

MUNI
ECON

Applied Financial Econometrics

Class 10: EWMA volatility model

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Alternative volatility model: EWMA

- Exponentially weighted moving average.
- Capable to address heteroskedasticity and volatility clustering
- This model assigns different weights to the past information, where more recent lags receive more importance than old observations.
- The weight assignation decays exponentially at a rate $0 < \lambda < 1$.

$$\hat{\sigma}_{i,t+1}^2 = (1 - \lambda) \sum_{n=0}^{\infty} \lambda^n r_{i,t-n}^2$$

EWMA model

- If λ moves away from 1, the EWMA assigns higher weights to the recent than the past observations.
- Then, the quality of the results depends on the election of the parameter λ .
- A value greater (lower) than the optimal goes to an under-reaction (over-reaction) to the new information input.
- Equivalently, the model could be expressed by the following recurrence relation:

$$\hat{\sigma}_{i,t+1}^2 = (1 - \lambda) r_{i,t}^2 + \lambda \sigma_{i,t}^2$$

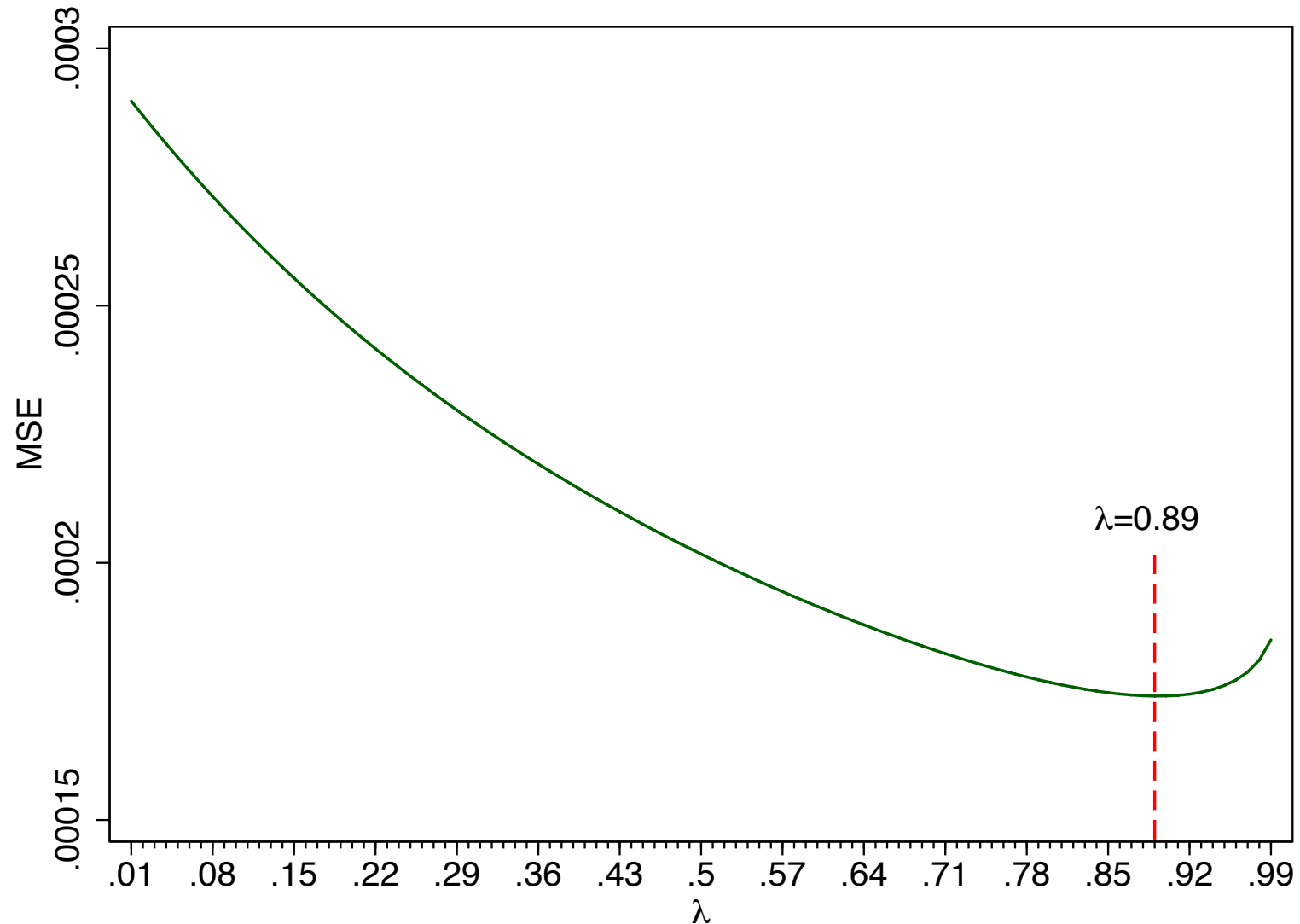
EWMA model

- The first RHS term of the previous equation updates the variance due to the new information, while the second one represents the persistence effect
- It is considered as a particular case of the of Engle and Bollerslev (1986) IGARCH(1,1), which at the same time is a restricted case of the Bollerslev (1986) standard GARCH(1,1) such that the coefficients of both lagged squared-returns and lagged variances sum one (i.e., a unit-root GARCH).

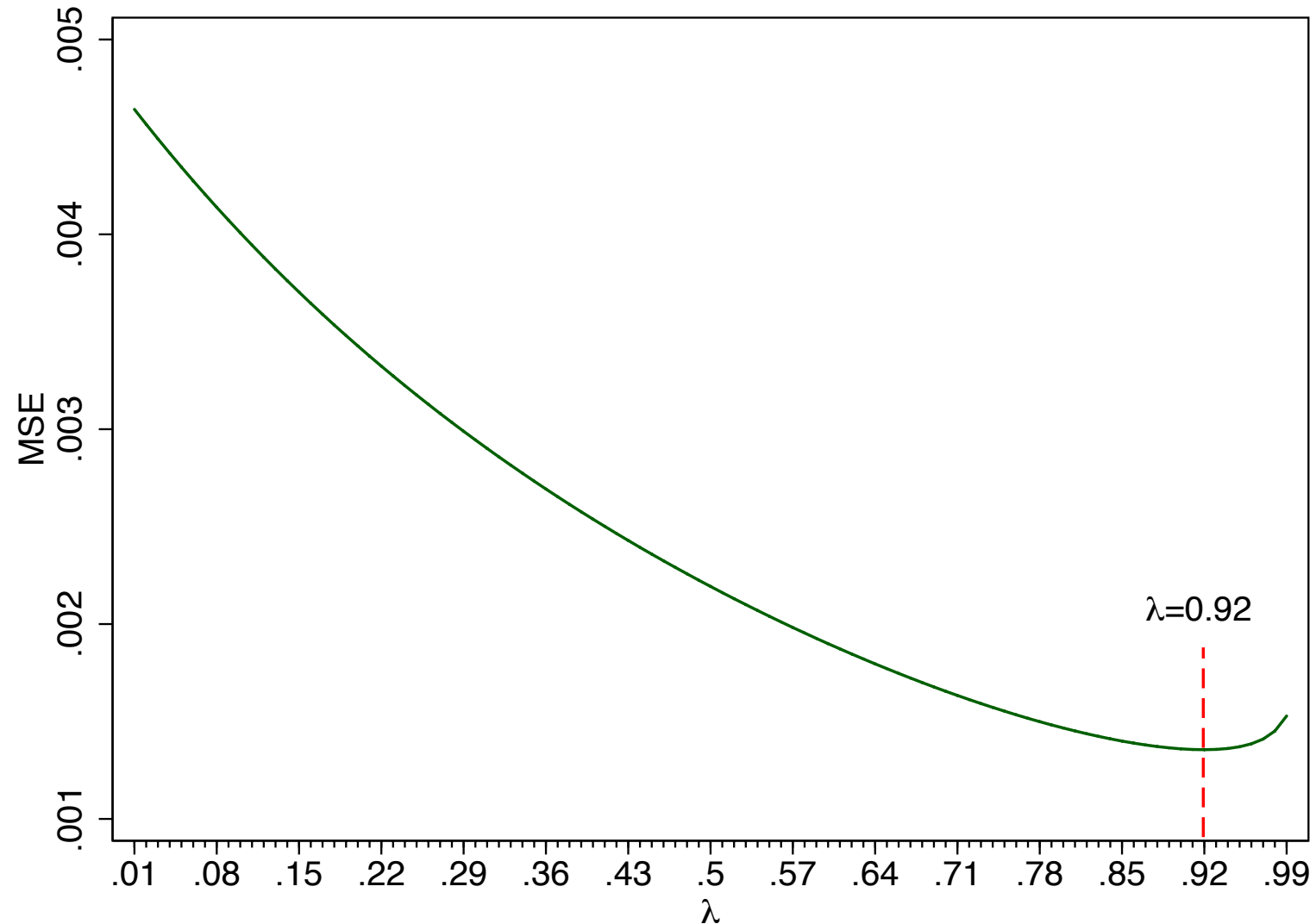
Alternative model 1: EWMA

- The EWMA method was popularized by RiskMetrics (1996), who recommends a smoothing factor equal to:
 - 0.94 for daily forecast.
 - 0.97 for 1-month forecast.
- These values are obtained minimizing the average squared errors for a large number of time-series

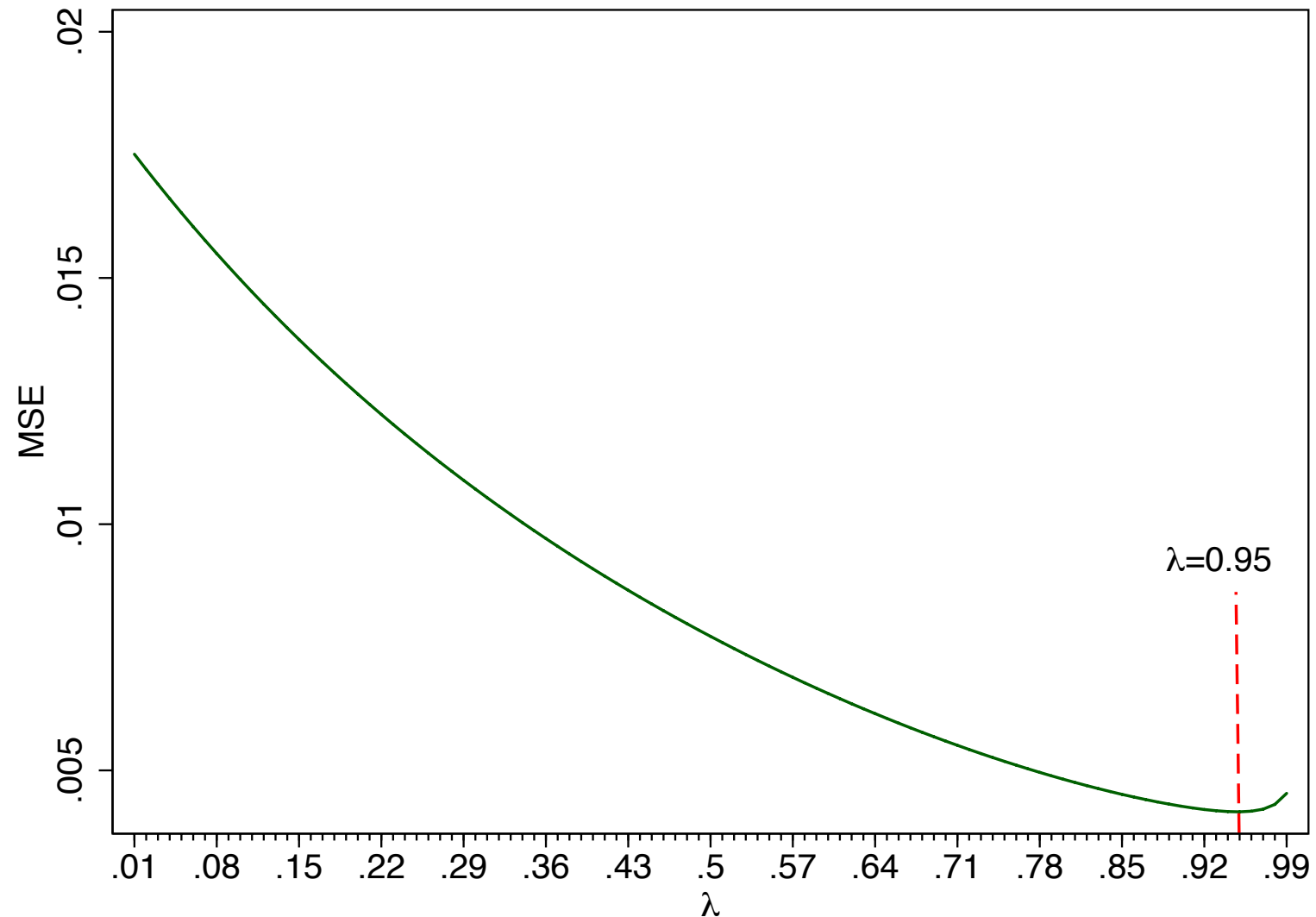
Optimal (in-sample) lambda for DJIA components for daily forecasting



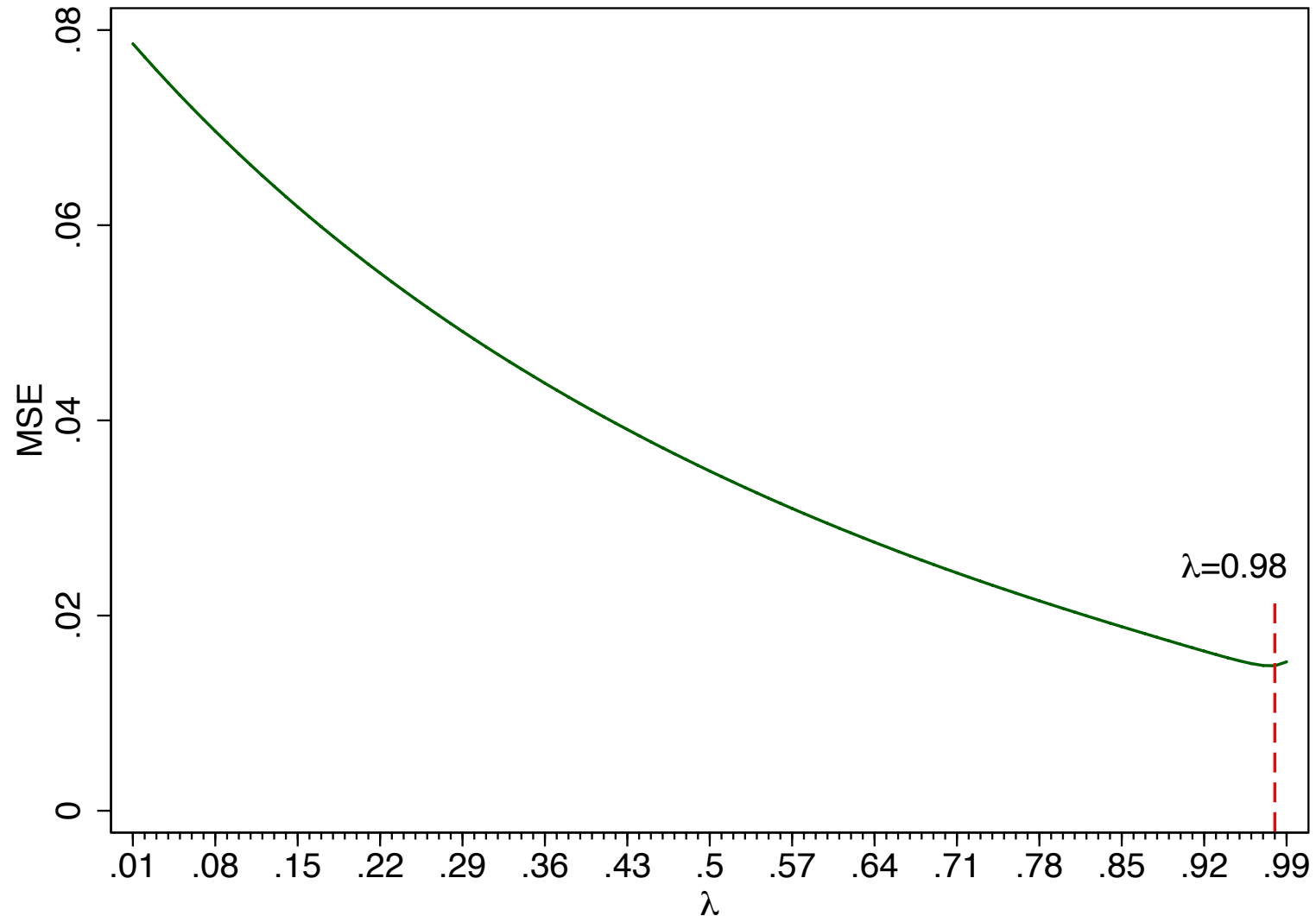
Optimal (in-sample) lambda for DJIA components for weekly forecasting



Optimal (in-sample) lambda for DJIA components for bi-weekly forecasting



Optimal (in-sample) lambda for DJIA components for monthly forecasting



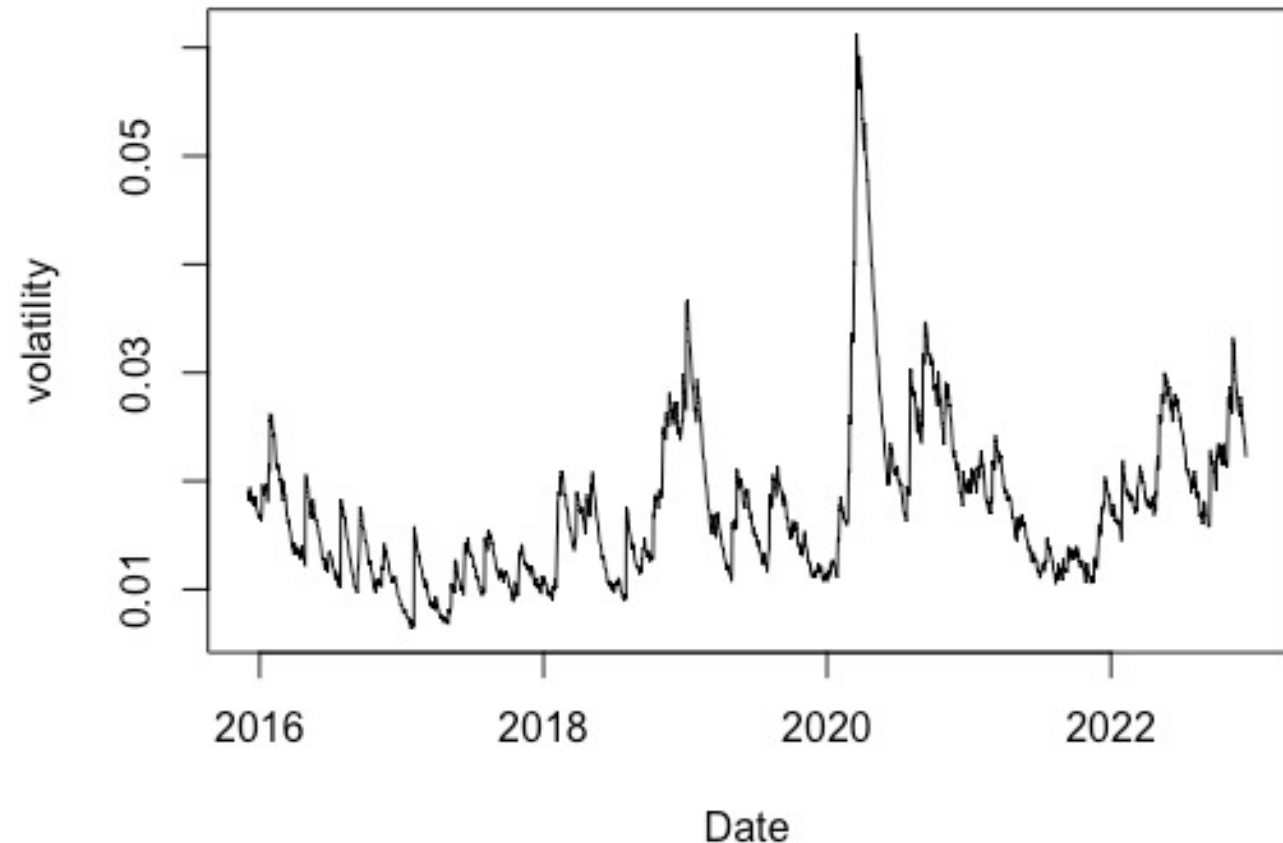
Implementing EWMA (constant lambda)

– Option 1: Quarks package

```
library('quantmod')
getSymbols(c('AAPL', '^GSPC'), src='yahoo',
          from="2015-12-01", periodicity = 'daily')
r.AAPL<-diff(log(AAPL[,6]))
r.AAPL<-na.omit(r.AAPL)
```

```
install.packages("quarks")
library('quarks')
EWMA_var<-ewma(r.AAPL, lambda = 0.94)
EWMA_vol<-sqrt(EWMA_VAR)
plot(time(r.AAPL), EWMA_vol, type='l',
     main='EWMA volatility (lambda=0.94)',
     xlab='Date', ylab='Volatility')
```

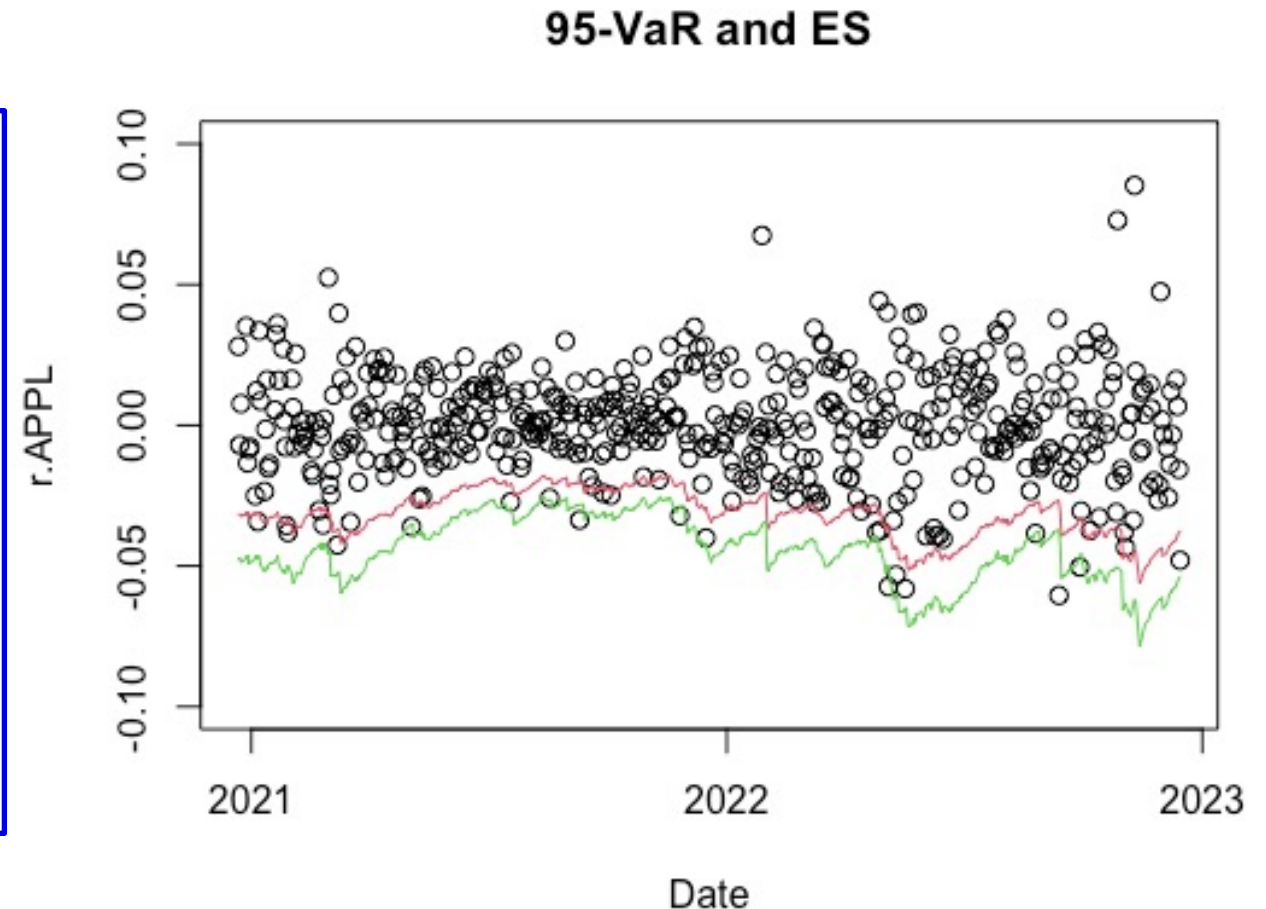
EWMA volatility (lambda=0.94)



VaR and ES calculation

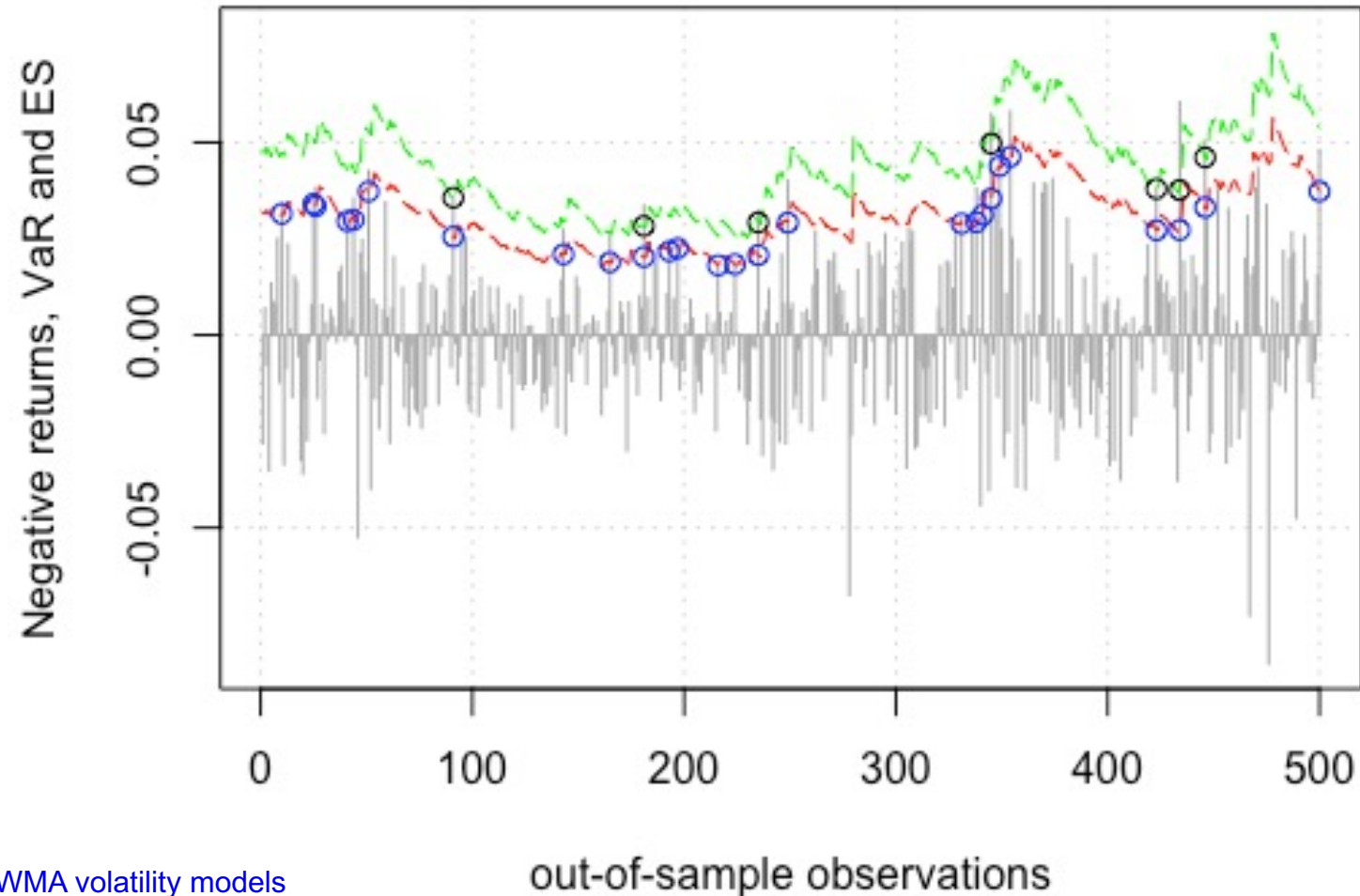
```
R<-as.numeric(r.AAPL)
n <- length(r.AAPL)
Rolling <- rollcast(R, p = 0.95, model = 'EWMA',
                  method = 'vwhs', lambda = 0.94,
                  nwin = 1000, nout=500)
#nout: number of obs. for out-of-sample forecasting
#nwin: window size for rolling forecasts
#vwhs: volatility weighted historical simulation
VaR95<-Rolling$VaR
ES95<-Rolling$ES

plot(time(r.AAPL[(n-499):n]),Rolling$xout,ylim=c(-0.1,0.1),
     ylab='r.APPL',xlab='Date',
     main='95-VaR and ES')
lines(time(r.AAPL[(n-499):n]),-VaR95,type='l',col=2)
lines(time(r.AAPL[(n-499):n]),-ES95,type='l',col=3)
```



VaR and ES calculation

VaR (red) and ES (green) - one-step forecasts



```
plot(Rolling)
```

Backtesting VaR

```
cvgtest(Rolling, conflvl = 0.95)
```

```
-----  
|                Test results                |  
-----  
Method: Volatility Weighting  
Model: EWMA  
-----  
|          Unconditional coverage test          |  
-----  
H0: w = 0.95  
  
p_[uc] = 0.8384  
  
Decision: Fail to reject H0
```

```
-----  
|                Independence test                |  
-----  
H0: w_[00] = w_[10]  
  
p_[ind] = 0.0137  
  
Decision: Reject H0
```

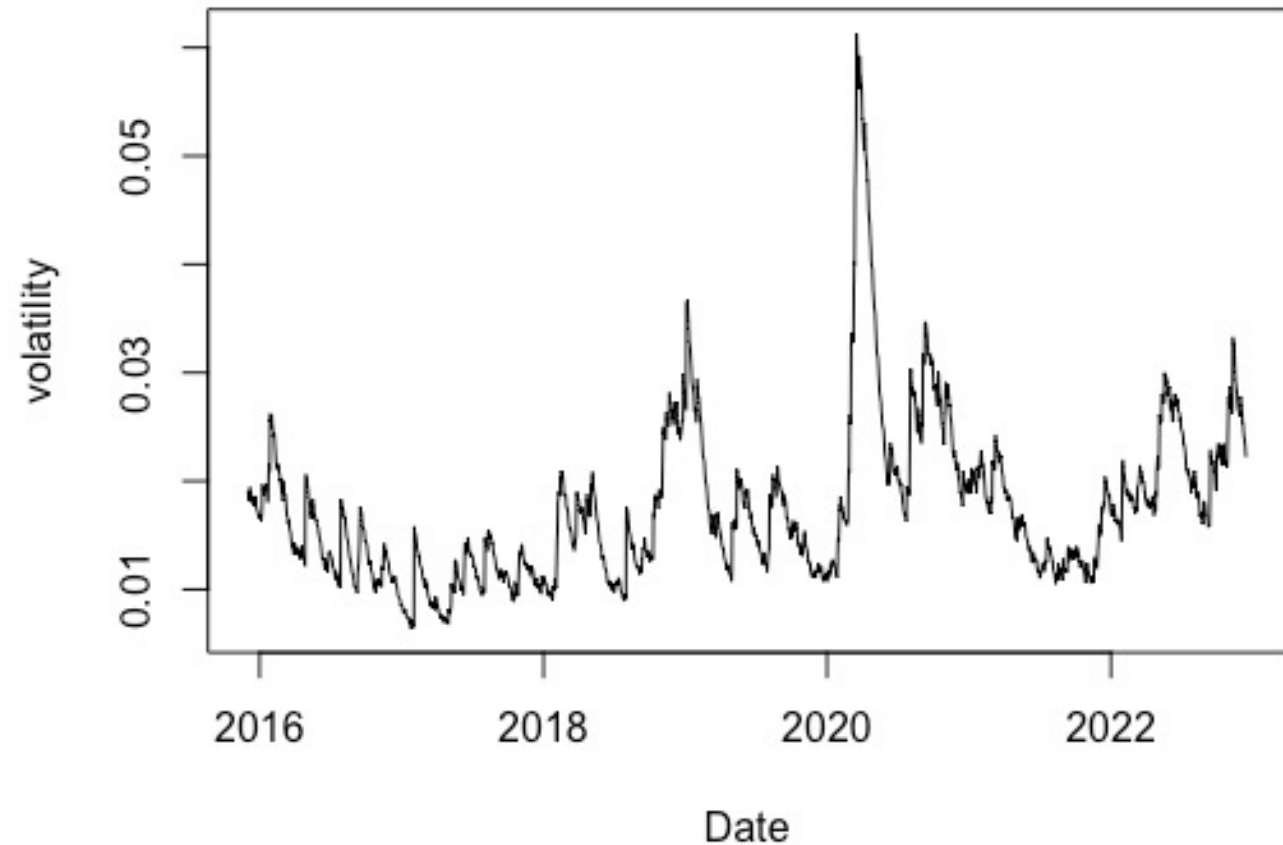
```
-----  
|          Conditional coverage test          |  
-----  
H0: w_[00] = w_[10] = 0.95  
  
p_[cc] = 0.0469  
  
Decision: Reject H0  
-----
```

Implementing EWMA (constant lambda)

– Option 2: Rugarch package

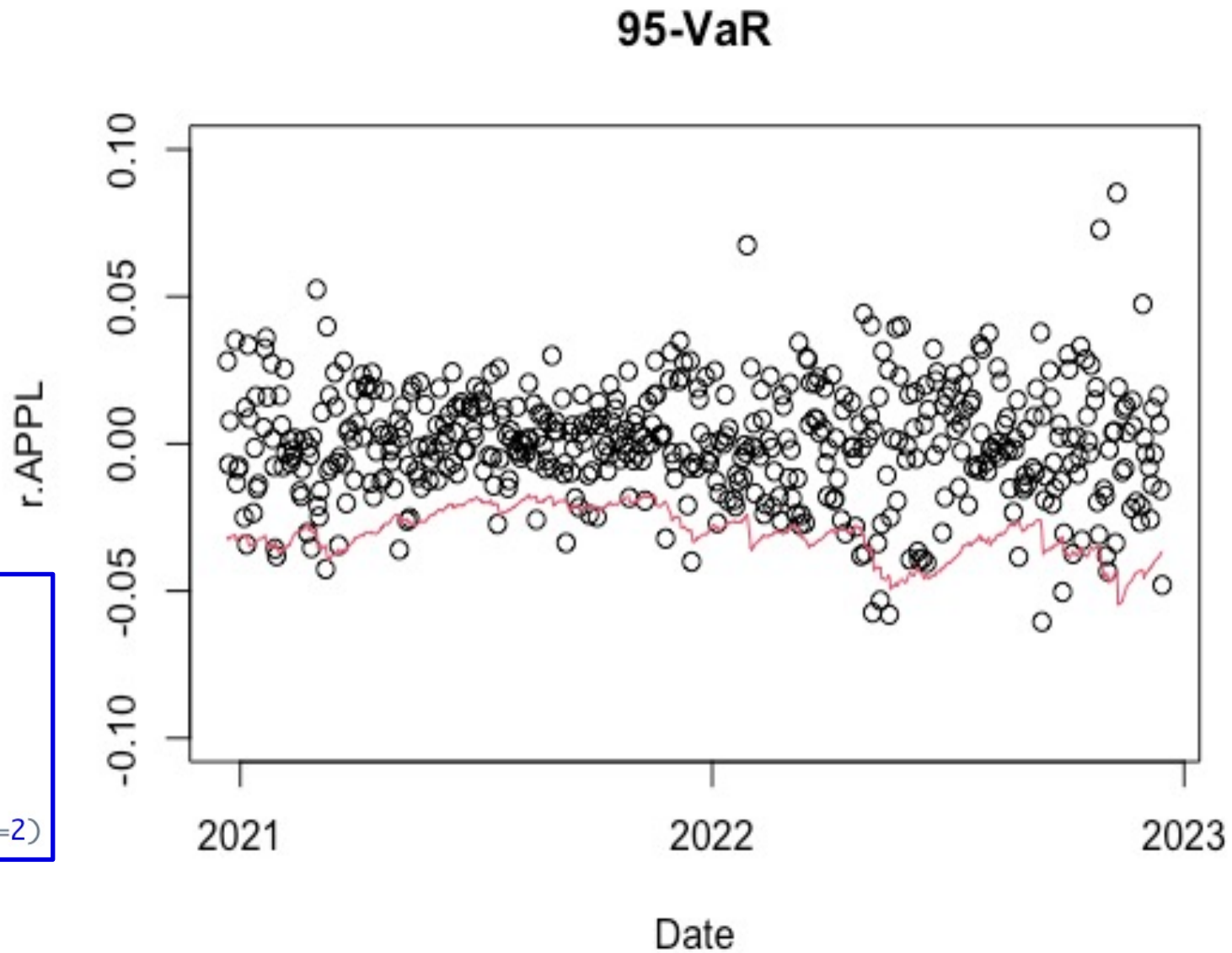
```
library('rugarch')
spec = ugarchspec(mean.model=list(armaOrder=c(0,0),
  include.mean=FALSE),
  variance.model = list(model = "iGARCH",
  garchOrder = c(1,1)),
  distribution.model = "norm",
  fixed.pars = list(omega=0, alpha1=1-0.94))
EWMA2<-ugarchfilter(spec,r.AAPL)
EWMA2_vol<-EWMA2@filter$sigma
plot(time(r.AAPL),EWMA2_vol,type='l',
  main='EWMA volatility (lambda=0.94)',
  xlab='Date',ylab='Volatility')
```

EWMA volatility (lambda=0.94)



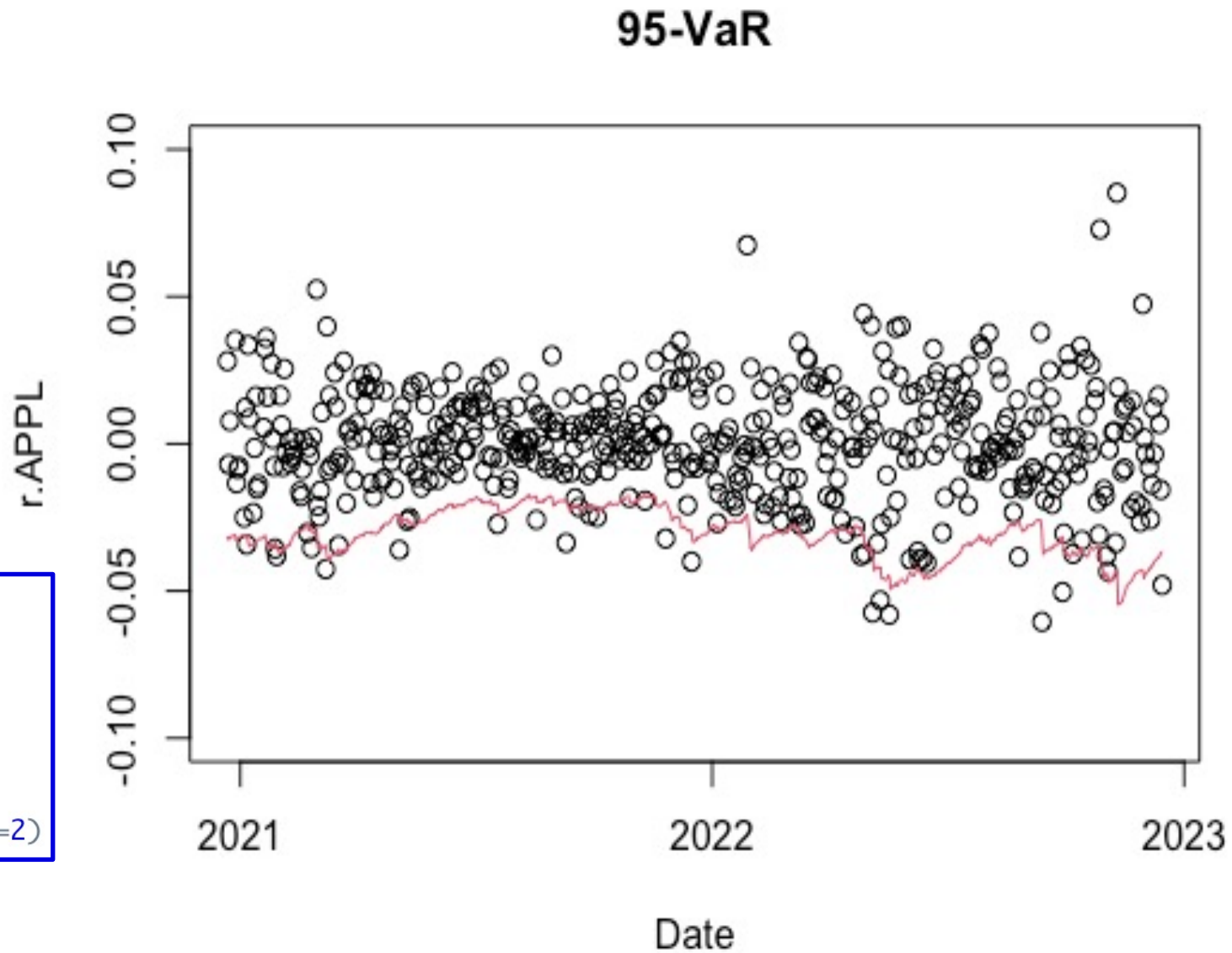
VaR Calculation

```
Q<-quantile(EWMA2,prob=0.05)
VaR_95_2<-Q[(n-499):n]
plot(time(r.AAPL[(n-499):n]),r.AAPL[(n-499):n],
     ylim=c(-0.1,0.1),
     ylab='r.AAPL',xlab='Date',
     main='95-VaR')
lines(time(r.AAPL[(n-499):n]),VaR_95_2,type='l',col=2)
```



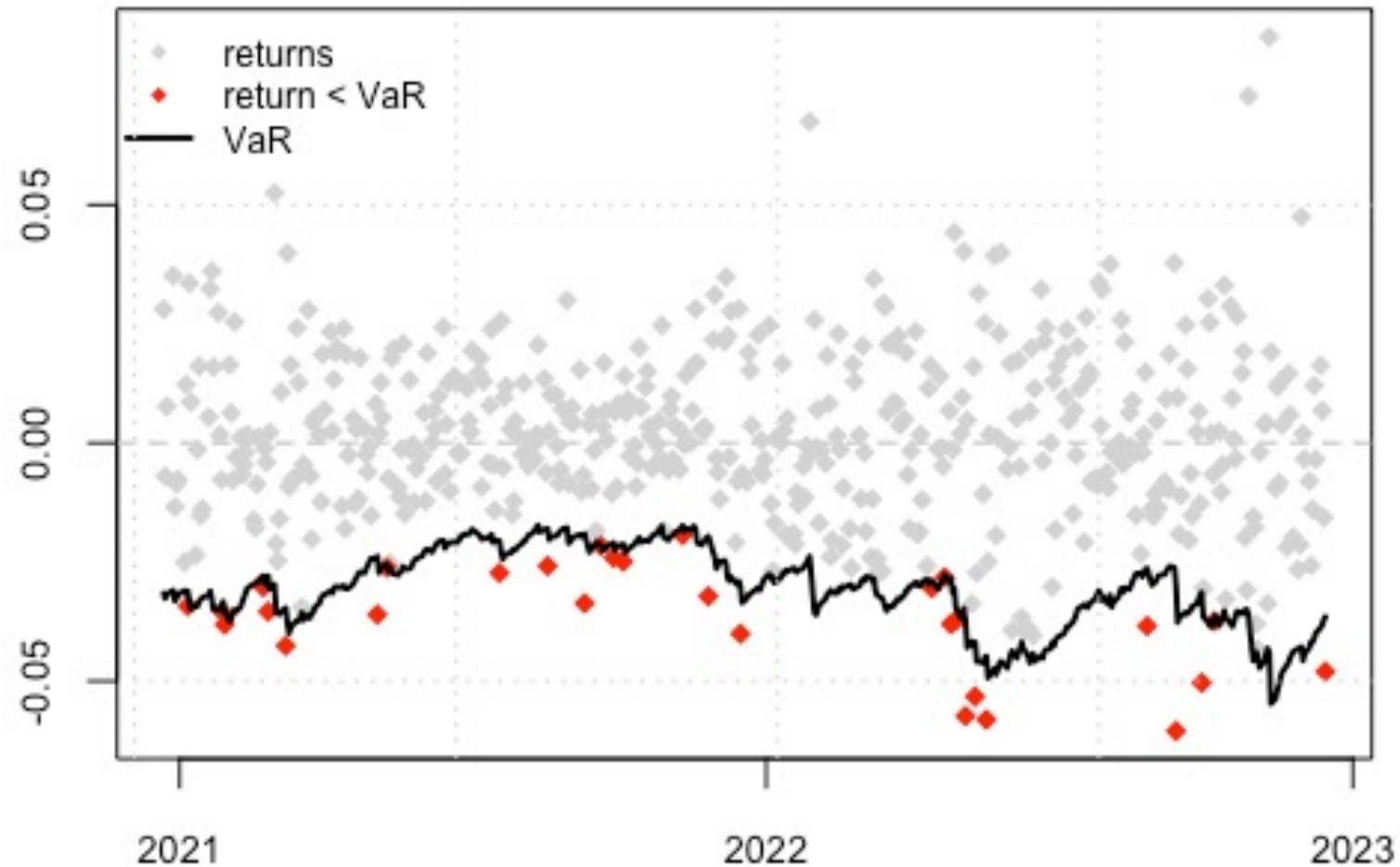
VaR Calculation

```
Q<-quantile(EWMA2,prob=0.05)
VaR_95_2<-Q[(n-499):n]
plot(time(r.AAPL[(n-499):n]),r.AAPL[(n-499):n],
     ylim=c(-0.1,0.1),
     ylab='r.APPL',xlab='Date',
     main='95-VaR')
lines(time(r.AAPL[(n-499):n]),VaR_95_2,type='l',col=2)
```



VaR Calculation

```
VaRplot(0.05, r.AAPL[(n-499):n], VaR_95_2)
```



Backtesting VaR

```
VaRTest(0.05, r.AAPL[(n-499):n], VaR_95_2, conf.level = 0.95)
```

```
$expected.exceed  
[1] 25  
  
$actual.exceed  
[1] 29  
  
$uc.H0  
[1] "Correct Exceedances"  
  
$uc.LRstat  
[1] 0.6421395  
  
$uc.critical  
[1] 3.841459  
  
$uc.LRp  
[1] 0.4229371  
  
$uc.Decision  
[1] "Fail to Reject H0"
```

```
$cc.H0  
[1] "Correct Exceedances & Independent"  
  
$cc.LRstat  
[1] 0.9528143  
  
$cc.critical  
[1] 5.991465  
  
$cc.LRp  
[1] 0.6210106  
  
$cc.Decision  
[1] "Fail to Reject H0"
```

References

- Tim Bollerslev. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31 (3):307–327, 1986.
- Robert F. Engle and Tim Bollerslev. Modelling the persistence of conditional variances. *Econometric Reviews*, 5(1):1–50, 1986.
- RiskMetrics. Technical Document, J.P.Morgan/Reuters, New York, 1996. Fourth Edition.