal)

– ω_k constrained by requiring that $\omega_k \omega_k^T = 1$ for all k.

Principal Component Analysis (PCA) - Continued

Correlation matrix C is an I x I diagonalizable symmetric matrix that can be written in the form:

$$C = \frac{1}{M} EDE^T$$

- $D =$ diagonal matrix of eigenvalues d
- $E =$ orthogonal matrix of corresponding eigenvectors

– Eigenvectors of correlation matrix C correspond to directions of maximal variance such that $\Omega = E^T$

– Statistical factors / principal components F are found using the diagonalization above

Proportion of Variance

Covariance matrix Σ_F for statistical factor matrix F written as:

$$\Sigma_F = \frac{1}{M} F F^T = \frac{1}{M} \Omega \hat{R} \hat{R}^T \Omega^T = D$$

Total variance of standardized returns $\hat{R}$ for I investments is:

$$\sum_{i=1}^{I} \sigma^2(\hat{r}_i) = tr(\Sigma_{\hat{R}}) = \sum_{i=1}^{I} d_i = \sum_{i=1}^{N} \sigma^2(f_i) = tr(D) = I$$

- $\Sigma_{\hat{R}}$ = covariance matrix for $\hat{R}$
- $\sigma^2(\hat{r}_i) = 1$ = variance of vector $\hat{r}_i$ of standardized returns for investment i

Proportion of total variance in $\hat{R}$ explained by k^{th} factor is:

$$\frac{\sigma^2(f_k)}{\Sigma_{i=1}^{I} \sigma^2(\hat{r}_i)} = \frac{d_k}{\Sigma_{i=1}^{I} d_k} = \frac{d_k}{I}$$

Inverse Participation Ratio (IPR)

IPR_k of k^{th} factor ω_k is defined as:

$$IPR_k = \sum_{i=1}^{I} (\omega_{k,i})^4$$

– IPR quantifies reciprocal of the number of elements that make a significant contribution to each eigenvector

– IPR is bounded by two cases:

1. An eigenvector with identical contributions $\omega_{k,i} = \frac{1}{\sqrt{I}}$ from all I investments has $IPR_k = \frac{1}{I}$
2. An eigenvector with a single factor $\omega_{k,i} = 1$ and remaining factors equal to zero has $IPR = 1$

Participation Ratio (PR)

– Inverse of IPR provides more intuitive measure of significance of a given factor

$$PR = \frac{1}{\sum_{i=1}^{I} \left(\omega_{k,i}\right)^4}$$

– Large PR indicates that many investments contribute to the factor; small PR indicates that few investments contribute to the factor

– PRs facilitate identification of statistical facotrs that represent macroeconomic scenarios, namely those with many participants

– Also help us identify factors that represent microeconomic scenarios, namely factors with few participants

Portfolio Return & Variability

– Portfolio compounded return for interval from months 1 to M:

$$r_{P,M} = \left(\prod_{1=m}^{M} \left(1 + \left(\sum_{i=1}^{I} (r_{i,m} w_{i,m}) \right) \right) \right) - 1 = \left(\prod_{1=m}^{M} (1 + r_{P,m}) \right) - 1$$

– Assume:

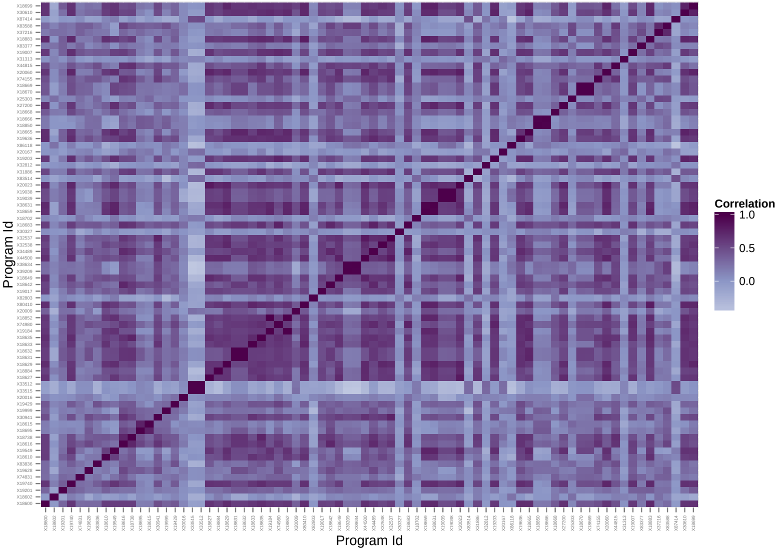
- Component returns are normally distributed
- Portfolio returns are multivariate normally distributed

– Standard deviation of portfolio returns (using matrix notation as_:

$$\sigma_{P,M} = \sqrt{Var\left({W_m}^T R_m \right)} = \sqrt{{W_m}^T \Sigma W_m}$$

- W_m = vector of portfolio component weights for month m, T denotes transpose operator, R_m = vector of month m component returns, and Σ = return covariance matrix

Correlation Matrix



Top 10 Factors

-First 10 factors explain a very significant proportion of total variance

Table 1:Top 5 Factors

Factors	% of Variance	Cumulative % of Variance
Factor 1	36.8	36.8
Factor 2	8.8	45.7
Factor 3	6.5	52.1
Factor 4	4.0	56.1
Factor 5	3.6	59.8
Factor 6	3.0	62.8
Factor 7	2.5	65.3
Factor 8	2.2	67.6
Factor 9	2.2	69.8
Factor 10	2.0	71.8

1^{st} Factor

–Sort factor loadings and look at top and bottom

- Long- and medium- term trend-following programs make strongest positive contributions
- Volatility selling, short-term and relative value programs having small or negative loadings

– Participation ratio indicates that 52 components make significant contributions to first factor

– In strong contrast to other factors where number of components making significant contributions is between 2 and 34

10 Largest Factor Loadings for Factor 1

Table 2:Largest Factor 1 Loadings

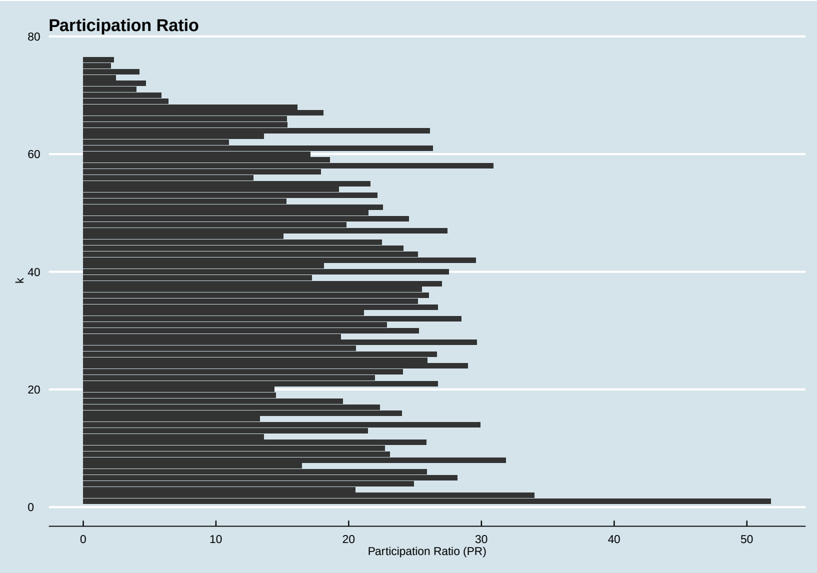
	Program Name	Factor 1
75	Global Directional Portfolio	0.1514
41	Genesis	0.1516
66	Diversified Futures	0.1522
28	Alpha Trend	0.1522
22	World Monetary and Agriculture (WMA)	0.1525
1	Abraham Diversified	0.1530
49	Global Diversified	0.1550
38	Systematic	0.1563
56	AlphaQuest Original (AQO)	0.1586
26	Classic	0.1603

10 Smallest Factor Loadings for Factor 1

Table 3:Smallest Factor 1 Loadings

	Program Name	Factor 1
18	Relative Value Volatility 2X	-0.0434
19	Relative Value Volatility 1X	-0.0410
74	Strategic Fund	-0.0228
52	Contrarian 3X Stock Index	-0.0209
50	S&P 500 Option Overwriting	-0.0039
54	Global	0.0023
42	Kinkopf S&P	0.0034
68	Systematic Alpha Futures	0.0044
2	Ag Trading	0.0052
32	Goldman Management Stock Index Futures	0.0079

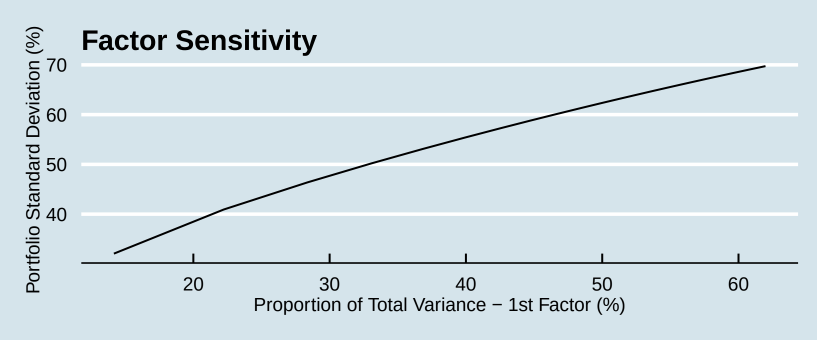
Participation Ratio (PR)



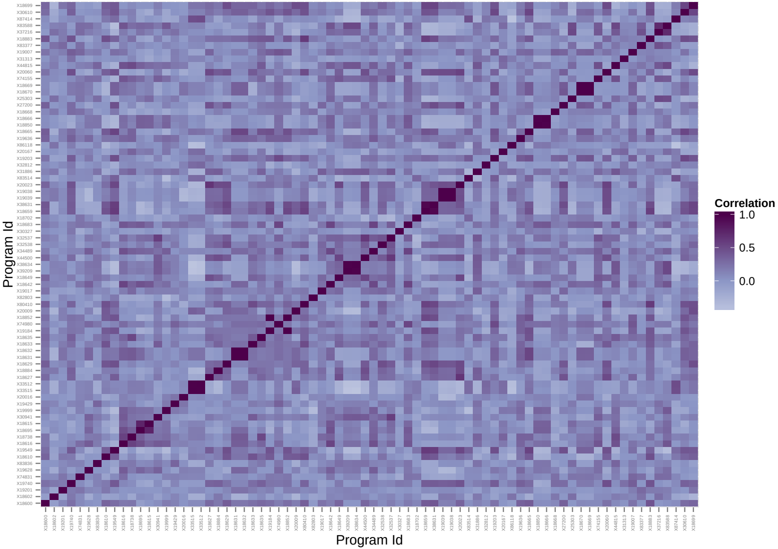
Determining Impact of Factors on Portfolio Variability

– Perturb ‘importance of first factor’ up and down

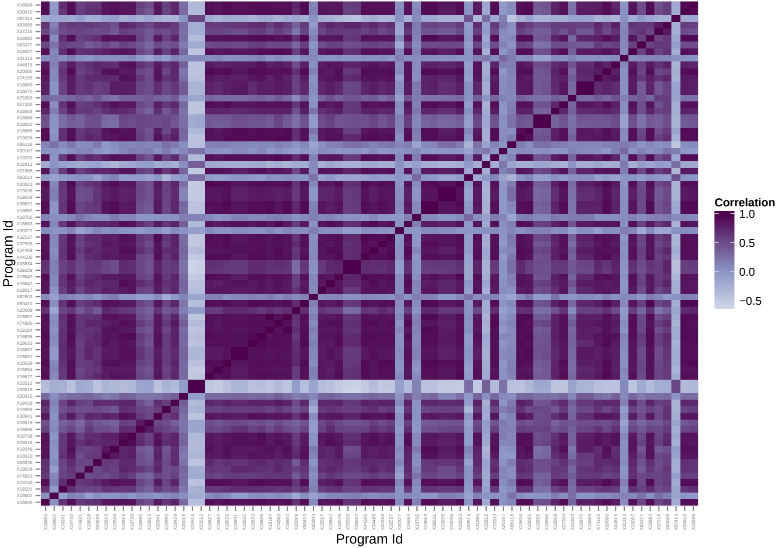
– Use equation for portfolio standard deviation to determine impact on portfolio



Scenario 1: Importance of First Factor Falls Hard - Way More Diversification



Scenario 1: Importance of First Factor Rises Hard - Way Less Diversification



Conclusions

– Factor analysis revealed a very significant proportion of the total variance of modeled managed futures universe can be captured by a single statistical factor

– First factor corresponds to a very intuitive scenario.

– Sensitivity analysis developed - given the intuitive interpretation of first factor - can be used to better understand variation in managed futures universe

– Can be used to identify programs that provide better diversification in different market regimes

– Will use my sophisticated versions of this to help my employer understand risk and return drivers of our $3.5 billion fund

References

1. C. Bacon [2008], Practical Portfolio Performance Measurement and Attribution, 2^{nd} Ed, John Wiley & Sons, Inc.
2. D. J. Fenn, N. F. Johnson, N. S. Jones, M. McDonald, M. A. Porter, S. Williams [2011], Temporal evolution of financial-market correlations, Physical Review E 84, 026109
3. F. J. Fabozzi, S. M. Focardi, P. N. Kolm [2010], Quantitative Equity Investing: Techniques and Strategies (Frank J. Fabozzi Series), John Wiley & Sons, Inc.
4. N. Fenton, M. Neil [2013], Risk Assessment and Decision Analysis With Bayesian Networks, CRC Press
5. D. Koller, N. Friedman [2009], Probabilistic graphical models: principles and techniques, MIT press.
6. A. Golub and Z. Guo [2012], Correlation Stress Tests Under the Random Matrix Theory: An Empirical Implementation to the Chinese Market
7. A Meucci [2009], Risk and Asset Allocation, 1^{st} Ed, Springer Berlin Heidelberg

References - Continued

8. R. Rebonato [2010], Plight of the Fortune Tellers: Why We Need to Manage Financial Risk Differently, Princeton University Press
9. R. Rebonato [2010], Coherent Stress Testing: A Bayesian Approach to the Analysis of Financial Stress , John Wiley & Sons, Inc.
10. R. Rebonato and A. Denev [2014], Portfolio Management Under Stress: A Bayesian-net Approach to Coherent Asset Allocation, Cambridge University Press
11. D. Skillicorn [2007], Understanding Complex Datasets: Data Mining with Matrix Decompositions, Chapman and Hall/CRC
12. R. Vince [2007], The Handbook of Portfolio Mathematics: Formulas for Optimal Allocation and Leverage, John Wiley & Sons, Inc.

Appendix A: GitHub Repository

All of the R code used to produce this paper can be found in the following github repository:

`https://github.com/dgn2/managed_futures`

The github repository also includes the .Rmd file used to generate the .pdf working paper file and includes code to:

- extract CTA manager, program, and monthly return data from the Altegris managed futures website
- create a MySQL database with tables to store extracted CTA manager, program, and monthly return data
- load CTA manager, program, and monthly return data to the MySQL database
- conduct limited exploratory analysis of the data
- conduct limited cleaning of the data used in subsequent statistical modeling
- estimate statistical factors based on the monthly returns of a select set of CTA programs
- compute sensitivities

Contact Information

Thank you! Please do not use this Altegris data for commercial applications!

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https://github.com/dgn2/managed_futures