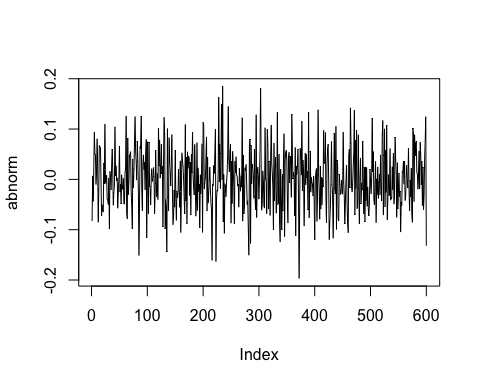
prob1

Lisa He

1. Becuase we have more flexibility with bernoulli normal misture model and that we can see more negative jumps than positive jumps which is consistent with the data. the variance is not consistent over time which is also consistent with market data. and the stock return can have fat tails under the bernoulli normal misture model

N <- 600  
set.seed(124)  
norm <- rnorm(N)  
abnorm <- norm\*0.063 + 0.0045  
plot(abnorm,type = "l")

 It does not look like the data, because the data is non-stationary. there are times where there's a lot of variance in the returns and times where there isnt, however, the simulation from normal distribution's variance is stationary aross time.

mu <- 0.012  
sig <- 0.05   
p<- 0.15  
muj<- -0.05  
sigj <- 0.17  
#mean 0.0045  
mu + p\*muj

## [1] 0.0045

#variance =0.00715375  
sig\*\*2+p\*muj\*\*2+p\*sigj\*\*2-p\*\*2\*muj\*\*2

## [1] 0.00715375

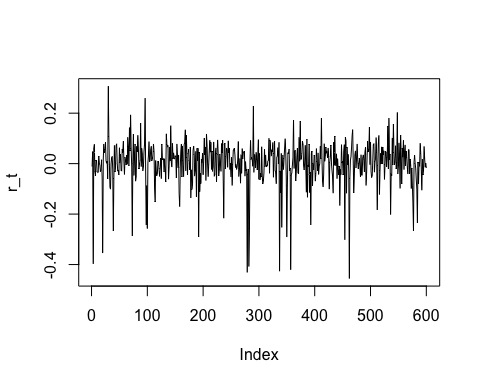
#skewness = -0.9319173  
(p\*muj\*\*3+3\*p\*muj\*sigj\*\*2+2\*p\*\*3\*muj\*\*3-3\*p\*p\*muj\*\*3-3\*p\*p\*muj\*sigj\*\*2)/(sig\*\*2+p\*muj\*\*2+p\*sigj\*\*2-p\*\*2\*muj\*\*2)\*\*(3/2)

## [1] -0.9319173

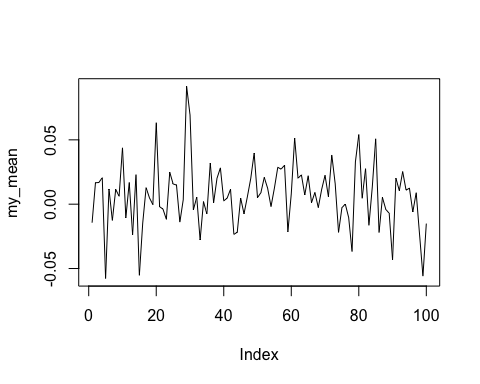
#kurtosis =7.002188  
(3\*sig\*\*4+6\*sig\*sig\*p\*muj\*\*2+6\*sig\*sig\*p\*sigj\*sigj-6\*sig\*sig\*p\*p\*muj\*muj+p\*muj\*\*4+6\*p\*muj\*muj\*sigj\*sigj+3\*p\*sigj\*\*4+6\*p\*\*3\*muj\*\*4+6\*p\*\*3\*muj\*\*2\*sigj\*\*2-3\*p\*\*4\*muj\*\*4-4\*p\*p\*muj\*\*4-12\*p\*p\*muj\*\*2\*sigj\*\*2)/(sig\*\*2+p\*muj\*\*2+p\*sigj\*\*2-p\*\*2\*muj\*\*2)\*\*2-3

## [1] 7.002188

delta\_t <- rnorm(N)  
epsilon\_t <- rnorm(N)  
B\_t <- rbinom(N, size = 1, prob = p)  
J\_t <- B\_t\*(muj+sigj\*delta\_t)  
r\_t <- mu + sig\*epsilon\_t+J\_t  
plot(r\_t,type = "l")

 It doesn't look like the data, but there is a lot more negative jumps than positive jumps. what;s missing is that in the real data, there's periods of times with a lot of negative jumps and positive jumps and some periods with neither. whereas the simulation doesn't achieve that

numN <- 100  
N<- 12  
my\_mean <- c()  
my\_error <-c()  
for (i in 1:numN) {  
delta\_t <- rnorm(N)  
epsilon\_t <- rnorm(N)  
B\_t <- rbinom(N, size = 1, prob = p)  
J\_t <- B\_t\*(muj+sigj\*delta\_t)  
r\_t <- mu + sig\*epsilon\_t+J\_t  
my\_mean[i] <- mean(r\_t)  
my\_error[i] <- std.error(r\_t)  
}  
t\_mean <- mean(my\_mean)  
t\_sd <- sqrt(var(my\_mean))  
#var is var(my\_mean) = 0.0006082747  
t\_stat <- t\_mean/(t\_sd/sqrt(numN))  
plot(my\_mean,type= "l")



# it looks like a distribution from the plot  
skewness(my\_mean) #0.1260242

## [1] 0.1707318

kurtosis(my\_mean)#1.373097

## [1] 1.406444

jarque.bera.test(my\_mean)

##   
## Jarque Bera Test  
##   
## data: my\_mean  
## X-squared = 9.8247, df = 2, p-value = 0.007355

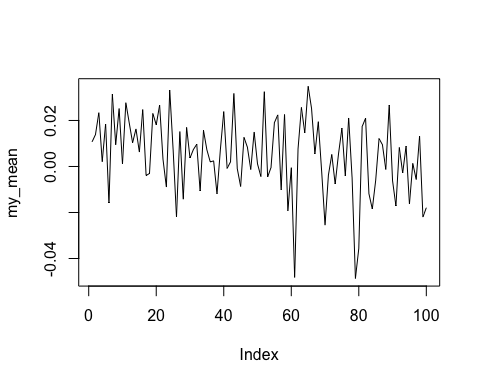
#p-value = 0.01017 so it couldn't be a normal distribution  
mean(my\_error)

## [1] 0.02123394

#the mean of the standard errors are 0.02217715 which is slightly higher than the standard deviation

t\_stat is 3.044169 which is greater than 1.96 so we reject the null hypothesis

numN <- 100  
N<- 24  
my\_mean <- c()  
my\_error <-c()  
for (i in 1:numN) {  
delta\_t <- rnorm(N)  
epsilon\_t <- rnorm(N)  
B\_t <- rbinom(N, size = 1, prob = p)  
J\_t <- B\_t\*(muj+sigj\*delta\_t)  
r\_t <- mu + sig\*epsilon\_t+J\_t  
my\_mean[i] <- mean(r\_t)  
my\_error[i] <- std.error(r\_t)  
}  
t\_mean <- mean(my\_mean)  
t\_sd <- sqrt(var(my\_mean))  
#var is var(my\_mean) = 0.0003389792  
t\_stat <- t\_mean/(t\_sd/sqrt(numN))  
plot(my\_mean,type= "l")



# it doesnt look like a distribution from the plot  
skewness(my\_mean) #-0.5748082

## [1] -0.647919

kurtosis(my\_mean)#0.5307763

## [1] 0.6570971

jarque.bera.test(my\_mean)

##   
## Jarque Bera Test  
##   
## data: my\_mean  
## X-squared = 9.4395, df = 2, p-value = 0.008918

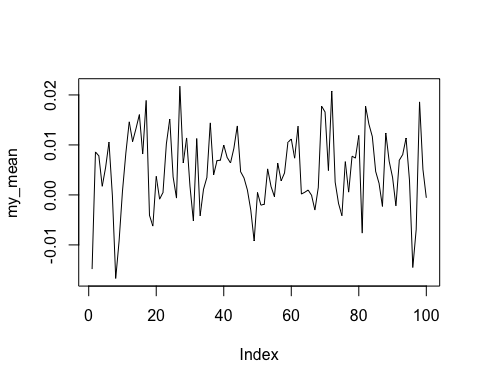
#p-value = 0.02749 so it couldn't be a normal distribution  
mean(my\_error)

## [1] 0.01653043

#the mean of the standard errors are 0.01663182 which is slightly lower than the standard deviation

t\_stat is 0.15277 which is less than 1.96 so we keep the null hypothesis

numN <- 100  
N<- 120  
my\_mean <- c()  
my\_error <-c()  
for (i in 1:numN) {  
delta\_t <- rnorm(N)  
epsilon\_t <- rnorm(N)  
B\_t <- rbinom(N, size = 1, prob = p)  
J\_t <- B\_t\*(muj+sigj\*delta\_t)  
r\_t <- mu + sig\*epsilon\_t+J\_t  
my\_mean[i] <- mean(r\_t)  
my\_error[i] <- std.error(r\_t)  
}  
t\_mean <- mean(my\_mean)  
t\_sd <- sqrt(var(my\_mean))  
#var is var(my\_mean) = 6.445296e-05  
t\_stat <- t\_mean/(t\_sd/sqrt(numN))  
plot(my\_mean,type= "l")



# it looks like a distribution from the plot  
skewness(my\_mean) #0.02659691

## [1] -0.2177322

kurtosis(my\_mean)#-0.3752769

## [1] 0.0683155

jarque.bera.test(my\_mean)

##   
## Jarque Bera Test  
##   
## data: my\_mean  
## X-squared = 0.88539, df = 2, p-value = 0.6423

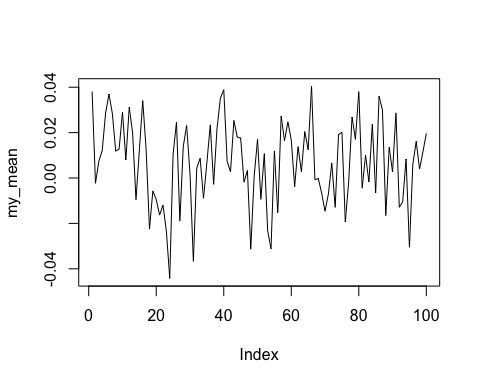
#p-value = 0.8009 so it could be a normal distribution  
mean(my\_error)

## [1] 0.007674494

#the mean of the standard errors are 0.007614783 which is slightly lower than the standard deviation

t\_stat is 6.69 which is greater than 1.96 so we reject the null hypothesis

numN <- 100  
N<- 24  
my\_mean <- c()  
my\_error <-c()  
for (i in 1:numN) {  
delta\_t <- rnorm(N)  
epsilon\_t <- rnorm(N)  
B\_t <- rbinom(N, size = 1, prob = p)  
J\_t <- B\_t\*(muj+sigj\*delta\_t)  
r\_t <- mu + sig\*epsilon\_t+J\_t  
my\_mean[i] <- mean(r\_t)  
my\_error[i] <- std.error(r\_t)  
}  
t\_mean <- mean(my\_mean)  
t\_sd <- sqrt(var(my\_mean))  
#var is var(my\_mean) = 0.0002818953  
t\_stat <- t\_mean/(t\_sd/sqrt(numN))  
plot(my\_mean,type= "l")



# it looks like a distribution from the plot  
skewness(my\_mean) #-0.1605593

## [1] -0.3708221

kurtosis(my\_mean)#-0.5593615

## [1] -0.3546094

jarque.bera.test(my\_mean)

##   
## Jarque Bera Test  
##   
## data: my\_mean  
## X-squared = 2.7392, df = 2, p-value = 0.2542

#p-value = 0.4663 so it could be a normal distribution  
mean(my\_error)

## [1] 0.01673394

#the mean of the standard errors are 0.01727482 which is slightly higherer than the standard deviation

t\_stat is 3.8055 which is less than 1.96 so we reject the null hypothesis