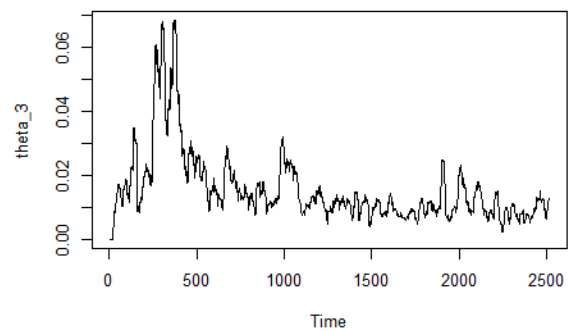
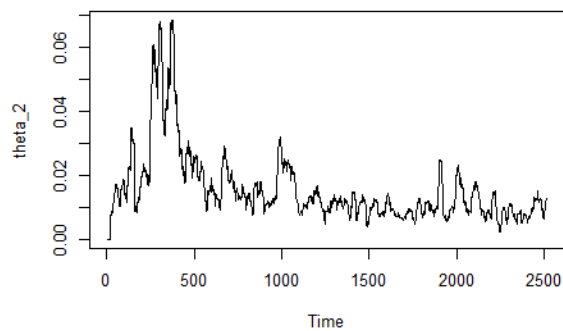
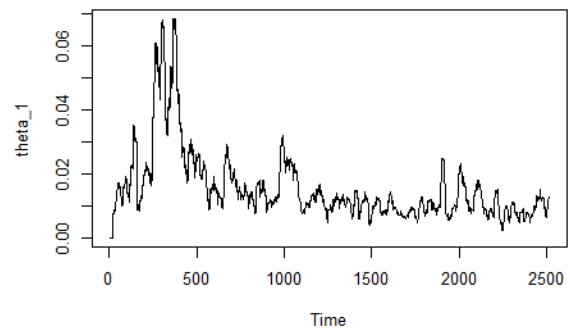
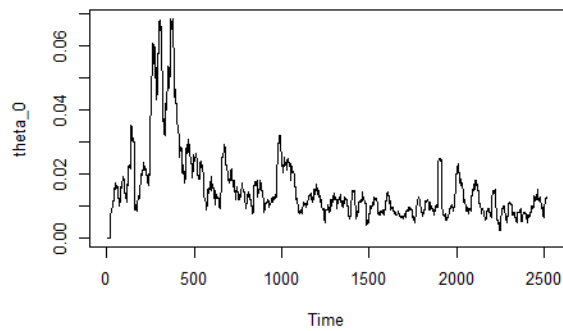


Q1:

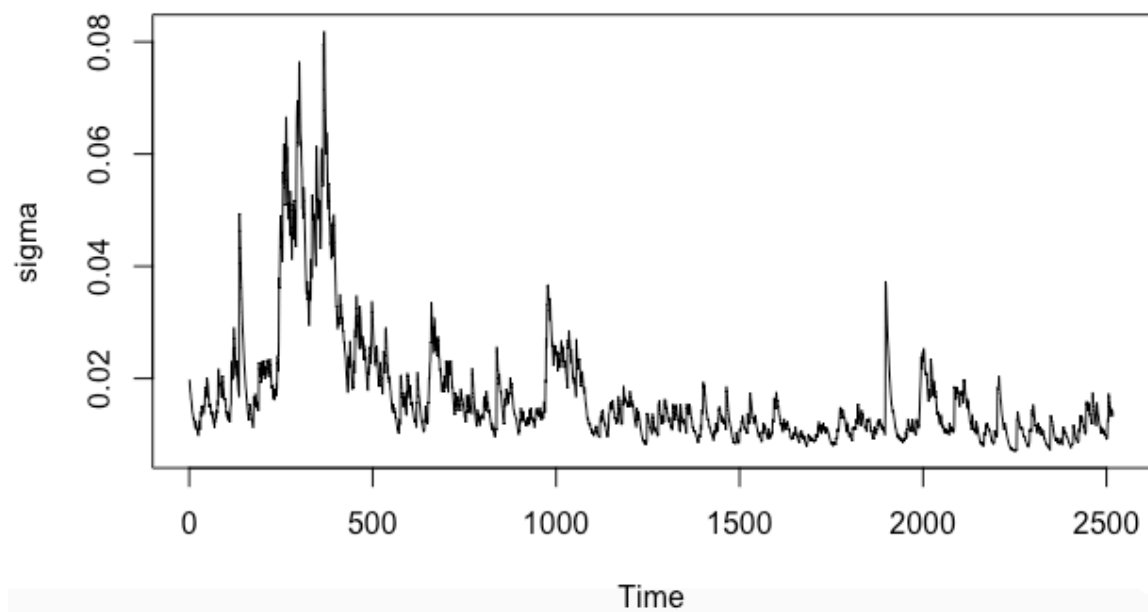


Comment:

The distribution of these 4 are similar, which give us the conclusion that the 3 estimate method are not much different from each other.

Q2:

a) Model Grach(1,1)



	0.012574305
	0.012574305
	0.012574305
	0.012966748
	0.013010396
b)EMWA	0.012965061

	0.01286618
	0.01299428
	0.01311964
	0.01324235
GRACH	0.01336250

Q3:1)

$$\begin{aligned}
 1) \gamma_1 &= \text{COV}(\Delta p_{t+1}, \Delta p_t) = E(\Delta p_{t+1} \cdot \Delta p_t) - E(\Delta p_{t+1}) \cdot E(\Delta p_t) \\
 &= \cancel{E(\Delta p_{t+1} \cdot \Delta p_t)} \\
 E(\Delta p_{t+1}) &= E(m_t + a_t c) = E(m_t) = E(m_{t-1} + u_t) = E(p_{t-1}) \\
 E(\Delta p_{t+1}) &= E(\Delta p_t) = 0 \\
 \gamma_1 &= E(\Delta p_{t+1} \cdot \Delta p_t) = E[c^2 (q_t \cdot q_{t+1} - a_{t+1} \cdot q_{t+1} - a_{t+1-1} \cdot q_t + a_{t+1-1} \cdot q_{t+1}) + \\
 &\quad c(a_{t+1} u_t - a_{t+1-1} u_t + a_t u_{t-1} q_{t+1} u_{t+1})] \\
 &= 0
 \end{aligned}$$

2)

Gama0

	-3.93669900696703e-06
--	-----------------------

Gama1

	-3.93669900696703e-06
--	-----------------------

C

theta_u	0.0279208118141753
---------	--------------------

Thetau

theta_u	0.0279208118141753
---------	--------------------

###Source code

```

2 getwd()
3 setwd("/Users/yifuhe/Desktop")
4 data<-read.csv("GE_2007-2017.csv")
5
6 n<-22
7 beta<-2/(n+1)
8
9 pt<-unlist(data[6])
10 rt<-c(NA)
11 rt[1]<-0
12 for(i in 2:nrow(data))
13   rt[i]<-log(pt[i])-log(pt[i-1])
14 |
15 t<-n
16 theta_0<-matrix(0,nrow=nrow(data))
17 while(t<=nrow(data)){
18   r_mean0<-mean(rt[(t-n+1):t]);
19   theta_0[t,1]=sqrt(1/n*sum((rt[(t-n+1):t]-r_mean0)^2));
20   t=t+1;
21 }
22
23 t<-n
24 theta_1<-matrix(0,nrow=nrow(data))
25 r_mean<-matrix(0,nrow=nrow(data))
26 while(t<=nrow(data)){
27   r_mean[t,1]<-mean(rt[(t-1-n+1):(t-1)]);
28   theta_1[t,1]=sqrt(1/n*sum((rt[(t-1-n+1):(t-1)]-r_mean[t,1])^2));
29   t=t+1;
30 }
31
32 t<-n
33 theta_2<-matrix(0,nrow=nrow(data))
34 theta_2[n-1,1]=sqrt(1/n*sum((rt[0:(n-1)]-mean(rt[0:(n-1)]))^2));
35 while(t<=nrow(data)){
36   theta_2[t,1]=(1-beta)*theta_1[t,1]+beta*theta_2[t-1,1];
37   t=t+1;
38 }
39

```

```

39
40 t<-n+1
41 theta_3<-matrix(0,nrow=nrow(data))
42 betas<-matrix(0,nrow=22)
43 for(j in 1:n) betas[j,1]=beta^j
44 betasum<-matrix(0,nrow=n)
45 while(t<=nrow(data)){
46   for(i in 1:n){
47     betasum[i,1]=betas[i,1]*theta_0[t-i,1];
48   }
49   theta_3[t,1]=sum(betasum[,1])/sum(betas[,1]);
50   t=t+1;
51 }
52
53 theta<-cbind(theta_0,theta_1,theta_2,theta_3)
54 par(mfrow = c(2,2))
55 ts.plot(theta_0)
56 ts.plot(theta_1)
57 ts.plot(theta_2)
58 ts.plot(theta_3)
59 par(mfrow = c(1,1))
60

```

Q2:

```
62 ###Q2|
63
64 library(fGarch)
65 r1<-garchFit(~garch(1,1),data=rt,trace=FALSE)
66
67 resi<-residuals(r1)
68 residual<-as.matrix(resi,ncol=1)
69
70 new5<-predict(r1,5)
71
72 ht<-as.matrix(r1@h.t)
73 sigma<-as.matrix(r1@sigma.t)
74
```

Q3:

```
76 ###Q3
77
78 gama1<-var(rt)
79
80 rt1<-as.vector(NA)
81 rt1[1]<-0
82 for(j in 2:nrow(data))
83   rt1[j]<-rt[j-1]
84
85 gama0<-cov(rt,rt1)
86
87 co_var<-as.vector(NA)
88 for(k in 1:nrow(data))
89   co_var[k]=(rt[k]-mean(rt))*(rt1[k]-mean(rt1))
90 gama_0<-1/(nrow(data)-1)*sum(co_var)
91
92 c<- sqrt(gama1)
93 theta_u<-sqrt(gama0+2*gama1)
94
```