

RLT: Moody's Analytics ESG Model and Calibration Training

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School of Mathematics

Session 2019

Introduction

- 1 Assignment 1 : Risk Neutral Valuation
- 2 Assignment 2 : Value at Risk
- 3 Assignment2 : Correlation Analysis

Assignment 1 : Risk Neutral Valuation

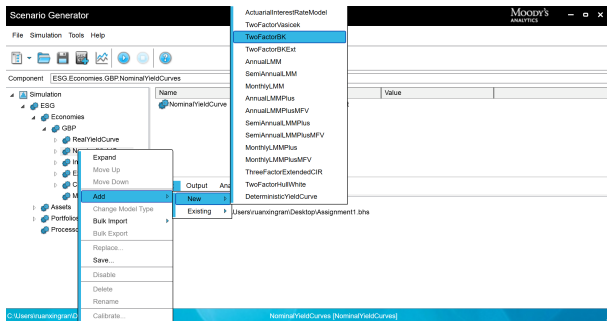
- Quick view of generating scenario
- Implement the answer of the Assignment 1

Assignment 1 : Risk Neutral Valuation

- Quick view of generating scenario
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Quick view of generating scenario

GBP-TwoFactorBK Model



Quick view of generating scenario

GBP-TwoFactorBK Model

- The risk-neutral process for the short rate r is :

$$d \log(r) = \alpha_1 [\log(m) - \log(r)] dt + \sigma_1 dZ_1$$

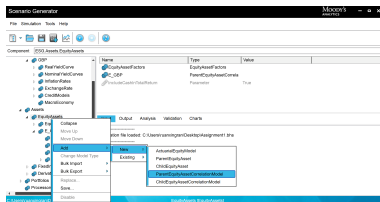
- Where the mean-reversion level m follows the stochastic process :

$$d \log(m) = \alpha_2 [\mu - \log(m)] dt + \sigma_2 dZ_2$$

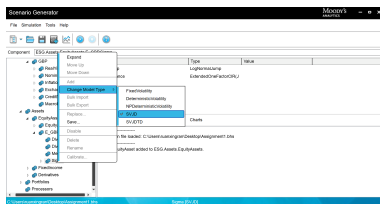
Quick view of generating scenario

Equity Asset-Parant equity correlation model and SVJD

- Using Parant equity correlation model



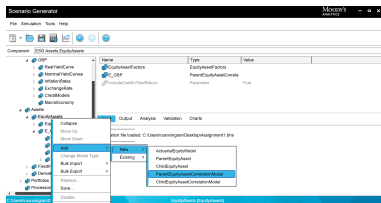
- Using SVJD model



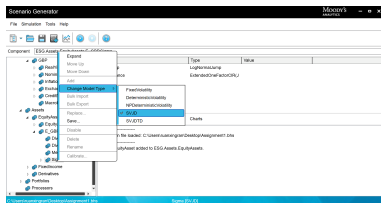
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- Using SVJD model



Quick view of generating scenario

Equity Asset-Parant equity correlation model and SVJD

- The log-return of asset $P(t)$ is :

$$\log\left(\frac{P(t + \Delta t)}{P(t)}\right) = (r(t) + \mu_p - \pi_p - \frac{1}{2}\sigma_p^2)\Delta t + \sigma_p Z_p(t)\sqrt{\Delta t} + CPP(\Delta t)$$

where,

$$CPP(\Delta t) = \sum_{f=1}^F \beta_f \sum_{i=1}^{N_f(\Delta t)} \log(J_{f,i}) + \sum_{k=1}^{N_s(\Delta t)} \log(J_{s,k})$$

- $v_t(\text{volatility}^2)$ follows a mean-reverting Stochastic Differential Equation :

$$dv_t = \alpha(\mu - v_t)dt + \sigma_v \sqrt{v_t}dW_t$$

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Implement the answer of the Assignment 1

The payoff structure of the portfolio

- One zero coupon bond paying 10000 in 10 years
- 10 years European call option on UK Equity with strike price of 7000
- 10 years European put option on UK Equity with strike price of 5000

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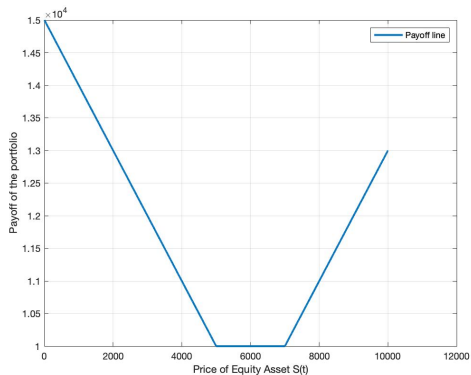
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Implement the answer of the Assignment 1

The payoff structure of the portfolio

$$Payoff = 10000 + (5000 - S)_{S \leq 5000} + (S - 7000)_{S \geq 7000}$$



Implement the answer of the Assignment 1

Calculate the market consistent value of the portfolio

- In terms of martingale X_t , it follows :

$$X_0 = E(X_t | F_0)$$

- The market consistent value of portfolio is :

$$P_0 = E\left(\frac{P_T}{B(T)} \mid X_0 = 5000\right) = 12066.67$$

Implement the answer of the Assignment 1

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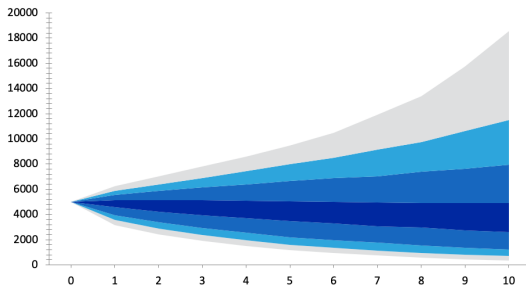
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Estimate the 95% confidence interval for the value of the portfolio

- The graph of price of Equity Asset :



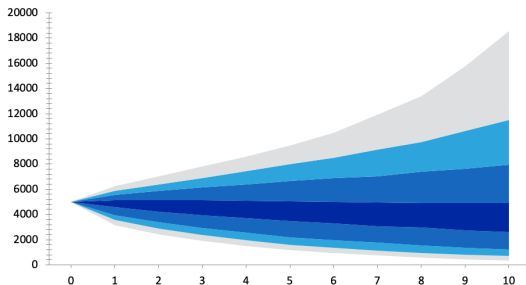
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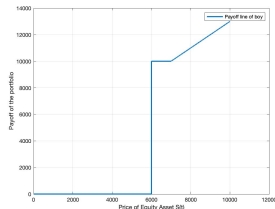
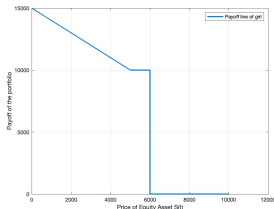
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Payoff structure of each child

- The graph payoff structure of each child :

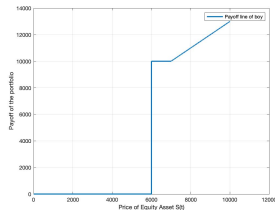
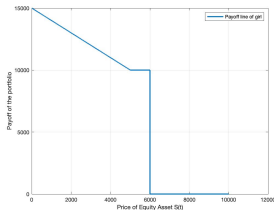


- The market consistent value :
 boy :3989.569.
 girl :8077.096.

Implement the answer of the Assignment 1

Payoff structure of each child

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Weakness of this valuation

- Waste computing resource.
- The result is unfair.

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Assignment 2 : Value at Risk

- Main difference between Real World and Market Consistent
- Value at Risk theory
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Real World Model

- Two Economics : GBP and EUR
- Two Equities : E-GBP and E-EUR
- Two Govt Bonds(annually) : GBP-GOV-30ys-0 and EUR-GOV-30ys-0
- Two Risky Bonds : GBP-BBB-30ys-2 (semiannually) and EUR-AAA-30ys-5 (annually)
- Two Portfolios : P-GBP and P-EUR

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Difference between RW and MC

Parent equity asset

- Parent Equity Asset :
Parent equity assets are addable models. Correlation of these assets is done via the equity asset factor loadings.

Difference between RW and MC

Difference

- Difference between Parent Equity Asset and Parent Equity Asset Correlation Model :

Depend on whether they are correlated using an equity asset factor model or the correlation matrix.

The fundamental difference between the two types, is that the former splits risk into systematic risk driven by factor loadings, and specific risk driven by the equity asset volatility model. Whereas the correlated version of the equity assets does not make this distinction, and all risk is driven by the equity asset volatility model.

VaR Theory

- From Financial Risky Theory course, VaR is a measure of the risk of loss for investments, i.e. 0.995 VaR is 0.5 means means that there is a 0.05 probability that the portfolio will increase in value by less than 0.5.
- The definition of Upper-Quantiles(1) :
For $\alpha \in (0, 1)$, the number $q^\alpha(X) = \inf\{x : \alpha < F_X(x)\}$, is called the upper- α -quantile of X .
- The definition of VaR(1) :
For $\alpha \in (0, 1)$, we define the VaR of X , at confidence level $1-\alpha$, as : $\text{VaR}^\alpha(X) = -q^\alpha(X) = -\inf\{x : \alpha < F_X(x)\}$.

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VaR Theory

- In usual case :

We now consider an investment where at time zero we buy x shares of risky assets and y units of the risk-free asset, and we use $V_{(x;y)}(t)$ to denote the value of the portfolio at time t , with $X_{(x;y)}$ to denote the value of the portfolio.

Thus, VaR is(1) :

$$\text{VaR}^\alpha(X_{(x;y)}) = V_{(x;y)}(0) - xe^{-rT}q^\alpha(S(T)) - y$$

- In my case, I decide to analyse VaR from Macro way, i.e. from the 0.5 percentage of lower bound in Total Return Index plot.

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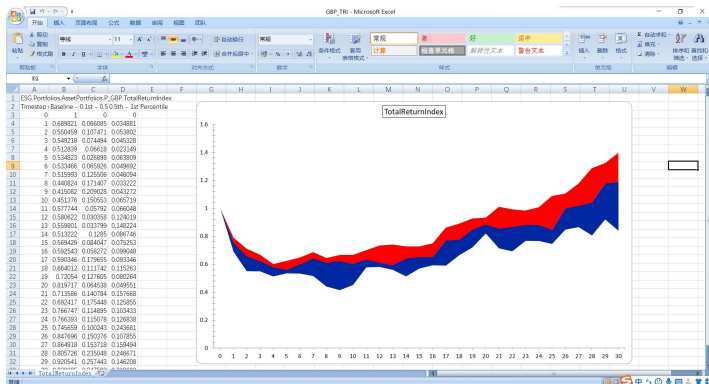
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Implement the answer of the Assignment 2 part 1 VaR change

- We observe the changes of VaR during these conditions :
 1. Assets' weights in the portfolio : (equity :gov bond :risky bond)
(based) 0.45 :0.1 :0.45 ; 0.25 :0.5 :0.25 ;
 2. Different random number of seed :
(based) 1 ; 100 ; 10000 ;
 3. Different numbers of trails :
100 ; (based) 1000 ; 10000 ;
 4. Different Economic :
GBP ; EUR.

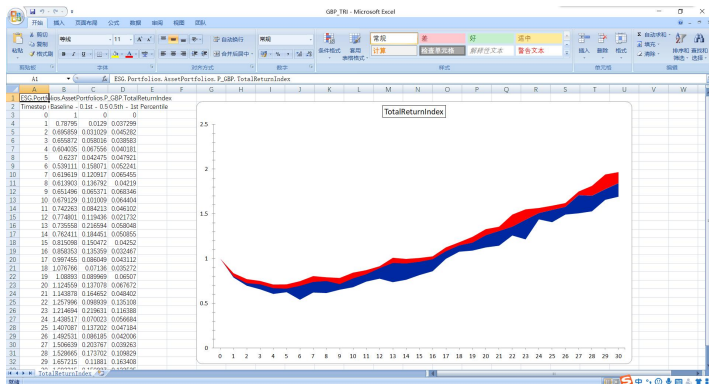
Implement the answer of the Assignment 2 Part 1 Conclusion

- The graph of 0.45 :0.1 :0.45 is :



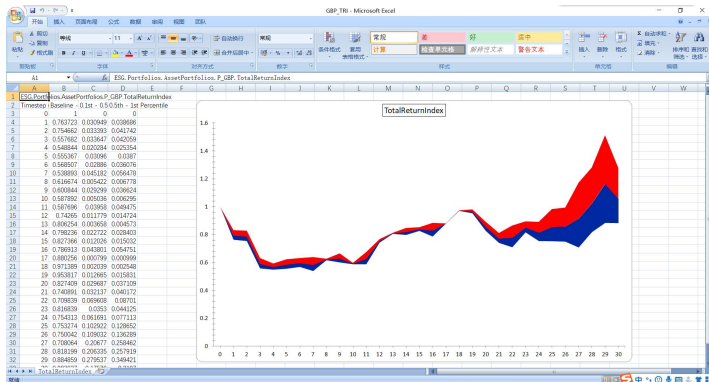
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- Change to 0.25 : 0.5 : 0.25 is :



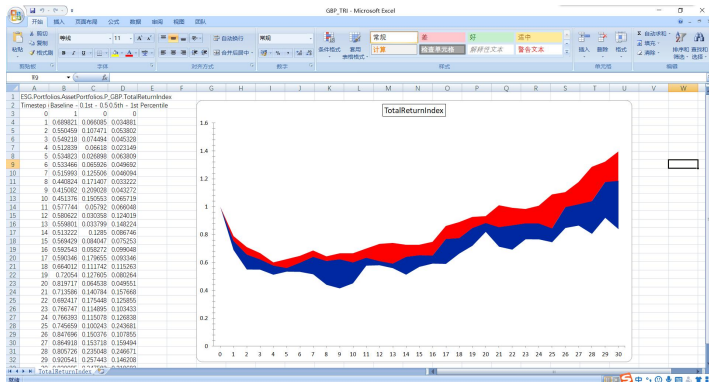
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- with 100 trails is :



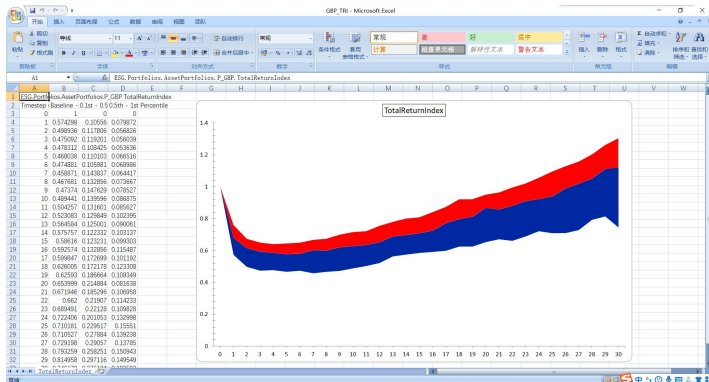
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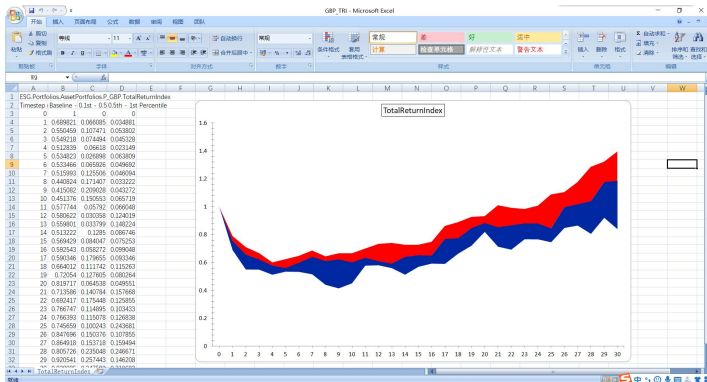
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- with 10000 trails is :



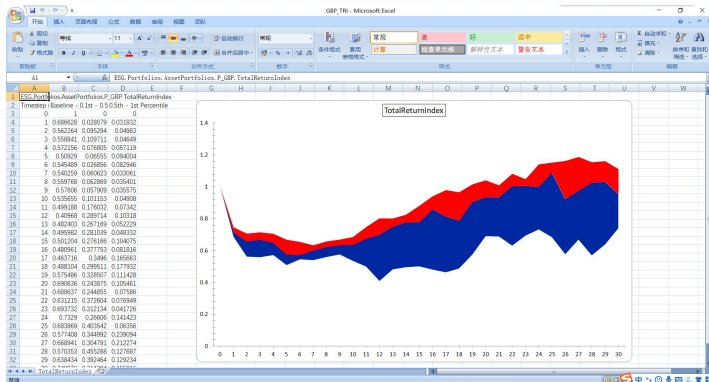
Implement the answer of the Assignment 2 Part 1 Conclusion

- with 1 random seed is :



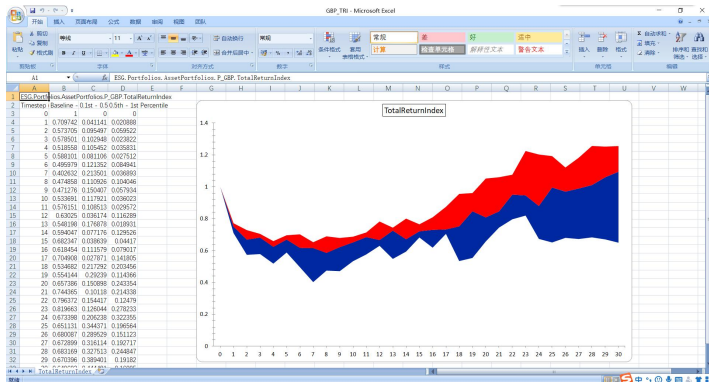
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- with 100 random seed is :



Implement the answer of the Assignment 2 Part 1 Conclusion

- with 10000 random seed is :



Implement the answer of the Assignment 2 Part 1

Conclusion

- What could we conclude are :
 1. Along with time, the 0.995 VaR changes from negative to positive, which means that if you want this portfolio to earn money, it is better to hold for a long time ;
 2. Changing higher the risk-free asset means you could gain much more, but still you need to hold for a long time ;

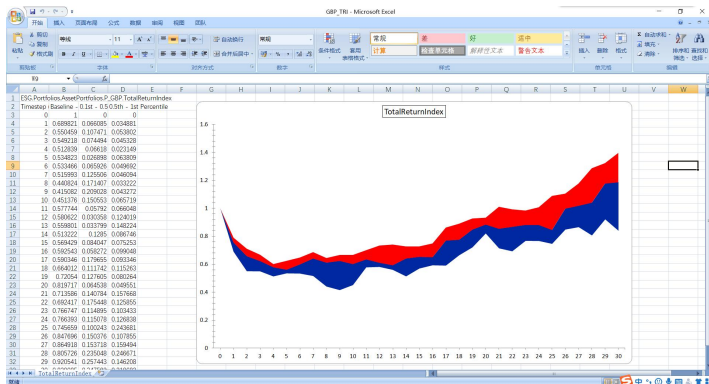
Implement the answer of the Assignment 2 Part 1

Conclusion

- What could we conclude are :
 3. More trails makes the plot more smoothly, which means during a certain range of value, it could get the point as large as possible, i.e. could simulate more suitable situations ;
 4. More random seeds makes the plot more fluctuating because the seed is an initial number of the pseudorandom number generator which is in fact fully deterministic. Larger numbers somehow returns a sequence of numbers that looks more random.

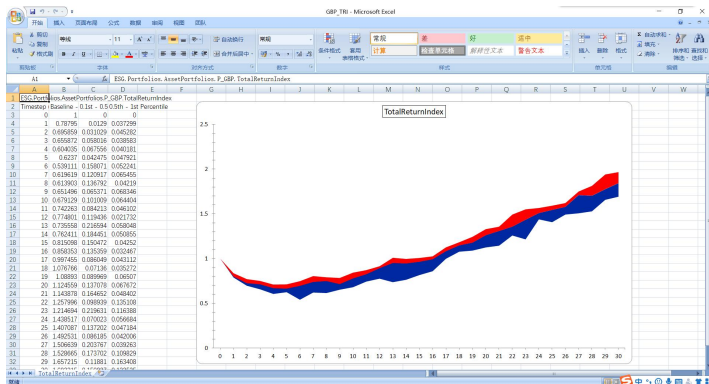
Implement the answer of the Assignment 2 Part 1 Conclusion

- Similarly, show the EUR plot in the same order :



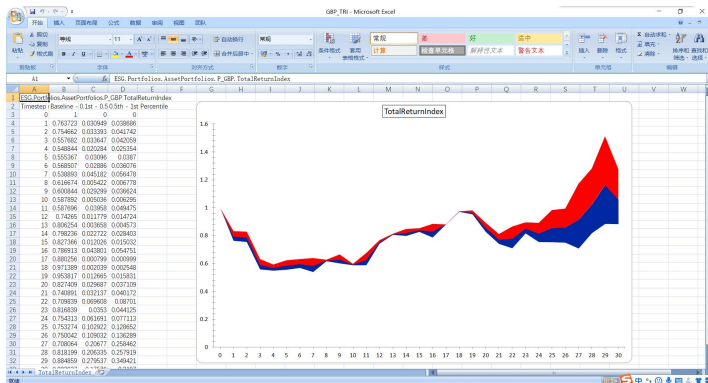
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- Change to 0.25 :0.5 :0.25 is :



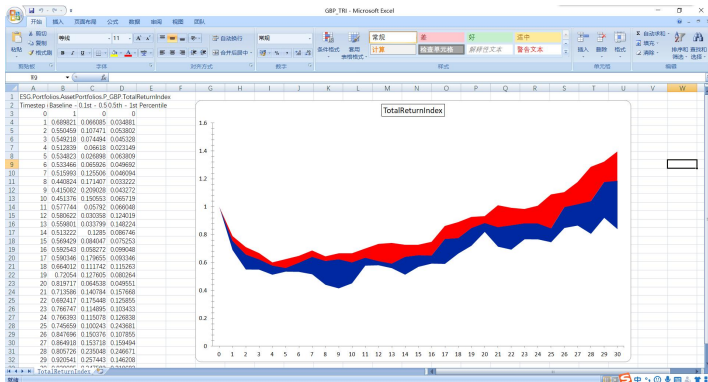
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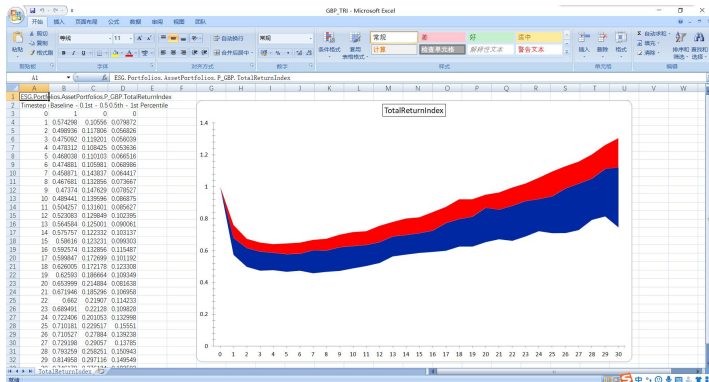
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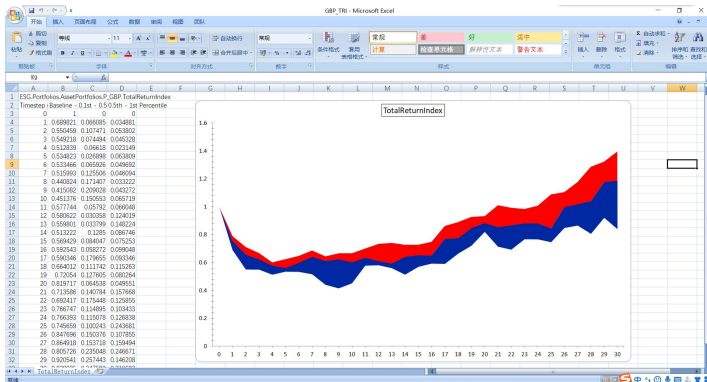
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- With 10000 trails is :



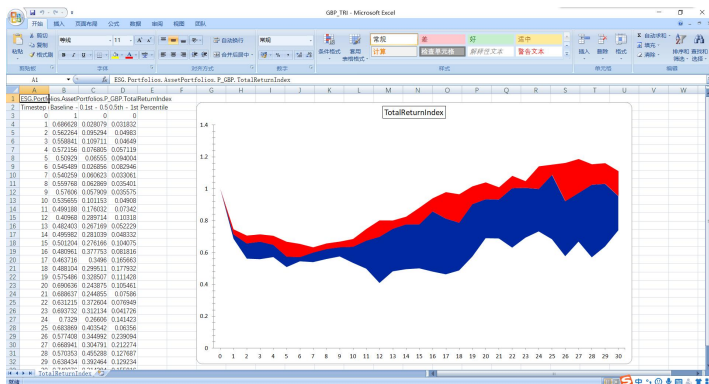
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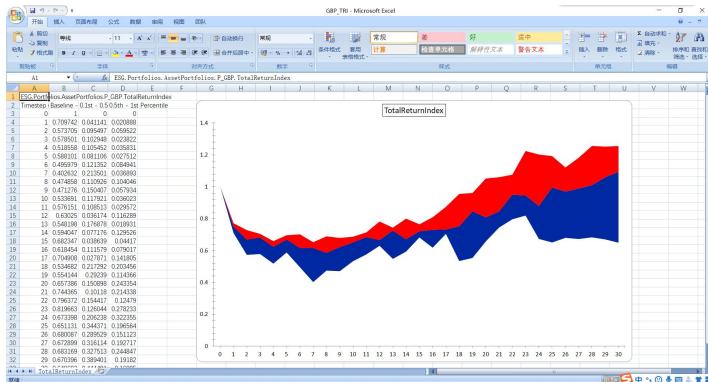
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- With 100 random seeds is :



Implement the answer of the Assignment 2 Part 1 Conclusion

- With 10000 random seeds is :



Implement the answer of the Assignment 2 Part 1

Conclusion

- What could we conclude from EUR and GBP are :
No marked difference. For each part compared in these two Economies, same trend means these two somehow have the similar market with each other, which could not be difficult to image from history.

Assignment 2 : Correlation Analysis

Correlation Analysis

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- Why we need **CORRELATION** ?
- Correlation in use

Mr.Pearson

$$\rho = \frac{E(V_1, V_2) - E(V_1)E(V_2)}{SD(V_1)SD(V_2)}$$

correlation \neq *dependence*

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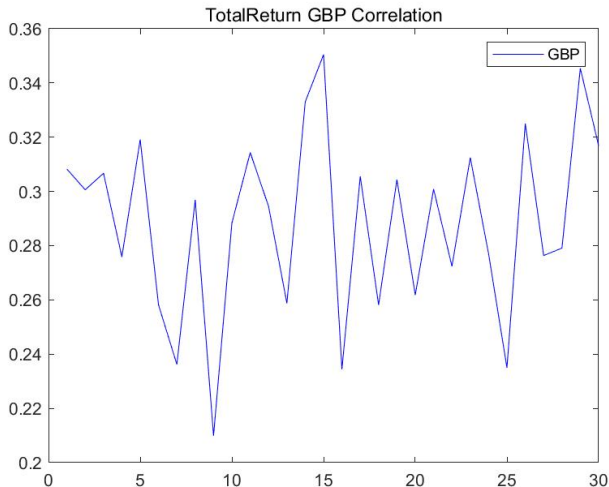
Simulation with ESG

- Equity asset : E_GBP
- Risky Bonds : Corporation Bond under GBP economy
AAA, 30 years, 2% coupon

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Vary Over Time – GARCH

- Log Return : Stochastic Process

Equity asset : $\{X_t\}$; Risky Bonds : $\{Y_t\}$ where $t \in \{1, \dots, 30\}$

- Reshaped Data : $X'_t = \frac{X_{t+1}-X_t}{X_t}, Y'_t = \frac{Y_{t+1}-Y_t}{Y_t}$
- Covariance rate of $\{X_t\}, \{Y_t\}$ = Covariance of $\{X'_t\}, \{Y'_t\}$
- $Cov_n = EX_nY_n - E(X_n)E(Y_n)$
(because this is year return, we cannot assume $E(X_n) = E(Y_n) = 0$)

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Vary Over Time – GARCH

GARCH models can also be used for updating covariance rate estimates and forecasting the future level of covariance rates. For example, the GARCH(1,1) model for updating a covariance rate between X and Y is

- $COV_n = \omega + \alpha X_{n-1}Y_{n-1} + \beta COV_{n-1}$
- $Cor_n = \frac{COV_n}{SD(X_{n-1})SD(Y_{n-1})}$
- where $\{X_t\}, \{Y_t\}$ donate log return
- Fit the model with our data, and we got α and β : $\alpha = -0.1839$; $\beta = 34.37$.

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- $Cor_n = \frac{COV_n}{SD(X_{n-1})SD(Y_{n-1})}$
- where $\{X_t\}, \{Y_t\}$ donate log return
- Fit the model with our data, and we got α and β : $\alpha = -0.1839$; $\beta = 34.37$.

Vary Over Time – GARCH

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- In this step, we cannot say it plausible confidently!
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- In real world, it is common for asset to be highly correlated and exhibit large losses at the same time during a financial crisis or some other extreme market condition, we may call it "black duck".

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Tail Dependence

- Define :

$$TailDependence(P : x, y) = \frac{JointTailEventCount(P; x, y)}{\sqrt{SingleTailEventCount(p; x) SingleTailEventCount(p; y)}}$$

- where $p \in (0, 100)$, *donate a user – specified percentage*
- $SingleTailEventCount(p; y) = \{n : X_n \leq y(p)\}$
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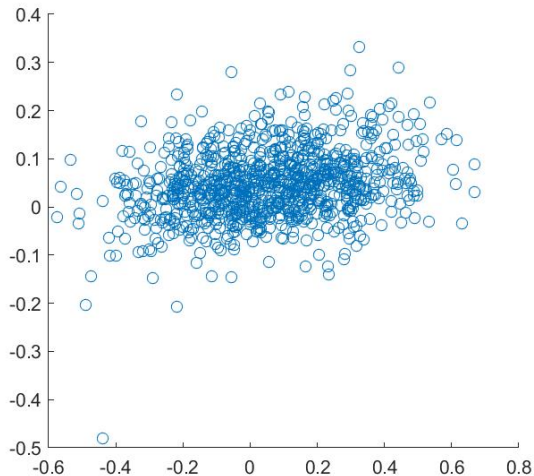
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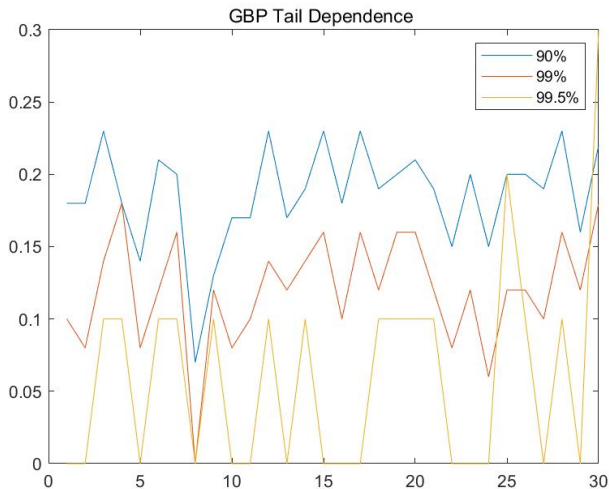
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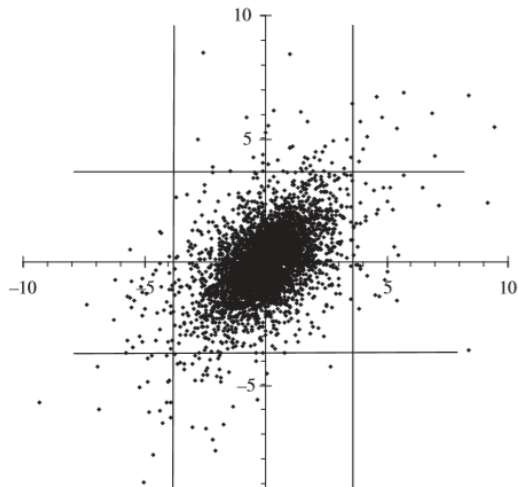


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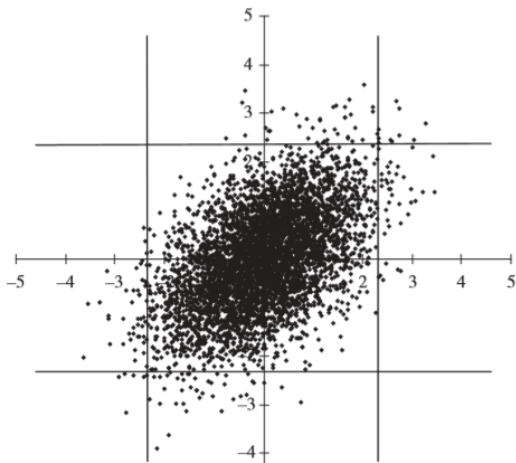
Copula

Student's t-distribution with mark tail dependence



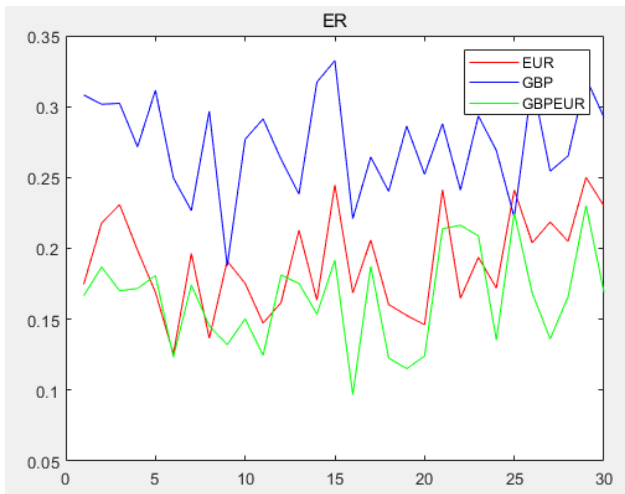
Copula

Gaussian distribution with slight tail dependence



ExcessReturn Anaysis

ExcessReturn Correlation



Conclusion

- We discuss the method to price the portfolio via Monte Carlo Simulation
- We use VaR to measure the risk of portfolio in real world
- We identify dependence between two assets via correlation, notice the weakness for model's plausibility, and suggest with some other tools, including copula, GARCH.

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Reference

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Thanks

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