

```
1 %load_ext autoreload
2 %autoreload 2
3
4 from google.colab import drive
5 drive.mount('/content/drive')
```

➞ Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_

Enter your authorization code:

.....

Mounted at /content/drive

```
1 import os, sys
2
3 DATAPATH = '/content/drive/My Drive/Coursera/EDHEC/investment-portfolio/data'
4 print(f"DATAPATH:{DATAPATH} contents:{os.listdir(DATAPATH)}")
5
6 MODULEPATH = '/content/drive/My Drive/Coursera/EDHEC/investment-portfolio/nb'
7 print(f"MODULEPATH:{MODULEPATH} contents:{os.listdir(MODULEPATH)}")
8
9 sys.path.append(MODULEPATH)
10 print(f"sys.path:{sys.path}")
```

➞ DATAPATH:/content/drive/My Drive/Coursera/EDHEC/investment-portfolio/data contents:
MODULEPATH:/content/drive/My Drive/Coursera/EDHEC/investment-portfolio/nb contents:
sys.path:['', '/env/python', '/usr/lib/python36.zip', '/usr/lib/python3.6', '/usr/lib/python3.6/lib-dynload', '/content/drive/My Drive/Coursera/EDHEC/investment-portfolio/nb']

▼ Downside Measures: SemiDeviation, VaR and CVaR

We're going to look at a few measures of downside risk. We've already seen how to compute drawdowns, which is a popular measure, and we are going to develop code to compute these and add them to our toolbox.

The first measure is the simplest, which is the semideviation, which is nothing more than the volatility of the negative returns.

The code is very simple:

```
def semideviation(r):
    """
    Returns the semideviation aka negative semideviation of r
    r must be a Series or a DataFrame, else raises a TypeError
    """
    is_negative = r < 0
    return r[is_negative].std(ddof=0)
```

```
1 import pandas as pd
2 import edhec_risk_kit_106_BBI as erk
3 %load_ext autoreload
4 %autoreload 2
5 %matplotlib inline
```

☞ The autoreload extension is already loaded. To reload it, use:

```
%reload_ext autoreload
```

```
1 hfi = erk.get_hfi_returns(DATAPATH)
```

```
1 hfi.describe()
```



	Convertible Arbitrage	CTA Global	Distressed Securities	Emerging Markets	Equity Market Neutral	Event Driven	F In Arbit
count	263.000000	263.000000	263.000000	263.000000	263.000000	263.000000	263.00
mean	0.005508	0.004074	0.006946	0.006253	0.004498	0.006344	0.00
std	0.016567	0.023335	0.017042	0.032538	0.008130	0.016744	0.01
min	-0.123700	-0.056800	-0.083600	-0.192200	-0.058700	-0.088600	-0.08
25%	-0.000150	-0.012050	-0.001450	-0.009750	0.001500	-0.001450	0.00
50%	0.006500	0.001400	0.008900	0.009600	0.005100	0.008400	0.00
75%	0.013600	0.019850	0.017750	0.025700	0.008300	0.016200	0.00
max	0.061100	0.069100	0.050400	0.123000	0.025300	0.044200	0.03



```
1 def semideviation(r):
2     """
3     Returns the semideviation aka negative semideviation of r
4     r must be a Series or a DataFrame, else raises a TypeError
5     """
6     is_negative = r < 0
7     return r[is_negative].std(ddof=0)
8
```

```
1 erk.semideviation(hfi)
```



```
Convertible Arbitrage    0.019540
CTA Global                0.012443
Distressed Securities     0.015185
Emerging Markets         0.028039
Equity Market Neutral    0.009566
Event Driven             0.015429
Fixed Income Arbitrage   0.017763
Global Macro             0.006579
Long/Short Equity        0.014051
Merger Arbitrage         0.008875
Relative Value           0.012244
Short Selling            0.027283
Funds Of Funds          0.012122
dtype: float64
```

```
1 hfi[hfi<0].std(ddof=0)
```

```
↳ Convertible Arbitrage      0.019540
   CTA Global                 0.012443
   Distressed Securities      0.015185
   Emerging Markets           0.028039
   Equity Market Neutral      0.009566
   Event Driven               0.015429
   Fixed Income Arbitrage     0.017763
   Global Macro               0.006579
   Long/Short Equity          0.014051
   Merger Arbitrage           0.008875
   Relative Value             0.012244
   Short Selling              0.027283
   Funds Of Funds            0.012122
   dtype: float64
```

```
1 erk.semideviation(hfi).sort_values()
```

```
↳ Global Macro               0.006579
   Merger Arbitrage           0.008875
   Equity Market Neutral      0.009566
   Funds Of Funds            0.012122
   Relative Value             0.012244
   CTA Global                 0.012443
   Long/Short Equity          0.014051
   Distressed Securities      0.015185
   Event Driven               0.015429
   Fixed Income Arbitrage     0.017763
   Convertible Arbitrage      0.019540
   Short Selling              0.027283
   Emerging Markets           0.028039
   dtype: float64
```

```
1 ffme = erk.get_ffme_returns(DATAPATH)
```

```
2 erk.semideviation(ffme)
```

```
↳ SmallCap      0.051772
   LargeCap      0.040245
   dtype: float64
```

```
1 # This will not work: erk.semideviation([1,2,3,4])
```

▼ VaR and CVaR

We'll look at three different ways to compute Value At Risk

1. Historic VaR
2. Parametric Gaussian VaR
3. Modified (Cornish-Fisher) VaR

To compute the historic VaR at a certain level, say 5%, all we have to do is to find the number such number and 95% of the returns fall above that number. In other words, we want the 5 percentile ret

Fortunately, numpy has a `np.percentile` function that computes exactly that.

Add the following code to the `edhec_risk_kit.py` file:

```
def var_historic(r, level=5):
    """
    Returns the historic Value at Risk at a specified level
    i.e. returns the number such that "level" percent of the returns
    fall below that number, and the (100-level) percent are above
    """
    if isinstance(r, pd.DataFrame):
        return r.aggregate(var_historic, level=level)
    elif isinstance(r, pd.Series):
        return -np.percentile(r, level)
    else:
        raise TypeError("Expected r to be a Series or DataFrame")

1 import numpy as np
2 np.percentile(hfi, 5, axis=0)

☐→ array([-0.01576, -0.03169, -0.01966, -0.04247, -0.00814, -0.02535,
          -0.00787, -0.01499, -0.02598, -0.01047, -0.01174, -0.06783,
          -0.02047])
```

```
1 erk.var_historic(hfi, level=1)
```

```
↳ Convertible Arbitrage      0.031776
   CTA Global                 0.049542
   Distressed Securities      0.046654
   Emerging Markets          0.088466
   Equity Market Neutral     0.018000
   Event Driven              0.048612
   Fixed Income Arbitrage    0.041672
   Global Macro              0.024316
   Long/Short Equity         0.049558
   Merger Arbitrage          0.025336
   Relative Value            0.026660
   Short Selling             0.113576
   Funds Of Funds           0.039664
dtype: float64
```

Note that for reporting purposes, it is common to invert the sign so we report a positive number to that is at risk.

▼ Conditional VaR aka Beyond VaR

Now that we have the VaR, the CVaR is very easy. All we need is to find the mean of the numbers th

```
1 erk.cvar_historic(hfi, level=1).sort_values()
```

```
↳ Global Macro              0.029333
   Equity Market Neutral    0.036100
   Merger Arbitrage         0.036233
   Relative Value           0.052367
   CTA Global               0.054767
   Funds Of Funds           0.061133
   Long/Short Equity        0.061867
   Distressed Securities    0.070967
   Event Driven             0.071267
   Fixed Income Arbitrage   0.072467
   Convertible Arbitrage    0.086100
   Short Selling            0.123867
   Emerging Markets        0.141167
dtype: float64
```

```
1 erk.cvar_historic(ffme)
```

```
➤ SmallCap      0.162609  
  LargeCap      0.121277  
dtype: float64
```

▼ Parametric Gaussian VaR

The idea behind this is very simple. If a set of returns is normally distributed, we know, for instance the mean and 50% are above.

We also know that approx two thirds of the returns lie within 1 standard deviation. That means one deviation from the mean. Since the normal distribution is symmetric, approximately one sixth (approx deviation away from the mean. Therefore, if we know the mean and standard deviation and if we are distributed, the 16% VaR would be the mean minus one standard deviation.

In general we can always convert a percentile point to a z-score (which is the number of standard deviations a number is). Therefore, if we can convert the VaR level (such as 1% or 5%) to a z-score, we can calculate percent of returns lie below it.

`scipy.stat.norm` contains a function `ppf()` which does exactly that. It takes a percentile such as a score corresponding to that in the normal distribution.

```
1 from scipy.stats import norm  
2 norm.ppf(.5)
```

```
➤ 0.0
```

```
1 norm.ppf(.16)
```

```
➤ -0.994457883209753
```

Therefore, all we need to do to estimate the VaR using this method is to find the z-score corresponding to that many standard deviations to the mean, to obtain the VaR.

```
from scipy.stats import norm
def var_gaussian(r, level=5):
    """
    Returns the Parametric Gaussian VaR of a Series or DataFrame
    """
    # compute the Z score assuming it was Gaussian
    z = norm.ppf(level/100)
    return -(r.mean() + z*r.std(ddof=0))
```

```
1 erk.var_gaussian(hfi)
```

```
↳ Convertible Arbitrage      0.021691
   CTA Global                 0.034235
   Distressed Securities      0.021032
   Emerging Markets           0.047164
   Equity Market Neutral      0.008850
   Event Driven               0.021144
   Fixed Income Arbitrage     0.014579
   Global Macro               0.018766
   Long/Short Equity          0.026397
   Merger Arbitrage           0.010435
   Relative Value             0.013061
   Short Selling              0.080086
   Funds Of Funds            0.021292
   dtype: float64
```

```
1 erk.var_historic(hfi)
```

```
↳ Convertible Arbitrage      0.01576
   CTA Global                 0.03169
   Distressed Securities      0.01966
   Emerging Markets           0.04247
   Equity Market Neutral      0.00814
   Event Driven               0.02535
   Fixed Income Arbitrage     0.00787
   Global Macro               0.01499
   Long/Short Equity          0.02598
   Merger Arbitrage           0.01047
   Relative Value             0.01174
   Short Selling              0.06783
   Funds Of Funds            0.02047
   dtype: float64
```


▼ Cornish-Fisher Modification

The Cornish-Fisher modification is an elegant and simple adjustment.

The z-score tells us how many standard deviations away from the mean we need to go to find the value. However, we know that z-score will give us an inaccurate number. The basic idea is that since we can observe the data, we can adjust the z-score up or down to come up with a modified z-score. e.g. intuitively, all of the time. If the skewness is negative, we'll decrease the z-score further down, and if the skewness is positive, we'll increase it.

The adjusted z-score which we'll call $z_{cornishfisher}$ given by:

$$z_{cornishfisher} = z + \frac{1}{6}(z^2 - 1)S + \frac{1}{24}(z^3 - 3z)(K - 3) - \frac{1}{36}(2z^5 - 5z^3 + 3z)S^2$$

We can modify the previous function by adding a "modified" parameter with a default value of `True`. The following piece of code is executed, which modifies `z`:

```
if modified:
    # modify the Z score based on observed skewness and kurtosis
    s = skewness(r)
    k = kurtosis(r)
    z = (z +
         (z**2 - 1)*s/6 +
         (z**3 - 3*z)*(k-3)/24 -
         (2*z**5 - 5*z**3 + 3*z)*(s**2)/36
        )
```

The rewritten function is:

```
from scipy.stats import norm

def var_gaussian(r, level=5, modified=False):
    """
    Returns the Parametric Gaussian VaR of a Series or DataFrame
    If "modified" is True, then the modified VaR is returned,
    using the Cornish-Fisher modification
    """
    # compute the Z score assuming it was Gaussian
    z = norm.ppf(level/100)
    if modified:
        # modify the Z score based on observed skewness and kurtosis
        s = skewness(r)
        k = kurtosis(r)
```

```

z = (z +
      (z**2 - 1)*s/6 +
      (z**3 - 3*z)*(k-3)/24 -
      (2*z**3 - 5*z)*(s**2)/36
    )

return -(r.mean() + z*r.std(ddof=0))

```

We can now compare the different methods:

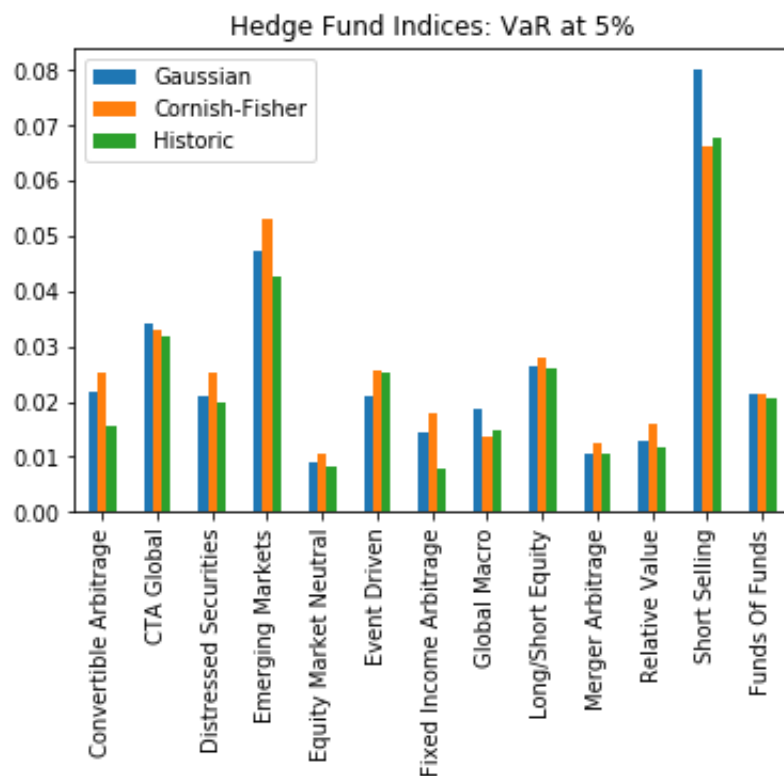
```

1 var_table = [erk.var_gaussian(hfi),
2               erk.var_gaussian(hfi, modified=True),
3               erk.var_historic(hfi)]
4 comparison = pd.concat(var_table, axis=1)
5 comparison.columns=['Gaussian', 'Cornish-Fisher', 'Historic']
6 comparison.plot.bar(title="Hedge Fund Indices: VaR at 5%")

```



<matplotlib.axes._subplots.AxesSubplot at 0x10db59ac8>



Note that in some cases, the cornish-fisher VaR is lower i.e. estimates a smaller loss than you would assume under the normal distribution assumption. That can happen if the observed skewness is positive, as is the case for "Short Selling

```
1 erk.skewness(hfi).sort_values(ascending=False)
```



Global Macro	0.982922
Short Selling	0.767975
CTA Global	0.173699
Funds Of Funds	-0.361783
Long/Short Equity	-0.390227
Emerging Markets	-1.167067
Distressed Securities	-1.300842
Merger Arbitrage	-1.320083
Event Driven	-1.409154
Relative Value	-1.815470
Equity Market Neutral	-2.124435
Convertible Arbitrage	-2.639592
Fixed Income Arbitrage	-3.940320
dtype: float64	