# HW2_code

July 1, 2020

HW 2

```
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```

\#

Part 2: LTCM Risk

\#\#

1. Summary Stats

a) For both the gross and net series of LTCM excess returns, report the mean and volatility. Since this is monthly &nbsp &nbsp &nbsp &nbsp &nbsp &nbsp data, scale the mean by 12, and scale the volatility by $\sqrt{12}$

```
[1]: import pandas as pd
     import numpy as np
     import math
     pd.options.display.float_format = '{:,.4f}'.format

     # ./ steps into this file's folder and lets you access the data file by just
      ↪its name
     path_to_data_file = './hedge_data.xls'
     LTCM_excess_returns = pd.read_excel(path_to_data_file)

     def mean_vol(data):

         mean = data.mean()*12
         vol = data.std()*math.sqrt(12)
         df = pd.DataFrame(data={'Mean': mean, 'Vol': vol});
         return df

     display(mean_vol(LTCM_excess_returns))
```

```
        Mean     Vol
```

```
gross 0.2572 0.1380
net   0.1689 0.1132
```

   b) Report the annualized Sharpe ratio, (the SR based on the annualized mean and volatility.)

```
[2]: def sharpe_calc(mean_vol):
         mean_vol['Sharpe'] = mean_vol['Mean']/mean_vol['Vol']
         return mean_vol
     sharpe_calc(mean_vol(LTCM_excess_returns))
```

```
[2]:        Mean     Vol  Sharpe
     gross 0.2572 0.1380  1.8636
     net   0.1689 0.1132  1.4924
```

   c) Comment on whether the mean, volatility, and Sharpe ratio seem especially high or low relative to other assets we have seen.

LTCM's Sharpe here is almost 1.5, which would be considered very good and higher than most other assets. While LTCM's Vol of .11 is higher than many asset classes, namely bonds and HY bonds, LTCM's higher Sharpe tells us that its returns are more than making up for the extra risk it is taking.

We saw on HW #1 that domestice equity had a Sharpe of 1.2 from 2009-2019, which was also when domestice equity saw a very long recovery and bull market.

## 0.1  2. Using the series of net LTCM excess returns, denoted $\tilde{r}t\text{LTCM}$, estimate the     following regression:

## 0.2                                        $\tilde{r}t\text{LTCM} = \alpha + \beta\mathbf{m}\tilde{r}t\mathbf{m} + \epsilon t$

### 0.2.1  a) Report $\alpha$ and $\beta\mathbf{m}$. Report the $R2$ stat.

```
[3]: from scipy import stats

     market_return = pd.read_excel('./hedge_data.xls', sheet_name='MktExcessRets', ␣
      ↪index_col='date')

     def alpha_beta_R2(market_data, security_return):

         x = market_data.values
         x = x.reshape(security_return.values.shape[0],)
         alpha_beta_R2.x = x

         y = security_return.values
         alpha_beta_R2.y = y

         alpha_beta_R2.beta_m,\
```

```
       alpha_beta_R2.alpha,\
       alpha_beta_R2.rsquared,\
       pvalue,\
       stderr\
       = stats.linregress(x, y)
       alpha_beta_R2.answer = pd.DataFrame([{'Alpha' : alpha_beta_R2.alpha, 'Beta'␣
   ↪: alpha_beta_R2.beta_m, 'RSquared' : alpha_beta_R2.rsquared}])

   alpha_beta_R2(market_return.loc['1994-04-30':'1998-06-30',:],␣
    ↪LTCM_excess_returns.loc[:,'net'])
   alpha_beta_R2.answer
```

[3]:     Alpha    Beta   RSquared
     0 0.0134 0.0420    0.0406

b) From this regression, does LTCM appear to have much exposure to the equity-market factor, $\tilde{r}t$m ?

No because the beta_m value tells us how much exposure the LTCM has to the market equity factor. So, since beta is relatively small, and a full one unit increase in the market equity is unlikely it appears that the LCTM does not have much exposure to the market equity factor.

### 0.3 3. Regression-based metrics.

a) Calculate the Treynor ratio.

```
[4]: def TR(net_return_data):

         expected_r = net_return_data.mean()
         treynor = expected_r / alpha_beta_R2.beta_m
         TR.answer = pd.DataFrame([{'Treynor Ratio' : treynor}])

     TR(LTCM_excess_returns.loc[:,'net'])
     TR.answer
```

[4]:     Treynor Ratio
     0          0.3349

b) Calculate the Information ratio.

```
[5]: def IR():

         predictions = alpha_beta_R2.beta_m*alpha_beta_R2.x + alpha_beta_R2.alpha
         residuals = predictions-alpha_beta_R2.y
         info_rat = alpha_beta_R2.alpha/(residuals).std()
         IR.answer = pd.DataFrame([{'Information Ratio' : info_rat}])

     IR()
```

```
IR.answer
```

[5]:        Information Ratio
      0               0.4155


## 0.4   4. Tail risk.

a) Calculate the 5th worst return of the sample.

```
[6]: #Using the net LTCM returns

     LTCM_excess_returns_sorted = LTCM_excess_returns.
      ↪sort_values(by=['net'],ascending=True, ignore_index=True)
     LTCM_excess_returns_sorted.index = LTCM_excess_returns_sorted.index + 1
     LTCM_excess_returns_sorted['date'] = LTCM_excess_returns_sorted['date'].
      ↪astype(str)
     df = LTCM_excess_returns_sorted.loc[5::-1,['date', 'net']].style.
      ↪set_properties(subset=pd.IndexSlice[pd.IndexSlice[5], pd.IndexSlice[:]],␣
      ↪**{'background-color': '#ff6666', 'color': 'black'})
     df
```

[6]: <pandas.io.formats.style.Styler at 0x1a1c724e50>


b) Calculate the mean of the worst 4 returns from the sample.

```
[7]: LTCM_excess_returns_sorted.loc[:4,['date','net']].mean()
```

[7]: net   -0.0566
     dtype: float64


c) Report the skewness of the return distribution. Compare to a normal distribution with skewness of 0.

The skewness of the returns is negative meaning the returns distrobutions are skewed left

```
[8]: from scipy.stats import kurtosis
     from scipy.stats import skew
     from scipy.stats import norm
     import matplotlib.pyplot as plt

     print("The Skewness of the return distribution is " +␣
      ↪str(skew(LTCM_excess_returns.iloc[:,2:])[0]))

     LTCM_excess_returns.loc[:,'net'].hist()
     x = np.linspace(-.1,.1,1000)
     y = norm.pdf(x, loc=0, scale=LTCM_excess_returns.loc[:,'net'].std())
     plt.plot(x,y, linewidth=3);
```

```
The Skewness of the return distribution is -0.8318899364747497
```
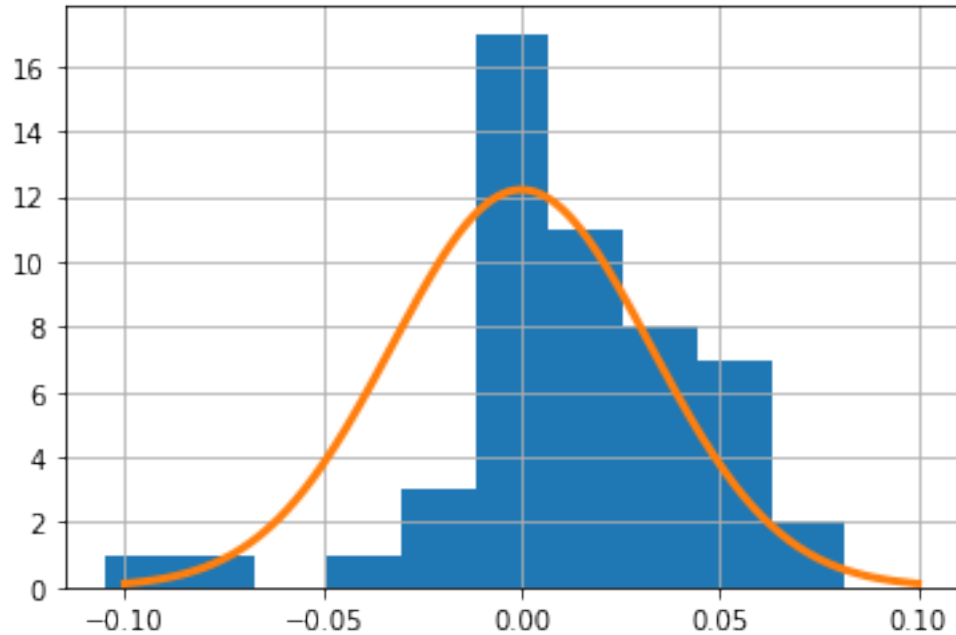


d) Report the kurtosis of the return distribution. Compare to a normal distribution with kurtosis of three.

The Kurt of the returns is larger than a normal distrobution. This means the returns have skinnier tails i.e. return distributions are more concentrated close to the mean and don't trail off in the same way a normal distrobution does.

```
[9]: print("The kurtosis of the return distribution is " +␣
      ↪str(kurtosis(LTCM_excess_returns.iloc[:,2:])[0]))
```

```
The kurtosis of the return distribution is 2.5874860101941097
```

\#

Part 3: Other Hedge Fund Indexes

Analyze the Total Index fund (of the second tab in the data file), by calculating the same statistics you estimated for LTCM. So if you wrote the code above well, it can mostly be re-used for this.

```
[10]: hedge_excess_rets = pd.read_excel('./hedge_data.xls',␣
       ↪sheet_name='HedgeFund_ExcessRets',  index_col='date')


      hedge_df = sharpe_calc(mean_vol(hedge_excess_rets))
      hedge_df['Skew'] = skew(hedge_excess_rets)
      hedge_df['Kurt'] = kurtosis(hedge_excess_rets)
      hedge_df['5th Percentile'] = hedge_excess_rets.quantile(0.05)
```

```
display(hedge_df)
```

|                             | Mean    | Vol    | Sharpe  | Skew     | Kurt     |
|-----------------------------|---------|--------|---------|----------|----------|
| Total Index                 | 0.0604  | 0.0732 | 0.8243  | -0.2558  | 2.6879   |
| Convertible Arbitrage       | 0.0458  | 0.0686 | 0.6677  | -2.6403  | 16.0553  |
| Dedicated Short Bias        | -0.0656 | 0.1682 | -0.3898 | 0.6864   | 1.4063   |
| Emerging Markets            | 0.0514  | 0.1457 | 0.3531  | -0.8801  | 5.4616   |
| Equity Market Neutral       | 0.0247  | 0.1019 | 0.2428  | -11.9950 | 163.8178 |
| Event Driven                | 0.0606  | 0.0622 | 0.9749  | -2.2978  | 11.3991  |
| Event Driven Distressed     | 0.0707  | 0.0649 | 1.0900  | -2.2738  | 11.7608  |
| Event Driven Multi-Strategy | 0.0559  | 0.0675 | 0.8276  | -1.7772  | 7.8675   |
| Event Driven Risk Arbitrage | 0.0337  | 0.0407 | 0.8259  | -1.1021  | 5.1140   |
| Fixed Income Arbitrage      | 0.0271  | 0.0568 | 0.4779  | -4.4191  | 30.8270  |
| Global Macro                | 0.0922  | 0.0938 | 0.9831  | -0.0720  | 4.3355   |
| Long/Short Equity           | 0.0661  | 0.0977 | 0.6771  | -0.0774  | 3.3262   |
| Managed Futures             | 0.0288  | 0.1172 | 0.2455  | 0.0370   | -0.0592  |
| Multi-Strategy              | 0.0484  | 0.0534 | 0.9078  | -1.6513  | 5.7122   |

|                             | 5th Percentile |
|-----------------------------|----------------|
| Total Index                 | -0.0266        |
| Convertible Arbitrage       | -0.0220        |
| Dedicated Short Bias        | -0.0757        |
| Emerging Markets            | -0.0707        |
| Equity Market Neutral       | -0.0130        |
| Event Driven                | -0.0264        |
| Event Driven Distressed     | -0.0242        |
| Event Driven Multi-Strategy | -0.0270        |
| Event Driven Risk Arbitrage | -0.0153        |
| Fixed Income Arbitrage      | -0.0137        |
| Global Macro                | -0.0285        |
| Long/Short Equity           | -0.0407        |
| Managed Futures             | -0.0507        |
| Multi-Strategy              | -0.0227        |

## 

2. For each series, run a regression of the series on the market-equity factor. Report the following for each regression:

-

### 0.4.1 Beta

-

### 0.4.2 Alpha

-

### 0.4.3 R-squared

- 

### 0.4.4 Treynor Ratio

- 

### 0.4.5 Information Ratio

```python
[11]: hedge_excess_rets = pd.read_excel('./hedge_data.xls',
      ↪sheet_name='HedgeFund_ExcessRets', index_col='date')
      regression_df = pd.DataFrame()

      for (columnData) in hedge_excess_rets.iteritems():

          alpha_beta_R2(market_return, columnData[1])
          TR(columnData[1])
          IR()

          regression_df[columnData[0]] = alpha_beta_R2.answer.loc[0,:].append(TR.
      ↪answer.loc[0,:]).append(IR.answer.loc[0,:])

      regression_df.T
```

```
[11]:                              Alpha     Beta  RSquared  Treynor Ratio  \
      Total Index                 0.0035   0.2839    0.6169         0.0177
      Convertible Arbitrage       0.0029   0.1667    0.3869         0.0229
      Dedicated Short Bias       -0.0008  -0.8665   -0.8198         0.0063
      Emerging Markets            0.0014   0.5320    0.5809         0.0081
      Equity Market Neutral       0.0010   0.1894    0.2959         0.0109
      Event Driven                0.0036   0.2606    0.6666         0.0194
      Event Driven Distressed     0.0045   0.2618    0.6417         0.0225
      Event Driven Multi-Strategy 0.0032   0.2633    0.6203         0.0177
      Event Driven Risk Arbitrage 0.0020   0.1447    0.5650         0.0194
      Fixed Income Arbitrage      0.0016   0.1203    0.3371         0.0188
      Global Macro                0.0069   0.1407    0.2386         0.0546
      Long/Short Equity           0.0030   0.4561    0.7431         0.0121
      Managed Futures             0.0028  -0.0767   -0.1042        -0.0312
      Multi-Strategy              0.0033   0.1365    0.4069         0.0296

                                   Information Ratio
      Total Index                             0.2101
      Convertible Arbitrage                   0.1598
      Dedicated Short Bias                   -0.0273
      Emerging Markets                        0.0409
      Equity Market Neutral                   0.0368
      Event Driven                            0.2724
```

```
Event Driven Distressed                  0.3120
Event Driven Multi-Strategy              0.2115
Event Driven Risk Arbitrage              0.2084
Fixed Income Arbitrage                   0.1044
Global Macro                             0.2638
Long/Short Equity                        0.1611
Managed Futures                          0.0838
Multi-Strategy                           0.2347
```

##

3. Optional: Re-run this for every hedge-fund index, not just the "Total Index".

a) The highest Sharpe ratio hedge fund type was Event Driven Distressed, with a Sharpe of 1.09
b) The highest Treynor ratio hedge fund type was Global Macro, with a Treynor ratio of .0546
c) The equity market neutral hedge fund had the most desirable tail-risk profile with a kurt of 163, meaning that the distrobution of returns were very concentrated around the mean return of that asset.

# 1 Sources

https://www.w3schools.com/html/html_styles.asp

https://developer.mozilla.org/en-US/docs/Web/HTML/Element/sup

https://csrgxtu.github.io/2015/03/20/Writing-Mathematic-Fomulars-in-Markdown/

https://www.w3schools.com/python/python_ml_linear_regression.asp

https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.io.formats.style.Styler.set_properties.html
Lecture slides and notes from class