BOOK	CHAPTER	FORMULA		VARIABLES
Book 1 Foundation of Risk Management	Modern Portfolio Theory (MPT) and the Capital Asset Pricing Model (CAPM)	CAPM formula (expected return on asset *i*)	$E(R_i) = R_f + \beta_i(R_m - R_f)$	$\beta_i = \rho_{(im)} \frac{\sigma_i}{\sigma_{m_i}} = \frac{Cov(i,m)}{\sigma_m^2} = \frac{\sigma_{im}}{\sigma_m^2}$ $R_m =$ expected market rate of return $R_f =$ risk-free rate $E(R_i) =$ expected return on asset i $\rho_{im} = \frac{Cov(i,m)}{\sigma_i \sigma_m} = \frac{\sigma_{im}}{\sigma_i \sigma_m}$
		Capital market line	$E(R_p) = R_f + \frac{\sigma_p}{\sigma_m}(R_m - R_f)$	$R_m =$ expected market rate of return $R_f =$ risk-free rate $E(R_p) =$ portfolio expected return $\sigma_p =$ portfolio standard deviation $\sigma_m =$ market standard deviation
		Capital allocation line	$E(R_p) = R_f + \frac{\sigma_p}{\sigma_i}(R_i - R_f)$	$R_i =$ expected rate of return on asset i $R_f =$ risk-free rate $E(R_p) =$ portfolio expected return $\sigma_p =$ portfolio standard deviation $\sigma_i =$ standard deviation of asset

		Sharpe ratio	$\text{Sharpe ratio} = \frac{E(R_p) - R_f}{\sigma(R_P)}$	$\sigma(R_P) =$ portfolio standard deviation $E(R_p) =$ portfolio expected return $R_f =$ risk-free rate
		Treynor ratio	$\text{Treynor ratio} = \frac{E(R_p) - R_f}{\beta_P}$	$\beta_P =$ portfolio beta $E(R_p) =$ portfolio expected return $R_f =$ risk-free rate
		The tracking error (TE)	$TE = \sigma(R_P - R_B)$	$R_P =$ return on the portfolio $R_B =$ return on the benchmark portfolio $(R_P - R_B) =$ active returns $\sigma(R_P - R_B) =$ standard deviation of active returns
		Jensen's Alpha	$\alpha = R_p - [R_f + \beta_p(R_m - R_f)]$	**α** (alpha**)** = Jensen's alpha (the excess return) $\boldsymbol{R_p}$ = Actual return of the portfolio $\boldsymbol{R_f}$ = Risk-free rate $\boldsymbol{\beta_p}$ = Beta of the portfolio (systematic risk) $\boldsymbol{R_m}$ = Return of the market
		Sortino ratio (SR)	$SR = \frac{R_p - T}{\frac{1}{N}\sum_{t=1}^{N} \min(0, R_{pt} - T)^2}$	$T =$ target or required rate of return $\frac{1}{N}\sum_{t=1}^{N} \min(0, R_{pt} - T)^2 =$ downside deviation, as measured by the standard deviation of negative returns

		Information ratio (IR)	$$IR = \frac{E(R_P - R_B)}{\sqrt{Var(R_P - R_B)}}$$	R_P = return on the portfolio $R_{Benchmark}$ = return on the benchmark portfolio
		Sortino ratio (SR)	$$SR = \frac{R_p - T}{\frac{1}{N}\sum_{t=1}^{N} min\left(0, R_{pt} - T\right)^2}$$	T = target or required rate of return $\frac{1}{N}\sum_{t=1}^{N}\left(0, R_{pt} - T\right)^2$ = downside deviation, as measured by the standard deviation of returns below the target.
	The Arbitrage Pricing Theory and Multifactor Models of Risk and Return	Return on a security	$$R_i = E(R_i) + \beta_{i1}[I_1 - E(I_1)] + \cdots + \beta_{iK}[I_k - E(I_k)] + e_i$$	R_i = rate of return on security i $I_1 - E(I_1)$ = difference between observed and expected values in factor k β_{ik} = coefficient measuring the effect of changes in a factor I_k on the rate of return of security i e_i =noise factor (i.e., the idiosyncratic factor).
		Variance/Covariance for a factor model with M factors	$$M + \frac{M^2 - M}{M}$$	M = number of factors in the model
		Number of covariances required	$$\frac{n^2 - n}{2}$$	n = number of variances
		The Fama-French Model (FFM)	$$E(R_i) = R_f + \beta_{i,MKT}E\left(R_m - R_f\right) + \beta_{i,SMB}E(SMB) + \beta_{i,HML}E(HML)$$	$E(R_i)$ = expected return on stock i Rf = risk-free interest rate SMB = size factor $\beta_{i,SMB}$ = factor-beta for the size factor

				HML = value factor $\beta_{i,HML}$ = factor-beta for the value factor $E(R_m - R_f)$ = CAPM market factor $\beta_{i,MKT}$ = factor-beta for the market-factor
<u>Book 2</u> Quantitative Analysis	Fundamentals of Probability	Mutually exclusive events	$P(A \cap B) = P(A\ and\ B) = 0$ $P(A \cup B) = P(A\ or\ B) = P(A) + P(B)$	$P(A \cap B)$ = probability A intersection B $P(A \cup B)$ = probability A union B
		Conditional probability	$P(A \mid B) = \frac{P(A \cap B)}{P(B)}$	$P(A \mid B)$ = probability of A given B $P(A \cap B)$ = P(A|B)P(B)
		Independent events	$P(A \cup B) = P(A\ or\ B) = P(A) + P(B) - P(A \cap B)$	
			$P(A \cap B) = P(A\ and\ B) = P(A) \times P(B)$	
			Conditional Probability: $P(A\|B) = \frac{P(A)P(B)}{P(B)} = P(A)$	
		Bayes' Theorem	$P(A\|B) = \frac{P(B\|A)P(A)}{P(B)}$	
	Univariate Random Variables	Binomial distribution	$P(X = x) = \frac{n!}{x!\,(n-x)!} p^x (1-p)^{n-x}, x = 0,1,2,\ldots,n$	$P(X = x)$ = probability mass function of X

			$F_X(x) = \sum_{i=1}^{\lfloor x \rfloor} \binom{n}{i} p^i (1-p)^{n-i}$	$F_X(x)$ = cumulative distribution function of X
			$E(X) = np$	$E(X)$ = expectation of X
			$V(X) = np(1-p)$	$V(X)$ = variance of X
		Bernoulli distribution	$P(X = x) = p^x (1-p)^{1-x}, x = 0,1 ; 0 < p < 1$	$P(X = x)$ = probability mass function
			$F_X(x) = \begin{cases} 0, & y < 0 \\ 1-p, & 0 \leq y < 1 \\ 1, & y \geq 1 \end{cases}$	$F_X(x)$ = cumulative distribution function
			$E(X) = p$	$E(X)$ = expectation of X
			$V(X) = p(1-p)$	$V(X)$ = variance of X
		Uniform distribution	$P(X = x) = \frac{1}{n}, x = 1,2, \dots, n$	$P(X = x)$ = probability mass function
			$E(X) = \frac{n+1}{2}$	$E(X)$ = expectation of X
			$V(X) = \frac{n^2 - 1}{12}$	$V(X)$ = variance of X
		Poisson distribution	$P(X = x) = \frac{\lambda^x e^{-\lambda}}{x!}, x = 0,1,2, \dots ; \lambda > 0$	$P(X = x)$ = probability mass function

			$F_X(x) = e^{-\lambda}\sum_{i=1}^{\lvert x\rvert}\frac{\lambda^i}{i!}$	$F_X(x)$ = cumulative distribution function of X
			$E(X) = V(X) = \lambda$	$E(X)$ = expectation of X
		Continuous uniform distribution	$f_X(x) = \frac{1}{b-a}, a \le X \le b$	$f(x)$ = probability density function of X
			$F_X(x) = \begin{cases} 0, & x < a \\ \frac{x-a}{b-a}, & a \le x \le b \\ 1, & x \ge b \end{cases}$	$F_X(x)$ = cumulative distribution function
			$E[X] = \frac{a+b}{2}$	$E(X)$ = Expectation of X
			$V[X] = \frac{(b-a)^2}{12}$	$V(X)$ = Variance of X
		Normal distribution	$f(x) = \frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}, -\infty < X < \infty$	$f(x)$ = probability density function of x
			$E(X) = \mu$	$E(X)$ = expectation of X
			$V(X) = \sigma^2$	$V(X)$ = variance of X
		Log-normal distribution	$f(x) = \frac{1}{x\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{lnx-\mu}{\sigma}\right)^2}$	$f(x)$ = probability density function of x

			$V(X) = \left(e^{\sigma^2} - 1\right)e^{2\mu+\sigma^2}$ $E[X] = e^{\mu+\frac{1}{2}\sigma 2}$	
			$F_X(x) = \Phi\left(\frac{lnX - \mu}{\sigma}\right)$	
		Chi-square distribution	$f(x) = \frac{1}{2^{\frac{k}{2}}\Gamma\left(\frac{k}{2}\right)} x^{\frac{k}{2}-1} e^{-\frac{x}{2}}, \quad x > 0$	$\Gamma(n) = \int_0^{\infty} x^{n-1} e^{-x}\, dx$
			$E(S) = k$	$S = \sum_{1=1}^{k} Z_i^2$
			$V(S) = 2k$	
		Student's t-distribution	$f(x) = \frac{\Gamma\left(k + \frac{1}{2}\right)}{\sqrt{k\pi}\,\Gamma\left(\frac{k}{2}\right)} \left(1 + \frac{x^2}{k}\right)^{-\frac{k+1}{2}}$	$X = \frac{Z}{\sqrt{\frac{U}{k}}}$ Z = standard normal variable, U = a chi-square variable with k degrees of freedom
			$E(X) = 0$ $V(X) = \frac{k}{k-2}$	
		F-distribution	$f(x) = \frac{\sqrt{\frac{(k_1X)^{k_1}\, k_2^{k_2}}{(k_1X + k_2)^{k_1+k_2}}}}{xB(\frac{k_1}{2}, \frac{k_2}{2})}$	$X = \frac{U_1/k_1}{U_2/k_2} \sim F(k_1, k_2)$ U_i = chi-squared distributions that are independent with k_i degrees of freedom.