# Portfolios 

BUSI 721: Data-Driven Finance I
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## Portfolio returns

- Two assets, prices $p_{1}$ and $p_{2}$
- Own shares $x_{1}$ and $x_{2}$
- Portfolio value is $p_{1} x_{1}+p_{2} x_{2}$
- Fraction of value in asset $i$ (weight of asset) is

$$
w_{i}=\frac{p_{i} x_{i}}{p_{1} x_{1}+p_{2} x_{2}}
$$

- Future prices + dividends $\Rightarrow$ returns $r_{1}$ and $r_{2}$
- Portfolio return is $w_{1} r_{1}+w_{2} r_{2}$.


## Example

- $\$ 200$ in asset 1 and $\$ 300$ in asset 2
- asset 1 goes up $10 \%$ and asset 2 goes up $5 \%$
- asset $1 \mapsto \$ 220$
- asset $2 \mapsto \$ 315$
- portfolio value is $\$ 535$
- This is a $7 \%$ gain and

$$
\frac{2}{5} \times 0.1+\frac{3}{5} \times 0.05=0.07
$$

## Expected return

- Returns are random variables
- Expected = mean
- mean portfolio return $w_{1} r_{1}+w_{2} r_{2}$ is

$$
w_{1} \times \text { mean of } r_{1}+w_{2} \times \text { mean of } r_{2}
$$

## Variance

- The variance of the portfolio return is

$$
w_{1}^{2} \sigma_{1}^{2}+w_{2} \sigma_{2}^{2}+2 w_{1} w_{2} \rho \sigma_{1} \sigma_{2}
$$

- where $\sigma_{i}=\operatorname{std}$ dev of $r_{i}$ and $\rho$ is the correlation of $r_{1}$ and $r_{2}$.
- Lower correlation implies lower portfolio risk!


## Proof of variance formula

- Variance is expected squared deviation from mean
- Set $r_{p}=w_{1} r_{1}+w_{2} r_{2}$ and use overbars to denote means
- Variance of $r_{p}$ is

$$
\text { mean of }\left(r_{p}-\bar{r}_{p}\right)^{2}
$$

- And

$$
r_{p}-\bar{r}_{p}=w_{1} r_{1}+w_{2} r_{2}-\left(w_{1} \bar{r}_{1}+w_{2} \bar{r}_{2}\right)
$$

- So

$$
r_{p}-\bar{r}_{p}=w_{1}\left(r_{1}-\bar{r}_{1}\right)+w_{2}\left(r_{2}-\bar{r}_{2}\right)
$$

- To square this, use
$(a+b)^{2}=a^{2}$
$+b^{2}+2 a b$
- So portfolio variance is

$$
\begin{aligned}
& w_{1}^{2} \times \text { mean of }\left(r_{1}-\bar{r}_{1}\right)^{2} \\
& +w_{2}^{2} \times \text { mean of }\left(r_{2}-\bar{r}_{2}\right)^{2} \\
& +2 w_{1} w_{2} \times \text { mean of }\left(r_{1}-{\overline{r_{1}}}_{1}\right)\left(r_{2}-\bar{r}_{2}\right)
\end{aligned}
$$

- This is

$$
w_{1}^{2} \sigma_{1}^{2}+w_{2} \sigma_{2}^{2}+2 w_{1} w_{2} \rho \sigma_{1} \sigma_{2}
$$

Example

In [2]: mu1, mu2 = 0.06, 0.1
sigma1, sigma2 $=0.2,0.3$
rho $=0.3$
$w 1, w 2=0.4,0.6$

```
import numpy as np
mn = w1*mu1 + w2*mu2
var = w1**2*sigma1**2 + w2**2*sigma2**2 + 2*w1*w2*rho*sigma1*sigma2
print(f"mean portfolio return is {mn:.2%}")
print(f"std dev of portfolio return is {np.sqrt(var):.2%}")
```

mean portfolio return is $8.40 \%$
std dev of portfolio return is $21.78 \%$

Simulation

```
In [4]: cov = [
        [sigma1**2, rho*sigma1*sigma2],
    [rho*sigma1*sigma2, sigma2**2]
]
from scipy.stats import multivariate_normal as multinorm
rets = multinorm.rvs(
    mean=[mu1, mu2],
    cov=cov,
    size=1000000
)
rp = w1*rets[:,0] + w2*rets[:,1]
print(f"simulated mean is {np.mean(rp):.2%}")
print(f"simulated std dev is {np.std(rp):.2%}")
simulated mean is 8.39%
simulated std dev is 21.77%
```


## Cash

- Adding cash (money market investment) to a portfolio has a simple effect on expected return and risk.
- Let asset 2 be cash. Its return has negligible risk. Call its return $r_{m m}$.
- Portfolio mean is $w_{1} \mu_{1}+w_{2} r_{m m}$
- Portfolio variance is $w_{1}^{2} \sigma_{1}^{2}$
- Portfolio std dev is $w_{1} \sigma_{1}$.


## Margin loans

- You can have negative cash by borrowing from your broker.
- Example: put $\$ 1,000$ in an account, borrow $\$ 200$ and buy $\$ 1,200$ of a stock.
- Continue to call asset 2 cash.
- Your portfolio weights are $w_{1}=1.2$ and $w_{2}=-0.2$.
- Your expected return is $1.2 \times \mu_{1}-0.2 \times r_{m l}$ where $r_{m l}$ is the margin loan rate.
- Your std dev is $1.2 \sigma_{1}$.


## Short selling

- You can have a negative weight on a stock by selling short.
- To sell short, your broker borrows shares on your behalf and sells them.
- You eventually have to buy the shares back in the market and return them.
- Profit by selling high and buying low.
- Example: short sell 100 shares $\$ 100$ stock.
- Stock falls to $\$ 90$ and you cover the short (buy and return shares).
- Paid $\$ 90$ and sold at $\$ 100 \Rightarrow$ profit $\$ 10$ per share on 100 shares.


## Long and short returns (simplified version)

- Assume we invest $\$ 1,000$, short sell $\$ 400$ of stock 2 and buy $\$ 1,400$ of stock 1 .
- The weights are 1.4 in stock 1 and -0.4 in stock 2.
- Suppose stock 1 goes up $10 \%$ and stock 2 goes up $5 \%$.
- Stock $1 \rightarrow \$ 1,540$.
- Stock 2 position $\rightarrow-\$ 420$.
- Portfolio value $\rightarrow \$ 1,120=12 \%$ return
- $w_{1} r_{1}+w_{2} r_{2}=1.4 \times 0.10-0.4 \times 0.05$
$=0.12$


## Long and short returns (practical version)

- Proceeds from short sales are retained as collateral
- Investor may get some interest on the proceeds while they are held (called short interest rebate)
- We can invest $\$ 1,000$, short sell $\$ 400$ of stock 2 and buy $\$ 1,400$ of stock 1 only if we take out a margin loan for $\$ 400$.
- Actual return in example is

$$
\begin{gathered}
1.4 \times 0.10-0.4 \times 0.05 \\
-0.4 \times r_{m l}+0.4 \times r_{s i r}-0.4 \times \text { short borrowing fee }
\end{gathered}
$$

- where $r_{\text {sir }}$ is the short interest rebate rate.


## Enhanced index return example

- Invest $\$ 1,000$. Borrow $\$ 1,000$ on margin loan.
- Buy $\$ 1,000$ of SPY and buy $\$ 1,000$ of CVX.
- Short sell $\$ 1,000$ of COP.
- Return is SPY return + CVX return - COP return minus margin loan/short interest rebate/short borrowing fee drag.
- If CVX beats COP enough, you will beat SPY.


## More assets

- $n$ stocks
- weights $w_{1}, \ldots, w_{n}$
- expected returns $\mu_{1}, \ldots, \mu_{n}$
- covariance matrix $\Sigma$
- diagonal elements of covariance matrix are variances
- off-diagonal elements are correlation $\times$ std dev $\times$ std dev.


## Portfolio risk

- Portfolio variance is $w^{\prime} \Sigma w$
- Portfolio std dev is $\sqrt{w^{\prime} \Sigma w}$

```
In [5]:
# example
w = np.array([0.2, 0.2, 0.4])
sigma1, sigma2, sigma3 = 0.2, 0.3, 0.1
rho12, rho13, rho23 = 0.3, 0.5, 0.4
cov = np.array([
    [sigma1**2, rho12*sigma1*sigma2, rho13*sigma1*sigma3],
    [rho12*sigma1*sigma2, sigma2**2, rho23*sigma2*sigma3],
    [rho13*sigma1*sigma3, rho23*sigma2*sigma3, sigma3**2]
])
stdev = np.sqrt(w @ cov @ w)
print(f"portfolio std dev is {stdev:.2%}")
portfolio std dev is 10.84%
```


## Portfolio expected return

- If $w_{i} \geq 0$ and sum to 1 , then portfolio mean is $w^{\prime} \mu$.
- If $w_{i} \geq 0$ and sum to less than 1 , then portfolio mean is

$$
w^{\prime} \mu+\left(1-\sum w_{i}\right) r_{m m}
$$

- If $w_{i} \geq 0$ and sum to more than 1 , then portfolio mean is

$$
w^{\prime} \mu+\left(1-\sum w_{i}\right) r_{m l}
$$

- So we can say that if $w_{i} \geq 0$, then portfolio mean is

$$
w^{\prime} \mu+\left(1-\sum w_{i}\right) r_{f}
$$

- where $r_{f}=r_{m m}$ if cash $>0$ and $r_{m}=r_{m l}$ if cash $<0$.
- With short sales, portfolio mean is also

$$
w^{\prime} \mu+\left(1-\sum w_{i}\right) r_{f}
$$

- minus the drag from difference between margin loan and short interest rebate rates and minus short borrowing fees.

In [6]:
\# continuing prior example
$r f=0.04$
mu1, mu2, mu3 $=0.1,0.12,0.08$
mu = np.array([mu1, mu2, mu3])
port_mean = w @ mu + (1-np.sum(w))*rf
print(f"portfolio mean is \{port_mean:.2\%\}")
portfolio mean is $8.40 \%$

## Estimating from historical returns

- Example:
- $\mathrm{SPY}=\mathrm{S} \& \mathrm{P} 500$
- IEF = Treasury bonds
- GLD = gold
- Get adjusted closing prices from Yahoo
- Compute returns as percent changes

```
In [7]: import yfinance as yf
tickers = ["SPY", "IEF", "GLD"]
prices = yf.download(tickers, start="1970-01-01")["Adj Close"]
rets = prices.pct_change().dropna()
rets.head(3)
[*********************100%%***********************] 3 of 3 completed
Out[7]:
GLD IEF SPY
Date
\begin{tabular}{rrrr} 
2004-11-19 & 0.009013 & -0.005480 & -0.011117 \\
\hline 2004-11-22 & 0.003796 & 0.000704 & 0.004769 \\
\hline 2004-11-23 & -0.004449 & -0.000938 & 0.001526
\end{tabular}
```

| In [8]: | rets | rr() |  |  |
| :---: | :---: | :---: | :---: | :---: |
| Out[8]: |  | GLD | IEF | SPY |
|  | GLD | 1.000000 | 0.208371 | 0.049425 |
|  | IEF | 0.208371 | 1.000000 | -0.320228 |
|  | SPY | 0.049425 | -0.320228 | 1.000000 |

## Annualizing

- May be easier to interpret means and std devs when expressed in annual terms
- Annualize daily means by multiplying by 252 (\# of trading days in a year)
- Annualize daily variances by multiplying by 252
- Annualize daily std devs by multiplying by square root of 252

```
In [9]: print(f"annualized means are \n{252*rets.mean()}")
print(f"\nannualized std devs are \n{np.sqrt(252)*rets.std()}")
annualized means are
GLD 0.090313
IEF 0.031442
SPY 0.106698
dtype: float64
annualized std devs are
GLD 0.176744
IEF 0.068225
SPY 0.193171
dtype: float64
```


## Portfolio returns

In [10]: w = np.array([0.2, 0.3, 0.5])
mean = w @ rets.mean()
var = w @ rets.cov() @ w
stdev = np.sqrt(var)
print(f"annualized mean portfolio return is \{252*mean:.2\%\}")
print(f"annualized std dev is \{np.sqrt(252)*stdev:.2\%\}")
annualized mean portfolio return is 8.08\%
annualized std dev is 10.18\%

