Package: Dowd (via r-universe)

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Type Package

Title Functions Ported from 'MMR2' Toolbox Offered in Kevin Dowd's Book Measuring Market Risk

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Author Dinesh Acharya <dines.acharya@gmail.com>

Maintainer Dinesh Acharya <dines.acharya@gmail.com>

Description 'Kevin Dowd's' book Measuring Market Risk is a widely read book in the area of risk measurement by students and practitioners alike. As he claims, 'MATLAB' indeed might have been the most suitable language when he originally wrote the functions, but, with growing popularity of R it is not entirely valid. As 'Dowd's' code was not intended to be error free and were mainly for reference, some functions in this package have inherited those errors. An attempt will be made in future releases to identify and correct them. 'Dowd's' original code can be downloaded from www.kevindowd.org/measuring-market-risk/. It should be noted that 'Dowd' offers both 'MMR2' and 'MMR1' toolboxes. Only 'MMR2' was ported to R. 'MMR2' is more recent version of 'MMR1' toolbox and they both have mostly similar function. The toolbox mainly contains different parametric and non parametric methods for measurement of market risk as well as backtesting risk measurement methods.

Depends R (>= 3.0.0), bootstrap, MASS, forecast

Suggests PerformanceAnalytics, testthat

License GPL

NeedsCompilation no

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Repository https://d-acharya.r-universe.dev

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Contents

`Dowd-package` *R-version of Kevin Dowd's MATLAB Toolbox from book "Measuring Market Risk".*

Description

`Dowd` Kevin Dowd's book "Measuring Market Risk" gives overview of risk measurement procedures with focus on Value at Risk (VaR) and Expected Shortfall (ES).

Acknowledgments

Without Kevin Dowd's book Measuring Market Risk and accompanying MATLAB toolbox, this project would not have been possible.

Peter Carl and Brian G. Peterson deserve special acknowledgement for mentoring me on this project.

Author(s)

Dinesh Acharya

Maintainer: Dinesh Acharya `<dines.acharya@gmail.com>`

References

Dowd, K. *Measuring Market Risk*. Wiley. 2005.

`AdjustedNormalESHotspots` *Hotspots for ES adjusted by Cornish-Fisher correction*

Description

Estimates the ES hotspots (or vector of incremental ESs) for a portfolio with portfolio return adjusted for non-normality by Cornish-Fisher corerction, for specified confidence level and holding period.

Usage

```
AdjustedNormalESHotspots(vc.matrix, mu, skew, kurtosis, positions, cl, hp)
```

Arguments

`vc.matrix`	Variance covariance matrix for returns
`mu`	Vector of expected position returns
`skew`	Return skew
`kurtosis`	Return kurtosis
`positions`	Vector of positions
`cl`	Confidence level and is scalar
`hp`	Holding period and is scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Hotspots for ES for randomly generated portfolio
   vc.matrix <- matrix(rnorm(16),4,4)
   mu <- rnorm(4)
   skew <- .5
   kurtosis <- 1.2
   positions <- c(5,2,6,10)
   cl <- .95
   hp <- 280
   AdjustedNormalESHotspots(vc.matrix, mu, skew, kurtosis, positions, cl, hp)
```

`AdjustedNormalVaRHotspots` *Hotspots for VaR adjusted by Cornish-Fisher correction*

Description

Estimates the VaR hotspots (or vector of incremental VaRs) for a portfolio with portfolio return adjusted for non-normality by Cornish-Fisher corerction, for specified confidence level and holding period.

Usage

```
AdjustedNormalVaRHotspots(vc.matrix, mu, skew, kurtosis, positions, cl, hp)
```

Arguments

vc.matrix	Variance covariance matrix for returns
mu	Vector of expected position returns
skew	Return skew
kurtosis	Return kurtosis
positions	Vector of positions
cl	Confidence level and is scalar
hp	Holding period and is scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Hotspots for ES for randomly generated portfolio
   vc.matrix <- matrix(rnorm(16),4,4)
   mu <- rnorm(4)
   skew <- .5
   kurtosis <- 1.2
   positions <- c(5,2,6,10)
   cl <- .95
   hp <- 280
   AdjustedNormalVaRHotspots(vc.matrix, mu, skew, kurtosis, positions, cl, hp)
```

AdjustedVarianceCovarianceES

Cornish-Fisher adjusted Variance-Covariance ES

Description

Function estimates the Variance-Covariance ES of a multi-asset portfolio using the Cornish - Fisher adjustment for portfolio return non-normality, for specified confidence level and holding period.

Usage

```
AdjustedVarianceCovarianceES(vc.matrix, mu, skew, kurtosis, positions, cl, hp)
```

Arguments

vc.matrix	Variance covariance matrix for returns
mu	Vector of expected position returns
skew	Return skew
kurtosis	Return kurtosis
positions	Vector of positions
cl	Confidence level and is scalar
hp	Holding period and is scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Variance-covariance ES for randomly generated portfolio
   vc.matrix <- matrix(rnorm(16), 4, 4)
   mu <- rnorm(4)
   skew <- .5
   kurtosis <- 1.2
   positions <- c(5, 2, 6, 10)
   cl <- .95
   hp <- 280
   AdjustedVarianceCovarianceES(vc.matrix, mu, skew, kurtosis, positions, cl, hp)
```

AdjustedVarianceCovarianceVaR

Cornish-Fisher adjusted variance-covariance VaR

Description

Estimates the variance-covariance VaR of a multi-asset portfolio using the Cornish-Fisher adjustment for portfolio-return non-normality, for specified confidence level and holding period.

Usage

```
AdjustedVarianceCovarianceVaR(vc.matrix, mu, skew, kurtosis, positions, cl, hp)
```

Arguments

vc.matrix	Assumed variance covariance matrix for returns
mu	Vector of expected position returns
skew	Portfolio return skewness
kurtosis	Portfolio return kurtosis
positions	Vector of positions
cl	Confidence level and is scalar or vector
hp	Holding period and is scalar or vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Variance-covariance for randomly generated portfolio
   vc.matrix <- matrix(rnorm(16),4,4)
   mu <- rnorm(4)
   skew <- .5
   kurtosis <- 1.2
   positions <- c(5,2,6,10)
   cl <- .95
   hp <- 280
   AdjustedVarianceCovarianceVaR(vc.matrix, mu, skew, kurtosis, positions, cl, hp)
```

ADTestStat — *Plots cumulative density for AD test and computes confidence interval for AD test stat.*

Description

Anderson-Darling(AD) test can be used to carry out distribution equality test and is similar to Kolmogorov-Smirnov test. AD test statistic is defined as:

$$A^2 = n \int_{-\infty}^{\infty} \frac{[\hat{F}(x) - F(x)]^2}{F(x)[1 - F(x)]} dF(x)$$

which is equivalent to

$$= -n - \frac{1}{n} \sum_{i=1}^{n} (2i-1)[\ln F(X_i) + \ln(1 - F(X_{n+1-i}))]$$

Usage

```
ADTestStat(number.trials, sample.size, confidence.interval)
```

Arguments

`number.trials` Number of trials

`sample.size` Sample size

`confidence.interval`
Confidence Interval

Value

Confidence Interval for AD test statistic

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Anderson, T.W. and Darling, D.A. Asymptotic Theory of Certain Goodness of Fit Criteria Based on Stochastic Processes, The Annals of Mathematical Statistics, 23(2), 1952, p. 193-212.

Kvam, P.H. and Vidakovic, B. Nonparametric Statistics with Applications to Science and Engineering, Wiley, 2007.

Examples

```
# Probability that the VaR model is correct for 3 failures, 100 number
   # observations and  95% confidence level
   ADTestStat(1000, 100, 0.95)
```

`AmericanPutESBinomial` *Estimates ES of American vanilla put using binomial tree.*

Description

Estimates ES of American Put Option using binomial tree to price the option and historical method to compute the VaR.

Usage

```
AmericanPutESBinomial(amountInvested, stockPrice, strike, r, volatility,
  maturity, numberSteps, cl, hp)
```

Arguments

`amountInvested`	Total amount paid for the Put Option.
`stockPrice`	Stock price of underlying stock.
`strike`	Strike price of the option.
`r`	Risk-free rate.
`volatility`	Volatility of the underlying stock.
`maturity`	Time to maturity of the option in days.
`numberSteps`	The number of time-steps considered for the binomial model.
`cl`	Confidence level for which VaR is computed.
`hp`	Holding period of the option in days.

Value

ES of the American Put Option

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Lyuu, Yuh-Dauh. Financial Engineering & Computation: Principles, Mathematics, Algorithms, Cambridge University Press, 2002.

Examples

```
# Market Risk of American Put with given parameters.
   AmericanPutESBinomial(0.20, 27.2, 25, .16, .05, 60, 20, .95, 30)
```

AmericanPutESSim — *Estimates ES of American vanilla put using binomial option valuation tree and Monte Carlo Simulation*

Description

Estimates ES of American Put Option using binomial tree to price the option valuation tree and Monte Carlo simulation with a binomial option valuation tree nested within the MCS. Historical method to compute the VaR.

Usage

```
AmericanPutESSim(amountInvested, stockPrice, strike, r, mu, sigma, maturity,
  numberTrials, numberSteps, cl, hp)
```

Arguments

amountInvested	Total amount paid for the Put Option and is positive (negative) if the option position is long (short)
stockPrice	Stock price of underlying stock
strike	Strike price of the option
r	Risk-free rate
mu	Expected rate of return on the underlying asset and is in annualised term
sigma	Volatility of the underlying stock and is in annualised term
maturity	The term to maturity of the option in days
numberTrials	The number of interations in the Monte Carlo simulation exercise
numberSteps	The number of steps over the holding period at each of which early exercise is checked and is at least 2
cl	Confidence level for which VaR is computed and is scalar
hp	Holding period of the option in days and is scalar

Value

Monte Carlo Simulation VaR estimate and the bounds of the 95 confidence interval for the VaR, based on an order-statistics analysis of the P/L distribution

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Lyuu, Yuh-Dauh. Financial Engineering & Computation: Principles, Mathematics, Algorithms, Cambridge University Press, 2002.

Examples

```
# Market Risk of American Put with given parameters.
   AmericanPutESSim(0.20, 27.2, 25, .16, .2, .05, 60, 30, 20, .95, 30)
```

AmericanPutPriceBinomial *Binomial Put Price*

Description

Estimates the price of an American Put, using the binomial approach.

Usage

```
AmericanPutPriceBinomial(stockPrice, strike, r, sigma, maturity, numberSteps)
```

Arguments

stockPrice	Stock price of underlying stock
strike	Strike price of the option
r	Risk-free rate
sigma	Volatility of the underlying stock and is in annualised term
maturity	The term to maturity of the option in days
numberSteps	The number of time-steps in the binomial tree

Value

Binomial American put price

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Lyuu, Yuh-Dauh. Financial Engineering & Computation: Principles, Mathematics, Algorithms, Cambridge University Press, 2002.

Examples

```
# Estimates the price of an American Put
   AmericanPutPriceBinomial(27.2, 25, .03, .2, 60, 30)
```

AmericanPutVaRBinomial   *Estimates VaR of American vanilla put using binomial tree.*

Description

Estimates VaR of American Put Option using binomial tree to price the option and historical method to compute the VaR.

Usage

```
AmericanPutVaRBinomial(amountInvested, stockPrice, strike, r, volatility,
  maturity, numberSteps, cl, hp)
```

Arguments

amountInvested	Total amount paid for the Put Option.
stockPrice	Stock price of underlying stock.
strike	Strike price of the option.
r	Risk-free rate.
volatility	Volatility of the underlying stock.
maturity	Time to maturity of the option in days.
numberSteps	The number of time-steps considered for the binomial model.
cl	Confidence level for which VaR is computed.
hp	Holding period of the option in days.

Value

VaR of the American Put Option

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Lyuu, Yuh-Dauh. Financial Engineering & Computation: Principles, Mathematics, Algorithms, Cambridge University Press, 2002.

Examples

```
# Market Risk of American Put with given parameters.
   AmericanPutVaRBinomial(0.20, 27.2, 25, .16, .05, 60, 20, .95, 30)
```

BinomialBacktest — *Carries out the binomial backtest for a VaR risk measurement model.*

Description

The basic idea behind binomial backtest (also called basic frequency test) is to test whether the observed frequency of losses that exceed VaR is consistent with the frequency of tail losses predicted by the mode. Binomial Backtest carries out the binomial backtest for a VaR risk measurement model for specified VaR confidence level and for a one-sided alternative hypothesis (H1).

Usage

```
BinomialBacktest(x, n, cl)
```

Arguments

x	Number of failures
n	Number of observations
cl	Confidence level for VaR

Value

Probability that the VaR model is correct

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Kupiec, Paul. Techniques for verifying the accuracy of risk measurement models, Journal of Derivatives, Winter 1995, p. 79.

Examples

```
# Probability that the VaR model is correct for 3 failures, 100 number
   # observations and  95% confidence level
   BinomialBacktest(55, 1000, 0.95)
```

BlackScholesCallESSim *ES of Black-Scholes call using Monte Carlo Simulation*

Description

Estimates ES of Black-Scholes call Option using Monte Carlo simulation

Usage

```
BlackScholesCallESSim(amountInvested, stockPrice, strike, r, mu, sigma,
  maturity, numberTrials, cl, hp)
```

Arguments

amountInvested	Total amount paid for the Call Option and is positive (negative) if the option position is long (short)
stockPrice	Stock price of underlying stock
strike	Strike price of the option
r	Risk-free rate
mu	Expected rate of return on the underlying asset and is in annualised term
sigma	Volatility of the underlying stock and is in annualised term
maturity	The term to maturity of the option in days
numberTrials	The number of interations in the Monte Carlo simulation exercise
cl	Confidence level for which ES is computed and is scalar
hp	Holding period of the option in days and is scalar

Value

ES

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Lyuu, Yuh-Dauh. Financial Engineering & Computation: Principles, Mathematics, Algorithms, Cambridge University Press, 2002.

Examples

```
# Market Risk of American call with given parameters.
   BlackScholesCallESSim(0.20, 27.2, 25, .16, .2, .05, 60, 30, .95, 30)
```

`BlackScholesCallPrice` *Price of European Call Option*

Description

Derives the price of European call option using the Black-Scholes approach

Usage

```
BlackScholesCallPrice(stockPrice, strike, rf, sigma, t)
```

Arguments

`stockPrice`	Stock price of underlying stock
`strike`	Strike price of the option
`rf`	Risk-free rate and is annualised
`sigma`	Volatility of the underlying stock
`t`	The term to maturity of the option in years

Value

Price of European Call Option

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Hull, John C.. Options, Futures, and Other Derivatives. 5th ed., p. 246.

Lyuu, Yuh-Dauh. Financial Engineering & Computation: Principles, Mathematics, Algorithms, Cambridge University Press, 2002.

Examples

```
# Estimates the price of an American Put
   BlackScholesCallPrice(27.2, 25, .03, .2, 60)
```

BlackScholesPutESSim *ES of Black-Scholes put using Monte Carlo Simulation*

Description

Estimates ES of Black-Scholes Put Option using Monte Carlo simulation

Usage

```
BlackScholesPutESSim(amountInvested, stockPrice, strike, r, mu, sigma, maturity,
  numberTrials, cl, hp)
```

Arguments

amountInvested	Total amount paid for the Put Option and is positive (negative) if the option position is long (short)
stockPrice	Stock price of underlying stock
strike	Strike price of the option
r	Risk-free rate
mu	Expected rate of return on the underlying asset and is in annualised term
sigma	Volatility of the underlying stock and is in annualised term
maturity	The term to maturity of the option in days
numberTrials	The number of interations in the Monte Carlo simulation exercise
cl	Confidence level for which ES is computed and is scalar
hp	Holding period of the option in days and is scalar

Value

ES

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Lyuu, Yuh-Dauh. Financial Engineering & Computation: Principles, Mathematics, Algorithms, Cambridge University Press, 2002.

Examples

```
# Market Risk of American Put with given parameters.
   BlackScholesPutESSim(0.20, 27.2, 25, .03, .12, .05, 60, 1000, .95, 30)
```

`BlackScholesPutPrice` *Price of European Put Option*

Description

Derives the price of European call option using the Black-Scholes approach

Usage

```
BlackScholesPutPrice(stockPrice, strike, rf, sigma, t)
```

Arguments

`stockPrice`	Stock price of underlying stock
`strike`	Strike price of the option
`rf`	Risk-free rate and is annualised
`sigma`	Volatility of the underlying stock
`t`	The term to maturity of the option in years

Value

Price of European Call Option

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Hull, John C.. Options, Futures, and Other Derivatives. 5th ed., p. 246.

Lyuu, Yuh-Dauh. Financial Engineering & Computation: Principles, Mathematics, Algorithms, Cambridge University Press, 2002.

Examples

```
# Estimates the price of an American Put
   BlackScholesPutPrice(27.2, 25, .03, .2, 60)
```

`BlancoIhleBacktest` *Blanco-Ihle forecast evaluation backtest measure*

Description

Derives the Blanco-Ihle forecast evaluation loss measure for a VaR risk measurement model.

Usage

```
BlancoIhleBacktest(Ra, Rb, Rc, cl)
```

Arguments

`Ra`	Vector of a portfolio profit and loss
`Rb`	Vector of corresponding VaR forecasts
`Rc`	Vector of corresponding Expected Tailed Loss forecasts
`cl`	VaR confidence interval

Value

First Blanco-Ihle score measure.

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Blanco, C. and Ihle, G. How Good is Your Var? Using Backtesting to Assess System Performance. Financial Engineering News, 1999.

Examples

```
# Blanco-Ihle Backtest For Independence for given confidence level.
   # The VaR and ES are randomly generated.
   a <- rnorm(1*100)
   b <- abs(rnorm(1*100))+2
   c <- abs(rnorm(1*100))+2
   BlancoIhleBacktest(a, b, c, 0.95)
```

BootstrapES *Bootstrapped ES for specified confidence level*

Description

Estimates the bootstrapped ES for confidence level and holding period implied by data frequency.

Usage

```
BootstrapES(Ra, number.resamples, cl)
```

Arguments

`Ra`	Vector corresponding to profit and loss distribution
`number.resamples`	Number of samples to be taken in bootstrap procedure
`cl`	Number corresponding to Expected Shortfall confidence level

Value

Bootstrapped Expected Shortfall

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates bootstrapped ES for given parameters
   a <- rnorm(100) # generate a random profit/loss vector
   BootstrapVaR(a, 50, 0.95)
```

BootstrapESConfInterval
Bootstrapped ES Confidence Interval

Description

Estimates the 90 level and holding period implied by data frequency.

Usage

```
BootstrapESConfInterval(Ra, number.resamples, cl)
```

Arguments

Ra	Vector corresponding to profit and loss distribution
number.resamples	Number of samples to be taken in bootstrap procedure
cl	Number corresponding to Expected Shortfall confidence level

Value

90

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# To be modified with appropriate data.
   # Estimates 90% confidence interval for bootstrapped ES for 95%
   # confidence interval
   Ra <- rnorm(1000)
   BootstrapESConfInterval(Ra, 50, 0.95)
```

BootstrapESFigure *Plots figure of bootstrapped ES*

Description

Plots figure for the bootstrapped ES, for confidence level and holding period implied by data frequency.

Usage

```
BootstrapESFigure(Ra, number.resamples, cl)
```

Arguments

`Ra` Vector corresponding to profit and loss distribution

`number.resamples` Number of samples to be taken in bootstrap procedure

`cl` Number corresponding to Expected Shortfall confidence level

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# To be modified with appropriate data.
   # Estimates 90% confidence interval for bootstrapped ES for 95%
   # confidence interval
   Ra <- rnorm(1000)
   BootstrapESFigure(Ra, 500, 0.95)
```

BootstrapVaR *Bootstrapped VaR for specified confidence level*

Description

Estimates the bootstrapped VaR for confidence level and holding period implied by data frequency.

Usage

```
BootstrapVaR(Ra, number.resamples, cl)
```

Arguments

`Ra`	Vector corresponding to profit and loss distribution
`number.resamples`	Number of samples to be taken in bootstrap procedure
`cl`	Number corresponding to Value at Risk confidence level

Value

Bootstrapped VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates bootstrapped VaR for given parameters
   a <- rnorm(100) # generate a random profit/loss vector
   BootstrapES(a, 50, 0.95)
```

BootstrapVaRConfInterval

Bootstrapped VaR Confidence Interval

Description

Estimates the 90 level and holding period implied by data frequency.

Usage

```
BootstrapVaRConfInterval(Ra, number.resamples, cl)
```

Arguments

`Ra`	Vector corresponding to profit and loss distribution
`number.resamples`	Number of samples to be taken in bootstrap procedure
`cl`	Number corresponding to Value at Risk confidence level

Value

90

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# To be modified with appropriate data.
   # Estimates 90% confidence interval for bootstrapped Var for 95%
   # confidence interval
   Ra <- rnorm(1000)
   BootstrapVaRConfInterval(Ra, 500, 0.95)
```

BootstrapVaRFigure *Plots figure of bootstrapped VaR*

Description

Plots figure for the bootstrapped VaR, for confidence level and holding period implied by data frequency.

Usage

```
BootstrapVaRFigure(Ra, number.resamples, cl)
```

Arguments

Ra	Vector corresponding to profit and loss distribution
number.resamples	Number of samples to be taken in bootstrap procedure
cl	Number corresponding to Value at Risk confidence level

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# To be modified with appropriate data.
   # Estimates 90% confidence interval for bootstrapped VaR for 95%
   # confidence interval
   Ra <- rnorm(1000)
   BootstrapESFigure(Ra, 500, 0.95)
```

BoxCoxES *Estimates ES with Box-Cox transformation*

Description

Function estimates the ES of a portfolio assuming P and L data set transformed using the BoxCox transformation to make it as near normal as possible, for specified confidence level and holding period implied by data frequency.

Usage

```
BoxCoxES(loss.data, cl)
```

Arguments

`loss.data`	Daily Profit/Loss data
`cl`	Confidence Level. It can be a scalar or a vector.

Value

Estimated Box-Cox ES. Its dimension is same as that of cl

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Hamilton, S. A. and Taylor, M. G. A Comparision of the Box-Cox transformation method and nonparametric methods for estimating quantiles in clinical data with repeated measures. J. Statist. Comput. Simul., vol. 45, 1993, pp. 185 - 201.

Examples

```
# Estimates Box-Cox VaR
   a<-rnorm(200)
   BoxCoxES(a,.95)
```

BoxCoxVaR *Estimates VaR with Box-Cox transformation*

Description

Function estimates the VaR of a portfolio assuming P and L data set transformed using the BoxCox transformation to make it as near normal as possible, for specified confidence level and holding period implied by data frequency.

Usage

```
BoxCoxVaR(PandLdata, cl)
```

Arguments

PandLdata	Daily Profit/Loss data
cl	Confidence Level. It can be a scalar or a vector.

Value

Estimated Box-Cox VaR. Its dimension is same as that of cl

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Hamilton, S. A. and Taylor, M. G. A Comparision of the Box-Cox transformation method and nonparametric methods for estimating quantiles in clinical data with repeated measures. J. Statist. Comput. Simul., vol. 45, 1993, pp. 185 - 201.

Examples

```
# Estimates Box-Cox VaR
   a<-rnorm(100)
   BoxCoxVaR(a,.95)
```

CdfOfSumUsingGaussianCopula

Derives prob (X + Y < quantile) using Gaussian copula

Description

If X and Y are position P/Ls, then the VaR is equal to minus quantile. In such cases, we insert the negative of the VaR as the quantile, and the function gives us the value of 1 minus VaR confidence level. In other words, if X and Y are position P/Ls, the quantile is the negative of the VaR, and the output is 1 minus the VaR confidence level.

Usage

```
CdfOfSumUsingGaussianCopula(quantile, mu1, mu2, sigma1, sigma2, rho,
  number.steps.in.copula)
```

Arguments

quantile	Portfolio quantile (or negative of Var, if X, Y are position P/Ls)
mu1	Mean of Profit/Loss on first position
mu2	Mean of Profit/Loss on second position
sigma1	Standard Deviation of Profit/Loss on first position
sigma2	Standard Deviation of Profit/Loss on second position
rho	Correlation between P/Ls on two positions
number.steps.in.copula	The number of steps used in the copula approximation

Value

Probability of X + Y being less than quantile

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Dowd, K. and Fackler, P. Estimating VaR with copulas. Financial Engineering News, 2004.

Examples

```
# Prob ( X + Y < q ) using Gaussian Copula for X with mean 2.3 and std. .2
   # and Y with mean 4.5 and std. 1.5 with beta 1.2 at 0.9 quantile
   CdfOfSumUsingGaussianCopula(0.9, 2.3, 4.5, 1.2, 1.5, 0.6, 15)
```

CdfOfSumUsingGumbelCopula
Derives prob (X + Y < quantile) using Gumbel copula

Description

If X and Y are position P/Ls, then the VaR is equal to minus quantile. In such cases, we insert the negative of the VaR as the quantile, and the function gives us the value of 1 minus VaR confidence level. In other words, if X and Y are position P/Ls, the quantile is the negative of the VaR, and the output is 1 minus the VaR confidence level.

Usage

```
CdfOfSumUsingGumbelCopula(quantile, mu1, mu2, sigma1, sigma2, beta)
```

Arguments

`quantile`	Portfolio quantile (or negative of Var, if X, Y are position P/Ls)
`mu1`	Mean of Profit/Loss on first position
`mu2`	Mean of Profit/Loss on second position
`sigma1`	Standard Deviation of Profit/Loss on first position
`sigma2`	Standard Deviation of Profit/Loss on second position
`beta`	Gumber copula parameter (greater than 1)

Value

Probability of X + Y being less than quantile

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Dowd, K. and Fackler, P. Estimating VaR with copulas. Financial Engineering News, 2004.

Examples

```
# Prob ( X + Y < q ) using Gumbel Copula for X with mean 2.3 and std. .2
   # and Y with mean 4.5 and std. 1.5 with beta 1.2 at 0.9 quantile
   CdfOfSumUsingGumbelCopula(0.9, 2.3, 4.5, 1.2, 1.5, 1.2)
```

CdfOfSumUsingProductCopula

Derives prob (X + Y < quantile) using Product copula

Description

If X and Y are position P/Ls, then the VaR is equal to minus quantile. In such cases, we insert the negative of the VaR as the quantile, and the function gives us the value of 1 minus VaR confidence level. In other words, if X and Y are position P/Ls, the quantile is the negative of the VaR, and the output is 1 minus the VaR confidence level.

Usage

```
CdfOfSumUsingProductCopula(quantile, mu1, mu2, sigma1, sigma2)
```

Arguments

`quantile`	Portfolio quantile (or negative of Var, if X, Y are position P/Ls)
`mu1`	Mean of Profit/Loss on first position
`mu2`	Mean of Profit/Loss on second position
`sigma1`	Standard Deviation of Profit/Loss on first position
`sigma2`	Standard Deviation of Profit/Loss on second position

Value

Probability of X + Y being less than quantile

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Dowd, K. and Fackler, P. Estimating VaR with copulas. Financial Engineering News, 2004.

Examples

```
# Prob ( X + Y < q ) using Product Copula for X with mean 2.3 and std. .2
   # and Y with mean 4.5 and std. 1.5 with beta 1.2 at 0.9 quantile
   CdfOfSumUsingProductCopula(0.9, 2.3, 4.5, 1.2, 1.5)
```

ChristoffersenBacktestForIndependence
Christoffersen Backtest for Independence

Description

Carries out the Christoffersen backtest of independence for a VaR risk measurement model, for specified VaR confidence level.

Usage

```
ChristoffersenBacktestForIndependence(Ra, Rb, cl)
```

Arguments

Ra	Vector of portfolio profit and loss observations
Rb	Vector of corresponding VaR forecasts
cl	Confidence interval for

Value

Probability that given the data set, the null hypothesis (i.e. independence) is correct.

Author(s)

Dinesh Acharya

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Christoffersen, P. Evaluating Interval Forecasts. International Economic Review, 39(4), 1992, 841-862.

Examples

```
# Has to be modified with appropriate data:
   # Christoffersen Backtest For Independence for given parameters
   a <- rnorm(1*100)
   b <- abs(rnorm(1*100))+2
   ChristoffersenBacktestForIndependence(a, b, 0.95)
```

ChristoffersenBacktestForUnconditionalCoverage

Christoffersen Backtest for Unconditional Coverage

Description

Carries out the Christiffersen backtest for unconditional coverage for a VaR risk measurement model, for specified VaR confidence level.

Usage

```
ChristoffersenBacktestForUnconditionalCoverage(Ra, Rb, cl)
```

Arguments

Ra	Vector of portfolio profit and loss observations
Rb	Vector of VaR forecasts corresponding to PandL observations
cl	Confidence level for VaR

Value

Probability, given the data set, that the null hypothesis (i.e. a correct model) is correct.

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Christoffersen, P. Evaluating interval forecasts. International Economic Review, 39(4), 1998, 841-862.

Examples

```
# Has to be modified with appropriate data:
   # Christoffersen Backtest For Unconditional Coverage for given parameters
   a <- rnorm(1*100)
   b <- abs(rnorm(1*100))+2
   ChristoffersenBacktestForUnconditionalCoverage(a, b, 0.95)
```

CornishFisherES *Corn-Fisher ES*

Description

Function estimates the ES for near-normal P/L using the Cornish-Fisher adjustment for non-normality, for specified confidence level.

Usage

```
CornishFisherES(mu, sigma, skew, kurtosis, cl)
```

Arguments

mu	Mean of P/L distribution
sigma	Variance of of P/L distribution
skew	Skew of P/L distribution
kurtosis	Kurtosis of P/L distribution
cl	ES confidence level

Value

Expected Shortfall

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Zangri, P. A VaR methodology for portfolios that include options. RiskMetrics Monitor, First quarter, 1996, p. 4-12.

Examples

```
# Estimates Cornish-Fisher ES for given parameters
   CornishFisherES(3.2, 5.6, 2, 3, .9)
```

`CornishFisherVaR` *Corn-Fisher VaR*

Description

Function estimates the VaR for near-normal P/L using the Cornish-Fisher adjustment for non-normality, for specified confidence level.

Usage

```
CornishFisherVaR(mu, sigma, skew, kurtosis, cl)
```

Arguments

`mu`	Mean of P/L distribution
`sigma`	Variance of of P/L distribution
`skew`	Skew of P/L distribution
`kurtosis`	Kurtosis of P/L distribution
`cl`	VaR confidence level

Value

Value at Risk

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Zangri, P. A VaR methodology for portfolios that include options. RiskMetrics Monitor, First quarter, 1996, p. 4-12.

Examples

```
# Estimates Cornish-Fisher VaR for given parameters
   CornishFisherVaR(3.2, 5.6, 2, 3, .9)
```

`DBPensionVaR` *Monte Carlo VaR for DB pension*

Description

Generates Monte Carlo VaR for DB pension in Chapter 6.7.

Usage

```
DBPensionVaR(mu, sigma, p, life.expectancy, number.trials, cl)
```

Arguments

`mu`	Expected rate of return on pension-fund assets
`sigma`	Volatility of rate of return of pension-fund assets
`p`	Probability of unemployment in any period
`life.expectancy`	Life expectancy
`number.trials`	Number of trials
`cl`	VaR confidence level

Value

VaR for DB pension

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates the price of an American Put
   DBPensionVaR(.06, .2, .05, 80, 100, .95)
```

`DCPensionVaR` *Monte Carlo VaR for DC pension*

Description

Generates Monte Carlo VaR for DC pension in Chapter 6.7.

Usage

```
DCPensionVaR(mu, sigma, p, life.expectancy, number.trials, cl)
```

Arguments

`mu`	Expected rate of return on pension-fund assets
`sigma`	Volatility of rate of return of pension-fund assets
`p`	Probability of unemployment in any period
`life.expectancy`	Life expectancy
`number.trials`	Number of trials
`cl`	VaR confidence level

Value

VaR for DC pension

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates the price of an American Put
   DCPensionVaR(.06, .2, .05, 80, 100, .95)
```

`DefaultRiskyBondVaR` *VaR for default risky bond portfolio*

Description

Generates Monte Carlo VaR for default risky bond portfolio in Chapter 6.4

Usage

```
DefaultRiskyBondVaR(r, rf, coupon, sigma, amount.invested, recovery.rate, p,
  number.trials, hp, cl)
```

Arguments

`r`	Spot (interest) rate, assumed to be flat
`rf`	Risk-free rate
`coupon`	Coupon rate
`sigma`	Variance
`amount.invested`	Amount Invested
`recovery.rate`	Recovery rate
`p`	Probability of default
`number.trials`	Number of trials
`hp`	Holding period
`cl`	Confidence level

Value

Monte Carlo VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# VaR for default risky bond portfolio for given parameters
   DefaultRiskyBondVaR(.01, .01, .1, .01, 1, .1, .2, 100, 100, .95)
```

`FilterStrategyLogNormalVaR` *Log Normal VaR with filter strategy*

Description

Generates Monte Carlo lognormal VaR with filter portfolio strategy

Usage

```
FilterStrategyLogNormalVaR(mu, sigma, number.trials, alpha, cl, hp)
```

Arguments

`mu`	Mean arithmetic return
`sigma`	Standard deviation of arithmetic return
`number.trials`	Number of trials used in the simulations
`alpha`	Participation parameter
`cl`	Confidence Level
`hp`	Holding Period

Value

Lognormal VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates standard error of normal quantile estimate
   FilterStrategyLogNormalVaR(0, .2, 100, 1.2, .95, 10)
```

`FrechetES` *Frechet Expected Shortfall*

Description

Estimates the ES of a portfolio assuming extreme losses are Frechet distributed, for specified confidence level and a given holding period.

Usage

```
FrechetES(mu, sigma, tail.index, n, cl, hp)
```

Arguments

`mu`	Location parameter for daily L/P
`sigma`	Scale parameter for daily L/P
`tail.index`	Tail index
`n`	Block size from which maxima are drawn
`cl`	Confidence level
`hp`	Holding period

Details

Note that the long-right-hand tail is fitted to losses, not profits.

Value

Estimated ES. If cl and hp are scalars, it returns scalar VaR. If cl is vector and hp is a scalar, or viceversa, returns vector of VaRs. If both cl and hp are vectors, returns a matrix of VaRs.

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Embrechts, P., Kluppelberg, C. and Mikosch, T., Modelling Extremal Events for Insurance and Finance. Springer, Berlin, 1997, p. 324.

Reiss, R. D. and Thomas, M. Statistical Analysis of Extreme Values from Insurance, Finance, Hydrology and Other Fields, Birkhaueser, Basel, 1997, 15-18.

Examples

```
# Computes ES assuming Frechet Distribution for given parameters
   FrechetES(3.5, 2.3, 1.6, 10, .95, 30)
```

`FrechetESPlot2DCl` *Plots Frechet Expected Shortfall against confidence level*

Description

Plots the ES of a portfolio against confidence level assuming extreme losses are Frechet distributed, for specified confidence level and a given holding period.

Usage

```
FrechetESPlot2DCl(mu, sigma, tail.index, n, cl, hp)
```

Arguments

`mu`	Location parameter for daily L/P
`sigma`	Scale parameter for daily L/P
`tail.index`	Tail index
`n`	Block size from which maxima are drawn
`cl`	Confidence level and should be a vector
`hp`	Holding period

Details

Note that the long-right-hand tail is fitted to losses, not profits.

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Embrechts, P., Kluppelberg, C. and Mikosch, T., Modelling Extremal Events for Insurance and Finance. Springer, Berlin, 1997, p. 324.

Reiss, R. D. and Thomas, M. Statistical Analysis of Extreme Values from Insurance, Finance, Hydrology and Other Fields, Birkhaueser, Basel, 1997, 15-18.

Examples

```
# Plots ES against vector of cl assuming Frechet Distribution for given parameters
   cl <- seq(0.9,0.99,0.01)
   FrechetESPlot2DCl(3.5, 2.3, 1.6, 10, cl, 30)
```

FrechetVaR *Frechet Value at Risk*

Description

Estimates the VaR of a portfolio assuming extreme losses are Frechet distributed, for specified range of confidence level and a given holding period.

Usage

```
FrechetVaR(mu, sigma, tail.index, n, cl, hp)
```

Arguments

`mu`	Location parameter for daily L/P
`sigma`	Scale parameter for daily L/P
`tail.index`	Tail index
`n`	Block size from which maxima are drawn
`cl`	Confidence level
`hp`	Holding period

Details

Note that the long-right-hand tail is fitted to losses, not profits.

Value

Value at Risk. If cl and hp are scalars, it returns scalar VaR. If cl is vector and hp is a scalar, or viceversa, returns vector of VaRs. If both cl and hp are vectors, returns a matrix of VaRs.

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Embrechts, P., Kluppelberg, C. and Mikosch, T., Modelling Extremal Events for Insurance and Finance. Springer, Berlin, 1997, p. 324.

Reiss, R. D. and Thomas, M. Statistical Analysis of Extreme Values from Insurance, Finance, Hydrology and Other Fields, Birkhaueser, Basel, 1997, 15-18.

Examples

```
# Computes VaR assuming Frechet Distribution for given parameters
   FrechetVaR(3.5, 2.3, 1.6, 10, .95, 30)
```

FrechetVaRPlot2DCl *Plots Frechet Value at Risk against Cl*

Description

Plots the VaR of a portfolio against confidence level assuming extreme losses are Frechet distributed, for specified range of confidence level and a given holding period.

Usage

```
FrechetVaRPlot2DCl(mu, sigma, tail.index, n, cl, hp)
```

Arguments

mu	Location parameter for daily L/P
sigma	Scale parameter for daily L/P
tail.index	Tail index
n	Block size from which maxima are drawn
cl	Confidence level and should be a vector
hp	Holding period and should be a scalar

Details

Note that the long-right-hand tail is fitted to losses, not profits.

Author(s)

Dinesh Acharya

References

Dowd, K. Measurh ing Market Risk, Wiley, 2007.

Embrechts, P., Kluppelberg, C. and Mikosch, T., Modelling Extremal Events for Insurance and Finance. Springer, Berlin, 1997, p. 324.

Reiss, R. D. and Thomas, M. Statistical Analysis of Extreme Values from Insurance, Finance, Hydrology and Other Fields, Birkhaueser, Basel, 1997, 15-18.

Examples

```
# Plots VaR against vector of cl assuming Frechet Distribution for given parameters
   cl <- seq(0.9, .99, .01)
   FrechetVaRPlot2DCl(3.5, 2.3, 1.6, 10, cl, 30)
```

GaussianCopulaVaR *Bivariate Gaussian Copule VaR*

Description

Derives VaR using bivariate Gaussian copula with specified inputs for normal marginals.

Usage

```
GaussianCopulaVaR(mu1, mu2, sigma1, sigma2, rho, number.steps.in.copula, cl)
```

Arguments

mu1	Mean of Profit/Loss on first position
mu2	Mean of Profit/Loss on second position
sigma1	Standard Deviation of Profit/Loss on first position
sigma2	Standard Deviation of Profit/Loss on second position
rho	Correlation between Profit/Loss on two positions
number.steps.in.copula	Number of steps used in the copula approximation (approximation being needed because Gaussian copula lacks a closed form solution)
cl	VaR confidece level

Value

Copula based VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Dowd, K. and Fackler, P. Estimating VaR with copulas. Financial Engineering News, 2004.

Examples

```
# VaR using bivariate Gaussian for X and Y with given parameters:
   GaussianCopulaVaR(2.3, 4.1, 1.2, 1.5, .6, 10, .95)
```

GParetoES *Expected Shortfall for Generalized Pareto*

Description

Estimates the ES of a portfolio assuming losses are distributed as a generalised Pareto.

Usage

```
GParetoES(Ra, beta, zeta, threshold.prob, cl)
```

Arguments

Ra	Vector of daily Profit/Loss data
beta	Assumed scale parameter
zeta	Assumed tail index
threshold.prob	Threshold probability
cl	VaR confidence level

Value

Expected Shortfall

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

McNeil, A., Extreme value theory for risk managers. Mimeo, ETHZ, 1999.

Examples

```
# Computes ES assuming generalised Pareto for following parameters
   Ra <- 5 * rnorm(100)
   beta <- 1.2
   zeta <- 1.6
   threshold.prob <- .85
   cl <- .99
   GParetoES(Ra, beta, zeta, threshold.prob, cl)
```

GParetoMEFPlot *Plot of Emperical and Generalised Pareto mean excess functions*

Description

Plots of emperical mean excess function and Generalized mean excess function.

Usage

```
GParetoMEFPlot(Ra, mu, beta, zeta)
```

Arguments

Ra	Vector of daily Profit/Loss data
mu	Location parameter
beta	Scale parameter
zeta	Assumed tail index

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes ES assuming generalised Pareto for following parameters
   Ra <- 5 * rnorm(100)
   mu <- 0
   beta <- 1.2
   zeta <- 1.6
   GParetoMEFPlot(Ra, mu, beta, zeta)
```

GParetoMultipleMEFPlot *Plot of Emperical and 2 Generalised Pareto mean excess functions*

Description

Plots of emperical mean excess function and two generalized pareto mean excess functions which differ in their tail-index value.

Usage

```
GParetoMultipleMEFPlot(Ra, mu, beta, zeta1, zeta2)
```

Arguments

Ra	Vector of daily Profit/Loss data
mu	Location parameter
beta	Scale parameter
zeta1	Assumed tail index for first mean excess function
zeta2	Assumed tail index for second mean excess function

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes ES assuming generalised Pareto for following parameters
   Ra <- 5 * rnorm(100)
   mu <- 1
   beta <- 1.2
   zeta1 <- 1.6
   zeta2 <- 2.2
   GParetoMultipleMEFPlot(Ra, mu, beta, zeta1, zeta2)
```

GParetoVaR *VaR for Generalized Pareto*

Description

Estimates the Value at Risk of a portfolio assuming losses are distributed as a generalised Pareto.

Usage

```
GParetoVaR(Ra, beta, zeta, threshold.prob, cl)
```

Arguments

Ra	Vector of daily Profit/Loss data
beta	Assumed scale parameter
zeta	Assumed tail index
threshold.prob	Threshold probability corresponding to threshold u and x
cl	VaR confidence level

Value

Expected Shortfall

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

McNeil, A., Extreme value theory for risk managers. Mimeo, ETHZ, 1999.

Examples

```
# Computes ES assuming generalised Pareto for following parameters
   Ra <- 5 * rnorm(100)
   beta <- 1.2
   zeta <- 1.6
   threshold.prob <- .85
   cl <- .99
   GParetoVaR(Ra, beta, zeta, threshold.prob, cl)
```

`GumbelCopulaVaR` *Bivariate Gumbel Copule VaR*

Description

Derives VaR using bivariate Gumbel or logistic copula with specified inputs for normal marginals.

Usage

```
GumbelCopulaVaR(mu1, mu2, sigma1, sigma2, beta, cl)
```

Arguments

`mu1`	Mean of Profit/Loss on first position
`mu2`	Mean of Profit/Loss on second position
`sigma1`	Standard Deviation of Profit/Loss on first position
`sigma2`	Standard Deviation of Profit/Loss on second position
`beta`	Gumber copula parameter (greater than 1)
`cl`	VaR onfidece level

Value

Copula based VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Dowd, K. and Fackler, P. Estimating VaR with copulas. Financial Engineering News, 2004.

Examples

```
# VaR using bivariate Gumbel for X and Y with given parameters:
   GumbelCopulaVaR(1.1, 3.1, 1.2, 1.5, 1.1, .95)
```

GumbelES *Gumbel ES*

Description

Estimates the ES of a portfolio assuming extreme losses are Gumbel distributed, for specified confidence level and holding period. Note that the long-right-hand tail is fitted to losses, not profits.

Usage

```
GumbelES(mu, sigma, n, cl, hp)
```

Arguments

`mu`	Location parameter for daily L/P
`sigma`	Assumed scale parameter for daily L/P
`n`	Assumed block size from which the maxima are drawn
`cl`	VaR confidence level
`hp`	VaR holding period

Value

Estimated ES. If cl and hp are scalars, it returns scalar VaR. If cl is vector and hp is a scalar, or viceversa, returns vector of VaRs. If both cl and hp are vectors, returns a matrix of VaRs.

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

National Institute of Standards and Technology, Dataplot Reference Manual. Volume 1: Commands. NIST: Washington, DC, 1997, p. 8-67.

Examples

```
# Gumber ES Plot
   GumbelES(0, 1.2, 100, c(.9,.88, .85, .8), 280)
```

GumbelESPlot2DCl *Gumbel VaR*

Description

Estimates the EV VaR of a portfolio assuming extreme losses are Gumbel distributed, for specified confidence level and holding period.

Usage

```
GumbelESPlot2DCl(mu, sigma, n, cl, hp)
```

Arguments

mu	Location parameter for daily L/P
sigma	Assumed scale parameter for daily L/P
n	size from which the maxima are drawn
cl	VaR confidence level
hp	VaR holding period

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots ES against Cl
   GumbelESPlot2DCl(0, 1.2, 100, seq(0.8,0.99,0.02), 280)
```

GumbelVaR *Gumbel VaR*

Description

Estimates the EV VaR of a portfolio assuming extreme losses are Gumbel distributed, for specified confidence level and holding period.

Usage

```
GumbelVaR(mu, sigma, n, cl, hp)
```

Arguments

mu	Location parameter for daily L/P
sigma	Assumed scale parameter for daily L/P
n	Size from which the maxima are drawn
cl	VaR confidence level
hp	VaR holding period

Value

Estimated VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Gumbel VaR
   GumbelVaR(0, 1.2, 100, c(.9,.88, .85, .8), 280)
```

GumbelVaRPlot2DCl *Gumbel VaR*

Description

Estimates the EV VaR of a portfolio assuming extreme losses are Gumbel distributed, for specified confidence level and holding period.

Usage

```
GumbelVaRPlot2DCl(mu, sigma, n, cl, hp)
```

Arguments

mu	Location parameter for daily L/P
sigma	Assumed scale parameter for daily L/P
n	size from which the maxima are drawn
cl	VaR confidence level
hp	VaR holding period

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots VaR against Cl
   GumbelVaRPlot2DCl(0, 1.2, 100, c(.9,.88, .85, .8), 280)
```

HillEstimator *Hill Estimator*

Description

Estimates the value of the Hill Estimator for a given specified data set and chosen tail size. Notes: 1) We estimate Hill Estimator by looking at the upper tail. 2) If the specified tail size is such that any included observations are negative, the tail is truncated at the point before observations become negative. 3) The tail size must be a scalar.

Usage

```
HillEstimator(Ra, tail.size)
```

Arguments

`Ra`	Data set
`tail.size`	Number of observations to be used to estimate the Hill estimator.

Value

Estimated value of Hill Estimator

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates Hill Estimator of
   Ra <- rnorm(15)
   HillEstimator(Ra, 10)
```

`HillPlot` *Hill Plot*

Description

Displays a plot of the Hill Estimator against tail sample size.

Usage

```
HillPlot(Ra, maximum.tail.size)
```

Arguments

`Ra`	The data set
`maximum.tail.size`	maximum tail size and should be greater than a quarter of the sample size.

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Hill Estimator - Tail Sample Size Plot for random normal dataset
   Ra <- rnorm(1000)
   HillPlot(Ra, 180)
```

`HillQuantileEstimator` *Hill Quantile Estimator*

Description

Estimates value of Hill Quantile Estimator for a specified data set, tail index, in-sample probability and confidence level.

Usage

```
HillQuantileEstimator(Ra, tail.index, in.sample.prob, cl)
```

Arguments

`Ra`	A data set
`tail.index`	Assumed tail index
`in.sample.prob`	In-sample probability (used as basis for projection)
`cl`	Confidence level

Value

Value of Hill Quantile Estimator

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Next reference

Examples

```
# Computes estimates value of hill estimator for a specified data set
   Ra <- rnorm(1000)
   HillQuantileEstimator(Ra, 40, .5, .9)
```

HSES — *Expected Shortfall of a portfolio using Historical Estimator*

Description

Estimates the Expected Shortfall (aka. Average Value at Risk or Conditional Value at Risk) using historical estimator approach for the specified confidence level and the holding period implies by data frequency.

Usage

```
HSES(Ra, cl)
```

Arguments

Ra	Vector corresponding to profit and loss distribution
cl	Number between 0 and 1 corresponding to confidence level

Value

Expected Shortfall of the portfolio

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Cont, R., Deguest, R. and Scandolo, G. Robustness and sensitivity analysis of risk measurement procedures. Quantitative Finance, 10(6), 2010, 593-606.

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Foellmer, H. and Scheid, A. Stochastic Finance: An Introduction in Discrete Time. De Gryuter, 2011.

Examples

```
# Computes Historical Expected Shortfall for a given profit/loss
   # distribution and confidence level
   a <- rnorm(100) # generate a random profit/loss vector
   HSES(a, 0.95)
```

HSESDFPerc — *Percentile of historical simulation ES distribution function*

Description

Estimates percentiles of historical simulation ES distribution function, using theory of order statistics, for specified confidence level.

Usage

```
HSESDFPerc(Ra, perc, cl)
```

Arguments

Ra	Vector of daily P/L data
perc	Desired percentile and is scalar
cl	VaR confidence level and is scalar

Value

Value of percentile of VaR distribution function

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates Percentiles for random standard normal returns and given perc
   # and cl
   Ra <- rnorm(100)
   HSESDFPerc(Ra, .75, .95)
```

HSESFigure *Figure of Historical SImulation VaR and ES and histogram of L/P*

Description

Plots figure showing the historical simulation VaR and ES and histogram of L/P for specified confidence level and holding period implied by data frequency.

Usage

```
HSESFigure(Ra, cl)
```

Arguments

Ra	Vector of profit loss data
cl	VaR confidence level

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots figure showing VaR and histogram of P/L data
   Ra <- rnorm(100)
   HSESFigure(Ra, .95)
```

HSESPlot2DCl *Plots historical simulation ES against confidence level*

Description

Function plots the historical simulation ES of a portfolio against confidence level, for specified range of confidence level and holding period implied by data frequency.

Usage

```
HSESPlot2DCl(Ra, cl)
```

Arguments

Ra	Vector of daily P/L data
cl	Vector of ES confidence levels

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots historical simulation ES against confidence level
   Ra <- rnorm(100)
   cl <- seq(.90, .99, .01)
   HSESPlot2DCl(Ra, cl)
```

HSVaR *Value at Risk of a portfolio using Historical Estimator*

Description

Estimates the Value at Risk (VaR) using historical estimator approach for the specified range of confidence levels and the holding period implies by data frequency.

Usage

```
HSVaR(Ra, Rb)
```

Arguments

Ra	Vector corresponding to profit and loss distribution
Rb	Scalar corresponding to VaR confidence levels.

Value

Value at Risk of the portfolio

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Jorion, P. Value at Risk: The New Benchmark for Managing Financial Risk. McGraw-Hill, 2006

Cont, R., Deguest, R. and Scandolo, G. Robustness and sensitivity analysis of risk measurement procedures. Quantitative Finance, 10(6), 2010, 593-606.

Artzner, P., Delbaen, F., Eber, J.M. and Heath, D. Coherent Risk Measures of Risk. Mathematical Finance 9(3), 1999, 203.

Foellmer, H. and Scheid, A. Stochastic Finance: An Introduction in Discrete Time. De Gryuter, 2011.

Examples

```
# To be added
   a <- rnorm(1000) # Payoffs of random portfolio
   HSVaR(a, .95)
```

HSVaRDFPerc *Percentile of historical simulation VaR distribution function*

Description

Estimates percentiles of historical simulation VaR distribution function, using theory of order statistics, for specified confidence level.

Usage

```
HSVaRDFPerc(Ra, perc, cl)
```

Arguments

Ra	Vector of daily P/L data
perc	Desired percentile and is scalar
cl	VaR confidence level and is scalar

Value

Value of percentile of VaR distribution function

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates Percentiles for random standard normal returns and given perc
   # and cl
   Ra <- rnorm(100)
   HSVaRDFPerc(Ra, .75, .95)
```

HSVaRESPlot2DCl *Plots historical simulation VaR and ES against confidence level*

Description

Function plots the historical simulation VaR and ES of a portfolio against confidence level, for specified range of confidence level and holding period implied by data frequency.

Usage

```
HSVaRESPlot2DCl(Ra, cl)
```

Arguments

Ra	Vector of daily P/L data
cl	Vectof of VaR confidence levels

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots historical simulation VaR and ES against confidence level
   Ra <- rnorm(100)
   cl <- seq(.90, .99, .01)
   HSVaRESPlot2DCl(Ra, cl)
```

HSVaRFigure *Figure of Historical SImulation VaR and histogram of L/P*

Description

Plots figure showing the historical simulation VaR and histogram of L/P for specified confidence level and holding period implied by data frequency.

Usage

```
HSVaRFigure(Ra, cl)
```

Arguments

Ra	Vector of profit loss data
cl	ES confidence level

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots figure showing VaR and histogram of P/L data
   Ra <- rnorm(100)
   HSVaRFigure(Ra, .95)
```

HSVaRPlot2DCl *Plots historical simulation VaR against confidence level*

Description

Function plots the historical simulation VaR of a portfolio against confidence level, for specified range of confidence level and holding period implied by data frequency.

Usage

```
HSVaRPlot2DCl(Ra, cl)
```

Arguments

Ra	Vector of daily P/L data
cl	Vector of VaR confidence levels

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots historical simulation VaR against confidence level
   Ra <- rnorm(100)
   cl <- seq(.90, .99, .01)
   HSVaRPlot2DCl(Ra, cl)
```

`InsuranceVaR` *VaR of Insurance Portfolio*

Description

Generates Monte Carlo VaR for insurance portfolio in Chapter 6.5

Usage

```
InsuranceVaR(mu, sigma, n, p, theta, deductible, number.trials, cl)
```

Arguments

`mu`	Mean of returns
`sigma`	Volatility of returns
`n`	Number of contracts
`p`	Probability of any loss event
`theta`	Expected profit per contract
`deductible`	Deductible
`number.trials`	Number of simulation trials
`cl`	VaR confidence level

Value

VaR of the specified portfolio

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates VaR of Insurance portfolio with given parameters
   InsuranceVaR(.8, 1.3, 100, .6, 21,  12, 50, .95)
```

InsuranceVaRES *VaR and ES of Insurance Portfolio*

Description

Generates Monte Carlo VaR and ES for insurance portfolio.

Usage

```
InsuranceVaRES(mu, sigma, n, p, theta, deductible, number.trials, cl)
```

Arguments

mu	Mean of returns
sigma	Volatility of returns
n	Number of contracts
p	Probability of any loss event
theta	Expected profit per contract
deductible	Deductible
number.trials	Number of simulation trials
cl	VaR confidence level

Value

A list with "VaR" and "ES" of the specified portfolio

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates VaR and ES of Insurance portfolio with given parameters
   y<-InsuranceVaRES(.8, 1.3, 100, .6, 21,  12, 50, .95)
```

`JarqueBeraBacktest` *Jarque-Bera backtest for normality.*

Description

Jarque-Bera (JB) is a backtest to test whether the skewness and kurtosis of a given sample matches that of normal distribution. JB test statistic is defined as

$$JB = \frac{n}{6}\left(s^2 + \frac{(k-3)^2}{4}\right)$$

where n is sample size, s and k are coefficients of sample skewness and kurtosis.

Usage

```
JarqueBeraBacktest(sample.skewness, sample.kurtosis, n)
```

Arguments

`sample.skewness`	Coefficient of Skewness of the sample
`sample.kurtosis`	Coefficient of Kurtosis of the sample
`n`	Number of observations

Value

Probability of null hypothesis H0

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Jarque, C. M. and Bera, A. K. A test for normality of observations and regression residuals, International Statistical Review, 55(2): 163-172.

Examples

```
# JB test statistic for sample with 500 observations with sample
   # skewness and kurtosis of -0.075 and 2.888
   JarqueBeraBacktest(-0.075,2.888,500)
```

KernelESBoxKernel *Calculates ES using box kernel approach*

Description

The output consists of a scalar ES for specified confidence level.

Usage

```
KernelESBoxKernel(Ra, cl)
```

Arguments

Ra	Profit and Loss data set
cl	VaR confidence level

Value

Scalar VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# VaR for specified confidence level using box kernel approach
   Ra <- rnorm(30)
   KernelESBoxKernel(Ra, .95)
```

KernelESEpanechinikovKernel *Calculates ES using Epanechinikov kernel approach*

Description

The output consists of a scalar ES for specified confidence level.

Usage

```
KernelESEpanechinikovKernel(Ra, cl, plot = TRUE)
```

Arguments

`Ra`	Profit and Loss data set
`cl`	ES confidence level
`plot`	Bool, plots cdf if true

Value

Scalar ES

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# ES for specified confidence level using Epanechinikov kernel approach
   Ra <- rnorm(30)
   KernelESEpanechinikovKernel(Ra, .95)
```

`KernelESNormalKernel` *Calculates ES using normal kernel approach*

Description

The output consists of a scalar ES for specified confidence level.

Usage

```
KernelESNormalKernel(Ra, cl)
```

Arguments

`Ra`	Profit and Loss data set
`cl`	VaR confidence level

Value

Scalar VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# ES for specified confidence level using normal kernel approach
   Ra <- rnorm(30)
   KernelESNormalKernel(Ra, .95)
```

KernelESTriangleKernel

Calculates ES using triangle kernel approach

Description

The output consists of a scalar ES for specified confidence level.

Usage

```
KernelESTriangleKernel(Ra, cl)
```

Arguments

Ra	Profit and Loss data set
cl	VaR confidence level

Value

Scalar VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# VaR for specified confidence level using triangle kernel approach
   Ra <- rnorm(30)
   KernelESTriangleKernel(Ra, .95)
```

`KernelVaRBoxKernel` *Calculates VaR using box kernel approach*

Description

The output consists of a scalar VaR for specified confidence level.

Usage

```
KernelVaRBoxKernel(Ra, cl, plot = TRUE)
```

Arguments

`Ra`	Profit and Loss data set
`cl`	VaR confidence level
`plot`	Bool which indicates whether the graph is plotted or not

Value

Scalar VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# VaR for specified confidence level using box kernel approach
   Ra <- rnorm(30)
   KernelVaRBoxKernel(Ra, .95)
```

`KernelVaREpanechinikovKernel`
Calculates VaR using epanechinikov kernel approach

Description

The output consists of a scalar VaR for specified confidence level.

Usage

```
KernelVaREpanechinikovKernel(Ra, cl, plot = TRUE)
```

Arguments

Ra	Profit and Loss data set
cl	VaR confidence level
plot	Bool, plots the cdf if true.

Value

Scalar VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# VaR for specified confidence level using epanechinikov kernel approach
   Ra <- rnorm(30)
   KernelVaREpanechinikovKernel(Ra, .95)
```

KernelVaRNormalKernel *Calculates VaR using normal kernel approach*

Description

The output consists of a scalar VaR for specified confidence level.

Usage

```
KernelVaRNormalKernel(Ra, cl, plot = TRUE)
```

Arguments

Ra	Profit and Loss data set
cl	VaR confidence level
plot	Bool, plots cdf if true

Value

Scalar VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# VaR for specified confidence level using normal kernel approach
   Ra <- rnorm(30)
   KernelVaRNormalKernel(Ra, .95)
```

KernelVaRTriangleKernel

Calculates VaR using triangle kernel approach

Description

The output consists of a scalar VaR for specified confidence level.

Usage

```
KernelVaRTriangleKernel(Ra, cl, plot = TRUE)
```

Arguments

Ra	Profit and Loss data set
cl	VaR confidence level
plot	Bool, plots cdf if true.

Value

Scalar VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# VaR for specified confidence level using triangle kernel approach
   Ra <- rnorm(30)
   KernelVaRTriangleKernel(Ra, .95)
```

KSTestStat *Plots cumulative density for KS test and computes confidence interval for KS test stat.*

Description

Kolmogorov-Smirnov (KS) test statistic is a non parametric test for distribution equality and measures the maximum distance between two cdfs. Formally, the KS test statistic is :

$$D = \max_i |F(X_i) - \hat{F}(X_i)|$$

Usage

```
KSTestStat(number.trials, sample.size, confidence.interval)
```

Arguments

`number.trials`	Number of trials
`sample.size`	Sizes of the trial samples
`confidence.interval`	Confidence interval expressed as a fraction of 1

Value

Confidence Interval for KS test stat

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Chakravarti, I. M., Laha, R. G. and Roy, J. Handbook of Methods of #' Applied Statistics, Volume 1, Wiley, 1967.

Examples

```
# Plots the cdf for KS Test statistic and returns KS confidence interval
   # for 100 trials with 1000 sample size and 0.95 confidence interval
   KSTestStat(100, 1000, 0.95)
```

KuiperTestStat *Plots cummulative density for Kuiper test and computes confidence interval for Kuiper test stat.*

Description

Kuiper test statistic is a non parametric test for distribution equality and is closely related to KS test. Formally, the Kuiper test statistic is :

$$D* = \max_i \{F(X_i) - F(\hat{x_i}) + \max_i \{\hat{F}(X_i) - F(X_i)\}$$

Usage

```
KuiperTestStat(number.trials, sample.size, confidence.interval)
```

Arguments

`number.trials` Number of trials

`sample.size` Sizes of the trial samples

`confidence.interval`
Confidence interval expressed as a fraction of 1

Value

Confidence Interval for KS test stat

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots the cdf for Kuiper Test statistic and returns Kuiper confidence
   # interval for 100 trials with 1000 sample size and 0.95 confidence
   # interval.
   KuiperTestStat(100, 1000, 0.95)
```

`LogNormalES` *ES for normally distributed geometric returns*

Description

Estimates the ES of a portfolio assuming that geometric returns are normally distributed, for specified confidence level and holding period.

Usage

```
LogNormalES(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

investment Size of investment

cl VaR confidence level

hp VaR holding period in days

Value

Matrix of ES whose dimension depends on dimension of hp and cl. If cl and hp are both scalars, the matrix is 1 by 1. If cl is a vector and hp is a scalar, the matrix is row matrix, if cl is a scalar and hp is a vector, the matrix is column matrix and if both cl and hp are vectors, the matrix has dimension length of cl * length of hp.

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes ES given geometric return data
   data <- runif(5, min = 0, max = .2)
   LogNormalES(returns = data, investment = 5, cl = .95, hp = 90)

   # Computes ES given mean and standard deviation of return data
   LogNormalES(mu = .012, sigma = .03, investment = 5, cl = .95, hp = 90)
```

`LogNormalESDFPerc` *Percentiles of ES distribution function for normally distributed geometric returns*

Description

Estimates the percentiles of ES distribution for normally distributed geometric returns, for specified confidence level and holding period using the theory of order statistics.

Usage

```
LogNormalESDFPerc(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 5 or 7. In case there 5 input arguments, the mean, standard deviation and number of samples is computed from return data. See examples for details.
returns Vector of daily geometric return data
mu Mean of daily geometric return data
sigma Standard deviation of daily geometric return data
n Sample size
investment Size of investment
perc Desired percentile
cl ES confidence level and must be a scalar
hp ES holding period and must be a a scalar

Value

Percentiles of ES distribution function

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates Percentiles of ES distribution
   data <- runif(5, min = 0, max = .2)
   LogNormalESDFPerc(returns = data, investment = 5, perc = .7, cl = .95, hp = 60)

  # Estimates Percentiles given mean, standard deviation and number of sambles of return data
  LogNormalESDFPerc(mu = .012, sigma = .03, n= 10, investment = 5, perc = .8, cl = .99, hp = 40)
```

`LogNormalESFigure` *Figure of lognormal VaR and ES and pdf against L/P*

Description

Gives figure showing the VaR and ES and probability distribution function against L/P of a portfolio assuming geometric returns are normally distributed, for specified confidence level and holding period.

Usage

```
LogNormalESFigure(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

investment Size of investment

cl VaR confidence level and should be scalar

hp VaR holding period in days and should be scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots lognormal VaR, ES and pdf against L/P data for given returns data
   data <- runif(5, min = 0, max = .2)
   LogNormalESFigure(returns = data, investment = 5, cl = .95, hp = 90)

   # Plots lognormal VaR, ES and pdf against L/P data with given parameters
   LogNormalESFigure(mu = .012, sigma = .03, investment = 5, cl = .95, hp = 90)
```

`LogNormalESPlot2DCL` *Plots log normal ES against confidence level*

Description

Plots the ES of a portfolio against confidence level assuming that geometric returns are normally distributed, for specified confidence level and holding period.

Usage

```
LogNormalESPlot2DCL(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

investment Size of investment

cl ES confidence level and must be a vector

hp ES holding period and must be a scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots ES against confidence level
   data <- runif(5, min = 0, max = .2)
   LogNormalESPlot2DCL(returns = data, investment = 5,
                       cl = seq(.9,.99,.01), hp = 60)

   # Plots ES against confidence level
   LogNormalESPlot2DCL(mu = .012, sigma = .03, investment = 5,
                       cl = seq(.9,.99,.01), hp = 40)
```

`LogNormalESPlot2DHP` *Plots log normal ES against holding period*

Description

Plots the ES of a portfolio against holding period assuming that geometric returns are normal distributed, for specified confidence level and holding period.

Usage

```
LogNormalESPlot2DHP(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

investment Size of investment

cl ES confidence level and must be a scalar

hp ES holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes ES given geometric return data
   data <- runif(5, min = 0, max = .2)
   LogNormalESPlot2DHP(returns = data, investment = 5, cl = .95, hp = 60:90)

   # Computes v given mean and standard deviation of return data
   LogNormalESPlot2DHP(mu = .012, sigma = .03, investment = 5, cl = .99, hp = 40:80)
```

`LogNormalESPlot3D` *Plots log normal ES against confidence level and holding period*

Description

Plots the ES of a portfolio against confidence level and holding period assuming that geometric returns are normally distributed, for specified confidence level and holding period.

Usage

```
LogNormalESPlot3D(...)
```

Arguments

`...`	The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details. returns Vector of daily geometric return data mu Mean of daily geometric return data sigma Standard deviation of daily geometric return data cl VaR confidence level and must be a vector hp VaR holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots VaR against confidene level given geometric return data
   data <- runif(5, min = 0, max = .2)
   LogNormalESPlot3D(returns = data, investment = 5, cl = seq(.9,.99,.01), hp = 1:100)

   # Computes VaR against confidence level given mean and standard deviation of return data
  LogNormalESPlot3D(mu = .012, sigma = .03, investment = 5, cl = seq(.9,.99,.01), hp = 1:100)
```

LogNormalVaR *VaR for normally distributed geometric returns*

Description

Estimates the VaR of a portfolio assuming that geometric returns are normally distributed, for specified confidence level and holding period.

Usage

```
LogNormalVaR(...)
```

Arguments

...	The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details. returns Vector of daily geometric return data mu Mean of daily geometric return data sigma Standard deviation of daily geometric return data investment Size of investment cl VaR confidence level hp VaR holding period in days

Value

Matrix of VaR whose dimension depends on dimension of hp and cl. If cl and hp are both scalars, the matrix is 1 by 1. If cl is a vector and hp is a scalar, the matrix is row matrix, if cl is a scalar and hp is a vector, the matrix is column matrix and if both cl and hp are vectors, the matrix has dimension length of cl * length of hp.

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes VaR given geometric return data
   data <- runif(5, min = 0, max = .2)
   LogNormalVaR(returns = data, investment = 5, cl = .95, hp = 90)

   # Computes VaR given mean and standard deviation of return data
   LogNormalVaR(mu = .012, sigma = .03, investment = 5, cl = .95, hp = 90)
```

`LogNormalVaRDFPerc` *Percentiles of VaR distribution function for normally distributed geometric returns*

Description

Estimates the percentile of VaR distribution function for normally distributed geometric returns, using the theory of order statistics.

Usage

```
LogNormalVaRDFPerc(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 5 or 7. In case there 5 input arguments, the mean, standard deviation and number of observations of data are computed from returns data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

n Sample size

investment Size of investment

perc Desired percentile

cl VaR confidence level and must be a scalar

hp VaR holding period and must be a a scalar

Percentiles of VaR distribution function and is scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates Percentiles of VaR distribution
   data <- runif(5, min = 0, max = .2)
   LogNormalVaRDFPerc(returns = data, investment = 5, perc = .7, cl = .95, hp = 60)

   # Computes v given mean and standard deviation of return data
  LogNormalVaRDFPerc(mu = .012, sigma = .03, n= 10, investment = 5, perc = .8, cl = .99, hp = 40)
```

`LogNormalVaRETLPlot2DCL` *Plots log normal VaR and ETL against confidence level*

Description

Plots the VaR and ETL of a portfolio against confidence level assuming that geometric returns are normally distributed, for specified confidence level and holding period.

Usage

```
LogNormalVaRETLPlot2DCL(...)
```

Arguments

...	The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there are 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details. returns Vector of daily geometric return data mu Mean of daily geometric return data sigma Standard deviation of daily geometric return data investment Size of investment cl VaR confidence level and must be a vector hp VaR holding period and must be a scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots VaR and ETL against confidene level given geometric return data
   data <- runif(5, min = 0, max = .2)
   LogNormalVaRETLPlot2DCL(returns = data, investment = 5, cl = seq(.85,.99,.01), hp = 60)

   # Computes VaR against confidence level given mean and standard deviation of return data
  LogNormalVaRETLPlot2DCL(mu = .012, sigma = .03, investment = 5, cl = seq(.85,.99,.01), hp = 40)
```

`LogNormalVaRFigure` *Figure of lognormal VaR and pdf against L/P*

Description

Gives figure showing the VaR and probability distribution function against L/P of a portfolio assuming geometric returns are normally distributed, for specified confidence level and holding period.

Usage

```
LogNormalVaRFigure(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

investment Size of investment

cl VaR confidence level and should be scalar

hp VaR holding period in days and should be scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots lognormal VaR and pdf against L/P data for given returns data
   data <- runif(5, min = 0, max = .2)
   LogNormalVaRFigure(returns = data, investment = 5, cl = .95, hp = 90)

   # Plots lognormal VaR and pdf against L/P data with given parameters
   LogNormalVaRFigure(mu = .012, sigma = .03, investment = 5, cl = .95, hp = 90)
```

LogNormalVaRPlot2DCL *Plots log normal VaR against confidence level*

Description

Plots the VaR of a portfolio against confidence level assuming that geometric returns are normally distributed, for specified confidence level and holding period.

Usage

```
LogNormalVaRPlot2DCL(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there are 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

investment Size of investment

cl VaR confidence level and must be a vector

hp VaR holding period and must be a scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots VaR against confidene level given geometric return data
   data <- runif(5, min = 0, max = .2)
   LogNormalVaRPlot2DCL(returns = data, investment = 5, cl = seq(.85,.99,.01), hp = 60)

  # Computes VaR against confidence level given mean and standard deviation of return data
  LogNormalVaRPlot2DCL(mu = .012, sigma = .03, investment = 5, cl = seq(.85,.99,.01), hp = 40)
```

LogNormalVaRPlot2DHP *Plots log normal VaR against holding period*

Description

Plots the VaR of a portfolio against holding period assuming that geometric returns are normal distributed, for specified confidence level and holding period.

Usage

```
LogNormalVaRPlot2DHP(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

investment Size of investment

cl VaR confidence level and must be a scalar

hp VaR holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes VaR given geometric return data
   data <- runif(5, min = 0, max = .2)
   LogNormalVaRPlot2DHP(returns = data, investment = 5, cl = .95, hp = 60:90)

   # Computes VaR given mean and standard deviation of return data
   LogNormalVaRPlot2DHP(mu = .012, sigma = .03, investment = 5, cl = .99, hp = 40:80)
```

LogNormalVaRPlot3D *Plots log normal VaR against confidence level and holding period*

Description

Plots the VaR of a portfolio against confidence level and holding period assuming that geometric returns are normal distributed, for specified confidence level and holding period.

Usage

```
LogNormalVaRPlot3D(...)
```

Arguments

... The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

investment Size of investment

cl VaR confidence level and must be a vector

hp VaR holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots VaR against confidene level given geometric return data
   data <- rnorm(5, .09, .03)
   LogNormalVaRPlot3D(returns = data, investment = 5, cl = seq(.9,.99,.01), hp = 1:100)

  # Computes VaR against confidence level given mean and standard deviation of return data
  LogNormalVaRPlot3D(mu = .012, sigma = .03, investment = 5, cl = seq(.9,.99,.01), hp = 1:100)
```

`LogtES` *ES for t distributed geometric returns*

Description

Estimates the ES of a portfolio assuming that geometric returns are Student-t distributed, for specified confidence level and holding period.

Usage

```
LogtES(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 5 or 6. In case there 5 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

investment Size of investment

df Number of degrees of freedom in the t distribution

cl VaR confidence level

hp VaR holding period

Value

Matrix of ES whose dimension depends on dimension of hp and cl. If cl and hp are both scalars, the matrix is 1 by 1. If cl is a vector and hp is a scalar, the matrix is row matrix, if cl is a scalar and hp is a vector, the matrix is column matrix and if both cl and hp are vectors, the matrix has dimension length of cl * length of hp.

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes ES given geometric return data
   data <- runif(5, min = 0, max = .2)
   LogtES(returns = data, investment = 5, df = 6, cl = .95, hp = 90)

   # Computes ES given mean and standard deviation of return data
   LogtES(mu = .012, sigma = .03, investment = 5, df = 6, cl = .95, hp = 90)
```

`LogtESDFPerc` *Percentiles of ES distribution function for Student-t*

Description

Plots the ES of a portfolio against confidence level assuming that geometric returns are Student t distributed, for specified confidence level and holding period.

Usage

```
LogtESDFPerc(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 6 or 8. In case there 6 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

n Sample size

investment Size of investment

perc Desired percentile

df Number of degrees of freedom in the t distribution

cl ES confidence level and must be a scalar

hp ES holding period and must be a a scalar

Value

Percentiles of ES distribution function

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates Percentiles of ES distribution
   data <- runif(5, min = 0, max = .2)
   LogtESDFPerc(returns = data, investment = 5, perc = .7, df = 6, cl = .95, hp = 60)

   # Computes v given mean and standard deviation of return data
  LogtESDFPerc(mu = .012, sigma = .03, n= 10, investment = 5, perc = .8, df = 6, cl = .99, hp = 40)
```

LogtESPlot2DCL *Plots log-t ES against confidence level*

Description

Plots the ES of a portfolio against confidence level assuming that geometric returns are Student t distributed, for specified confidence level and holding period.

Usage

```
LogtESPlot2DCL(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 5 or 6. In case there 5 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

investment Size of investment

df Number of degrees of freedom in the t distribution

cl ES confidence level and must be a vector

hp ES holding period and must be a scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes ES given geometric return data
   data <- runif(5, min = 0, max = .2)
   LogtESPlot2DCL(returns = data, investment = 5, df = 6, cl = seq(.9,.99,.01), hp = 60)

   # Computes v given mean and standard deviation of return data
  LogtESPlot2DCL(mu = .012, sigma = .03, investment = 5, df = 6, cl = seq(.9,.99,.01), hp = 40)
```

`LogtESPlot2DHP` *Plots log-t ES against holding period*

Description

Plots the ES of a portfolio against holding period assuming that geometric returns are Student t distributed, for specified confidence level and holding period.

Usage

```
LogtESPlot2DHP(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 5 or 6. In case there 5 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

investment Size of investment

df Number of degrees of freedom in the t distribution

cl ES confidence level and must be a scalar

hp ES holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes ES given geometric return data
   data <- runif(5, min = 0, max = .2)
   LogtESPlot2DHP(returns = data, investment = 5, df = 6, cl = .95, hp = 60:90)

   # Computes v given mean and standard deviation of return data
   LogtESPlot2DHP(mu = .012, sigma = .03, investment = 5, df = 6, cl = .99, hp = 40:80)
```

`LogtESPlot3D` *Plots log-t ES against confidence level and holding period*

Description

Plots the ES of a portfolio against confidence level and holding period assuming that geometric returns are Student-t distributed, for specified confidence level and holding period.

Usage

```
LogtESPlot3D(...)
```

Arguments

`...`	The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 5 or 6. In case there 5 input arguments, the mean and standard deviation of data is computed from return data. See examples for details. returns Vector of daily geometric return data mu Mean of daily geometric return data sigma Standard deviation of daily geometric return data investment Size of investment df Number of degrees of freedom in the t distribution cl VaR confidence level and must be a vector hp VaR holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots ES against confidene level given geometric return data
   data <- rnorm(5, .09, .03)
   LogtESPlot3D(returns = data, investment = 5, df = 6, cl = seq(.9,.99,.01), hp = 1:100)

   # Computes ES against confidence level given mean and standard deviation of return data
  LogtESPlot3D(mu = .012, sigma = .03, investment = 5, df = 6, cl = seq(.9,.99,.01), hp = 1:100)
```

LogtVaR *VaR for t distributed geometric returns*

Description

Estimates the VaR of a portfolio assuming that geometric returns are Student t distributed, for specified confidence level and holding period.

Usage

```
LogtVaR(...)
```

Arguments

`...`	The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 5 or 6. In case there 5 input arguments, the mean and standard deviation of data is computed from return data. See examples for details. returns Vector of daily geometric return data mu Mean of daily geometric return data sigma Standard deviation of daily geometric return data investment Size of investment df Number of degrees of freedom in the t distribution cl VaR confidence level hp VaR holding period

Value

Matrix of VaRs whose dimension depends on dimension of hp and cl. If cl and hp are both scalars, the matrix is 1 by 1. If cl is a vector and hp is a scalar, the matrix is row matrix, if cl is a scalar and hp is a vector, the matrix is column matrix and if both cl and hp are vectors, the matrix has dimension length of cl * length of hp.

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes VaR given geometric return data
   data <- runif(5, min = 0, max = .2)
   LogtVaR(returns = data, investment = 5, df = 6, cl = .95, hp = 90)

   # Computes VaR given mean and standard deviation of return data
   LogtVaR(mu = .012, sigma = .03, investment = 5, df = 6, cl = .95, hp = 90)
```

LogtVaRDFPerc *Percentiles of VaR distribution function for Student-t*

Description

Plots the VaR of a portfolio against confidence level assuming that geometric returns are Student t distributed, for specified confidence level and holding period.

Usage

```
LogtVaRDFPerc(...)
```

Arguments

... The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 6 or 8. In case there 6 input arguments, the mean, standard deviation and number of observations of the data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

n Sample size

investment Size of investment

perc Desired percentile

df Number of degrees of freedom in the t distribution

cl VaR confidence level and must be a scalar

hp VaR holding period and must be a a scalar

Percentiles of VaR distribution function

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates Percentiles of VaR distribution
   data <- runif(5, min = 0, max = .2)
   LogtVaRDFPerc(returns = data, investment = 5, perc = .7,
                 df = 6, cl = .95, hp = 60)

   # Computes v given mean and standard deviation of return data
   LogtVaRDFPerc(mu = .012, sigma = .03, n= 10, investment = 5,
                 perc = .8, df = 6, cl = .99, hp = 40)
```

`LogtVaRPlot2DCL` *Plots log-t VaR against confidence level*

Description

Plots the VaR of a portfolio against confidence level assuming that geometric returns are Student-t distributed, for specified confidence level and holding period.

Usage

```
LogtVaRPlot2DCL(...)
```

Arguments

...	The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 5 or 6. In case there 5 input arguments, the mean and standard deviation of data is computed from return data. See examples for details. returns Vector of daily geometric return data mu Mean of daily geometric return data sigma Standard deviation of daily geometric return data investment Size of investment df Number of degrees of freedom in the t distribution cl VaR confidence level and must be a vector hp VaR holding period and must be a scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots VaR against confidene level given geometric return data
   data <- runif(5, min = 0, max = .2)
   LogtVaRPlot2DCL(returns = data, investment = 5, df = 6, cl = seq(.85,.99,.01), hp = 60)

   # Computes VaR against confidence level given mean and standard deviation of return data
  LogtVaRPlot2DCL(mu = .012, sigma = .03, investment = 5, df = 6, cl = seq(.85,.99,.01), hp = 40)
```

`LogtVaRPlot2DHP` *Plots log-t VaR against holding period*

Description

Plots the VaR of a portfolio against holding period assuming that geometric returns are Student t distributed, for specified confidence level and holding period.

Usage

```
LogtVaRPlot2DHP(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 5 or 6. In case there 5 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

investment Size of investment

df Number of degrees of freedom in the t distribution

cl VaR confidence level and must be a scalar

hp VaR holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes VaR given geometric return data
   data <- runif(5, min = 0, max = .2)
   LogtVaRPlot2DHP(returns = data, investment = 5, df = 6, cl = .95, hp = 60:90)

   # Computes VaR given mean and standard deviation of return data
   LogtVaRPlot2DHP(mu = .012, sigma = .03, investment = 5, df = 6, cl = .99, hp = 40:80)
```

`LogtVaRPlot3D` *Plots log-t VaR against confidence level and holding period*

Description

Plots the VaR of a portfolio against confidence level and holding period assuming that geometric returns are Student-t distributed, for specified confidence level and holding period.

Usage

```
LogtVaRPlot3D(...)
```

Arguments

...	The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 5 or 6. In case there 5 input arguments, the mean and standard deviation of data is computed from return data. See examples for details. returns Vector of daily geometric return data mu Mean of daily geometric return data sigma Standard deviation of daily geometric return data investment Size of investment df Number of degrees of freedom in the t distribution cl VaR confidence level and must be a vector hp VaR holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots VaR against confidene level given geometric return data
   data <- runif(5, min = 0, max = .2)
   LogtVaRPlot3D(returns = data, investment = 5, df = 6, cl = seq(.9,.99,.01), hp = 1:100)

   # Computes VaR against confidence level given mean and standard deviation of return data
  LogtVaRPlot3D(mu = .012, sigma = .03, investment = 5, df = 6, cl = seq(.9,.99,.01), hp = 1:100)
```

`LongBlackScholesCallVaR` *Derives VaR of a long Black Scholes call option*

Description

Function derives the VaR of a long Black Scholes call for specified confidence level and holding period, using analytical solution.

Usage

```
LongBlackScholesCallVaR(stockPrice, strike, r, mu, sigma, maturity, cl, hp)
```

Arguments

`stockPrice`	Stock price of underlying stock
`strike`	Strike price of the option
`r`	Risk-free rate and is annualised
`mu`	Mean return
`sigma`	Volatility of the underlying stock
`maturity`	Term to maturity and is expressed in days
`cl`	Confidence level and is scalar
`hp`	Holding period and is scalar and is expressed in days

Value

Price of European Call Option

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Hull, John C.. Options, Futures, and Other Derivatives. 4th ed., Upper Saddle River, NJ: Prentice Hall, 200, ch. 11.

Lyuu, Yuh-Dauh. Financial Engineering & Computation: Principles, Mathematics, Algorithms, Cambridge University Press, 2002.

Examples

```
# Estimates the price of an American Put
   LongBlackScholesCallVaR(27.2, 25, .03, .12, .2, 60, .95, 40)
```

LongBlackScholesPutVaR

Derives VaR of a long Black Scholes put option

Description

Function derives the VaR of a long Black Scholes put for specified confidence level and holding period, using analytical solution.

Usage

```
LongBlackScholesPutVaR(stockPrice, strike, r, mu, sigma, maturity, cl, hp)
```

Arguments

stockPrice	Stock price of underlying stock
strike	Strike price of the option
r	Risk-free rate and is annualised
mu	Mean return
sigma	Volatility of the underlying stock
maturity	Term to maturity and is expressed in days
cl	Confidence level and is scalar
hp	Holding period and is scalar and is expressed in days

Value

Price of European put Option

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Hull, John C.. Options, Futures, and Other Derivatives. 4th ed., Upper Saddle River, NJ: Prentice Hall, 200, ch. 11.

Lyuu, Yuh-Dauh. Financial Engineering & Computation: Principles, Mathematics, Algorithms, Cambridge University Press, 2002.

Examples

```
# Estimates the price of an American Put
   LongBlackScholesPutVaR(27.2, 25, .03, .12, .2, 60, .95, 40)
```

`LopezBacktest` *First (binomial) Lopez forecast evaluation backtest score measure*

Description

Derives the first Lopez (i.e. binomial) forecast evaluation score for a VaR risk measurement model.

Usage

```
LopezBacktest(Ra, Rb, cl)
```

Arguments

`Ra`	Vector of portfolio of profit loss distribution
`Rb`	Vector of corresponding VaR forecasts
`cl`	VaR confidence level

Value

Something

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Lopez, J. A. Methods for Evaluating Value-at-Risk Estimates. Federal Reserve Bank of New York Economic Policy Review, 1998, p. 121.

Lopez, J. A. Regulatory Evaluations of Value-at-Risk Models. Journal of Risk 1999, 37-64.

Examples

```
# Has to be modified with appropriate data:
   # LopezBacktest for given parameters
   a <- rnorm(1*100)
   b <- abs(rnorm(1*100))+2
   LopezBacktest(a, b, 0.95)
```

MEFPlot *Mean Excess Function Plot*

Description

Plots mean-excess function values of the data set.

Usage

```
MEFPlot(Ra)
```

Arguments

Ra Vector data

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots mean-excess function values
   Ra <- rnorm(1000)
   MEFPlot(Ra)
```

NormalES *ES for normally distributed P/L*

Description

Estimates the ES of a portfolio assuming that P/L is normally distributed, for specified confidence level and holding period.

Usage

```
NormalES(...)
```

Arguments

... The input arguments contain either return data or else mean and standard deviation data along with the remaining arguments. Accordingly, number of input arguments is either 3 or 4. In case there 3 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

cl VaR confidence level

hp VaR holding period in days

Value

Matrix of ES whose dimension depends on dimension of hp and cl. If cl and hp are both scalars, the matrix is 1 by 1. If cl is a vector and hp is a scalar, the matrix is row matrix, if cl is a scalar and hp is a vector, the matrix is column matrix and if both cl and hp are vectors, the matrix has dimension length of cl * length of hp.

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes VaR given P/L
   data <- runif(5, min = 0, max = .2)
   NormalES(returns = data, cl = .95, hp = 90)

   # Computes VaR given mean and standard deviation of P/L data
   NormalES(mu = .012, sigma = .03, cl = .95, hp = 90)
```

NormalESConfidenceInterval

Generates Monte Carlo 95% Confidence Intervals for normal ES

Description

Generates 95% confidence intervals for normal ES using Monte Carlo simulation

Usage

```
NormalESConfidenceInterval(mu, sigma, number.trials, sample.size, cl, hp)
```

Arguments

mu	Mean of the P/L process
sigma	Standard deviation of the P/L process
number.trials	Number of trials used in the simulations
sample.size	Sample drawn in each trial
cl	Confidence Level
hp	Holding Period

Value

95% confidence intervals for normal ES

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Generates 95\% confidence intervals for normal ES for given parameters
   NormalESConfidenceInterval(0, .5, 20, 20, .95, 90)
```

NormalESDFPerc — *Percentiles of ES distribution function for normally distributed P/L data*

Description

Estimates the percentiles of ES distribution for normally distributed P/L data, for specified confidence level and holding period using the theory of order statistics.

Usage

```
NormalESDFPerc(...)
```

Arguments

...	The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 6. In case there 4 input arguments, the mean, standard deviation and number of samples is computed from return data. See examples for details. returns Vector of daily geometric return data mu Mean of daily geometric return data sigma Standard deviation of daily geometric return data n Sample size perc Desired percentile cl ES confidence level and must be a scalar hp ES holding period and must be a a scalar

Value

Percentiles of ES distribution function

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates Percentiles of ES distribution
   data <- runif(5, min = 0, max = .2)
   NormalESDFPerc(returns = data, perc = .7, cl = .95, hp = 60)

  # Estimates Percentiles given mean, standard deviation and number of sambles of return data
   NormalESDFPerc(mu = .012, sigma = .03, n= 10, perc = .8, cl = .99, hp = 40)
```

NormalESFigure *Figure of normal VaR and ES and pdf against L/P*

Description

Gives figure showing the VaR and ES and probability distribution function against L/P of a portfolio assuming geometric returns are normally distributed, for specified confidence level and holding period.

Usage

```
NormalESFigure(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 3 or 4. In case there 3 input arguments, the mean and standard deviation of data is computed from return data. See examples for details. returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

cl VaR confidence level and should be scalar

hp VaR holding period in days and should be scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots lognormal VaR, ES and pdf against L/P data for given returns data
   data <- runif(5, min = 0, max = .2)
   NormalESFigure(returns = data, cl = .95, hp = 90)

   # Plots lognormal VaR, ES and pdf against L/P data with given parameters
   NormalESFigure(mu = .012, sigma = .03, cl = .95, hp = 90)
```

NormalESHotspots *Hotspots for normal ES*

Description

Estimates the ES hotspots (or vector of incremental ESs) for a portfolio assuming individual asset returns are normally distributed, for specified confidence level and holding period.

Usage

```
NormalESHotspots(vc.matrix, mu, positions, cl, hp)
```

Arguments

`vc.matrix`	Variance covariance matrix for returns
`mu`	Vector of expected position returns
`positions`	Vector of positions
`cl`	Confidence level and is scalar
`hp`	Holding period and is scalar

Value

Hotspots for normal ES

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Hotspots for ES for randomly generated portfolio
   vc.matrix <- matrix(rnorm(16),4,4)
   mu <- rnorm(4,.08,.04)
   positions <- c(5,2,6,10)
   cl <- .95
   hp <- 280
   NormalESHotspots(vc.matrix, mu, positions, cl, hp)
```

NormalESPlot2DCL *Plots normal ES against confidence level*

Description

Plots the ES of a portfolio against confidence level assuming that P/L are normally distributed, for specified confidence level and holding period.

Usage

```
NormalESPlot2DCL(...)
```

Arguments

... The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 3 or 4. In case there 3 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

cl ES confidence level and must be a vector

hp ES holding period and must be a scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots ES against confidence level
   data <- runif(5, min = 0, max = .2)
   NormalESPlot2DCL(returns = data, cl = seq(.9,.99,.01), hp = 60)

   # Plots ES against confidence level
   NormalESPlot2DCL(mu = .012, sigma = .03, cl = seq(.9,.99,.01), hp = 40)
```

`NormalESPlot2DHP` *Plots normal ES against holding period*

Description

Plots the ES of a portfolio against holding period assuming that P/L distribution is normally distributed, for specified confidence level and holding period.

Usage

```
NormalESPlot2DHP(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 3 or 4. In case there 3 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

cl ES confidence level and must be a scalar

hp ES holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes ES given geometric return data
   data <- runif(5, min = 0, max = .2)
   NormalESPlot2DHP(returns = data, cl = .95, hp = 60:90)

   # Computes v given mean and standard deviation of return data
   NormalESPlot2DHP(mu = .012, sigma = .03, cl = .99, hp = 40:80)
```

`NormalESPlot3D` *Plots normal ES against confidence level and holding period*

Description

Plots the ES of a portfolio against confidence level and holding period assuming that P/L is normally distributed, for specified ranges of confidence level and holding period.

Usage

```
NormalESPlot3D(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 3 or 4. In case there 3 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

cl VaR confidence level and must be a vector

hp VaR holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots VaR against confidene level given geometric return data
   data <- runif(5, min = 0, max = .2)
   NormalESPlot3D(returns = data, cl = seq(.9,.99,.01), hp = 1:100)

  # Computes VaR against confidence level given mean and standard deviation of return data
   NormalESPlot3D(mu = .012, sigma = .03, cl = seq(.9,.99,.01), hp = 1:100)
```

NormalQQPlot *Normal Quantile Quantile Plot*

Description

Produces an emperical QQ-Plot of the quantiles of the data set 'Ra' versus the quantiles of a normal distribution. The purpose of the quantile-quantile plot is to determine whether the sample in 'Ra' is drawn from a normal (i.e., Gaussian) distribution.

Usage

```
NormalQQPlot(Ra)
```

Arguments

Ra	Vector data set

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Normal QQ Plot for randomly generated standard normal data
   Ra <- rnorm(100)
   NormalQQPlot(Ra)
```

NormalQuantileStandardError *Standard error of normal quantile estimate*

Description

Estimates standard error of normal quantile estimate

Usage

```
NormalQuantileStandardError(prob, n, mu, sigma, bin.size)
```

Arguments

prob	Tail probability. Can be a vector or scalar
n	Sample size
mu	Mean of the normal distribution
sigma	Standard deviation of the distribution
bin.size	Bin size. It is optional parameter with default value 1

Value

Vector or scalar depending on whether the probability is a vector or scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates standard error of normal quantile estimate
   NormalQuantileStandardError(.8, 100, 0, .5, 3)
```

NormalSpectralRiskMeasure

Estimates the spectral risk measure of a portfolio

Description

Function estimates the spectral risk measure of a portfolio assuming losses are normally distributed, assuming exponential weighting function with specified gamma.

Usage

```
NormalSpectralRiskMeasure(mu, sigma, gamma, number.of.slices)
```

Arguments

mu	Mean losses
sigma	Standard deviation of losses
gamma	Gamma parameter in exponential risk aversion
number.of.slices	Number of slices into which density function is divided

Value

Estimated spectral risk measure

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Generates 95% confidence intervals for normal VaR for given parameters
   NormalSpectralRiskMeasure(0, .5, .8, 20)
```

`NormalVaR` *VaR for normally distributed P/L*

Description

Estimates the VaR of a portfolio assuming that P/L is normally distributed, for specified confidence level and holding period.

Usage

```
NormalVaR(...)
```

Arguments

`...`	The input arguments contain either return data or else mean and standard deviation data along with the remaining arguments. Accordingly, number of input arguments is either 3 or 4. In case there 3 input arguments, the mean and standard deviation of data is computed from return data. See examples for details. returns Vector of daily geometric return data mu Mean of daily geometric return data sigma Standard deviation of daily geometric return data cl VaR confidence level hp VaR holding period in days

Value

Matrix of VaR whose dimension depends on dimension of hp and cl. If cl and hp are both scalars, the matrix is 1 by 1. If cl is a vector and hp is a scalar, the matrix is row matrix, if cl is a scalar and hp is a vector, the matrix is column matrix and if both cl and hp are vectors, the matrix has dimension length of cl * length of hp.

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes VaR given geometric return data
   data <- runif(5, min = 0, max = .2)
   NormalVaR(returns = data, cl = .95, hp = 90)

   # Computes VaR given mean and standard deviation of return data
   NormalVaR(mu = .012, sigma = .03, cl = .95, hp = 90)
```

NormalVaRConfidenceInterval

Generates Monte Carlo 95% Confidence Intervals for normal VaR

Description

Generates 95% confidence intervals for normal VaR using Monte Carlo simulation

Usage

```
NormalVaRConfidenceInterval(mu, sigma, number.trials, sample.size, cl, hp)
```

Arguments

mu	Mean of the P/L process
sigma	Standard deviation of the P/L process
number.trials	Number of trials used in the simulations
sample.size	Sample drawn in each trial
cl	Confidence Level
hp	Holding Period

Value

95% confidence intervals for normal VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Generates 95\% confidence intervals for normal VaR for given parameters
   NormalVaRConfidenceInterval(0, .5, 20, 15, .95, 90)
```

NormalVaRDFPerc *Percentiles of VaR distribution function for normally distributed P/L*

Description

Estimates the percentile of VaR distribution function for normally distributed P/L, using the theory of order statistics.

Usage

```
NormalVaRDFPerc(...)
```

Arguments

`...`	The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 6. In case there 4 input arguments, the mean, standard deviation and number of observations of data are computed from returns data. See examples for details. returns Vector of daily geometric return data mu Mean of daily geometric return data sigma Standard deviation of daily geometric return data n Sample size perc Desired percentile cl VaR confidence level and must be a scalar hp VaR holding period and must be a a scalar

Value

Percentiles of VaR distribution function and is scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates Percentiles of VaR distribution
   data <- runif(5, min = 0, max = .2)
   NormalVaRDFPerc(returns = data, perc = .7, cl = .95, hp = 60)

   # Estimates Percentiles of VaR distribution
   NormalVaRDFPerc(mu = .012, sigma = .03, n= 10, perc = .8, cl = .99, hp = 40)
```

`NormalVaRFigure` *Figure of normal VaR and pdf against L/P*

Description

Gives figure showing the VaR and probability distribution function against L/P of a portfolio assuming P/L are normally distributed, for specified confidence level and holding period.

Usage

```
NormalVaRFigure(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 3 or 4. In case there 3 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

cl VaR confidence level and should be scalar

hp VaR holding period in days and should be scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots normal VaR and pdf against L/P data for given returns data
   data <- runif(5, min = 0, max = .2)
   NormalVaRFigure(returns = data, cl = .95, hp = 90)

   # Plots normal VaR and pdf against L/P data with given parameters
   NormalVaRFigure(mu = .012, sigma = .03, cl = .95, hp = 90)
```

`NormalVaRHotspots` *Hotspots for normal VaR*

Description

Estimates the VaR hotspots (or vector of incremental VaRs) for a portfolio assuming individual asset returns are normally distributed, for specified confidence level and holding period.

Usage

```
NormalVaRHotspots(vc.matrix, mu, positions, cl, hp)
```

Arguments

`vc.matrix`	Variance covariance matrix for returns
`mu`	Vector of expected position returns
`positions`	Vector of positions
`cl`	Confidence level and is scalar
`hp`	Holding period and is scalar

Value

Hotspots for normal VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Hotspots for ES for randomly generated portfolio
   vc.matrix <- matrix(rnorm(16),4,4)
   mu <- rnorm(4,.08,.04)
   positions <- c(5,2,6,10)
   cl <- .95
   hp <- 280
   NormalVaRHotspots(vc.matrix, mu, positions, cl, hp)
```

NormalVaRPlot2DCL *Plots normal VaR against confidence level*

Description

Plots the VaR of a portfolio against confidence level assuming that P/L are normally distributed, for specified confidence level and holding period.

Usage

```
NormalVaRPlot2DCL(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 3 or 4. In case there are 3 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

cl VaR confidence level and must be a vector

hp VaR holding period and must be a scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots VaR against confidene level given P/L data
   data <- runif(5, min = 0, max = .2)
   NormalVaRPlot2DCL(returns = data, cl = seq(.85,.99,.01), hp = 60)

  # Computes VaR against confidence level given mean and standard deviation of return data
   NormalVaRPlot2DCL(mu = .012, sigma = .03, cl = seq(.85,.99,.01), hp = 40)
```

`NormalVaRPlot2DHP` *Plots normal VaR against holding period*

Description

Plots the VaR of a portfolio against holding period assuming that P/L are normally distributed, for specified confidence level and holding period.

Usage

```
NormalVaRPlot2DHP(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 3 or 4. In case there 3 input arguments, the mean and standard deviation of data is computed from return data. See examples for details. returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

cl VaR confidence level and must be a scalar

hp VaR holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes VaR given P/L data
   data <- runif(5, min = 0, max = .2)
   NormalVaRPlot2DHP(returns = data, cl = .95, hp = 60:90)

   # Computes VaR given mean and standard deviation of P/L data
   NormalVaRPlot2DHP(mu = .012, sigma = .03, cl = .99, hp = 40:80)
```

NormalVaRPlot3D *Plots normal VaR in 3D against confidence level and holding period*

Description

Plots the VaR of a portfolio against confidence level and holding period assuming that P/L are normally distributed, for specified confidence level and holding period.

Usage

```
NormalVaRPlot3D(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 3 or 4. In case there 3 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

cl VaR confidence level and must be a vector

hp VaR holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots VaR against confidene level given geometric return data
   data <- rnorm(5, .07, .03)
   NormalVaRPlot3D(returns = data, cl = seq(.9,.99,.01), hp = 1:100)

  # Computes VaR against confidence level given mean and standard deviation of return data
   NormalVaRPlot3D(mu = .012, sigma = .03, cl = seq(.9,.99,.01), hp = 1:100)
```

`PCAES` *Estimates ES by principal components analysis*

Description

Estimates the ES of a multi position portfolio by principal components analysis, using chosen number of principal components and a specified confidence level or range of confidence levels.

Usage

```
PCAES(Ra, position.data, number.of.principal.components, cl)
```

Arguments

`Ra`	Matrix return data set where each row is interpreted as a set of daily observations, and each column as the returns to each position in a portfolio
`position.data`	Position-size vector, giving amount invested in each position
`number.of.principal.components`	Chosen number of principal components
`cl`	Chosen confidence level

Value

ES

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes PCA ES
   Ra <- matrix(rnorm(4*6),4,6)
   position.data <- rnorm(6)
   PCAES(Ra, position.data, 2, .95)
```

PCAESPlot *ES plot*

Description

Estimates ES plot using principal components analysis

Usage

```
PCAESPlot(Ra, position.data)
```

Arguments

Ra	Matrix return data set where each row is interpreted as a set of daily observations, and each column as the returns to each position in a portfolio
position.data	Position-size vector, giving amount invested in each position

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes PCA ES
   Ra <- matrix(rnorm(15*20),15,20)
   position.data <- rnorm(20)
   PCAESPlot(Ra, position.data)
```

PCAPrelim *Estimates VaR plot using principal components analysis*

Description

Estimates VaR plot using principal components analysis

Usage

```
PCAPrelim(Ra)
```

Arguments

Ra	Matrix return data set where each row is interpreted as a set of daily observations, and each column as the returns to each position in a portfolio position

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes PCA Prelim
   # This code was based on Dowd's code and similar to Dowd's code,
   # it is inconsistent for non-scalar data (Ra).
   library(MASS)
   Ra <- .15
   PCAPrelim(Ra)
```

PCAVaR *Estimates VaR by principal components analysis*

Description

Estimates the VaR of a multi position portfolio by principal components analysis, using chosen number of principal components and a specified confidence level or range of confidence levels.

Usage

```
PCAVaR(Ra, position.data, number.of.principal.components, cl)
```

Arguments

`Ra`	Matrix return data set where each row is interpreted as a set of daily observations, and each column as the returns to each position in a portfolio
`position.data`	Position-size vector, giving amount invested in each position
`number.of.principal.components`	Chosen number of principal components
`cl`	Chosen confidence level

Value

VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes PCA VaR
   Ra <- matrix(rnorm(4*6),4,6)
   position.data <- rnorm(6)
   PCAVaR(Ra, position.data, 2, .95)
```

`PCAVaRPlot` *VaR plot*

Description

Estimates VaR plot using principal components analysis

Usage

```
PCAVaRPlot(Ra, position.data)
```

Arguments

`Ra`	Matrix return data set where each row is interpreted as a set of daily observations, and each column as the returns to each position in a portfolio
`position.data`	Position-size vector, giving amount invested in each position

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes PCA VaR
   Ra <- matrix(rnorm(15*20),15,20)
   position.data <- rnorm(20)
   PCAVaRPlot(Ra, position.data)
```

PickandsEstimator *Pickands Estimator*

Description

Estimates the Value of Pickands Estimator for a specified data set and chosen tail size. Notes: (1) We estimate the Pickands Estimator by looking at the upper tail. (2) The tail size must be less than one quarter of the total sample size. (3) The tail size must be a scalar.

Usage

```
PickandsEstimator(Ra, tail.size)
```

Arguments

Ra	A data set
tail.size	Number of observations to be used to estimate the Pickands estimator

Value

Value of Pickands estimator

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes estimated Pickands estimator for randomly generated data.
   Ra <- rnorm(1000)
   PickandsEstimator(Ra, 40)
```

PickandsPlot *Pickand Estimator - Tail Sample Size Plot*

Description

Displays a plot of the Pickands Estimator against Tail Sample Size.

Usage

```
PickandsPlot(Ra, maximum.tail.size)
```

Arguments

Ra The data set

maximum.tail.size
: maximum tail size and should be greater than a quarter of the sample size.

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Pickand - Sample Tail Size Plot for random standard normal data
   Ra <- rnorm(1000)
   PickandsPlot(Ra, 40)
```

ProductCopulaVaR *Bivariate Product Copule VaR*

Description

Derives VaR using bivariate Product or logistic copula with specified inputs for normal marginals.

Usage

```
ProductCopulaVaR(mu1, mu2, sigma1, sigma2, cl)
```

Arguments

mu1	Mean of Profit/Loss on first position
mu2	Mean of Profit/Loss on second position
sigma1	Standard Deviation of Profit/Loss on first position
sigma2	Standard Deviation of Profit/Loss on second position
cl	VaR onfidece level

Value

Copula based VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Dowd, K. and Fackler, P. Estimating VaR with copulas. Financial Engineering News, 2004.

Examples

```
# VaR using bivariate Product for X and Y with given parameters:
   ProductCopulaVaR(.9, 2.1, 1.2, 1.5, .95)
```

`ShortBlackScholesCallVaR`
Derives VaR of a short Black Scholes call option

Description

Function derives the VaR of a short Black Scholes call for specified confidence level and holding period, using analytical solution.

Usage

```
ShortBlackScholesCallVaR(stockPrice, strike, r, mu, sigma, maturity, cl, hp)
```

Arguments

`stockPrice`	Stock price of underlying stock
`strike`	Strike price of the option
`r`	Risk-free rate and is annualised
`mu`	Mean return
`sigma`	Volatility of the underlying stock
`maturity`	Term to maturity and is expressed in days
`cl`	Confidence level and is scalar
`hp`	Holding period and is scalar and is expressed in days

Value

Price of European Call Option

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Hull, John C.. Options, Futures, and Other Derivatives. 4th ed., Upper Saddle River, NJ: Prentice Hall, 200, ch. 11.

Lyuu, Yuh-Dauh. Financial Engineering & Computation: Principles, Mathematics, Algorithms, Cambridge University Press, 2002.

Examples

```
# Estimates the price of an American Put
   ShortBlackScholesCallVaR(27.2, 25, .03, .12, .2, 60, .95, 40)
```

`ShortBlackScholesPutVaR` *Derives VaR of a short Black Scholes put option*

Description

Function derives the VaR of a Short Black Scholes put for specified confidence level and holding period, using analytical solution.

Usage

```
ShortBlackScholesPutVaR(stockPrice, strike, r, mu, sigma, maturity, cl, hp)
```

Arguments

`stockPrice`	Stock price of underlying stock
`strike`	Strike price of the option
`r`	Risk-free rate and is annualised
`mu`	Mean return
`sigma`	Volatility of the underlying stock
`maturity`	Term to maturity and is expressed in days
`cl`	Confidence level and is scalar
`hp`	Holding period and is scalar and is expressed in days

Value

Price of European put Option

Author(s)

Dinesh Acharya

References

Dowd, Kevin. Measuring Market Risk, Wiley, 2007.

Hull, John C.. Options, Futures, and Other Derivatives. 4th ed., Upper Saddle River, NJ: Prentice Hall, 200, ch. 11.

Lyuu, Yuh-Dauh. Financial Engineering & Computation: Principles, Mathematics, Algorithms, Cambridge University Press, 2002.

Examples

```
# Derives VaR of a short Black Scholes put option
   ShortBlackScholesPutVaR(27.2, 25, .03, .12, .2, 60, .95, 40)
```

`StopLossLogNormalVaR` *Log Normal VaR with stop loss limit*

Description

Generates Monte Carlo lognormal VaR with stop-loss limit

Usage

```
StopLossLogNormalVaR(mu, sigma, number.trials, loss.limit, cl, hp)
```

Arguments

`mu`	Mean arithmetic return
`sigma`	Standard deviation of arithmetic return
`number.trials`	Number of trials used in the simulations
`loss.limit`	Stop Loss limit
`cl`	Confidence Level
`hp`	Holding Period

Value

Lognormal VaR

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates standard error of normal quantile estimate
   StopLossLogNormalVaR(0, .2, 100, 1.2, .95, 10)
```

`tES` *ES for t distributed P/L*

Description

Estimates the ES of a portfolio assuming that P/L are t-distributed, for specified confidence level and holding period.

Usage

```
tES(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily P/L data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

df Number of degrees of freedom in the t-distribution

cl ES confidence level

hp ES holding period in days

Value

Matrix of ES whose dimension depends on dimension of hp and cl. If cl and hp are both scalars, the matrix is 1 by 1. If cl is a vector and hp is a scalar, the matrix is row matrix, if cl is a scalar and hp is a vector, the matrix is column matrix and if both cl and hp are vectors, the matrix has dimension length of cl * length of hp.

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Evans, M., Hastings, M. and Peacock, B. Statistical Distributions, 3rd edition, New York: John Wiley, ch. 38,39.

Examples

```
# Computes ES given P/L data
   data <- runif(5, min = 0, max = .2)
   tES(returns = data, df = 6, cl = .95, hp = 90)

   # Computes ES given mean and standard deviation of P/L data
   tES(mu = .012, sigma = .03, df = 6, cl = .95, hp = 90)
```

`tESDFPerc` *Percentiles of ES distribution function for t-distributed P/L*

Description

Estimates percentiles of ES distribution function for t-distributed P/L, using the theory of order statistics

Usage

```
tESDFPerc(...)
```

Arguments

`...`	The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 5 or 7. In case there 5 input arguments, the mean, standard deviation and assumed sampel size of data is computed from return data. See examples for details. returns Vector of daily geometric return data mu Mean of daily geometric return data sigma Standard deviation of daily geometric return data n Sample size df Degrees of freedom perc Desired percentile df Number of degrees of freedom in the t distribution cl ES confidence level and must be a scalar hp ES holding period and must be a a scalar

Value

Percentiles of ES distribution function

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates Percentiles of ES distribution given P/L data
   data <- runif(5, min = 0, max = .2)
   tESDFPerc(returns = data, perc = .7, df = 6, cl = .95, hp = 60)

   # Estimates Percentiles of ES distribution given mean, std. deviation and sample size
   tESDFPerc(mu = .012, sigma = .03, n= 10, perc = .8, df = 6, cl = .99, hp = 40)
```

`tESFigure` *Figure of t - VaR and ES and pdf against L/P*

Description

Gives figure showing the VaR and ES and probability distribution function assuming P/L is t- distributed, for specified confidence level and holding period.

Usage

```
tESFigure(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details. returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

df Number of degrees of freedom

cl VaR confidence level and should be scalar

hp VaR holding period in days and should be scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Evans, M., Hastings, M. and Peacock, B. Statistical Distributions, 3rd edition, New York: John Wiley, ch. 38,39.

Examples

```
# Plots lognormal VaR, ES and pdf against L/P data for given returns data
   data <- runif(5, min = 0, max = .2)
   tESFigure(returns = data, df = 10, cl = .95, hp = 90)

   # Plots lognormal VaR, ES and pdf against L/P data with given parameters
   tESFigure(mu = .012, sigma = .03, df = 10, cl = .95, hp = 90)
```

`tESPlot2DCL` *Plots t- ES against confidence level*

Description

Plots the ES of a portfolio against confidence level, assuming that L/P is t distributed, for specified confidence level and holding period.

Usage

```
tESPlot2DCL(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

df Number of degrees of freedom in the t distribution

cl ES confidence level and must be a vector

hp ES holding period and must be a scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Evans, M., Hastings, M. and Peacock, B. Statistical Distributions, 3rd edition, New York: John Wiley, ch. 38,39.

Examples

```
# Computes ES given geometric return data
   data <- runif(5, min = 0, max = .2)
   tESPlot2DCL(returns = data, df = 6, cl = seq(.9,.99,.01), hp = 60)

   # Computes v given mean and standard deviation of return data
   tESPlot2DCL(mu = .012, sigma = .03, df = 6, cl = seq(.9,.99,.01), hp = 40)
```

`tESPlot2DHP` *Plots t ES against holding period*

Description

Plots the ES of a portfolio against holding period assuming that L/P is t distributed, for specified confidence level and holding periods.

Usage

```
tESPlot2DHP(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily P/L data

mu Mean of daily P/L data

sigma Standard deviation of daily P/L data

df Number of degrees of freedom in the t distribution

cl ES confidence level and must be a scalar

hp ES holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Evans, M., Hastings, M. and Peacock, B. Statistical Distributions, 3rd edition, New York: John Wiley, ch. 38,39.

Examples

```
# Computes ES given geometric return data
   data <- runif(5, min = 0, max = .2)
   tESPlot2DHP(returns = data, df = 6, cl = .95, hp = 60:90)

   # Computes v given mean and standard deviation of return data
   tESPlot2DHP(mu = .012, sigma = .03, df = 6, cl = .99, hp = 40:80)
```

`tESPlot3D` *Plots t ES against confidence level and holding period*

Description

Plots the ES of a portfolio against confidence level and holding period assuming that P/L are Student-t distributed, for specified confidence level and holding period.

Usage

```
tESPlot3D(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily P/L data

mu Mean of daily P/L data

sigma Standard deviation of daily P/L data

df Number of degrees of freedom in the t distribution

cl VaR confidence level and must be a vector

hp VaR holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots ES against confidene level given P/L data
   data <- runif(5, min = 0, max = .2)
   tESPlot3D(returns = data, df = 6, cl = seq(.85,.99,.01), hp = 60:90)

  # Computes ES against confidence level given mean and standard deviation of return data
   tESPlot3D(mu = .012, sigma = .03, df = 6, cl = seq(.85,.99,.02), hp = 40:80)
```

TQQPlot *Student's T Quantile - Quantile Plot*

Description

Creates emperical QQ-plot of the quantiles of the data set x versus of a t distribution. The QQ-plot can be used to determine whether the sample in x is drawn from a t distribution with specified number of degrees of freedom.

Usage

```
TQQPlot(Ra, df)
```

Arguments

Ra	Sample data set
df	Number of degrees of freedom of the t distribution

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# t-QQ Plot for randomly generated standard normal data
   Ra <- rnorm(100)
   TQQPlot(Ra, 20)
```

tQuantileStandardError *Standard error of t quantile estimate*

Description

Estimates standard error of t quantile estimate

Usage

```
tQuantileStandardError(prob, n, mu, sigma, df, bin.size)
```

Arguments

`prob`	Tail probability. Can be a vector or scalar
`n`	Sample size
`mu`	Mean of the normal distribution
`sigma`	Standard deviation of the distribution
`df`	Number of degrees of freedom
`bin.size`	Bin size. It is optional parameter with default value 1

Value

Vector or scalar depending on whether the probability is a vector or scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates standard error of normal quantile estimate
   tQuantileStandardError(.8, 100, 0, .5, 5, 3)
```

`tVaR` *VaR for t distributed P/L*

Description

Estimates the VaR of a portfolio assuming that P/L are t distributed, for specified confidence level and holding period.

Usage

```
tVaR(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data df Number of degrees of freedom in the t distribution

cl VaR confidence level

hp VaR holding period

Value

Matrix of VaRs whose dimension depends on dimension of hp and cl. If cl and hp are both scalars, the matrix is 1 by 1. If cl is a vector and hp is a scalar, the matrix is row matrix, if cl is a scalar and hp is a vector, the matrix is column matrix and if both cl and hp are vectors, the matrix has dimension length of cl * length of hp.

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Evans, M., Hastings, M. and Peacock, B. Statistical Distributions, 3rd edition, New York: John Wiley, ch. 38,39.

Examples

```
# Computes VaR given P/L data
   data <- runif(5, min = 0, max = .2)
   tVaR(returns = data, df = 6, cl = .95, hp = 90)

   # Computes VaR given mean and standard deviation of P/L data
   tVaR(mu = .012, sigma = .03, df = 6, cl = .95, hp = 90)
```

`tVaRDFPerc` *Percentiles of VaR distribution function*

Description

Plots the VaR of a portfolio against confidence level assuming that P/L are t- distributed, for specified confidence level and holding period.

Usage

```
tVaRDFPerc(...)
```

Arguments

... The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 5 or 7. In case there 6 input arguments, the mean, standard deviation and number of observations of the data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

n Sample size

perc Desired percentile

df Number of degrees of freedom in the t distribution

cl VaR confidence level and must be a scalar

hp VaR holding period and must be a a scalar

Percentiles of VaR distribution function

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Estimates Percentiles of VaR distribution
   data <- runif(5, min = 0, max = .2)
   tVaRDFPerc(returns = data, perc = .7,
                 df = 6, cl = .95, hp = 60)

   # Computes v given mean and standard deviation of return data
   tVaRDFPerc(mu = .012, sigma = .03, n= 10,
                 perc = .8, df = 6, cl = .99, hp = 40)
```

---

tVaRESPlot2DCL *Plots t VaR and ES against confidence level*

Description

Plots the VaR and ES of a portfolio against confidence level assuming that P/L data are t distributed, for specified confidence level and holding period.

Usage

```
tVaRESPlot2DCL(...)
```

Arguments

... The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there are 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data

mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

cl VaR confidence level and must be a vector

hp VaR holding period and must be a scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots VaR and ETL against confidene level given P/L data
   data <- runif(5, min = 0, max = .2)
   tVaRESPlot2DCL(returns = data, df = 7, cl = seq(.85,.99,.01), hp = 60)

   # Computes VaR against confidence level given mean and standard deviation of P/L data
   tVaRESPlot2DCL(mu = .012, sigma = .03, df = 7, cl = seq(.85,.99,.01), hp = 40)
```

---

tVaRFigure *Figure of t- VaR and pdf against L/P*

Description

Gives figure showing the VaR and probability distribution function against L/P of a portfolio assuming P/L are normally distributed, for specified confidence level and holding period.

Usage

```
tVaRFigure(...)
```

Arguments

... The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily geometric return data mu Mean of daily geometric return data

sigma Standard deviation of daily geometric return data

df Number of degrees of freedom

cl VaR confidence level and should be scalar

hp VaR holding period in days and should be scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots normal VaR and pdf against L/P data for given returns data
   data <- runif(5, min = 0, max = .2)
   tVaRFigure(returns = data, df = 7, cl = .95, hp = 90)

   # Plots normal VaR and pdf against L/P data with given parameters
   tVaRFigure(mu = .012, sigma = .03, df=7, cl = .95, hp = 90)
```

---

tVaRPlot2DCL *Plots t VaR against confidence level*

Description

Plots the VaR of a portfolio against confidence level assuming that P/L data is t distributed, for specified confidence level and holding period.

Usage

```
tVaRPlot2DCL(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily P/L data data

mu Mean of daily P/L data data

sigma Standard deviation of daily P/L data data

df Number of degrees of freedom in the t distribution

cl VaR confidence level and must be a vector

hp VaR holding period and must be a scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots VaR against confidene level given P/L data data
   data <- runif(5, min = 0, max = .2)
   tVaRPlot2DCL(returns = data, df = 6, cl = seq(.85,.99,.01), hp = 60)

   # Computes VaR against confidence level given mean and standard deviation of P/L data
   tVaRPlot2DCL(mu = .012, sigma = .03, df = 6, cl = seq(.85,.99,.01), hp = 40)
```

`tVaRPlot2DHP` *Plots t VaR against holding period*

Description

Plots the VaR of a portfolio against holding period assuming that P/L are t- distributed, for specified confidence level and holding period.

Usage

```
tVaRPlot2DHP(...)
```

Arguments

`...` The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details.

returns Vector of daily P/L data data

mu Mean of daily P/L data data

sigma Standard deviation of daily P/L data data

df Number of degrees of freedom in the t distribution

cl VaR confidence level and must be a scalar

hp VaR holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Computes VaR given P/L data data
   data <- runif(5, min = 0, max = .2)
   tVaRPlot2DHP(returns = data, df = 6, cl = .95, hp = 60:90)

   # Computes VaR given mean and standard deviation of return data
   tVaRPlot2DHP(mu = .012, sigma = .03, df = 6, cl = .99, hp = 40:80)
```

---

tVaRPlot3D *Plots t VaR against confidence level and holding period*

Description

Plots the VaR of a portfolio against confidence level and holding period assuming that P/L are t distributed, for specified confidence level and holding period.

Usage

```
tVaRPlot3D(...)
```

Arguments

...	The input arguments contain either return data or else mean and standard deviation data. Accordingly, number of input arguments is either 4 or 5. In case there 4 input arguments, the mean and standard deviation of data is computed from return data. See examples for details. returns Vector of daily geometric return data mu Mean of daily geometric return data sigma Standard deviation of daily geometric return data df Number of degrees of freedom in the t distribution cl VaR confidence level and must be a vector hp VaR holding period and must be a vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Plots VaR against confidene level given geometric return data
   data <- runif(5, min = 0, max = .2)
   tVaRPlot3D(returns = data, df = 6, cl = seq(.85,.99,.01), hp = 60:90)

  # Computes VaR against confidence level given mean and standard deviation of return data
   tVaRPlot3D(mu = .012, sigma = .03, df = 6, cl = seq(.85,.99,.02), hp = 40:80)
```

VarianceCovarianceES *Variance-covariance ES for normally distributed returns*

Description

Estimates the variance-covariance VaR of a portfolio assuming individual asset returns are normally distributed, for specified confidence level and holding period.

Usage

```
VarianceCovarianceES(vc.matrix, mu, positions, cl, hp)
```

Arguments

vc.matrix	Variance covariance matrix for returns
mu	Vector of expected position returns
positions	Vector of positions
cl	Confidence level and is scalar
hp	Holding period and is scalar

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

Examples

```
# Variance-covariance ES for randomly generated portfolio
   vc.matrix <- matrix(rnorm(16), 4, 4)
   mu <- rnorm(4)
   positions <- c(5, 2, 6, 10)
   cl <- .95
   hp <- 280
   VarianceCovarianceES(vc.matrix, mu, positions, cl, hp)
```

`VarianceCovarianceVaR` *Variance-covariance VaR for normally distributed returns*

Description

Estimates the variance-covariance VaR of a portfolio assuming individual asset returns are normally distributed, for specified confidence level and holding period.

Usage

```
VarianceCovarianceVaR(vc.matrix, mu, positions, cl, hp)
```

Arguments

`vc.matrix`	Assumed variance covariance matrix for returns
`mu`	Vector of expected position returns
`positions`	Vector of positions
`cl`	Confidence level and is scalar or vector
`hp`	Holding period and is scalar or vector

Author(s)

Dinesh Acharya

References

Dowd, K. Measuring Market Risk, Wiley, 2007.

See Also

AdjustedVarianceCovarianceVaR

Examples

```
# Variance-covariance VaR for randomly generated portfolio
   vc.matrix <- matrix(rnorm(16),4,4)
   mu <- rnorm(4)
   positions <- c(5,2,6,10)
   cl <- .95
   hp <- 280
   VarianceCovarianceVaR(vc.matrix, mu, positions, cl, hp)
```

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