Group D
Final Project Report

Dynamic Regime Strategy for Stress Testing and Optimizing Institutional Investor Portfolios

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Abstract

Our work aims to develop a stand-alone trading system to construct portfolios that show the benefits of value and momentum style integration and presents the effectiveness of alternative integration methods for long-only absolute return funds, which seeks absolute returns that are not highly correlated to traditional assets such as stocks and bonds. Our approach uses the CRoss Industry Standard Process for Data Mining (CRISP-DM) model to guide the necessary steps, processes, and workflows for executing our project. We believe that this approach will be instrumental to our completing the project within the set timeframe.

Keywords: *CRISP-DM;Alternative Risk Premia; Absolute long returns, Pairs of Pairs Futures Trading, Portfolio construction*

1. Introduction

In the aftermath of that global financial crisis, institutional investors were concerned about the inherent volatility of equity markets (Wurtz, 2018). At the same time, the introduction of ultra-low monetary policy has worsened those concerns, with their liabilities increasing as bond rates fell. In addition, these investors typically have liabilities with varying horizons tied to duration or cash flows. In order to best meet the needs of shareholders, many institutional investors look to hedge funds to provide another source of diversifying returns for their portfolios. The 2008 financial crisis clearly showed that diversification was not sufficient to avoid large drawdowns (Nystrup et al. 2017). As diversification failed, when it was needed the most, because correlations between risky assets tends to strengthen during times of crisis (Boyd, et al., 2017). Additionally, many investors diversify their portfolios on the basis of capital and not by risk. This leads to a common problem for retail and institutional investors alike, who find the results of their portfolios highly concentrated in equity risk, and therefore are overly susceptible to equity market drawdowns, regardless of their portfolios being seemingly "diversified."

These challenges have provided a fertile ground for disruptive financial innovations that are significantly affecting the investment and asset management industry (Kahn & Lemmon, 2016).

For instance, institutional investors are now able to choose an exchange traded fund (ETF) that will systematically select stocks with characteristics like low volatility and growth at lower cost. Wurtz (2018) observes that the development of the exchange-traded fund (ETF) wrapper and the ability of asset managers and index providers to handle higher quantities of data, has resulted in more choices for institutional investors. With more choices institutional investors can now choose quantitative investment strategies that span the spectrum of market risk to active risk. Quantitative investment strategies have evolved into four general approaches to diversifying and helping to mitigate equity risk: 1) long Treasuries, 2) trend-following, 3) tail risk hedging and 4) alternative risk premia diversifiers, such as carry and value strategies (Baz, Davis, Sapra, Tsai, & Gillmann, 2019).

Our project finds itself located within the growing alternative risk premia (ARP) strategies, which according to Carroll & Ramaswamy (2018), seeks absolute returns that are not highly correlated to traditional assets such as stocks and bonds. The ARP strategies continue to evolve with the development of new methods and techniques to sharpen existing signals and systematically extract premia from expensive “hedge” fund strategies. Given the increased complexity and diversity of these strategies, our project will build on a blend of fundamental and technical analysis frameworks and literature guided by Carroll & Ramaswamy (2018) ARP framework and the Baz et al.’s (2019) Theoretical Framework for Equity-Defensive Strategies. While, the project contributes to recent and growing literature on dynamic asset allocation for varied financial markets under regime switching frameworks (Bae, Kim, & Mulvey, 2014; Nystrup, Hansen, Madsen, & Lindström, 2015, 2018; Kotsalis & Lan, 2018; Fons, Dawson, Yau, Zeng, & Keane, 2019), style integration for assets (Fitzgibbons et al., 2016; DeMiguel et al., 2017; Fernandez-Perez, Fuertes, & Miffre, 2017) and time-varying portfolio optimization (Chakravorty, Awasthi, Da Silva, & Singhal, 2018; Dangl & Weissensteiner, 2018; Platanakis, Sakkas, & Sutcliffe, 2019; Jin, Chen, & Yuan., 2019).

Our project’s competitive edge is leveraged from the fact that many of the portfolios of institutional investors fall under two extreme types of investment strategies of spectrum: at one end is the most common risk premium long only strategy, which is a high capacity and low-cost allocation that is extremely sensitive to market directional risk and macroeconomic sensitivities (Wurtz, 2018); and on the other end is extremely differentiated strategies like convertible arbitrage, managed futures, and merger arbitrage etc., low capacity and high cost allocations that have almost zero market directional risk and macroeconomic sensitives due to their idiosyncratic nature (Lester, 2017).

Our opportunity here was to create an absolute return strategy that fits between these two extremes which can diversify an institutional investor’s exposure to long only market betas, yet lacks the drawbacks of some of the most sophisticated hedge fund strategies such as significant cost, illiquidity, and capacity constraints (Kahn & Lemmon, 2016). The competition in this space comes from the institutional investors who desire absolute return strategies to diversify the risk in their portfolios but also from asset managers competing to garner similar risk premiums (Moore, 2015).

When competing with other market participants, the differentiator in our approach is the thoughtful implementation to portfolio construction and how our integrated approach creates a more robust absolute return strategy without depending on a single return driver.

2. Literature Review and Competitor Analysis

The competitive landscape for absolute return trading systems are extremely robust; when you add the institutional desires of reduced directional market risk and macroeconomic sensitivities, a prudent researcher would seemingly need to account for almost every investor on the street. This is driven by the fact that due to their size and sophistication, institutional investors have access to almost any investment strategy possible.

Many institutional investors such as the Harvard Endowment and CalPERS are extremely mature. In their youth, these investors allocated in a similar manner to most other investors; beginning with risk premiums that were the easiest to attain. In most cases, these risk premiums would be the ones that were the least expensive and generally had the largest capacity. Long only, market capitalization weighted exposure to asset classes such as equity, fixed income, and commodities, have almost infinite capacity and are thus, some of the least expensive risk premiums to garner.

On the other extreme end of the spectrum, institutional investors looked to add extremely differentiated strategies to complement their very traditional, long only, broad market exposures. Today, many of these strategies are extremely well known and reside within the world of hedge funds; convertible arbitrage, managed futures, and merger arbitrage are some of the most popular. As one would expect, these strategies target a very specific risk premium, and thus, are extremely capacity constrained. Due to the idiosyncratic nature of the return source, these types of strategies are also associated with significant fee loads as the portfolio managers demand a higher level of compensation for their abilities.

In short, many institutional investors contain a portfolio of two extremes; high capacity and low cost allocations that are extremely sensitive to market directional risk and macroeconomic sensitivities as well as low capacity and high cost allocations that have almost zero market directional risk and macroeconomic sensitives due to their idiosyncratic nature.This leaves a large gap for institutional investors, especially the larger ones, who desire absolute return strategies to diversify the majority of the risk in their portfolios which is primarily allocated to long only market betas. Their largest problem is that capacity of the diversifying strategies they seek such as convertible arbitrage are extremely finite, and that the size of the allocation they desire simply is not possible in the real world. In addition, many of these strategies require lockups and suffer from illiquidity; thus creating problems for investors such as CalPERS who may need to service unforeseen liabilities, yet may not be able to access their capital.

In order to solve for issues with cost, illiquidity, and capacity, many of the strategies we propose on an individual level are well known, and are rife with competitors. These competitors come in the form of not only products but also other asset managers competing to garner similar risk premiums. Below we outline some of our largest core tenants, and their associated challenges as well as much of the opportunity for our strategy has been outlined above. The component we feel is our largest differentiator for what may seem like well-known and seemingly commoditized risk premiums, would be our thoughtful implementation to portfolio construction and how our integrated approach creates a more robust absolute return strategy without depending on a single return driver.

3. Research problem, aims and objectives

The Ideal:

Large institutional investors such as pensions, endowments, and sovereign wealth funds invest large amounts of capital with long-run time horizons. In addition, these investors typically have liabilities with varying horizons tied to the duration or cash flows. In order to best meet the needs of shareholders, many institutional investors look to hedge funds to provide another source of diversifying returns for their portfolios. These relatively unconstrained and absolute return focused investment pools generally pursue a variety of complex trading strategies, which involves hedging or reducing market risk through investments in both long and short positions. Thus, ensuring that institutional investors are successful in meeting their liabilities through reducing the vulnerability of their portfolios to regime shifts in the macroeconomic environment.

The Reality:

However, in reality, most institutional investors are extremely exposed to regime shifts in the macroeconomic environment. As a result, these long-horizon investors tend to focus excessively on equity-like asset classes and often rely far too heavily on harvesting an illiquidity premium, as a source of return. Moreover, institutional investors typically use diversification as their only tool for risk management. All these features contribute to a heightened vulnerability to economic regime shifts. The lack of an absolute return approach makes it difficult for institutional investors have to meet the challenging goals of attaining a high return target with limited drawdown risk. In the face of macroeconomic and regulatory uncertainty, compounded by a world in a state of oscillation and a climate of financial repression.

The Consequences:

If the institutional investors continue to invest in equity and illiquidity risk premium centric-strategies, with minimal portfolio risk management tools, they are destined to experience losses during adverse shifts in the inflation and economic growth. During the 2008 global financial crisis, decisions to invest in poorly diversified portfolios, that lacked proactive drawdown control systems, helped fuel the sharp drawdowns in institutional portfolios. Therefore, regime shifts in economic conditions presents critical challenges for many long-horizon investors with positive directional risk exposure to equity markets and economic growth.

Our Contribution:

Our commitment is to develop an absolute return-oriented trading system that would aid institutional investors in dynamically adapting their portfolio exposures to the prevailing market risk environment. Our program will also help in managing downside tail risk through a proactive drawdown control system, that will achieve higher risk-adjusted returns regardless of changing economic conditions. Most importantly, our program's complementary blending of deep value and momentum styles, along with a strong focus on balanced risk control, will help institutional investors in meeting their obligations through modest high returns and limited drawdown risk.

Aims and Objectives:

Our project aims to develop a portfolio allocation framework that show the benefits of value and momentum style integration and presents the effectiveness of alternative integration methods for long-only absolute return funds. The framework is flexible enough to be applicable to any asset class for either long-short, long-only, and short-only styles in line with Fernandez-Perez, Fuertes, & Miffre's (2017) approach. The project output is a stand-alone trading system, that can be classified as an alternative risk premia (ARP) strategy, which uses a portfolio construction philosophy rooted in the principles of consistency, diversification, and downside protection. Specifically, we draw on three building blocks; a timing portfolio, construction portfolio, and combining them in order to pursue a range of risk and return objectives. Each component or portfolio is built from the bottom up with a specific objective in mind. For instance, we generated our portfolios with exposure to risk factors widely acknowledged in academia such as Value, Size, Quality, Momentum and Low Volatility (Mikaelsson & Nilsson, 2017).

4. Methodology

This section provides a description of the data and methodology used in the project. It starts by describing the data followed by the portfolio generation section, which is intended to explain the portfolio selection, scoring and weighting process. This is then followed up by tools used and the time-line the project.

4.1 The Data

The asset universe considered for this project consists of daily closing prices of economic indicators, futures, commodity contracts. Data-set is downloaded from multiple sources like Quandl, Investment.com etc (financial data feeds). To capture the data from financial data feeds we used two methods 1) Web scraping, 2) using API. Collected data for 23 commodity futures (divided into 5 related sub-sectors), 5 currency exchange rates against USD and 4 Commodity Indices (Appendix C). All the data are daily data from the mentioned platforms. The trading strategy will be back-tested for 4000 days. The first 6000 days is used to develop pairs.

In addition, data accessibility availability is usually a challenge, therefore we created a data preprocessing notebook that we used to explore the data to get assets or indices that was used to improve our diversification. Most of the data collected for our asset universe is available from Investment.com, Quandl and Thomson Reuters DataStream websites. All indices measure the total net return in USD covering the period from 1990 through 2019 (Jun).

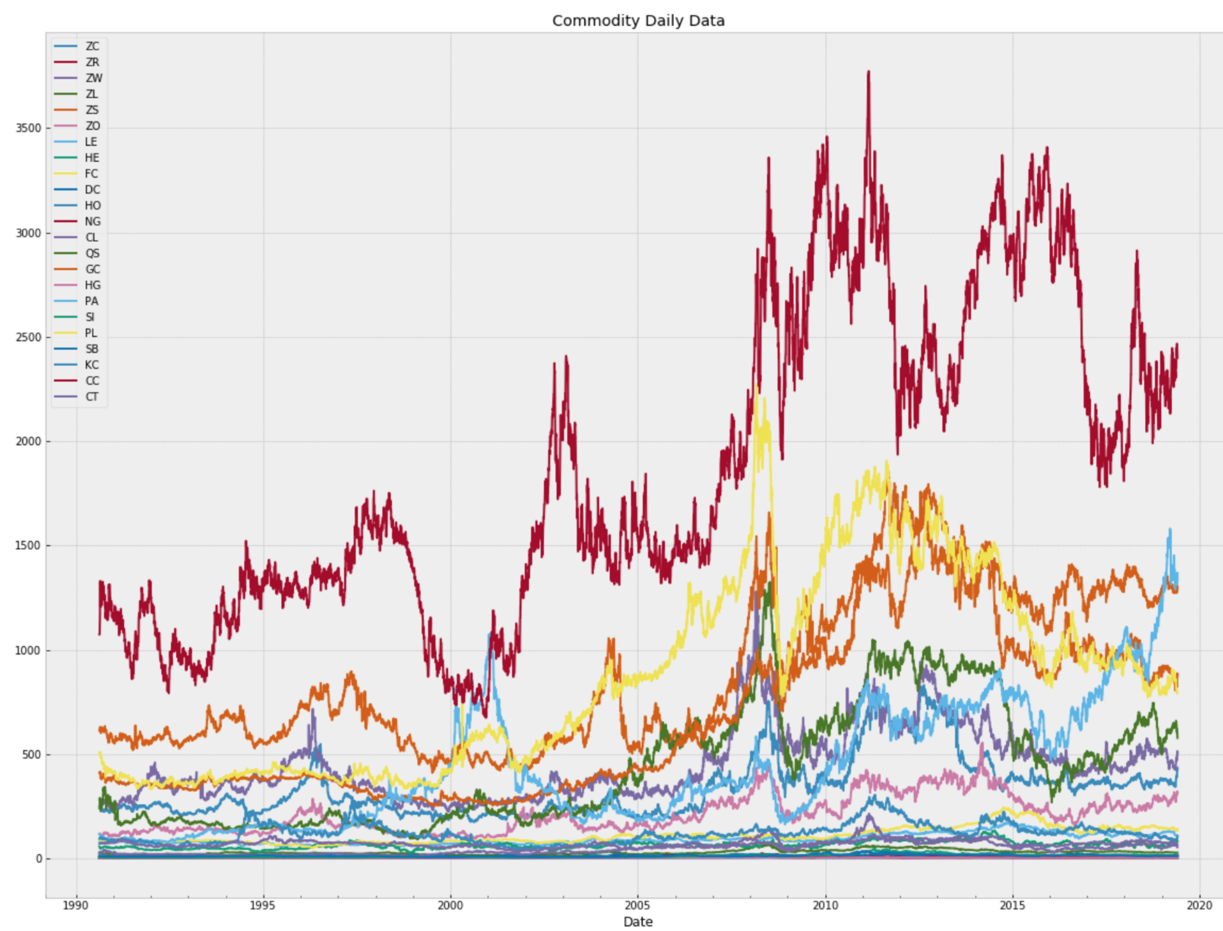

Fig 1: Daily data

Collected data is mostly numerical (closing price), we also collected other information about data like symbols, sectors, traded months and exchange in which they are traded, which are mostly symbolic and textual. We tried different sampling methods (time bar, tick bar, volume bar and dollar bars) to know which sampling method will give predictable information. After the analysis we chose to stick with the time bars. Given the current data available to our group, we believe that our model could be significantly more robust if given access to order flow data found at some of the world's most prememinemt prime brokerages houses. This claim is far from audacious, as increasingly detailed information about the transactions of market participants in aggregate can only help a strategy become more profitable. Additionally, this information is extremely expensive, and closely held as such an information advantage in time and availability can help set one firm's trading strategy apart from the next. Finally, sampling markets at intervals which are different than everyone else also helps to reduce the correlation and sensitivity of one's trading strategy as compared to competing market participants. This notion was exemplified during the quant crash of the summer of 2007 when many statistical arbitrage and equity based trading strategies experienced a violent drawdown due to a commonality of return drivers and implementation styles. Developing a profitable trading strategy is difficult enough, also considering what strategies other market participants are implementing and how they will react is an often overlooked, yet fundamental consideration in developing a robust and profitable trading strategy. As increased data would become available to our team, we would look to integrate it within our strategy in order to become as differentiated as possible.

4.2 Tools and Model

Our project uses the CRoss Industry Standard Process for Data Mining (CRISP-DM) model to guide the necessary steps, processes, and workflows for executing our project right from formalizing business requirements to testing and deploying a solution to transform data into insights (Sarkar, Bali, & Sharma, 2018). The CRISP-DM model entail building an end-to-end solution by following six major steps or phases, some of them being iterative. The lessons learned during the process can trigger new, often more focused business questions, and subsequent data mining processes will benefit from the experiences of previous ones. While our modelling will follow the standard Machine Learning pipeline in Figure 1(Sarkar, Bali, & Sharma, 2018).

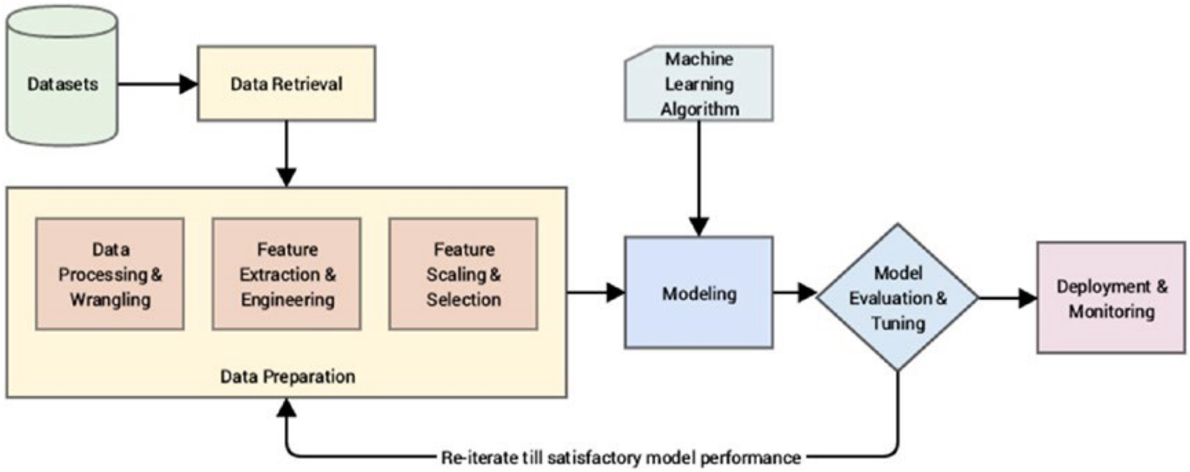

Fig 2: CRISP-DM model

4.3A Portfolio Construction - Initial Idea

The portfolio we are building is one that will look to reduce a long-biased portfolio's exposure to episodic drawdowns concurrent with, or precluded by extreme changes in volatility and valuation. The strategy will integrate four primary themes; diversification by risk, volatility targeting, momentum and trend-following, and extreme valuation. The contribution to risk on a total portfolio basis will be the largest for diversification by risk, progressing to the smallest for extreme valuation. We will lay out the following horizontal "layers" as if they were a pyramid where the tip of the pyramid would be the total portfolio integrated as one, and represented by the highest number. The components of each layer are described in Figure 1 below:

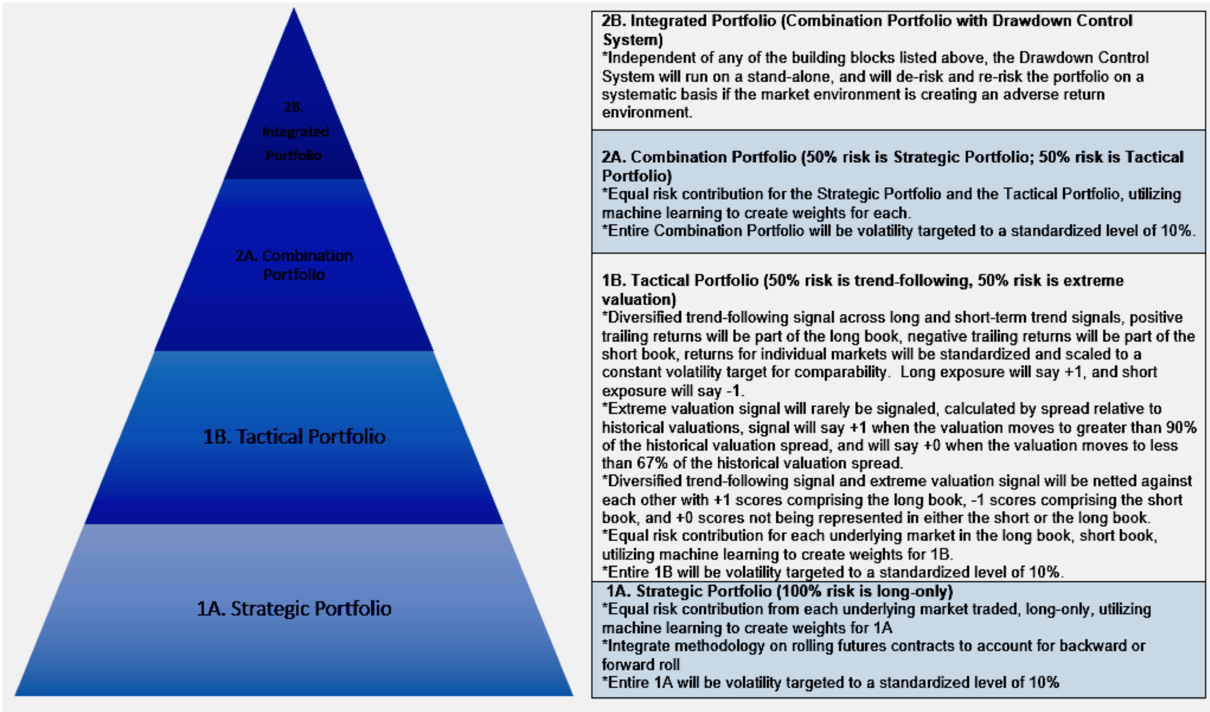

Fig 3: Portfolio Construction

Our first step in adopting to regime changes would be to diversify the portfolio by risk. This theme will be pervasive across the portfolio and will help our strategy in reducing its exposure and dependency to a shock felt in one or a few specific markets.

Model Y. Volatility Targeting

Our second step in adopting to regime changes would be to target a constant level of volatility at each layer of the strategy as well as each subcomponent, most notably, 1A and 1B. While "Diversifying by Risk" in Z should help our strategy from suffering when a specific market we trade moves in a dramatically different fashion from the others, it doesn't help us reduce losses when all of our markets in aggregate begin to exhibit materially different profiles from their long-term averages. If on average, all the markets we trade roughly double in risk over a shorter-term time period, it won't matter if we are diversifying by risk as stated in Z, because our portfolio will be much more risky than desired. Volatility Targeting will help us solve for the shortcomings of Z, "Diversification by Risk."

Model X. Momentum and Trend-Following

Our third step in adopting to regime changes would be to have a strategy that helps us to determine when the core of our portfolio, the Strategic Portfolio, could be particularly vulnerable, due to the fact that it is long-only. While we want to be long-biased since we can earn the market premiums tied to investing in various asset classes, shorter-term time periods such as the Great Depression and the Global Financial Crisis can destroy decades of compounded return. Because of this, we want to have a signal less driven by a risk premium as with our Strategic Portfolio, but more driven by a behavioral tendency. The Strategic Portfolio will also be driven by very long-run assumptions, while this piece, will be driven by shorter and more medium-term market environments. This "market beta filter" will help us to determine when the long-only exposures of Z and Y could leave our portfolio particularly exposed to large losses.

Model W. Extreme Valuation (smallest contribution, most time period centric)

Our fourth step in adopting to regime changes would be to have a signal that helps us solve for some of the factors that would leave our Momentum and Trend-Following signals contained within X, particularly vulnerable. While the signals contained within X do a great job at helping filter when it may not be the most advantageous to have long only exposures, these signals can suffer episodic losses tied to a sharp reversal in sentiment, many times driven by news. This is most exemplified in the spring of 2009 when trends sharply reversed on news of strong central bank intervention. This countertrend signal will help reduce the vulnerability of the momentum and trend-following signals highlighted in X, and will tell us that even though the behaviorally driven trends are still largely negative, that those signals could be particularly vulnerable to sharp reversals due to the markets we trade being excessively cheap in valuation. Because the signal will only kick in during the most extreme times, this signal will be most acutely targeting regime changes such as in the spring of 2009 which would have caused outsized losses for our momentum and trend-following components.

Model Z should be the most robust, while having the least to do with a specific return environment tied to a sharp change in regime. On the other end of the spectrum, W should be the closest to a true change in regime signal, and should have the most to do with creating profitability and/or reducing losses tied to an episodic change in market regime. Model W (Extreme Valuation) should solve for vulnerabilities in Model X (Momentum and Trend Following) when sharp reversals in sentiment cause outsized losses.

Model X (Momentum and Trend Following) should solve for vulnerabilities in Model Y (Volatility Targeting) when broad based asset class declines still create losses for the portfolio. With asset classes declining and the signals in Model Y (Volatility Targeting) reducing broad market, that side of the portfolio is long-only and remains exposed to declining asset prices.

Model Y (Volatility Targeting) should solve for vulnerabilities in Model Z (Diversification by Risk) when the level of risk broadly in the portfolio or within specific markets deviate from their longer-term averages. We want to make sure to have a consistent exposure to long-term risk premiums, regardless of changing environments and the underlying deviation from long-run assumptions.

Model Z (Diversification by Risk) should solve for the fact that we want to be the least susceptible idiosyncratic risk driven by any one market, but that we want to capture the risk premiums in any of the markets we trade in the most all-weather fashion, and regardless of the differences between different markets, most notability in multi-asset portfolios.

Total Portfolio (Drawdown Control System) should solve for the fact that no matter how strong or robust our portfolio's signals are, we fully understand that we could experience time periods of sustained underperformance. Regardless if this underperformance is driven by a changing market regime or simply by an adverse return environment for the markets we trade, humility in reducing broad market exposure when everything seems to not be working, is the most prudent course of action.

4.3B Portfolio Construction - Change in idea

The development of our strategy was to target a major void in the allocations of institutional investors; portfolios which contain strategies of two extremes. As discussed above, low cost, lowly differentiated strategies with high capacity, yet contain high amounts of market directional risk and high cost, highly differentiated strategies with low capacity, yet contain almost no market directional risk.

Our initial path set out to develop an alternative risk premia strategy, which at a high level focused on delivering value, momentum, and risk balanced characteristics; most importantly, our strategy must trade highly liquid and tradable securities in order to offer a higher level of capacity and liquidity to investors as compared to the characteristics of many of the most highly differentiated and well known hedge fund strategies. While the results delivered strongly address the original goals we set out to achieve, the path taken could be categorized as meaningfully different, yet fundamentally similar at the same time. Portfolio construction decisions evolved greatly during our development process with the final results appearing unrelated to our origins, but the factors underneath the surface, both risk based and behaviorally based, of why the strategy should be lucrative, are unchanged.

The greatest challenge and threat our group believed that we would have to have to overcome is the brutal competition within the alternative risk premia space, most notably those competing for value and momentum premiums. While our initial approach favored more traditional forms value and momentum, we believed that our largest differentiator and our contribution would come from thoughtful integration of these well known sources of risk and behaviorally driven return drivers.

To make an analogy, we believed that while the underlying businesses of Berkshire Hathaway such as GEICO, Burlington Northern Santa Fe, and Dairy Queen, it was the interaction effect of their togetherness that would drive our differentiation. As we continued to focus on the interaction effect between the underlying strategies, we found them to not be differentiated enough, and that no matter how robust our construction process was, we would not be able to drive enough differentiation to make our strategy truly unique.

To continue with our analogy of Berkshire Hathaway, we decided to focus specifically on the most meaningful opportunity for differentiation and the most important component of Berkshire Hathaway's business, the GEICO insurance brand. While we would continue to develop on our original core tenants, but it would become much more focused approach in delivering a regime adaptive, absolute return strategy which lacked capacity and liquidity issues.

5. Results

With our newfound focus, the obvious starting point became the choice to only use highly liquid futures contracts; while our approach only utilized commodity futures, we could have applied the methodology to any highly liquid and tradable universe. Using only highly liquid markets easily allows our strategy to give investors liquidity from our strategy if they need it and allows a higher level of capacity than many other flagship strategies hedge fund strategies often reliant on an illiquidity premium.

Next, we decided to revisit what we believe should make our strategy the most robust over time; those being risk premiums driven by both risk and behavioral characteristics. As initially stated, those would be value and momentum. Additionally, we needed to revisit what would make our strategy absolute return in nature, and thus, make our strategy more all-weather to a wider array of macroeconomic environments. The most natural process in making a strategy less vulnerable to market moving is to incorporate one of the following three characteristics; direct hedges such as a put option on a specific stock a portfolio holds, indirect hedges such as an index put on a specific stock a portfolio holds, and strategies which have historically profited when main return driver of one's portfolio is particularly susceptible, such as a managed futures strategy alongside an equity centric portfolio.

5.1 Developing Pairs

For finding potential trading pairs, every possible stock pair will be tested for cointegration. There are 54 pairs with p-values less than 0.05 (or 5%) (Appendix A).

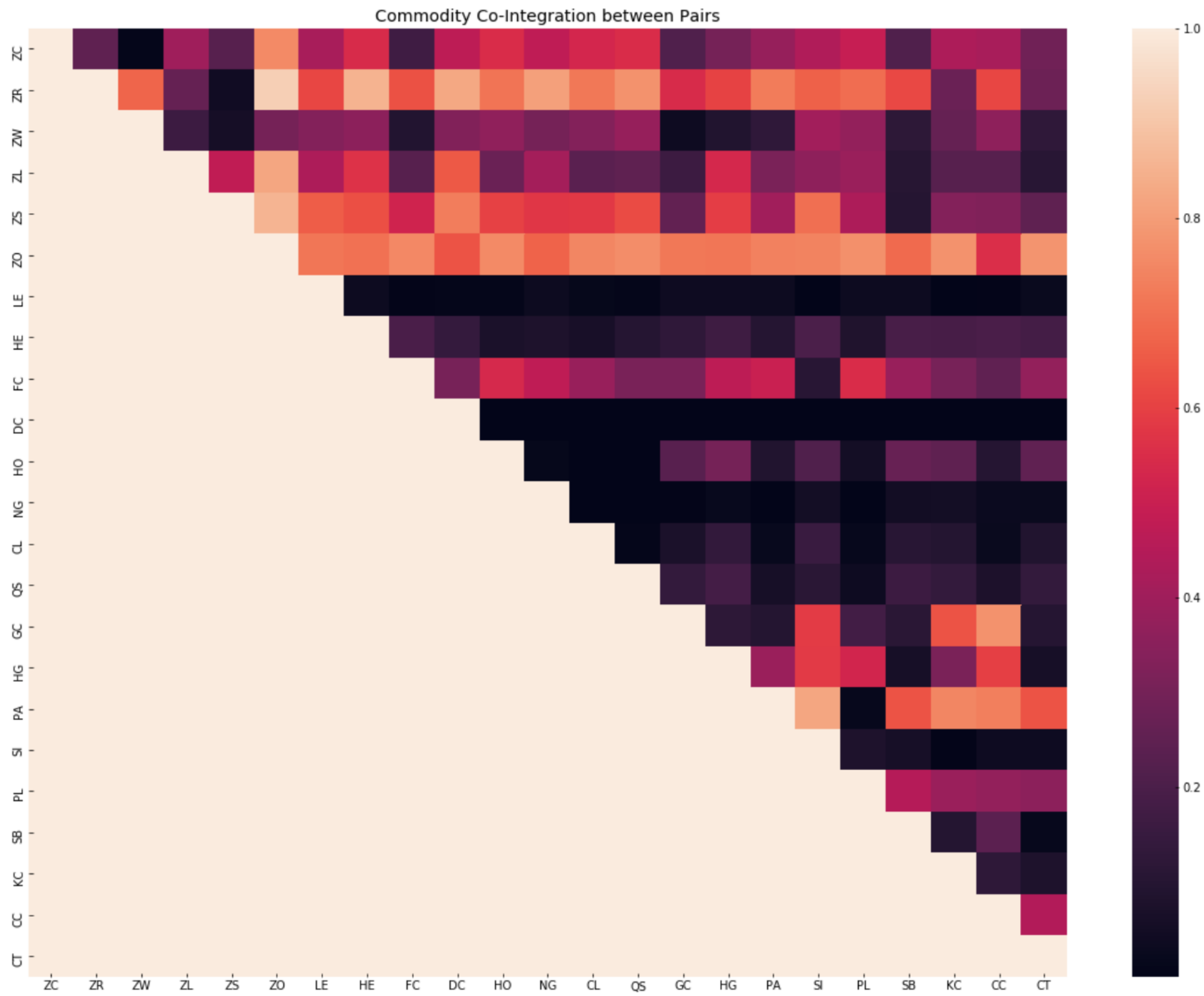

Fig 4. The heatmap of p-values

Steps followed to create Pairs

1. Hedge ratio is calculated using Kalman Filter Regression
2. Spread is calculated using formula: Spread = Asset 1 – hedge ratio * Asset 2
3. Z-Score of Spread is calculated using using rolling mean and standard deviation for the time period (t)
4. time period (t) is calculated using ‘half-life function’ to get the intervals intervals
5. Set entry entry Z-score and exit Z-score
6. As Z-score crosses positive entry Z-score, go SHORT and close the position with Z-score return exit Z-score
7. As Z-score crosses negative entry Z-score, go LONG and close the position with Z-score return exit Z-score
8. Each pair has been Back-tested and only filtered pairs with sharpe ratio more than 1. So at the end we got 39 pairs which satisfies all the conditions (Appendix B)

9. Various Portfolio Diversification Techniques were used to find optimal weights. Output plot of Portfolio Diversification Techniques

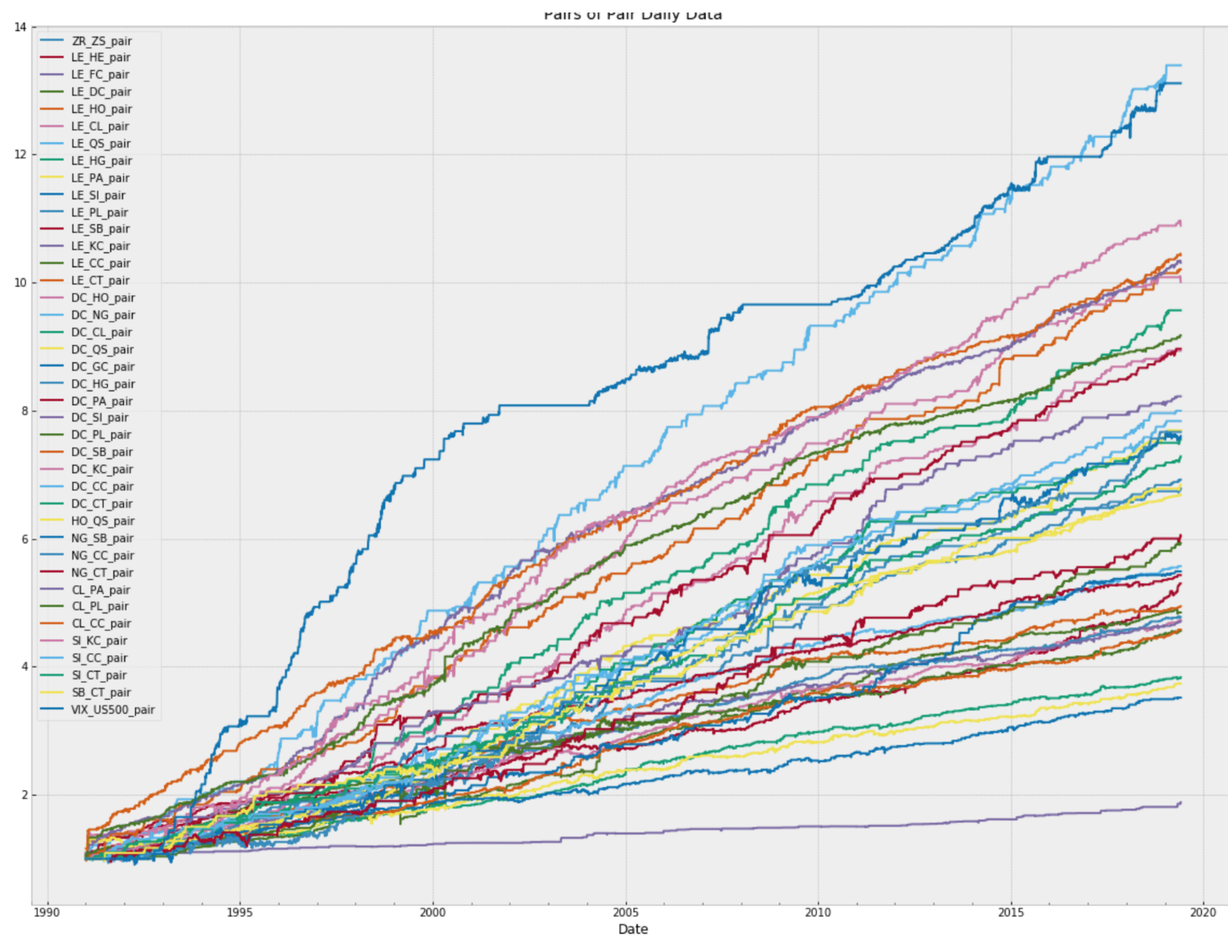

Fig 5: Returns of pairs

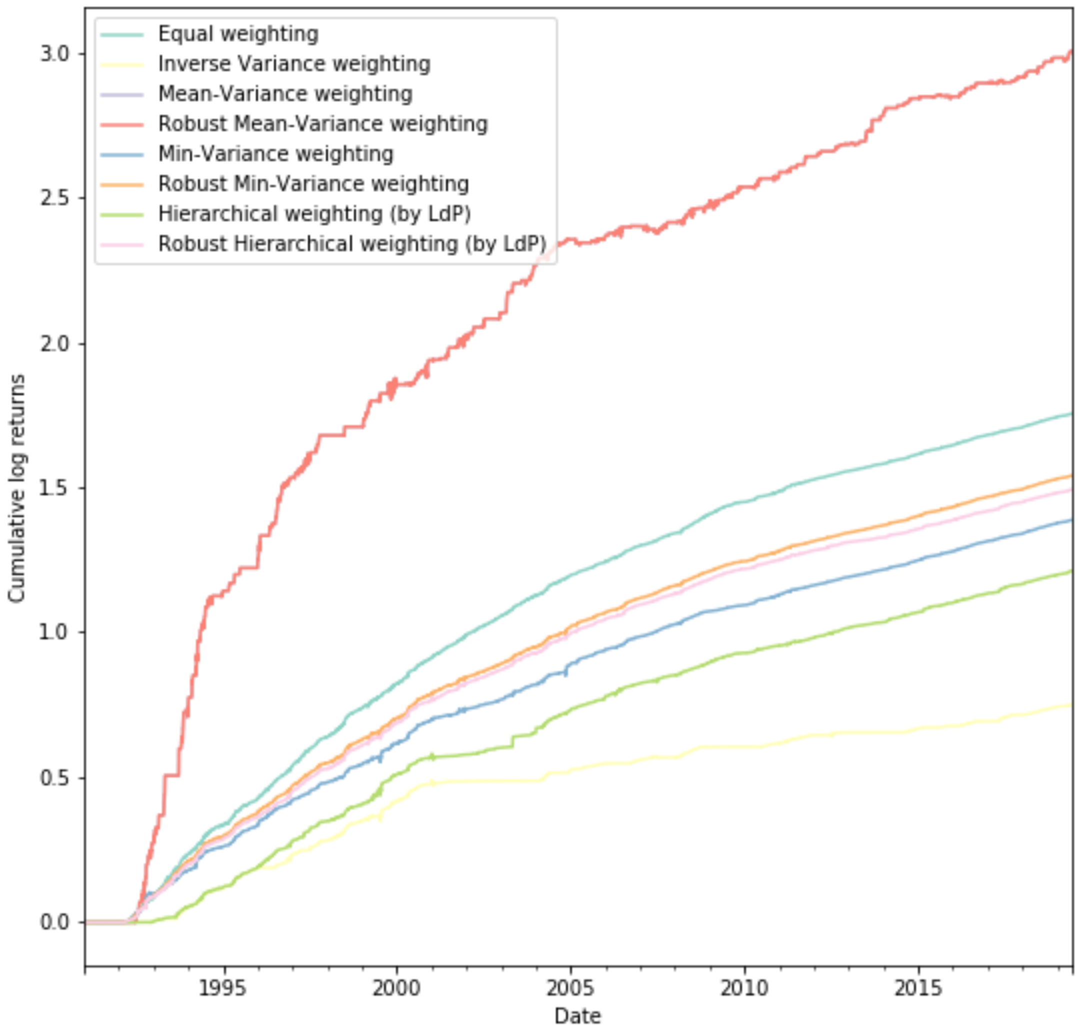

Fig 6: Cumulative log Returns of diversification technique

5.2 Portfolio Diversification Techniques

To build a diversified Portfolio that outperform out-of-sample we used 8 different methods to find optimal weight of assets in portfolio and tested the performance on actual stock-market data. Equal weighting, Inverse Variance weighting and non robust uses covariance matrix directly computed from returns of stock while robust instead of computing the covariance matrix directly regularized model has been used to create the matrix using scikit-learn and the Oracle Approximating Shrinkage Estimator.

List of methods used

- Equal weighting
- Inverse Variance weighting
- Mean-Variance (robust and non-robust)
- Minimum-Variance (robust and non-robust)
- Hierarchical Risk Parity (robust and non-robust

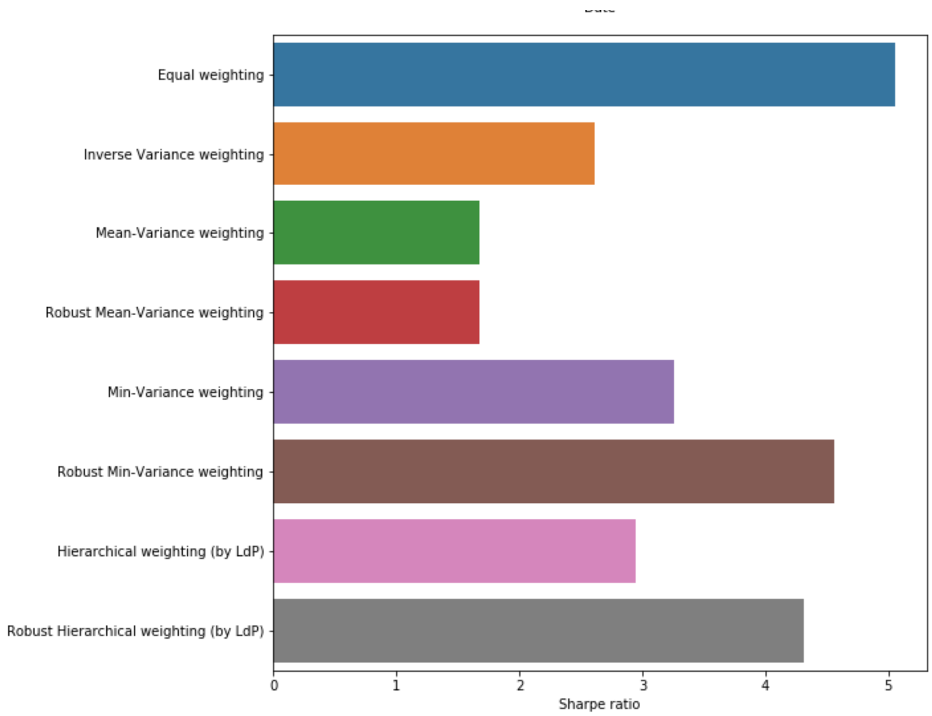

Fig 7: Sharpe Ratio of different diversification

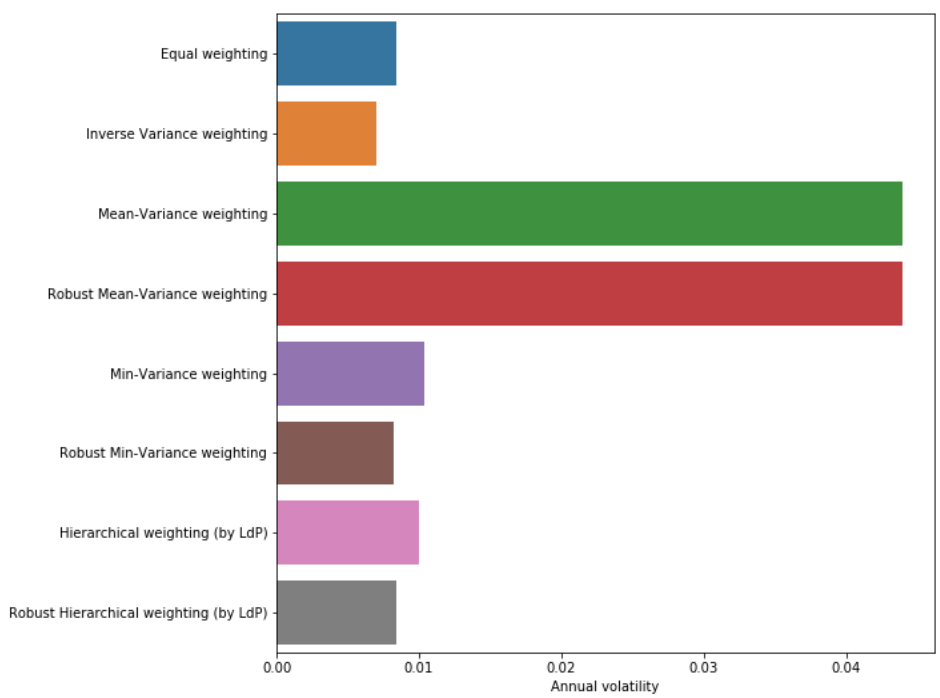

Fig 8: Annual Volatility of different diversification

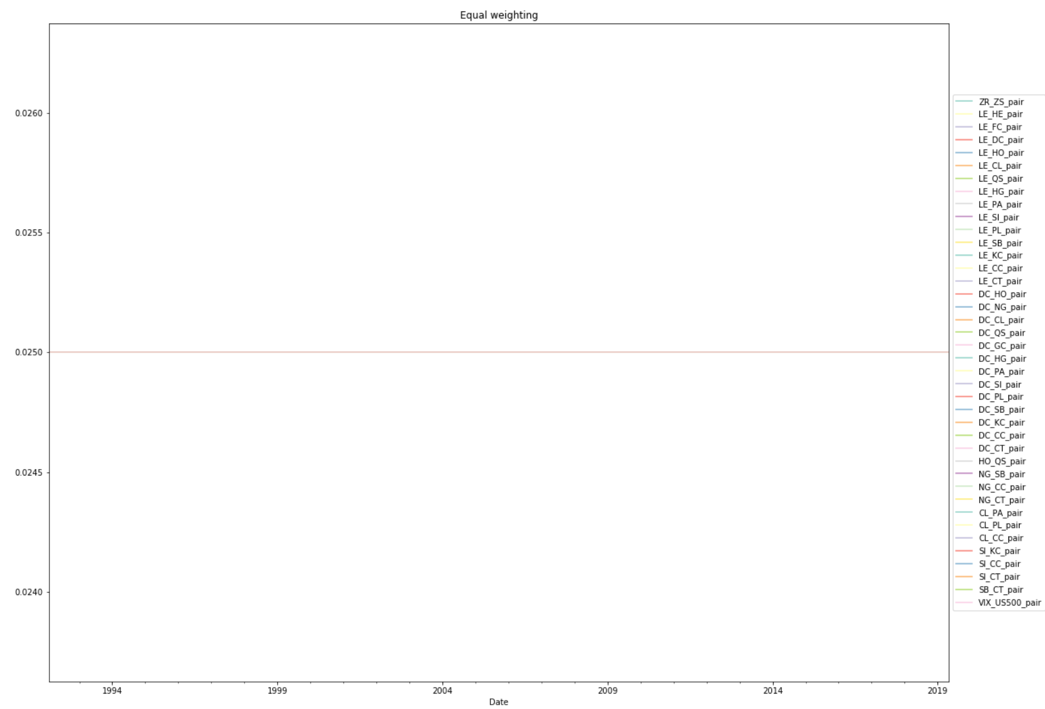

Fig 9: Asset allocation with Equal weighting

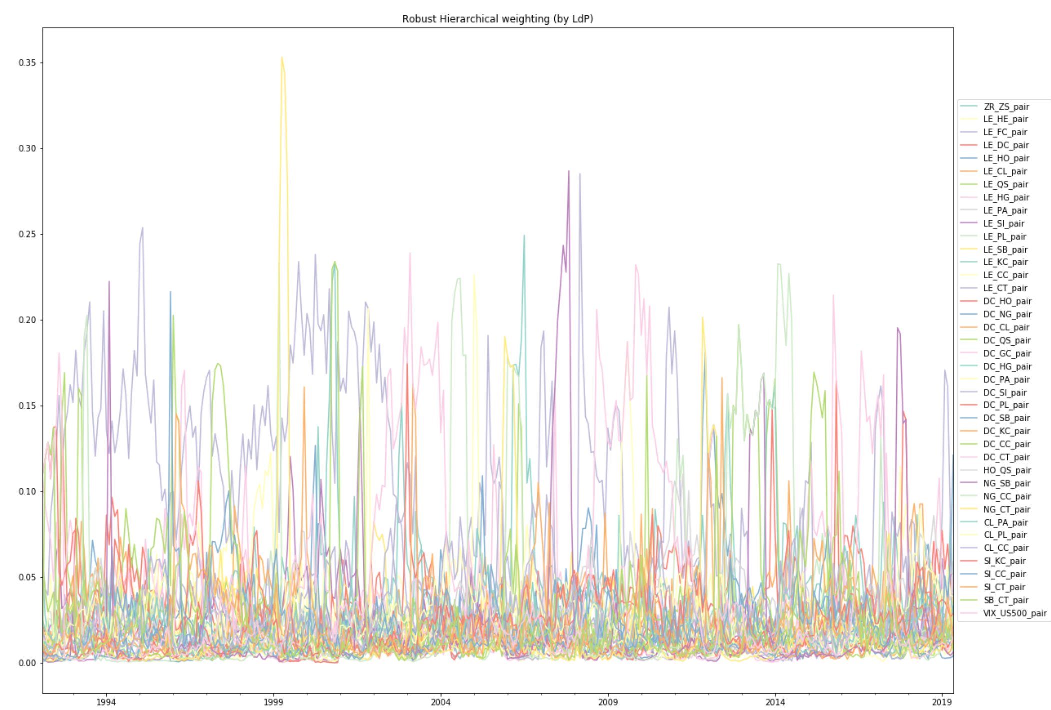

Fig 10: Asset allocation with Robust Hierarchical Risk Parity

Robust Hierarchical Risk Parity shows good diversification with better share ratio though less than Equal weighting. For other asset allocation plots please go to appendix D. Mean-Variance optimization techniques results were not acceptable as there is not diversification.

6. Discussion

Widely known strategies such as statistical arbitrage between pairs of dual listed companies such as Alphabet or Royal Dutch Shell, and fixed income arbitrage between pairs of on-the-run and off-the-run treasury bonds, offer much of the benefits of direct hedges to make a portfolio lowly sensitive to market direction movements. While the directly hedged characteristics of these strategies are extremely desirable, they suffer during times of illiquidity when spreads widen and often require significant amounts of leverage to deliver a return commensurate with the needs of institutions. Additionally, these convergence trading strategies require significant design in risk control due to the fact that when the underlying pairs are increasing in risk and thus, increasing the risk of the overall portfolio, they are also increasing in expected return. Although hedged to directional market movements, this Catch-22 makes convergence trading strategies extremely susceptible to behavioral bias; just ask anyone who worked at Long Term Capital Management.

Strategies which are directly hedged are inherently lowly correlated to directional market movements and extremely diversifying due to their obvious nature of a lack of any directional market exposure; developing a strategy in this vain would help our focus in building the most robust GEICO insurance brand, while not providing exposures to the rest of the Berkshire Hathaway portfolio that may not be nearly as differentiated.

In order to allow our portfolio to become adaptable to changing macroeconomic environments, we wanted to account for how asset relationships change over time. Over the long-run, high-quality government bonds and developed market equities exhibit a correlation roughly close to zero; this is intuitive as equites are strongly impacted by changes in growth rates, while fixed income securities are strongly impacted by changes in inflation. While this relationship holds over the long term, there are times when the relationship between these two types of securities meaningfully change, many times associated with a shorter term change in macroeconomic fundamentals or regime. A near term example of a breakdown in the long term relationship between government bonds and equities, was when fear higher than expected inflation in the United States caused sharply higher correlation than historically as government bonds exhibited losses due to increased inflation expectations while equities also exhibited losses due to hawkish expected monetary policy from the Federal Reserve as a result of a potentially overheating economy.

Given that the relationship between any assets can change, regardless of their historical tendencies and especially over the shorter term, we focused our attention on finding securities who were acting in a cointegrated fashion and if there was value in the spread between the two. Traditionally, as with statistical arbitrage strategies, you might invest on the basis of convergence of two identical or almost identical assets due to the law of one price. The problem with this approach is that it fails to account for changing market dynamics and that betting on convergence can increase the risk to a portfolio if spreads continue to widen over the short term due to changing shorter term macroeconomic regimes.

Instead of seeking value between two long-term historically cointegrated assets, our strategy is driven by seeking value between two shorter-term cointegrated assets, many times driven by shorter-term macroeconomic characteristics that may not hold over the long run. Our strategy continually assesses the universe of investable securities for cointegration above a 5% p-value, and only considers those pairs as part of the current investable universe; a hedge ratio is then calculated utilizing a Kalman Filter Regression. Based on the combination of these two processes, our portfolio will contain pairs which are as close to delta neutral as possible, thus reducing our market directional risk as possible. We believe that seeking a value premium between two securities that may not have a long-run economic relationship, yet are driven by extremely similar shorter term macroeconomic fundamentals creates an extremely differentiated strategy which fluidly adapts to changing regimes.

One of the largest problems with convergence trading cointegrated pairs is the Catch-22 between risk and return; as the spread between the two securities increases, so does the expected return along with the expected risk in the pair. This difficult compromise was most notably exemplified by the iconic hedge fund Long Term Capital Management requiring a capital injection from the Federal Reserve and a consortium of more than twenty of the largest financial institutions in the world following the default of Russian government bonds, as its primary strategies focused on highly levered converge trades.

The inherent compromise necessary for convergence trading and fostered by our value seeking nature, offered the opportunity for the perfect marriage of value and momentum in the name of risk control. As with all convergence trading and not unique to our strategy, when the spread between two highly related securities diverge, the portfolio will take positions within each pair betting on a compression of the spread back to normal.

Our strategy calculates a rolling Z-Score for each spread of the currently considered cointegrated pairs utilizing the historical mean and standard deviation during the rolling window. Utilizing a banded Z-Score range above and below the current value, we initiate positions in the direction of mean reversion, and not meaningfully dissimilar from other convergence trading models which may or may not use a different signal to initiate a position between two cointegrated securities.

The first point of risk management incorporated into our strategy, is that from the list of pairs eligible because they exceed our p-value cointegration threshold, we continue to pare back the universe to only contain pairs with a trailing Sharpe Ratio which exceeds 1.0. Adding highly volatile pairs, or pairs which do not provide a return commensurate with the risk taken, help in restricting pairs with outlier characteristics and pairs that could create outsized losses for the portfolio.

The second point of risk management incorporated into our strategy which highlights the marriage of value and momentum, is when a position is initiated and when a position is closed. Many investors have asymmetrical preferences when weighing their preferences for gains and losses; most prefer to avoid losses at a significantly greater rate than to participate in gains of similar magnitude. This behavioral tendency perpetuates the disposition effect where investors prematurely close out profitable positions, yet hold onto losing positions of equal and greater magnitude. Most sophisticated investors understand this phenomenon as a primary driver of the momentum phenomenon and one of the reasons managed futures strategies have experienced success over their lifetime.

Utilizing momentum and the disposition effect as a risk management tool should be a marquee feature in preventing the strategy from being overexposed to the risk of the widening spreads in converge trades which doomed Long Term Capital Management in the late 1990's. As such, the strategy utilizes a 3:1 ratio of profit seeking to loss taking. Thus, after filtering for pairs above a Sharpe Ratio of 1.0, the strategy will take short positions when the Z-Score crosses a positive three and long positions when the Z-Score crosses a negative three. If the pair converges as planned, the position will be closed when the Z-Score returns to zero.

Capturing the momentum premium and its diversification relative to the value premium occurs when the spread begins to widen, and the pair continues to diverge instead of converging as expected. Any time the Z-Score on the spread for a pair moves from a positive three or negative three where positions were initiated to a positive four or negative four respectively, the position will be closed and a loss will be taken. The strategy will be relatively much quicker to take losses as spreads continue to widen relative to when any trade would be closed out due to spreads compressing. This asymmetric profit to loss filter helps the strategy capture a momentum premium as well as strongly benefit from its negative correlation relative to value; this characteristic also becomes a cornerstone as a risk management tool against the adverse consequences of widening spreads in convergence trades and their associated drawdowns.

To continue with the analogy, the focused approach into GEICOs insurance business has led our strategy to continue to focus on value and momentum but in a meaningfully different way. As with all strategies, no matter how profitable a strategy's trading signal, a lack of thoughtful portfolio construction can undermine any amount of alpha generation. As such, we viewed each of the pairs as one asset within the portfolio and applied a wide array of allocation methodologies to the pairs. As with our initial process, balanced risk contribution was a major hallmark to our process, and as such, within the universe of methodologies tested.

The primary focus of our portfolio allocation process was Sharpe Ratio, as any highly liquid and futures trading strategy can be levered or unlevered to meet almost any client's desired level of risk. Much to our surprise, the naive equal weighted process had the highest risk adjusted returns, although our most robust application of risk balancing was not far behind, as seen in the above graphics. While the results during our testing demonstrated that equal weighting the pairs to be the most robust methodology of allocation, we believe the risk balancing each of the pairs within the portfolio to be the most suitable for out of sample investing for if no other reason than humility and risk control.

In the future, the robust addition of other futures based markets such as government bonds, equities, and foreign exchange, could provide further diversification as our current approach of primarily commodity markets only yielded roughly forty pairs which were utilized within the process. Further developments in hierarchical risk balancing, the asymmetric filter, and additional pair evaluation beyond Z-Score pose exciting challenges ahead.

7. Conclusion

The absolute return focused alternative risk premia strategy outlined above relies on the differentiated application of the following three tenants; value, momentum, and balanced risk control. The strategy achieves its lack of market directional risk and absolute return tendencies through exposure to convergence trades of highly cointegrated and high Sharpe Ratio pairs of securities. During our testing, a naive portfolio of equal weighted pairs resulted in a Sharpe Ratio of 4.8, while the more sophisticated and risk balanced Oracle Approximating Shrinkage Hierarchical weighted pairs resulted in a Sharpe Ratio of 4.4. Due to the strategy's market neutrality and lack of market directional risk to any broad based asset classes such as equities, fixed income, and commodities, finding a representative benchmark for the portfolio is extremely difficult, as the case with almost all highly differentiated investment strategies.

Although the portfolio primarily trades commodity futures, the strategy has zero long term beta to commodity markets; the strategy only requires highly liquid and tradable markets, and could be implemented on almost any collection of securities. Therefore, we would believe that an appropriate benchmark, would be an excess return of cash relative to the long-run Sharpe Ratio for the risk level desired by the client. For benchmarking purposes, we understand a 1.0 Sharpe Ratio translates to a 10% rate of return above cash when implemented at a 10% level of risk, and thus, it would be highly unlikely for our strategy to demonstrate returns above cash that are commensurate with the more humble 4.4 Sharpe Ratio of our risk balanced approach if implemented at a 10% level of risk. We are extremely excited about the results of the strategy, but realize continued work related to out of sample testing and transaction costs are essential in order to truly test the robustness of the outlined strategy.

Presentation Link: https://docs.google.com/presentation/d/1QGlFP82OTxYQw-UffgYuPFeKz3a0mala1mGYlprDDY8/edit#slide=id.g5e72331ebd_0_15

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- Lopez de Prado, Marcos, Advances in Financial Machine Learning p 221-p 239

Resources

1. Github: Code and Source repository - https://github.com/RavindraNathRapaka/WQU_Capstone_Group_D
2. Slack: Brainstorming and discussions - WQU Capstone- wqucapstone.slack.com
3. Google Drive - Collaborative Report writing
4. Jupyter Notebooks - Interactive Coding
5. Quantopian Platform - to build pipeline
6. Presentation: https://docs.google.com/presentation/d/1QGlFP82OTxYQw-UffgYuPFeKz3a0mala1mGYlprDDY8/edit#slide=id.g5e72331ebd_0_15

Appendix

Appendix A

stock_1	**stock_2**	**Co-integration (P_value, 5% cut-off)**
ZC	ZW	0.80%
ZR	ZS	4.47%
ZW	GC	3.68%
LE	HE	3.16%
LE	FC	0.62%
LE	DC	0.95%
LE	HO	0.79%
LE	NG	3.26%
LE	CL	1.33%
LE	QS	0.79%
LE	GC	3.55%
LE	HG	3.53%
LE	PA	3.40%
LE	SI	0.01%

LE	PL	3.29%
LE	SB	3.33%
LE	KC	0.37%
LE	CC	0.55%
LE	CT	2.40%
DC	HO	0.01%
DC	NG	0.07%
DC	CL	0.01%
DC	QS	0.01%
DC	GC	0.07%
DC	HG	0.04%
DC	PA	0.07%
DC	SI	0.08%
DC	PL	0.04%
DC	SB	0.07%
DC	KC	0.07%
DC	CC	0.01%
DC	CT	0.08%

HO	NG	1.25%
HO	CL	0.00%
HO	QS	0.25%
NG	CL	0.09%
NG	QS	0.30%
NG	GC	0.66%
NG	HG	2.00%
NG	PA	0.00%
NG	PL	0.00%
NG	SB	4.82%
NG	CC	2.99%
NG	CT	2.41%
CL	QS	0.89%
CL	PA	2.04%
CL	PL	1.58%
CL	CC	2.48%
QS	PL	3.86%
PA	PL	1.92%

SI	KC	0.65%
SI	CC	3.69%
SI	CT	3.68%
SB	CT	1.88%

Appendix B

stock_1	stock_2	Sharpe Ratio	CAGR
ZR	ZS	1.59	4.69%
LE	HE	1.28	4.08%
LE	FC	1.09	1.53%
LE	DC	1.47	3.86%
LE	HO	1.26	3.90%
LE	CL	1.11	3.79%
LE	QS	1.53	4.20%
LE	HG	1.34	3.27%
LE	PA	1.04	3.21%
LE	SI	1.05	3.06%
LE	PL	1.11	3.82%
LE	SB	1.42	4.14%
LE	KC	1.18	3.78%
LE	CC	1.28	3.70%
LE	CT	1.39	3.71%

DC	HO	1.78	5.39%
DC	NG	1.56	6.42%
DC	CL	1.86	5.56%
DC	QS	1.83	5.01%
DC	GC	1.23	4.16%
DC	HG	1.64	4.75%
DC	PA	1.67	5.40%
DC	SI	1.82	5.18%
DC	PL	1.04	4.36%
DC	SB	2.02	5.73%
DC	KC	1.7	5.68%
DC	CC	1.59	5.06%
DC	CT	1.86	4.97%
HO	QS	1.65	4.66%
NG	SB	1.09	4.98%
NG	CC	1.13	5.00%
NG	CT	1.11	4.40%

CL	PA	1.91	5.75%
CL	PL	1.66	5.46%
CL	CC	1.9	5.78%
SI	KC	1.79	5.89%
SI	CC	1.7	5.11%
SI	CT	1.64	4.87%
SB	CT	1.47	4.72%

Appendix C

Description	Symbol	Sectors	Sector Description	Maturity
US Corn Futures Historical Data (ZCN9)	ZC	Agriculture	COMMODITY_GRAINS_AND_OILSEEDS	HKNUZ
Rough Rice Futures (RRN9)	ZR	Agriculture	COMMODITY_GRAINS_AND_OILSEEDS	FHKNUX
US Wheat Futures (ZWN9)	ZW	Agriculture	COMMODITY_GRAINS_AND_OILSEEDS	HKNUZ
US Soybean Oil Futures (ZLN9)	ZL	Agriculture	COMMODITY_GRAINS_AND_OILSEEDS	FHKNQUVZ
US Soybeans Futures (ZSN9)	ZS	Agriculture	COMMODITY_GRAINS_AND_OILSEEDS	FHKNQUX
Oats Futures (Oc1)	ZO	Agriculture	COMMODITY_GRAINS_AND_OILSEEDS	HKNUZ
Live Cattle Futures (LEQ9)	LE	Agriculture	COMMODITY_LIVESTOCK	GJMQVZ
Lean Hogs Historical Data (HEM9)	HE	Agriculture	COMMODITY_LIVESTOCK	GJKMNQVZ
Feeder Cattle Futures (FCQ9)	FC	Agriculture	COMMODITY_LIVESTOCK	FHJKQUVX
Class III Milk Futures (DCSc1)	DC	Agriculture	COMMODITY_LIVESTOCK	FGHJKMNQUVXZ
Heating Oil Futures Historical Data (HON9)	HO	Energy	COMMODITY_ENERGY	FGHJKMNQUVXZ
Natural Gas Futures Historical Data (NGF8)	NG	Energy	COMMODITY_ENERGY	FGHJKMNQUVXZ
Crude Oil WTI Futures Historical Data (CLN9)	CL	Energy	COMMODITY_ENERGY	FGHJKMNQUVXZ
Gas Oil Futures (LGOQ9)	QS	Energy	COMMODITY_ENERGY	FGHJKMNQUVXZ
Gold Futures (GCQ9)	GC	Metals	COMMODITY_METALS	GJMQVZ
Copper Futures (HGN9)	HG	Metals	COMMODITY_METALS	HKNUZ
Palladium Contract (PAU9)	PA	Metals	COMMODITY_METALS	HMUZ
Silver Futures (SIN9)	SI	Metals	COMMODITY_METALS	FHKUNZ
Platinum Futures (PLN9)	PL	Metals	COMMODITY_METALS	FJNV
US Sugar #11 Futures (SBN9)	SB	Agriculture	COMMODITY_SOFTS	HKNV
US Coffee C Futures (KCN9)	KC	Agriculture	COMMODITY_SOFTS	HKNUZ
US Cocoa Futures (CCN9)	CC	Agriculture	COMMODITY_SOFTS	HKNUZ
US Cotton #2 Futures (CTN9)	CT	Agriculture	COMMODITY_SOFTS	HKNVZ
Canadian Dollar US Dollar (CADUSD)	CAD_USD	Forex	FOREX_CURRENCY	FGHJKMNQUVXZ
Japanese Yen US Dollar (JPYUSD)	JPY_USD	Forex	FOREX_CURRENCY	FGHJKMNQUVXZ
Indian Rupee US Dollar (INRUSD)	INR_USD	Forex	FOREX_CURRENCY	FGHJKMNQUVXZ
Australian Dollar US Dollar (AUDUSD)	AUD_USD	Forex	FOREX_CURRENCY	FGHJKMNQUVXZ
British Pound US Dollar (GBPUSD)	GBP_USD	Forex	FOREX_CURRENCY	FGHJKMNQUVXZ
Bloomberg Commodity (BCOM)	BCOM	Index	EXCHANGE	FGHJKMNQUVXZ
S&P GSCI Commodity Total Return (SPGSCITR)	SPGSCITR	Index	EXCHANGE	FGHJKMNQUVXZ
CBOE Volatility Index (VIX)	VIX	Index	EXCHANGE	FGHJKMNQUVXZ
S&P 500 Contract (US500)	US500	Index	EXCHANGE	FGHJKMNQUVXZ

Table 1: Description of data

Appendix D

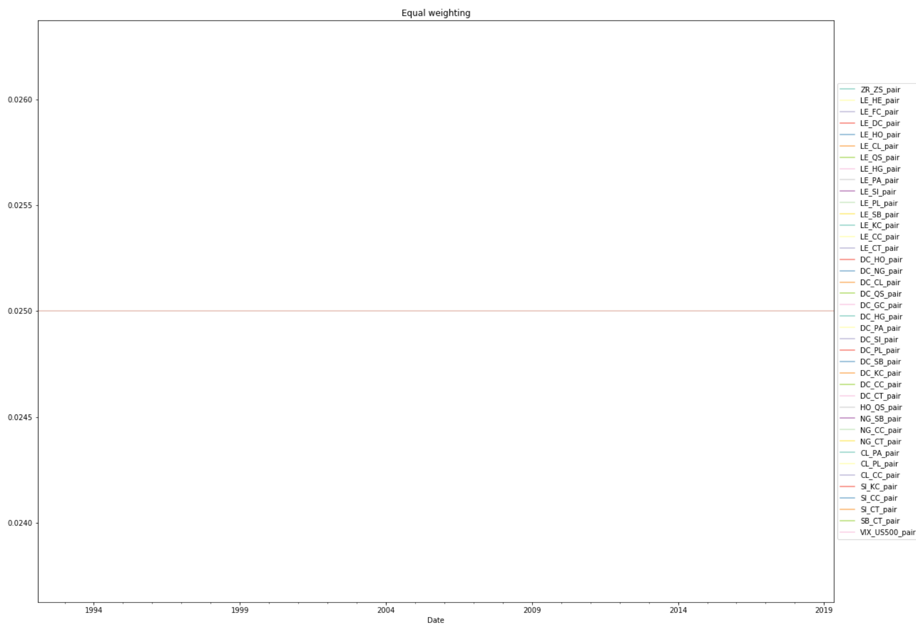

Fig 11: Asset allocation with Equal weighting

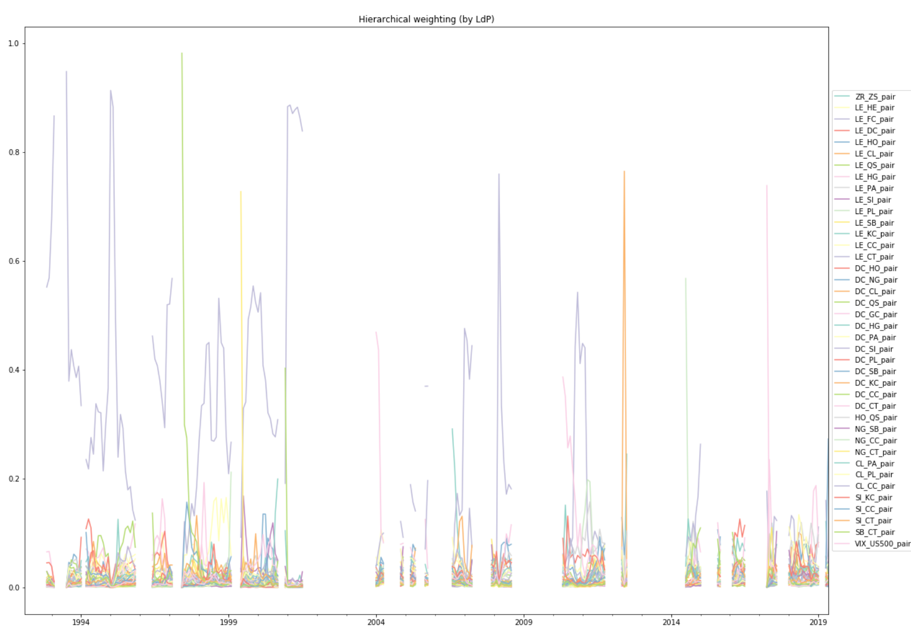

Fig 12: Asset allocation with Hierarchical weighting (by LdP)

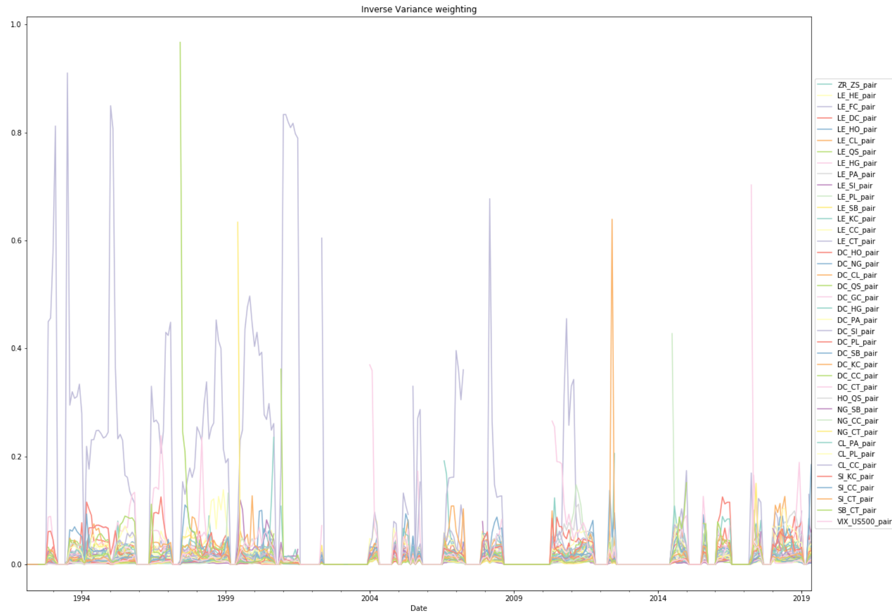

Fig 13: Asset allocation with Inverse Variance weighting

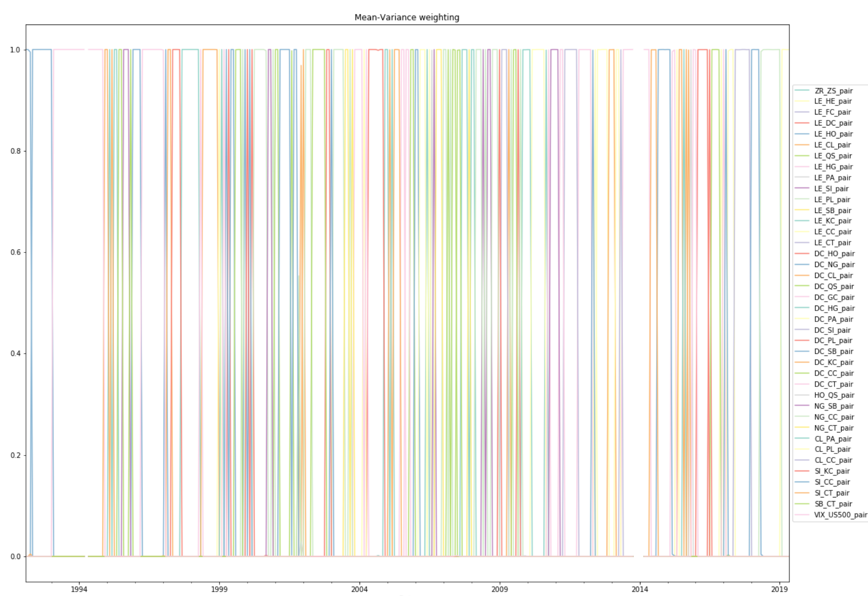

Fig 14: Asset allocation with Mean-Variance weighting

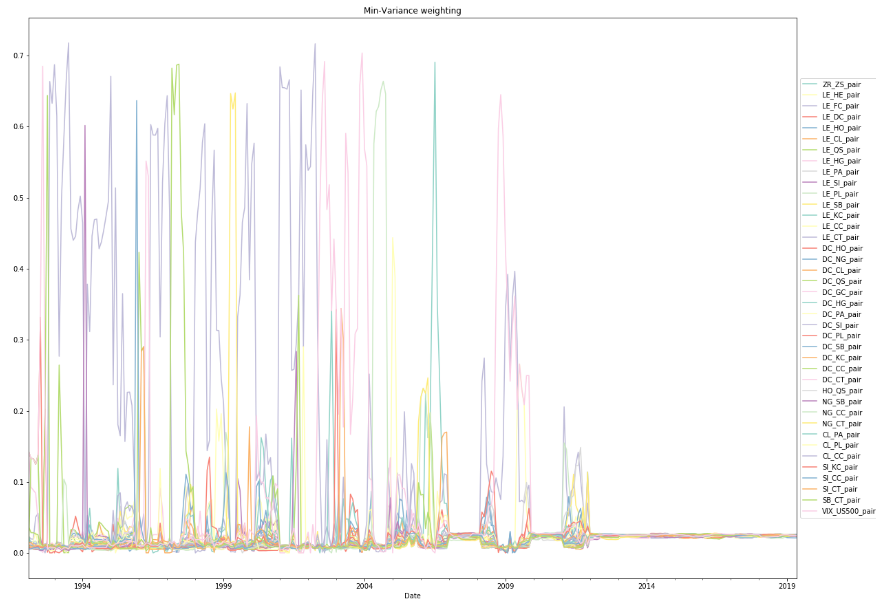

Fig 15: Asset allocation with Min-Variance weighting

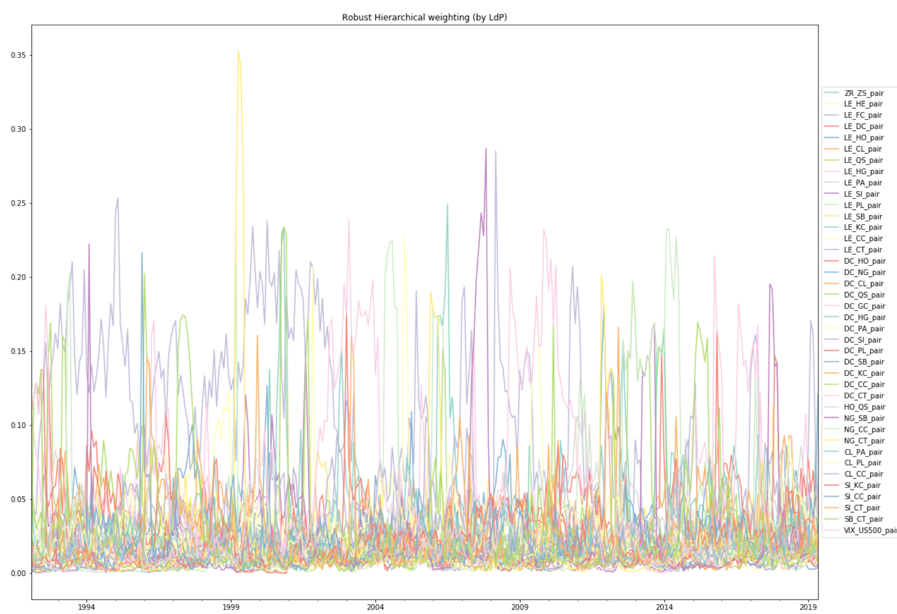

Fig 16: Asset allocation with Robust Hierarchical weighting (by LdP)

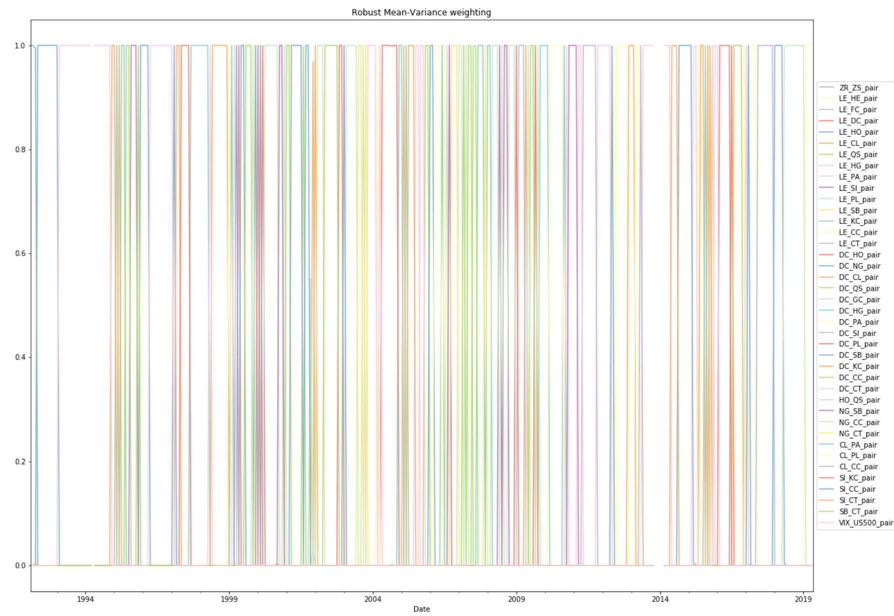

Fig 17: Asset allocation with Robust Mean-Variance weighting

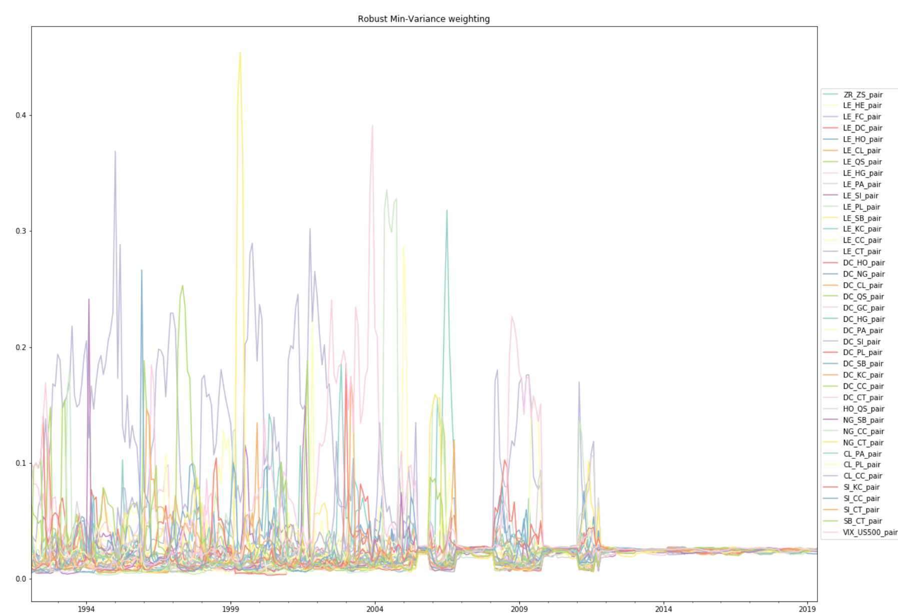

Fig 18: Asset allocation with Robust Min-Variance weighting