Volatility and Risk

We've seen that the volatility is measured by the average squared deviation from the mean, which i

Let's read the sample returns that we've been working with.

```
from google.colab import drive
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
```

```
import os

DATAPATH = '/content/drive/My Drive/Coursera/EDHEC/investment-portfolio/data'
print(f"DATAPATH:{DATAPATH} contents:{os.listdir(DATAPATH)}")
```

```
DATAPATH:/content/drive/My Drive/Coursera/EDHEC/investment-portfolio/data cont
```

```
import pandas as pd
prices = pd.read_csv(DATAPATH + "/sample_prices.csv")
returns = prices.pct_change()
returns
```

	BLUE	ORANGE
0	NaN	NaN
1	0.023621	0.039662
2	-0.021807	-0.033638
3	-0.031763	0.082232
4	0.034477	0.044544
5	0.037786	-0.026381
6	-0.011452	-0.049187
7	0.032676	0.117008
8	-0.012581	0.067353
9	0.029581	0.078249
10	0.006151	-0.168261
11	0.012162	0.024041
12	0.021149	-0.055623

Notice that the first set of returns are NaN, which is Pandas way of saying that it's an NA. We can c
method.

```
returns = returns.dropna()
returns
```

	BLUE	ORANGE
1	0.023621	0.039662
2	-0.021807	-0.033638
3	-0.031763	0.082232
4	0.034477	0.044544
5	0.037786	-0.026381
6	-0.011452	-0.049187
7	0.032676	0.117008
8	-0.012581	0.067353
9	0.029581	0.078249
10	0.006151	-0.168261
11	0.012162	0.024041
12	0.021149	-0.055623

Let's compute the standard deviation from first principals:

```
deviations = returns - returns.mean()
squared_deviations = deviations**2
mean_squared_deviations = squared_deviations.mean()

import numpy as np

volatility = np.sqrt(mean_squared_deviations)
volatility
```

```
BLUE      0.022957
ORANGE    0.076212
dtype: float64
```

Let's see if we get the same answer when we use the built-in `.std()` method.

```
returns.std()
```

```
BLUE      0.023977
ORANGE    0.079601
dtype: float64
```

Why don't they match? Because, by default, the `.std()` method computes the *sample standard de* denominator of $n-1$. On the other hand, we computed the *population* standard deviation, which u observed returns are thought of as observed samples from a distribution, it is probably more accur $n-1$, so let's redo our calculation to see if we get the same number.

To get the number of observations, we can use the `.shape` attribute of a DataFrame that returns a columns.

```
returns.shape
```

```
(12, 2)
```

Just as we can with a list, we can access the elements of a tuple using an index, starting at 0. Ther the DataFrame, we extract the 0th element of the tuple.

```
number_of_obs = returns.shape[0]
mean_squared_deviations = squared_deviations.sum()/(number_of_obs-1)
volatility = np.sqrt(mean_squared_deviations)
volatility
```

```
BLUE      0.023977
ORANGE    0.079601
dtype: float64
```

```
returns.std()
```

```
BLUE      0.023977
ORANGE    0.079601
dtype: float64
```

Annualizing Volatility

We annualize volatility by scaling (multiplying) it by the square root of the number of periods per ol

Therefore, to annualize the volatility of a monthly series, we muiltiply it by the square root of 12. Ins can raise it to the power of 0.5

```
annualized_vol = returns.std()*(12**0.5)
annualized_vol
```

```
BLUE      0.083060
ORANGE    0.275747
dtype: float64
```

Risk Adjusted Returns

Let's get beyond the sample data series and start working with some real data. Read in the monthl formed on market caps, or market equities of the companies. Of the 10 portfolios, we only want to smallest cap companies:

```
me_m = pd.read_csv(DATAPATH + "/Portfolios_Formed_on_ME_monthly_EW.csv",
                   header=0, index_col=0, parse_dates=True, na_values=-99.99)
me_m.head()
```

	<= 0	Lo 30	Med 40	Hi 30	Lo 20	Qnt 2	Qnt 3	Qnt 4	Hi 20	Lo 10	Dec 2	Dec 3	Dec 4
192607	NaN	-0.43	1.52	2.68	-0.57	0.59	1.60	1.47	3.33	-1.45	0.29	-0.15	1.33
192608	NaN	3.90	3.04	2.09	3.84	3.59	3.71	1.61	2.33	5.12	2.59	4.03	3.15
192609	NaN	-1.08	-0.54	0.16	-0.48	-1.40	0.00	-0.50	-0.09	0.93	-1.87	-2.27	-0.53
192610	NaN	-3.32	-3.52	-3.06	-3.29	-4.10	-2.89	-3.36	-2.95	-4.84	-1.77	-3.36	-4.83
192611	NaN	-0.46	3.82	3.09	-0.55	2.18	3.41	3.39	3.16	-0.78	-0.32	-0.29	4.65

```
cols = ['Lo 10', 'Hi 10']
returns = me_m[cols]
returns.head()
```

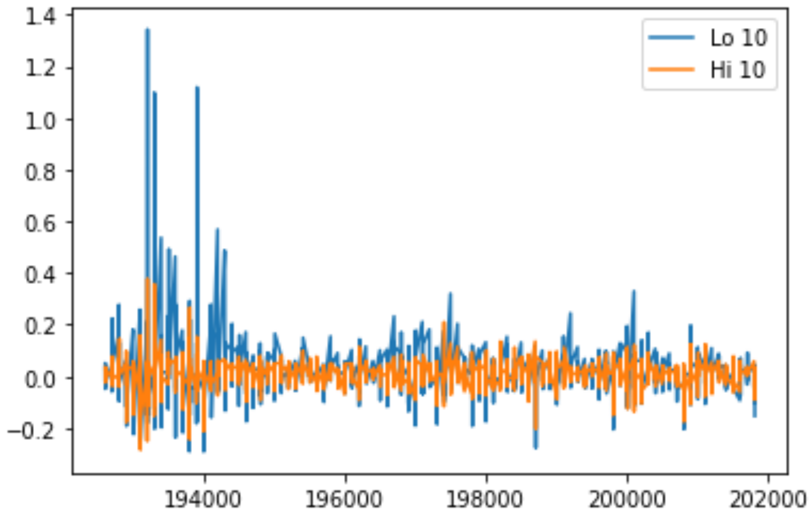
	Lo 10	Hi 10
192607	-1.45	3.29
192608	5.12	3.70
192609	0.93	0.67
192610	-4.84	-2.43
192611	-0.78	2.70

Note that the data is already given in percentages (i.e 4.5 instead of 0.045) and we typically want t
instead of 4.5) so we should divide the raw data from the file by 100.

```
1 returns = returns/100
```

```
1 returns.plot()
```

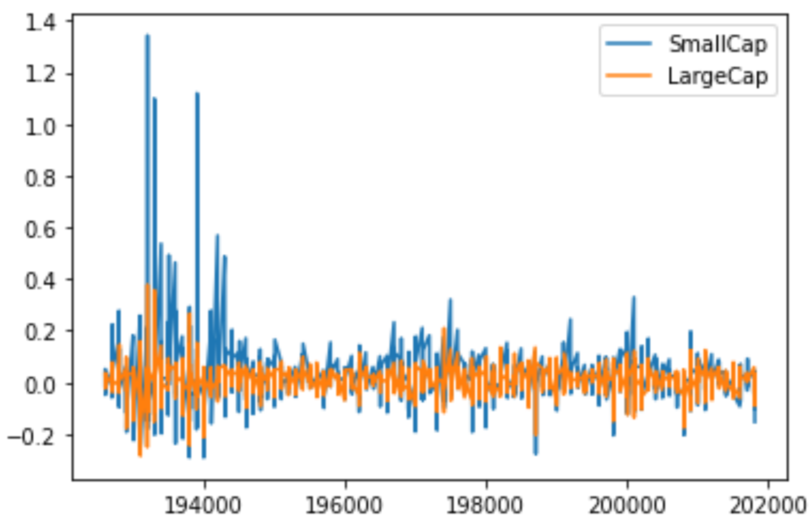
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f811cccb860>
```




```
1 returns.columns = ['SmallCap', 'LargeCap']
```

```
1 returns.plot()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f811c76e2b0>
```



```
annualized_vol = returns.std()*np.sqrt(12)
annualized_vol
```

```
SmallCap    0.368193
LargeCap    0.186716
dtype: float64
```

We can now compute the annualized returns as follows:

```
n_months = returns.shape[0]
return_per_month = (returns+1).prod()**(1/n_months) - 1
return_per_month
```

```
SmallCap    0.012986
LargeCap    0.007423
dtype: float64
```

```
annualized_return = (return_per_month + 1)**12-1
```

```
annualized_return = (returns+1).prod()**(12/n_months) - 1
annualized_return
```

```
SmallCap    0.167463
LargeCap    0.092810
dtype: float64
```

```
annualized_return/annualized_vol
```

```
SmallCap    0.454825
LargeCap    0.497063
dtype: float64
```

```
riskfree_rate = 0.03
excess_return = annualized_return - riskfree_rate
sharpe_ratio = excess_return/annualized_vol
sharpe_ratio
```

```
SmallCap    0.373346
LargeCap    0.336392
dtype: float64
```