WORLDQUANT UNIVERSITY

Compiled Notes Module 4

MScFE 660

Case Studies in Risk Management

Revised: 06/22/2020

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Module 4: Understanding Hedge Fund Failures (e.g. LTCM)

Module 4 uses data modeling, comparative risk assessment, and contextual framing to explain how hedge fund failures occur and how they may trigger major financial market crashes. The module begins by introducing hedge funds and their regulation and by using models to test the market efficiency, which is key for a successful hedge fund. The module continues by analyzing major hedge fund failures, namely Long-Term Capital Management (LTCM), Tiger Management, and Atticus Global. Methodologies to manage risks in using hedge funds such as the Inverse Reinforcement Learning (IRL) are discussed at the end of the module.

Unit 1: Hedging Your Bets

Throughout the history of investment markets and financial decision making, there have been different types of traded items. From stocks to mutual funds to hedge funds, the variety informs how the market plays out, how fluctuation in the market is generated and how certain contexts inform the growth or decline in the value of investment portfolios. What is important specifically in hedge funds is firstly how they have come to play a fundamental role in the financial sector today, and how they have, over time, played significant roles in the collapses of some major companies and some major financial crises.

The simple principles

Hedging refers to techniques used to mitigate risk, usually by taking positions whose values moves inversely with that of the positions being hedged. Using subtle risk management strategies and approaches to limit their exposures, hedge funds are able to reap rewards without suffering too heavily during market crashes or instability. This, at least, is the theory of hedge fund institutions. Hedge funds act as an "investment union" or "partnership" that operates with the pooled assets of all investors who participate within the fund.

A.W. Jones & Co. started the first investment fund that was truly a hedge fund in 1949. He was a writer for Fortune Magazine at the time and, having written about investing wanted to see if he could succeed at the process he had been describing. He implemented what is now referred to as a long/short equities model by hedging his long positions with short positions in other names, Jones also employed leverage to enhance his returns, as many hedge funds do.[1]

The ultimate goal of a hedge fund is to employ techniques that are profitable whether the market rises or falls. While the term "hedge fund" implies risk minimization, most hedge funds take materially more risk than mutual funds.

The use of the term "hedge" was important at the time of economic prosperity – as a meaningful way for wealthy investors to have a unique means of investing above the normal selling and buying found on exchange hall floors – and at times of economic despair – where safety and surety was more valuable than the stocks themselves. In time, the strategies of hedge funds began to develop.

[1] https://www.investopedia.com/articles/investing/102113/what-are-hedge-funds.asp

The critical consideration in hedge funds is, naturally, risk: in most financial systems and stock markets, the investors who participate in hedge fund management are under heavy scrutiny, for the risks posed are similar and can be more pronounced. For example, liquidity is the same with any kind of investment, and in the case of hedge funds there is often a limitation on how someone can liquidate their assets that are held in a fund. This, in turn, could create situations of panic and overuse of leverage, a process of using money or assets that are borrowed to purchase other assets in the hope that the situation will recover. Thus, there are major concerns that are associated with the regulatory principles applied to hedge funds.

The creation of the first major hedge fund in 1949 saw it grow in strength owing to the series of incentives for investors. If investors were willing to opt into the long and short dynamic of hedging financial decisions, they would reap high rewards.

During the next few decades, hedge funds continued to outperform all other fund schemes on the market, though this did create the circumstances for riskier hedging, which in turn exacerbated the crashes in the late 1960s and early 1970s. A number of hedge funds closed during this time. Hedge funds really took off in the 1990s when some high-profile money managers left the relatively staid mutual fund industry to pursue more profit while taking more risk, effectively creating a distinct asset class.[2]

However, the dot-com bubble of the late 90s and early 2000s struck, causing the same issue of speculation to hit the hedge funds hard. The bubble – created by over-speculation on the recent growth in online businesses that were taking advantage of the World Wide Web technological advances – ran from around 1994 until the crash in the early 2000s, lasting from 2000 until 2002. Internet companies that attracted investment did not necessarily pan out into profitable companies. For example, online pets store Pets.com earned over $80 million in its initial IPO in 2000 and was essentially worthless a few years later. What created a crisis situation, however, was the same situation found in many previous crashes: overzealous enthusiasm in investing without due checks and balances that ought to be taken by both investors and the government when the market begins to expand. Similarly, the expansion of access to the stock market through the Internet itself made for an expanded base of investors that clubbed together to generate more interest. By creating websites for investment information, data and collective forums, the Internet helped

[2] Ibid.

expand the dot-com bubble in more than one way. There is no defining trigger for the bursting of the dot-com bubble, but it is largely connected to the increase in interest rates, the minor collapse of the Japanese market – a country that contributed heavily to the technology sector globally – and the eventual bankruptcy of numerous Internet-based companies that weren't generating as much profit as was expected.

The 2008 financial crisis (Module 5) and the 2010 Flash Crash (Module 6) were also partially attributable results of the hedge fund issue, but there is more to be said about those individually. Development of strategies have turned hedge funds into a multifaceted investment approach that tackles pension funds, insurance efforts, credit and debit management, risk assessment on localized and global trade and the creation of globalized trading schemes.

Since the financial crisis, the hedge fund industry has continued to expand with total assets under management (AUM) estimated to be between $3 and $3.5 trillion.[3] According to BarclayHedge, which tracks hedge fund size and performance, the total AUM for hedge funds jumped by 2,656% between 1997 and 2019.[4]

Regulatory powers

The regulation of hedge funds is generally very different form that of other asset classes because of the presumption that hedge fund investors are sophisticated. That started to shift, however, after the financial crisis with the implementation in the US of recording and recordkeeping requirements associate with eth Dodd-Frank Act. Hedge funds tend to be actively managed by individual traders and institutions, so are not easily regulated by typical governmental efforts. Generally, there is less scrutiny of hedge funds, however. To that end, hedge funds exhibit many of the characteristics we might expect from investors that embrace risk – high profit potentials and also high volatility.

[3] Barrth, Joenvaara, Kauppila, Wormers, The Hedge Fund Industry is Bigger (and has Performed Better) Than You Think, Office of Financial Research (OFR) Working Paper Series, February 2020

[4] https://www.statista.com/statistics/271771/assets-of-the-hedge-funds-worldwide/

Unit 2: When the Hedgerow Collapses

Not so random…

The success of hedge funds fundamentally boils down to the question of market efficiency. If markets are perfectly efficient, the ability for hedge funds to return above-market risk-adjusted returns should be at best a matter of luck. While the religious believers of Efficient Market Hypothesis (EMH) might justify the notable successes of the Buffets, Simons and the Griffins of this world through the law of large numbers, the majority of studies indicate prices in most markets to be, at most, weak-form efficient. While this may seem obvious, we can test this for ourselves, using a range of different methods for testing serial correlation. Using the statsmodels package, we can make use of the Durbin-Watson and Ljung Box-test to test the presence of serial correlation in a stock. In the plot below, we can perform a Ljung box-test on a year's worth of Apple stock market returns. Using this data, we see a strong argument in against market efficiency, given the Durbin-Watson Statistic shown in our test.

In [1]:
```
import os
import pickle
from functools import reduce
from operator import mul

import pandas as pd
import numpy as np

from statsmodels.regression.linear_model import OLS
from statsmodels.stats.stattools import durbin_watson
from statsmodels.stats.diagnostic import acorr_ljungbox
from sklearn import linear_model
from sklearn.decomposition import PCA

import holoviews as hv
import hvplot
import hvplot.pandas
```

In [2]:
```
np.random.seed(42)
hv.extension('bokeh')
```

```
In [3]: # There is a compatilibility issue with this library \
        #and newer versions of Pandas, this is short fix to the problem, \
        #if you have issues at this chunk comment it out and you should be fine.
        pd.core.common.is_list_like = pd.api.types.is_list_like
        import pandas_datareader as pdr
```

```
In [4]: apple = pdr.robinhood.RobinhoodHistoricalReader(['AAPL'],
                                                        retry_count=3,
                                                        pause=0.1,
                                                        timeout=30,
                                                        session=None,
                                                        freq=None,
                                                        interval='day',
                                                        span='year').read().reset_index()

        dw = durbin_watson(pd.to_numeric(apple.close_price).pct_change().dropna().values)
        print(f'DW-statistic of {dw}')
```

```
DW-statistic of 1.9028156953447164
```

This strongly exceeds the upper-bound of the DW-statistic at the 5% level, indicating the presence of first order correlation.

The question then remains: if markets are inefficient, where is this inefficiency? This question has remained at the forefront of research for decades. Fundamentally, investors not only want to be able to quantify sources of return but also want to identify sources of potential portfolio risk. If market returns can be considered white noise, is there some trend or underlying factor which will allow us to identify and understand these risks?

The simplest of these models, Capital Asset Pricing Model (CAPM) developed by Treynor (1961), Treynor (1962), Sharpe (1964), Lintner (1965), Mossin (1966) and Black, Jensen & Scholes (1972), remains at the core of modern financial theory by providing investors with a framework in determining how the expected return of an investment is affected by its exposure to the systematic risk.

$$Expected\ Return = r_f + \beta(r_m - r_f)$$

Where Expected Return is the expected returns of a share in the market, r_f, is the risk-free rate, r_m are the returns of the market, and, β is a coefficient computed using Ordinary Least Squares Regression, under the assumption of normally distributed errors.

Under the CAPM, an asset may only earn a higher average return given an increase in exposure to a comprehensive market portfolio, as denoted by β, which should capture all systematic risk in the market. However, given that the market portfolio, which should exist as the universe of all investable assets, is not identifiable in reality, a market index is used as a proxy. While the application of CAPM is ubiquitous both in practice and in research, there exists numerous papers investigating markets around the work which critique its application over concerns over the emergence of stylized facts, the existence of cohesive market portfolios and many practical concerns over market concentration and liquidity.

While this set of notes will not aim to investigate the validity of the CAPM model, we will investigate the Arbitrage Pricing Theory (APT) as a segue into its implications on hedge fund construction, analysis and risk (Ross, 1976). Sadly, as discussed in the lecture recordings, the availability of public, open hedge fund data is limited, and so this module will be relying primarily on market-data, data on ETF's and famous academic datasets.

APT is a generalized framework for asset pricing that sets the expected return of an asset as a linear function of various factors, denoted below:

$$Expected\ Value = \beta_0 + \beta_1 F_1 + \cdots + \beta_n F_n$$

While this may appear simple, given your exposure to advanced methods in statistical learning, the use of linear models in this application allows for computational stability and inference – crucial to many of its extensions.

While a number of behavioral studies have been investigated in understanding non-randomness in markets, one on-going area of research has been in the use of factor models. Most factor models explore some combination of portfolio fundamentals in trying to analyze sources of non-systematic return. In seminal papers by Banz (1981) and Basu (1983), researchers explore the presence of a size- and value-effect in predicting expected returns. These factors analyze the Market Cap and PE-ratios of companies, under the APT framework, including these variables alongside the traditional market returns and risk-free rate.

While research into these anomalies has varied in their findings, suggesting them a possible function of market dynamics at a point in time, studies by Lizenverg & Ramasamy (1979), Stattman (1980) and Rosenberg (1885) suggest Dividend Yield and Book-to-Market as other significant stylized facts. This research is not limited to American and European markets. In studies around the world, researchers have identified factors like momentum, cashflows, NAV and sector index as factors relevant to particular markets. Some of the most famous studies in the area of factor models has been in the Fama-French 3- and 5-Factor models. These models include market returns, size, book-to-market, operating profitability and investment.

While the presence of these factors, many argue, provide a strong argument for the use of an exploration of statistical modelling in finance, there exist a number of counter-arguments which aim to break down the idea of just trying everything. The first argument raised by most efficiency market believers is about liquidity risk. While the size effect does indicator a negative correlation between size and expected returns, many smaller stocks are far less liquid on an exchange and, as such, present a risk to investors during times of extreme market failure. Secondly, opponents argue that many of these anomalies are temporal. In the book, *The Quants*, author Scott Patterson details the increasingly large leverage required by many funds towards the end of a particular trading strategies life-time as many new copy-cats enter a particular strategy. Lastly, often simple cost can limit the ability to act on a particular trade. Fundamentally, if one cannot realistically profit from a market anomaly or market inefficiency, then its ability to be realistically considered an argument in favor of market inefficiency is void.

Additionally, in the case of hedge funds, not only do these strategies need to exceed transaction costs and overcome liquidity risk in the market, but for the investor, trades must justify the cost structure of a hedge fund and the common lockup clause – which many argue presents an implied cost to the investor. While some may argue that active management ensures the pricing efficiency necessary in order to ensure passive funds can profit the reality is, from an investor point of view, Passive Funds have on average outperformed active management over a long time horizon.

For students unfamiliar with the research discussed in these notes, I would recommend reading further in your own time. The Podcast Freakonomics Radio, has an interesting show on passive vs active investments. The show interviews Vanguage founder John C. Bogle who shares a lifetime of knowledge into running a passive fund and its growing acceptance among consumers. I would also recommend a blogpost in Turing Finance on testing market efficiency.

Unit 3: The Many Hedge Fund Failures

Three major hedge fund failures are worth consideration to put their role in financial market crashes into context. What is critical to assess is the time each of the three below – Long-Term Capital Management, Tiger Management and Atticus Global – all started, how they behaved in times of fluctuation and change, and how they all ultimately ceased to be.

Opting out

Founded by Julian Robertson in 1980, Tiger Management Corp. was a hedge fund open to the public until it reformed into a public equity investment firm in 2009. Robertson, a stockbroker who had worked for Kidder, Peabody and Co. until 1980, when he used investments from his personal assets and from family and friends to found Tiger Management with 8 million US dollars. By the end of the 1990s, it had grown exponentially to $10.5 billion in value, making it one of the biggest asset-holding fund managers of the time. However, while the fund was growing, troubles began to surface.

The first was that one of the biggest investments Tiger Management had was U.S. Airways, which during the 1990s was plagued with management problems and fluctuations in value. These woes were largely limited to the decreasing competitiveness of the airline which largely restricted itself to the North-East of America, while other companies like American Airlines were able to do more cross-country flights. Because of the turbulence of the 1997 Asian crises and the 1998 Russian financial crisis and the growing changes of the dot-com era market, Robertson decided in 2000 to close the firm and return all owing capital. In 2001, the devalued U.S. Airways shares were likewise returned, shortly before the airline declared bankruptcy in 2002. Robertson ultimately decided not to interact with the rapidly changing and evolving late 1990s and early 2000s investment sector, opting instead towards growing opportunities for other hedge fund investors, known as "Tiger Seeds."

Intervention

Long-Term Capital Management (LTCM), formed by John W. Merriwether in 1994, was a hedge fund management firm centered in Connecticut, US. Merriwether, an experienced financier who had worked in arbitrage – the practice of finding profit in the gaps between sales in two or more assets, creating transactions that generate little to no cashflow loss – left the high-profile investment bank Salomon Brothers in 1991 after a banking scandal. Using his many connections – that included Nobel Prize in Economics laureates Myron S. Scholes and Robert C. Merton, famed for creating a new way to measure derivatives, or the change in value of something being measured by another asset, stock value or something of that sort – Merriwether created LTCM as a low-cost, high-yield option for investors that wanted to avoid regulation that applied to mutual funds. This meant that hedge funds, in the context of the financial world in 1994, were the best option, as the Investment Company Act of 1940 stated that companies that had a fewer number of investors with higher asset value per individual were less regulated than other investment platforms.

The core to the hedging used by LTCM was the use of arbitrage that relied on a fixed income index for each investment and investor. Much like a monthly or scheduled interest pay-out, LTCM ensured investors that at pre-determined times, money would be paid out. Keep the money in the investment longer, and the pay-out would increase, making long-term investment a more lucrative offer, hence the name of the company. Arbitrage operates on a very low risk principle but faces severe fluctuation and difficulty during any kind of financial instability, commonly found in a financial crash. This is because if leverage is used to try and float the differences in value, it may, ultimately lead to instability and liquidity problems.

This was the case with LTCM, as it began to leverage positions that were not as low-risk as they anticipated. Furthermore, as the 1997 Asian financial crises (Module 3) and the 1998 Russian financial crisis – which occurred when the Russian Central Bank had to devalue the ruble after defaulting on post-Soviet debt – both hit around the same time, instability on the market meant that high risk decisions were made by LTCM affiliates and managers. LTCM had heavily invested in currency exchanges, which were dramatically impacted by the Russian financial crisis. This, in turn, caused instability and heavy liquidity problems, prompting speculators to suggest a collapse was imminent. This did not bode well for LTCM, who was forced to liquidate at poor positions, causing further capital loss. Owing to their position as a high-profile investment hub for Wall Street and the New York Stock Exchange, LTCM was forced to accept a bailout from the US Federal Reserve in 1998, with its eventual dissolution in 2000.

The stormy one

Tim Baraket, currently the Chairman of TRB Advisors LB, formed Atticus Global in 1995 to create a diversified asset management platform for "event-driven" equity. This largely refers to the process of hedging financial decisions and orders during times where major financial decisions – for example, interest rate hikes, the collapse of a company or currency, or the merger of major companies – are taken and speculation is rife. While high risk, these kinds of equity decisions are commonly only made by companies and hedge funds with sufficient experience in the field.

Atticus Global made it big with these kinds of orders and grew from 6 million US dollars in 1995 to 20 billion US dollars in 2007, making it one of the biggest when the 2007 and 2008 financial crisis hit (Module 5). The instability of the global and American market during 2008 caused too much instability for Baraket to ride out, prompting him to follow Robertson's example and dissolve Atticus Global as major losses continued to accrue each year. All trading funds were dissolved, and assets returned to investors by December 2009, with Baraket citing family and philanthropy as the pressing reasons for his decision to wind down the investment giant.

Unit 4: Tracking the Failure

An IRL approach

Having outlined the types of Hedge Funds, as well as their strategies, it is now time to begin analyzing the sources of risk present in these strategies and incorporate much of our knowledge in Statistical Learning to explore these dynamics over time. In the notes, we have investigated a number of famous Hedge Fund disasters over time. The major theme in these disasters is the over-reliance and over-leverage of particular trades and positions when markets shift. We have also discussed the concept of market efficiency and analyze the use and application of factor models in the ongoing active vs passive debate.

One challenge in analyzing the risk exposure to particular Hedge Funds is our inability to dissect and understand their trading philosophies and current market strategies. A method by which to get around this challenge has been the use of Style Analysis in order to identify the correlation of particular funds with various fundamentals over time. Style analysis can be thought of as a form of Inverse Reinforcement Learning (IRL). In IRL, rather than being given an input data and a label and using a cost function and model to give a prediction, we use the known response of a person's behavior to figure out what goal that behavior seems to be trying to achieve, given known inputs or a known state-space. While we may use a cost function like Mean-Squared Error (MSE), in this approach, the aim is to find out an unbiased linear approximation of the investor's investment philosophy, rather than a function which predicts an output. While style analysis is the simplest version of this, just observing the weight-space of a linear model over-time and for different funds it provides key insights into the risk exposure of a particular fund.

If a fund appears highly correlated with interest rates at a point in time, we can assume they have strategies which expose them to interest rate risk. If a particular fund is highly correlated with equity, we can imagine despite the intricacies of that strategy, over-time the fund is exposed to market risk. The value in these techniques is its ability to understand the changing exposure of funds over time and how they respond to different market conditions.

In [1]:

```
# We will be importing many of the #
#  common libraries we have used before
import os
import pickle
from functools import reduce
from operator import mul

import pandas as pd
import numpy as np

from statsmodels.regression.linear_model import OLS
from sklearn import linear_model
from sklearn.decomposition import PCA

import holoviews as hv
import hvplot
import hvplot.pandas
```

In [2]:

```
# We set teh seed and
#  import the javascipt extensions for our plots
np.random.seed(42)
hv.extension('bokeh')
```

In [3]:

```
# There is a compatilibility issue with this library \
#and newer versions of Pandas, this is short fix to the problem, \
#if you have issues at this chunk comment it out and you should be fine.
pd.core.common.is_list_like = pd.api.types.is_list_like
import pandas_datareader as pdr
```

A warning to some of you running this code: the 3D plots do take a while to render. Please try your best to close other application which may be using a large number of system resources. This set of notes is going to look at a common dataset of different Hedge Fund Strategies. Funds with these strategies have been grouped to form strategy indexes, namely a: Liquid Alternative Beta Index, Event Driven Liquid Index, Global Strategies Liquid Index, Long/Short Liquid Index, Managed Futures Liquid Index and a Merger Arbitrage Liquid Index.

For those that are interested, we have included some code to download data on NASDAQ ETF's which should provide an interesting comparison in the types of funds. Most ETF should be highly market correlated, so you will see a very different correlation and scaling to the plots- which you may need to change. Unlike our previous note packs and peer review exercises there we have had to interpolate, detrend, scale and shape out data, this set of notes is far simpler as we will look at the daily returns on our different strategy indexes.

In [4]:
```
##### using this code, you can perform the code below on NASDAQ ETFs ####

# tickers = pdr.nasdaq_trader.get_nasdaq_symbols(retry_count=3, timeout=30, pause=None)
# etfs = tickers.loc[tickers.ETF == True, :]
# symbols = etfs.sample(75).index.tolist()

# packet = pdr.robinhood.RobinhoodHistoricalReader(symbols, retry_count=3, pause=0.1, timeout=30, session=None, freq=None, inter
val='day', span='year')

# data = packet.read().reset_index()
# pivot = data.loc[:,['symbol', 'begins_at', 'close_price']].drop_duplicates().pivot(index='begins_at', columns='symbol', values
='close_price')
```

In [5]:
```
# We import our data from CSV
indexes = pd.read_csv(os.path.join('..','Data','StyleIndexes.csv'))

# We ensure the dates are recorded correctly and compute returns
indexes.Date = pd.to_datetime(indexes.Date)
indexes.index = indexes.Date
indexes = indexes.drop(columns=['Date'])
indexes = indexes.pct_change().dropna()
```

In [6]:
```
# As this is a large dataset, we will only look
#  at the last 1000 trading-days
pivot = indexes.iloc[::-1,:].iloc[-1000:,:]
pivot.head()
```

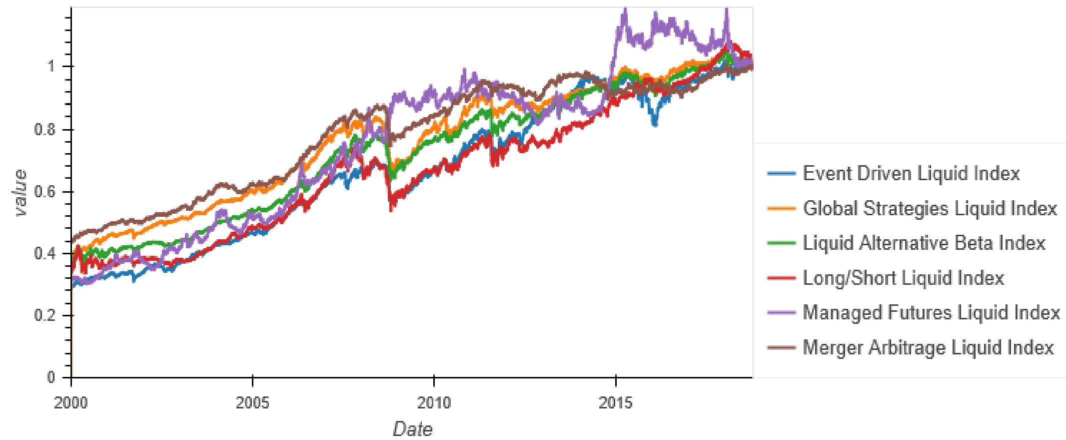
Out[6]:

Date	Liquid Alternative Beta Index	Event Driven Liquid Index	Global Strategies Liquid Index	Long/Short Liquid Index	Managed Futures Liquid Index	Merger Arbitrage Liquid Index
2016-01-26	0.003407	0.003849	0.004988	0.004456	0.000782	-0.002519
2016-01-27	-0.007023	-0.002224	-0.002998	0.000437	0.001592	-0.000699
2016-01-28	0.002243	-0.009758	-0.003897	0.003343	0.006831	-0.001829
2016-01-29	-0.004865	0.002451	-0.000707	-0.003317	0.002221	0.005409
2016-01-30	0.006049	-0.000521	-0.000447	0.001144	-0.001196	-0.008144

Using the data above, the plot below shows the returns the different strategies achieved over time. While these strategies may seem very different in their investment approach, it is easy to see how correlated they appear over long periods of time. In 2008, hedge fund strategies took a serious hit, driven- in part- to investor confidence and liquidity within the funds. It appears in recent years that Long/Short Liquid and Managed Futures Strategies have performed strongly. The question remains: can we identify common risks to these strategies, and can we identify the exposure of these risks to common market fundamentals.

```
In [7]: %%opts Curve [width=800 height=300] NdOverlay [legend_position='right']
        pd.melt(indexes.add(1).cumprod().reset_index(), id_vars=['Date']).hvplot.line(y='value', x='Date', by='variable')
```

Out[7]:



The first technique we are going to look at is Principle Component Analysis (PCA). As you have covered this method already in your Machine Learning Module, we will not go into the details of the technique or its derivation. Using PCA we can identify sources of variance across the funds. Using the slider, you can identify a start point in time and a window and observe over time the drift in the strategies. It appears over the 1000 days used in this interactive plot, that two components are a fairly strong predictor of strategy movements explaining roughly 70% of the variance between them.

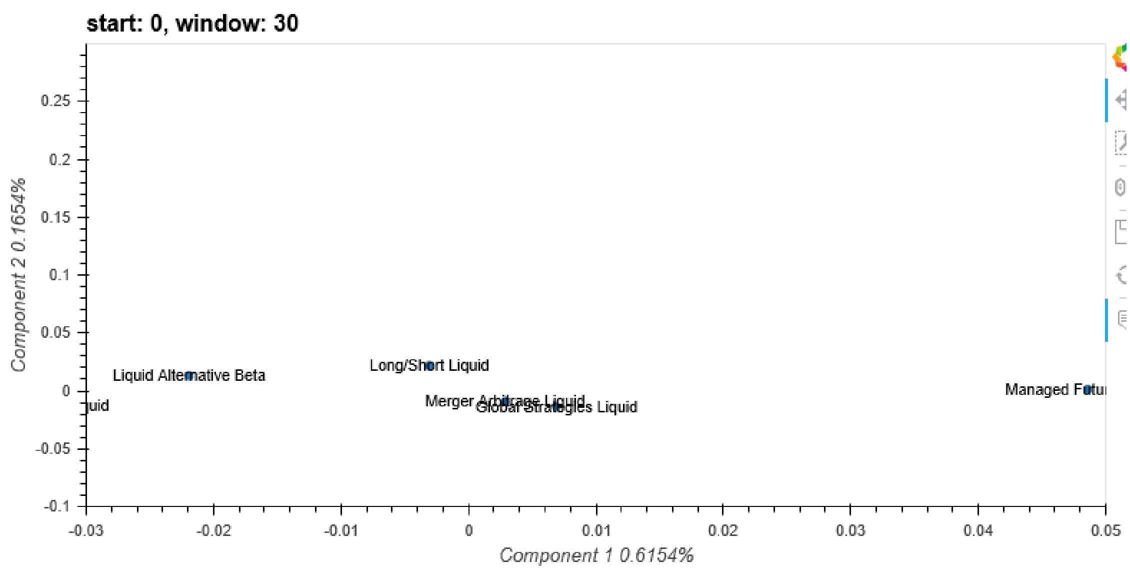
Obviously, it is difficult to identify clearly what these components might represent, but we can imagine equity markets being a large source of variance. What is interesting to note from this plot, is that while many strategies move dramatically, Global Strategies remains fairly central- perhaps indicating its diversified exposure.

In [8]:
```
# you can replace PCA with CCA, kernel PCA, FA or
#  any other relevent method for dimensionality reduction
# labels just tells the function to include the
#  names of the duffernt funds on the plot
class Component_Plots:
    def __init__(self, data=pivot, transformer=PCA(2), labels=True):
        self.data = data
        self.transformer = transformer
        self.labels = labels

    def components(self, start, window):
        component_data = self.transformer.fit_transform(self.data.iloc[start:(start+window),:].T)

        if self.labels:
            data_labels = reduce(mul, pd.DataFrame(component_data, index=self.data.columns.tolist(),
                                             columns=['Component_1', 'Component_2'])\
                                              .reset_index()\
                                              .apply(lambda x: hv.Text(x[1], x[2],
                                                                      ' '.join(x[0].split()[:-1]), fontsize=8), axis=1)\
                                              .tolist())
        else:
            data_labels = hv.Text(0,0,'')

        return pd.DataFrame(component_data, columns=['Component_1', 'Component_2'])\
                .hvplot.scatter(x='Component_1', y='Component_2')\
                .redim(Component_2={'range': (-0.1, 0.3)}, Component_1={'range': (-0.03, 0.05)})\
                .redim.label(Component_1=f'Component 1 {self.transformer.explained_variance_ratio_[0].round(4)}%',
                             Component_2=f'Component 2 {self.transformer.explained_variance_ratio_[1].round(4)}%').options(alpha
=1)*\
                data_labels
```

In [9]:
```
CompPlots = Component_Plots()
```

In [10]:
```
%%opts Scatter [width=800, height=400]
hv.DynamicMap(CompPlots.components, kdims=['start', 'window']).redim.range(start=(0,len(pivot.index))).redim.range(window=(30,9
0))
```

Out[10]:



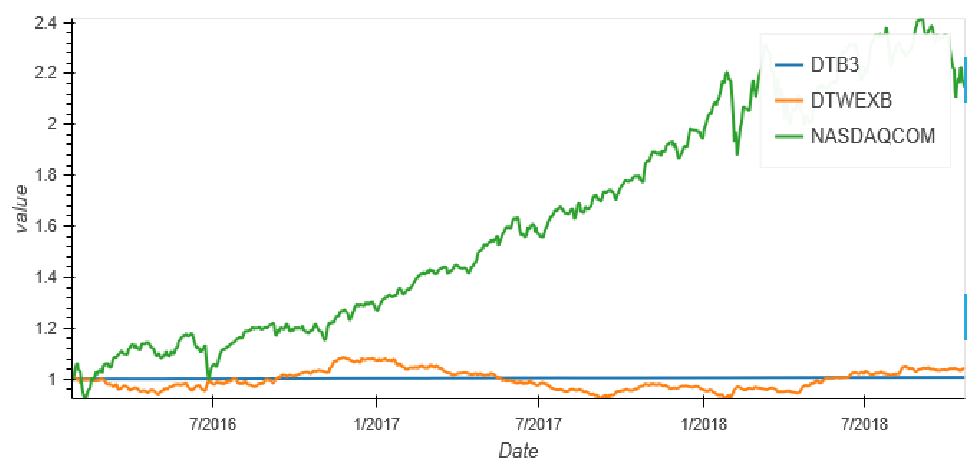
While PCA may provide insights into latent risk, given market information, we may also want to understand how these strategies respond over time to changing market conditions. For this we are going to analyze three primary factors: 3-month US T-bills, NASDAQ Composite Returns and the US Weighted Exchange Rate. We will be sourcing this data through the pandas_datareader API, from the [FRED website](). Using this data, we are going to fit models to understand the covariance of these models to factors over time. In order to analyze this, we are going to try observing not the input or output of these models, but the weight-space, to determine the effects of changes in strategies in response to changing factors. We imagine for Global Strategies Exchange Rate covariance may be high, while for Long/Short Strategies, Equity Exposure may be most important.

```
In [11]: # We download FRED data on 3-month Tbills,
         #  NASDAQ Comp and Exchnage rate mvts.
         factors = pdr.data.DataReader(['DTB3','NASDAQCOM','DTWEXB'], 'fred', start=str(pivot.index.min()), end=str(pivot.index.max()))
         factors.loc[:,['NASDAQCOM','DTWEXB']] = factors.loc[:,['NASDAQCOM','DTWEXB']].pct_change()
         factors.loc[:,['DTB3']]  = ((factors.loc[:,['DTB3']]+1)**(1/365)).pct_change()
         factors = factors.dropna()
         factors = factors.loc[pivot.index,:].interpolate().fillna(0)
```

While most of our factors appear fairly stable, it is clear how astronomical the growth in the NASDAQ has been over this period. As we imagine funds respond to changes in interest rates, we will look at changes to interest rates. As such, we will be using:

```
In [12]: pd.melt(factors.add(1).cumprod().reset_index(), id_vars=['Date']).hvplot.line(y='value', x='Date', by='variable')
```

Out[12]:




```
In [13]: # We must change the holoview
         #  backend to view a historic plot
         hv.extension('matplotlib')
```

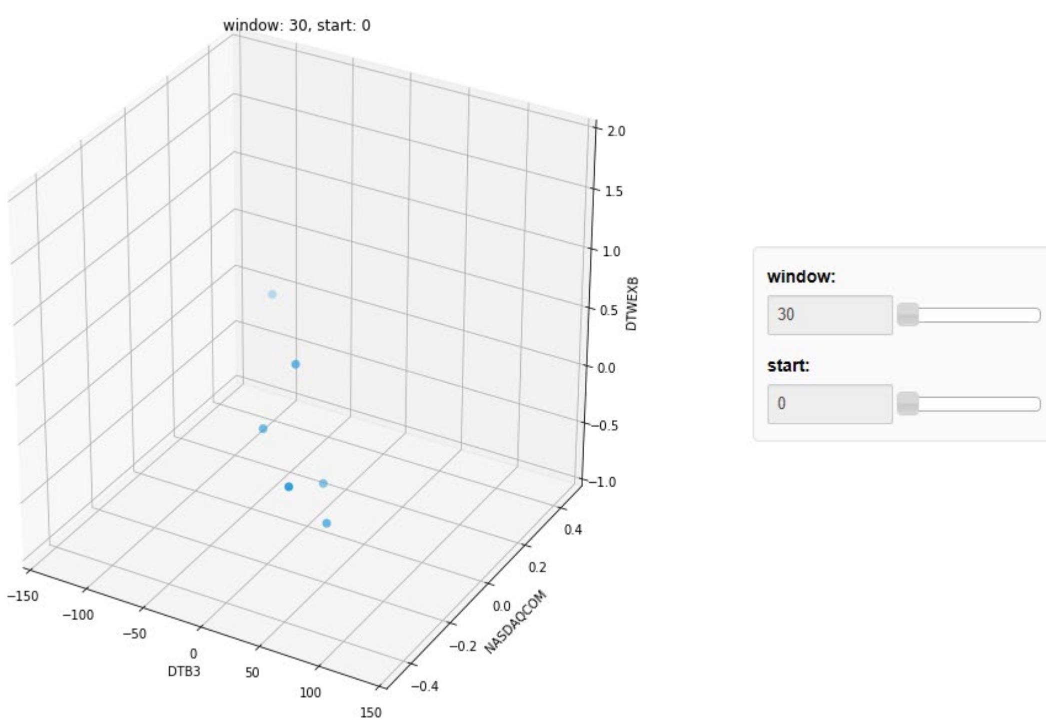
Given our three factors, we can use a 3-dimensional plot to best visualize and represent our weight-space and the movement of our strategies over time. Sadly, Holoview lacks functionality for 3D-text, though you should be able to track the movements of the dots to get an idea of the movements of strategies in this weight space over time. Using the sliders, you should be able to adjust the starting point and window over which the weights are calculated.

In [14]:
```
class Weight_Plots:
    def __init__(self, x=factors, y=pivot, transformer=linear_model.LinearRegression()):
        self.data = {'x':x,'y':y}
        self.transformer = transformer

    def weights(self, start=0, window=90):
        self.transformer.fit(X=self.data['x'].iloc[start:(start+window),:], y=self.data['y'].iloc[start:(start+window),:])
        a = pd.DataFrame(self.transformer.coef_, columns=['x','y','z'])
        a.index = pivot.columns.tolist()
        a = a.reset_index()


        return reduce(mul, a.apply(lambda x: hv.Scatter3D(pd.DataFrame([x[1:]], columns=['x','y','z']), label=x[0])\
                          .redim(y={'range': (-0.5*2, 0.5*2)}, x={'range': (-150*2, 150*2)},  z={'range': (-1*2, 2*2)})\
                          .redim.label(x=self.data['x'].columns[0], y=self.data['x'].columns[1], z=self.data['x'].columns[2])\
                          ,1))
```

In [17]:
```
WeightPlots = Weight_Plots()
curve_dict_2D = {(s,w):WeightPlots.weights(s,w) for s in range(0,len(pivot.index),25) for w in range(30,180,30)}
hmap = hv.HoloMap(curve_dict_2D, kdims=['start', 'window']).collate()
```

In [18]:
```
%%opts Scatter3D [fig_inches=10 color_index='index'] (s=65 cmap='viridis')
hmap.options(legend_position='right')
```

Out[16]:



Analyzing this plot, it is again clear the volatility in beta-derived strategies, such as Managed Futures, Long/Short Liquid and Liquid Alternative. In comparison, other strategies remain fairly central in our vector-space indicator their low correlations to T-bills, Beta and the Exchange Rate.

From the analysis in these notes we have begun to integrate our knowledge in machine learning and quantitative finance, to use method in IRL to analyze the risk exposures of various hedge fund strategies over time. Using this analysis, we can begin to understand how strategies respond to market events and the correlation between different strategies, from a fund of funds perspective.

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Collaborative Review Task

In this module, you are required to complete a collaborative review task, in addition to a multiple-choice quiz. The collaborative review task is designed to test your ability to apply and analyze the knowledge you have learned in the module.

Task

Using the dataset from Eugene Fama and Kenneth French's 2013 paper *"A Five-Factor Asset Pricing Model"*,

1 Visually analyze the covariance between various factors and identify the variance explained in principle components of these factors.

2 Using PCA provide a 2-dimensional representation of the weight-space of a set of linear models representing the covariance between our factors and the different benchmark portfolios. Comment on the distribution of the benchmark portfolios across the weight-space.

3 Using linear regression test for the significance of these factors, as per the original work of Fama and French, under the equation:

$$Expected\ Returns = r_f + \beta_1(r_m - r_f) + \beta_2 SMB = \beta_2 HML + \beta_3 RMW + \beta_4 CMA$$

You can download the dataset using the *_pandasdatareader* API, using the following code:

```
In [2]: import pandas as pd

        pd.np.random.seed(42)

        pd.core.common.is_list_like = pd.api.types.is_list_like
        import pandas_datareader.data as web
```

```
In [ ]: portfolios = web.DataReader('100_Portfolios_10x10_Daily', 'famafrench')
        factors = web.DataReader('F-F_Research_Data_5_Factors_2x3_daily', 'famafrench')
```