**CAPM - Capital Asset Pricing Model** Watch the video for the full overview. Portfolio Returns:  $r_p(t) = \sum\limits_{i}^{n} w_i r_i(t)$ Market Weights:  $w_i = rac{MarketCap_i}{\sum_{j}^{n} MarketCap_j}$ CAPM of a portfolio  $r_p(t) = eta_p r_m(t) + \sum\limits_i^n w_i lpha_i(t)$ # Model CAPM as a simple linear regression In [20]: from scipy import stats In [3]: help(stats.linregress) Help on function linregress in module scipy.stats. stats mstats common: linregress(x, y=None) Calculate a linear least-squares regression for two sets of measurements. Parameters x, y : array like Two sets of measurements. Both arrays should have the same length. If only x is given (and y=None), then it must be a two-dimensional array where one dimension has length 2. The two sets of measurements are then found by splitting the array along the length-2 dimension. Returns slope : float slope of the regression line intercept : float intercept of the regression line rvalue : float correlation coefficient two-sided p-value for a hypothesis test whose null hypothesis is that the slope is zero. stderr : float Standard error of the estimated gradient. See also :func:`scipy.optimize.curve fit` : Use non-linear least squares to fit a function to data. :func:`scipy.optimize.leastsq` : Minimize the sum of squares of a set of equations. >>> import matplotlib.pyplot as plt >>> from scipy import stats >>> np.random.seed(12345678) >>> x = np.random.random(10)>>> y = np.random.random(10) >>> slope, intercept, r\_value, p\_value, std\_err = stats.linregress(x, y) To get coefficient of determination (r squared) >>> print("r-squared:", r value\*\*2) ('r-squared:', 0.080402268539028335) Plot the data along with the fitted line >>> plt.plot(x, y, 'o', label='original data') >>> plt.plot(x, intercept + slope\*x, 'r', label='fitted line') >>> plt.legend() >>> plt.show() In [7]: import pandas as pd In [13]: #import pandas\_datareader as web In [3]: #spy\_etf = web.DataReader('SPY', 'google') import yfinance as yf spy\_etf = yf.download("SPY", start="2010-01-04", end="2017-07-18") In [4]: spy\_etf.info() <class 'pandas.core.frame.DataFrame'> DatetimeIndex: 1897 entries, 2010-01-04 to 2017-07-17 Data columns (total 6 columns): # Column Non-Null Count Dtype 0 Open 1897 non-null float64
1 High 1897 non-null float64
2 Low 1897 non-null float64
3 Close 1897 non-null float64
4 Adj Close 1897 non-null float64
5 Volume 1897 non-null int64 dtypes: float64(5), int64(1) memory usage: 103.7 KB In [5]: spy\_etf.head() Out[5]: Open High Close Adj Close Volume Low **Date 2010-01-04** 112.370003 113.389999 111.510002 113.330002 88.860367 118944600 **2010-01-05** 113.260002 113.680000 112.849998 113.629997 89.095604 111579900 **2010-01-06** 113.519997 113.989998 113.430000 113.709999 89.158325 116074400 **2010-01-07** 113.500000 114.330002 113.180000 114.190002 89.534691 131091100 **2010-01-08** 113.889999 114.620003 113.660004 114.570000 89.832649 126402800 In [8]: | start = pd.to\_datetime('2010-01-04') end = pd.to datetime('2017-07-18') In [9]: #aapl = web.DataReader('AAPL','google',start,end) aapl = yf.download("AAPL", start="2010-01-04", end="2017-07-18") In [10]: | aapl.head() Out[10]: Open High Low Close Adj Close Date 6.526019 493729600 **2010-01-04** 7.622500 7.660714 7.585000 7.643214 **2010-01-05** 7.664286 7.699643 7.616071 7.656429 6.537303 601904800 **2010-01-06** 7.656429 7.686786 7.526786 7.534643 6.433318 552160000 6.421427 477131200 **2010-01-07** 7.562500 7.571429 7.466071 7.520714 **2010-01-08** 7.510714 7.571429 7.466429 7.570714 import matplotlib.pyplot as plt In [11]: %matplotlib inline aapl['Close'].plot(label='AAPL',figsize=(10,8)) spy etf['Close'].plot(label='SPY Index') plt.legend() <matplotlib.legend.Legend at 0xd8ba52f0a0> Out[12]: 250 AAPL SPY Index 200 150 100 50 2012 2016 2020 2022 2013 2015 2024 2017 **Compare Cumulative Return** In [13]: | aapl['Cumulative'] = aapl['Close']/aapl['Close'].iloc[0] spy\_etf['Cumulative'] = spy\_etf['Close']/spy\_etf['Close'].iloc[0] In [14]: aapl['Cumulative'].plot(label='AAPL', figsize=(10,8)) spy\_etf['Cumulative'].plot(label='SPY Index') plt.legend() plt.title('Cumulative Return') Text(0.5, 1.0, 'Cumulative Return') Out[14]: Cumulative Return AAPL SPY Index 3 2 1 2020 2013 2026 2024 Date **Get Daily Return** aapl['Daily Return'] = aapl['Close'].pct\_change(1) In [15]: spy\_etf['Daily Return'] = spy\_etf['Close'].pct\_change(1) plt.scatter(aapl['Daily Return'], spy\_etf['Daily Return'], alpha=0.3) In [16]: <matplotlib.collections.PathCollection at 0xd8b4db2940> Out[16]: 0.04 0.02 0.00 -0.02-0.04-0.06-0.10 -0.050.00 0.05 aapl['Daily Return'].hist(bins=100) In [17]: <AxesSubplot:> Out[17]: 140 120 100 80 60 40 20 -0.10-0.050.00 spy\_etf['Daily Return'].hist(bins=100) In [18]: <AxesSubplot:> Out[18]: 160 140 120 100 80 60 40 20 0.00 0.02 -0.06-0.04-0.02beta, alpha, r value, p value, std err = stats.linregress(aapl['Daily Return'].iloc[1:], spy etf['Daily Return'].ilo In [21]: In [22]: 0.32572226197243687 Out[22]: In [23]: alpha 0.0001373797735205996 Out[23]: r\_value In [40]: 0.33143080741409325 Out[40]: What if our stock was completely related to SP500? In [24]: | spy\_etf['Daily Return'].head() Date Out[24]: 2010-01-04 2010-01-05 0.002647 2010-01-06 0.000704 2010-01-07 0.004221 2010-01-08 0.003328 Name: Daily Return, dtype: float64 In [50]: import numpy as np In [63]: noise = np.random.normal(0,0.001,len(spy\_etf['Daily Return'].iloc[1:])) In [64]: noise array([ 0.00089285, 0.00056301, -0.00022182, ..., -0.00075069, Out[64]: -0.00017751, -0.00034175]) In [65]: spy\_etf['Daily Return'].iloc[1:] + noise Date Out[65]: 2010-01-05 0.003540 2010-01-06 0.001267 2010-01-07 0.003999 2010-01-08 0.003744 2010-01-11 0.002430 2010-01-12 -0.008178 2010-01-13 0.006244 2010-01-14 0.003002 2010-01-15 -0.010593 2010-01-19 0.012289 2010-01-20 -0.010683 2010-01-21 -0.019239 2010-01-22 -0.022449 2010-01-25 0.003428 2010-01-26 -0.003510 2010-01-27 0.004741 2010-01-28 -0.011874 2010-01-29 -0.010649 0.015995 2010-02-01 2010-02-02 0.011317 2010-02-03 -0.006852 2010-02-04 -0.029828 2010-02-05 0.000845 2010-02-08 -0.007362 2010-02-09 0.010399 2010-02-10 -0.000745 2010-02-11 0.008745 2010-02-12 -0.001782 2010-02-16 0.016414 0.003658 2010-02-17 2017-06-06 -0.001963 0.003158 2017-06-07 2017-06-08 -0.000087 2017-06-09 -0.000582 2017-06-12 -0.001564 2017-06-13 0.006079 2017-06-14 -0.002911 2017-06-15 -0.001163 2017-06-16 -0.004836 0.008102 2017-06-19 2017-06-20 -0.008464 -0.000669 2017-06-21 2017-06-22 -0.000532 0.002970 2017-06-23 0.001098 2017-06-26 2017-06-27 -0.009717 0.008961 2017-06-28 2017-06-29 -0.010516 2017-06-30 0.001965 2017-07-03 0.001218 0.003210 2017-07-05 2017-07-06 -0.008497 2017-07-07 0.005798 0.000335 2017-07-10 2017-07-11 -0.001653 0.008218 2017-07-12 0.003311 2017-07-13 2017-07-14 0.003913 -0.000300 2017-07-17 2017-07-18 0.000188 Name: Daily Return, Length: 1896, dtype: float64 beta, alpha, r\_value, p\_value, std\_err = stats.linregress(spy\_etf['Daily Return'].iloc[1:]+noise, spy\_etf['Daily Ret In [67]: 0.9902145894162997 Out[67]: In [68]: 1.4861814214210613e-05 Out[68]: Looks like our understanding is correct!