Stats509 Homework 9

Di Lu, Apr.4, 2018

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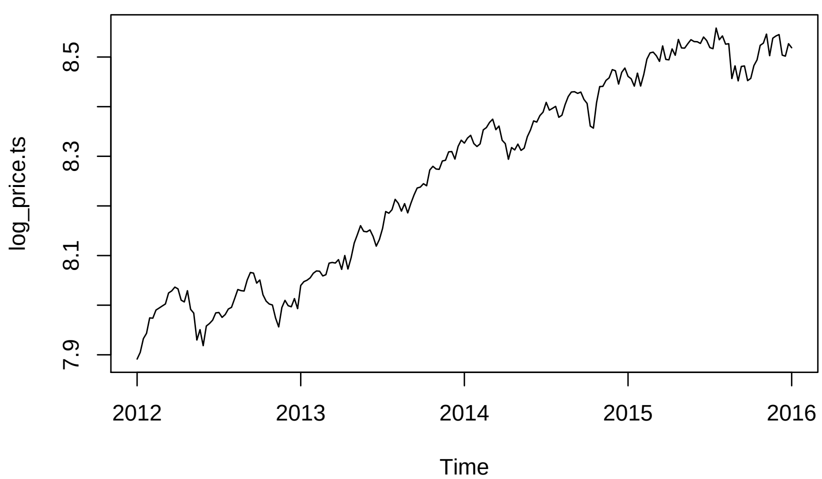
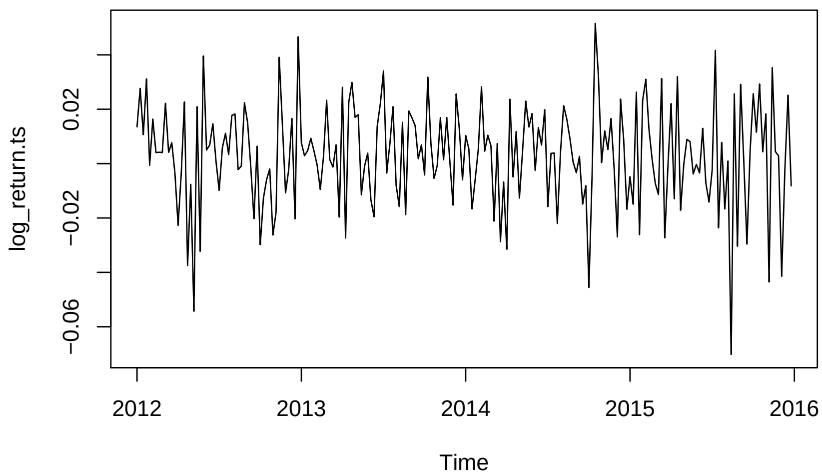
(a)

Log adj.price and log returns have time sieres as below:

```
XX = read.csv("NASDAQ_Wkly_Jan1_2012_Dec31_2015.csv",header=TRUE)
N_wk <- rev(XX$Adj.Close)
log_price = log(N_wk)
log_return = diff(log(N_wk)) # generating log returns
net_return = diff(N_wk)/N_wk[1:208]
adj.price.ts = ts(data = N_wk ,start = c(2012,1), frequency = 52)
log_price.ts = ts(data = log_price ,start = c(2012,1), frequency = 52)
log_return.ts = ts(data = log_return ,start = c(2012,1), frequency = 52)
net_return.ts = ts(data = net_return, start = c(2012,1), frequency = 52)
plot(log_price.ts, type = "l")
```

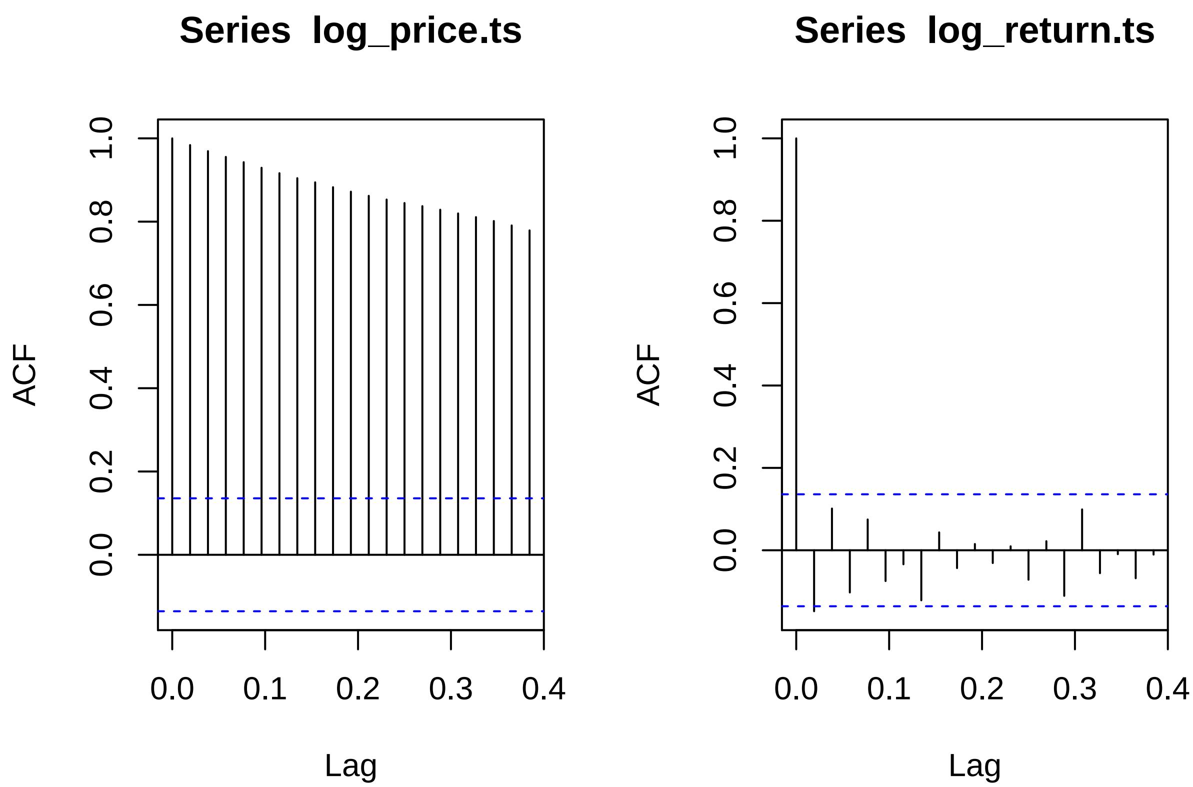



```
plot(log_return.ts, type = "l")
```



Log adj.price and log returns have ACF function as below. From the plots we can see: log adj.price is non-stationary with an upward trend. And from ACF plot, it has significant ACF different from 0 even at lag 20. log return is swinging around 0 and seems like a positive drift. At lag 1, it has ACF different from 0. Log return looks like a stationary time series.

```
par(mfrow=c(1,2))
acf(log_price.ts, lag.max = 20)
acf(log_return.ts, lag.max = 20)
```



(b)

Fitting the Arima model for log adj.price and use AIC as criteria to choose model, we choose the best model is ARIMA(1,1,1) with drift. Carrying out diagnostic on the fitting, we can find out ACF shows no sign of autocorrelation, the Ljung box test shows there is little correlation in the residuals. The normal QQ plot shows that the lower tail the residual does not follow normal well.

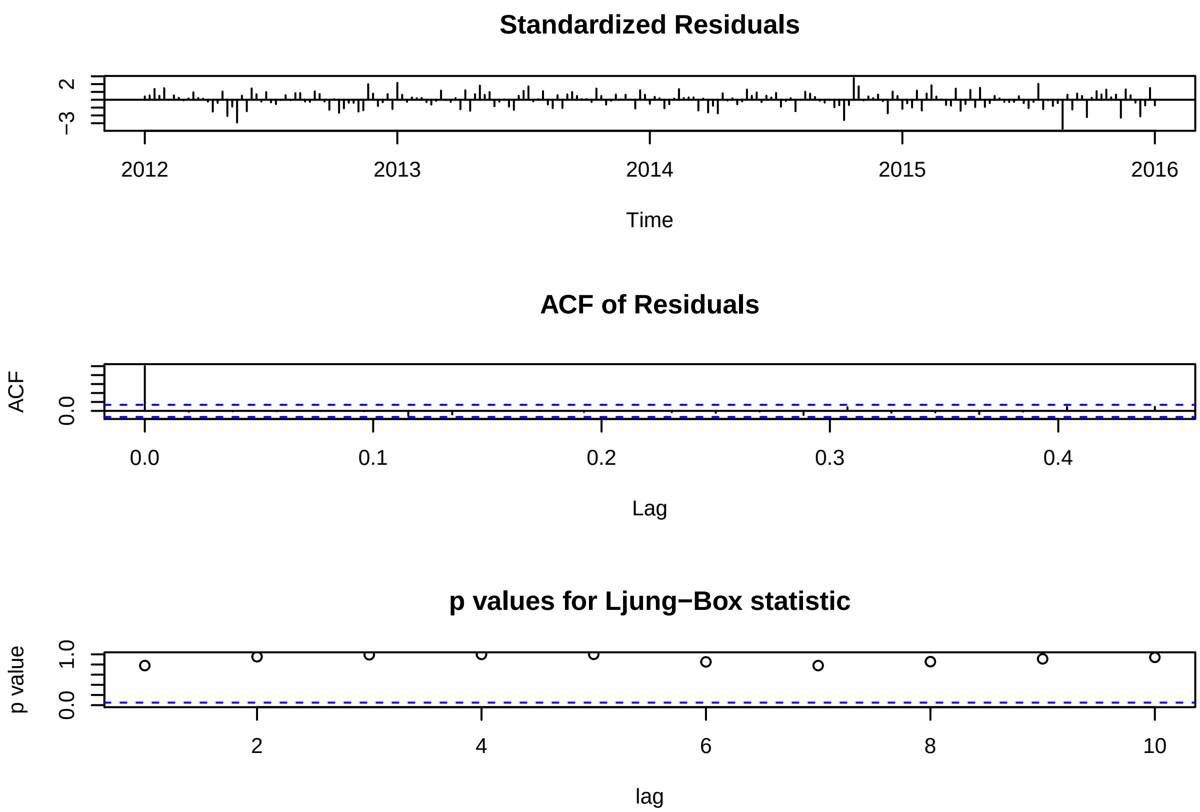
```
library(forecast)# 10 step prediction on log Adj. Close Price
```

```
## Warning: package 'forecast' was built under R version 3.4.4
```

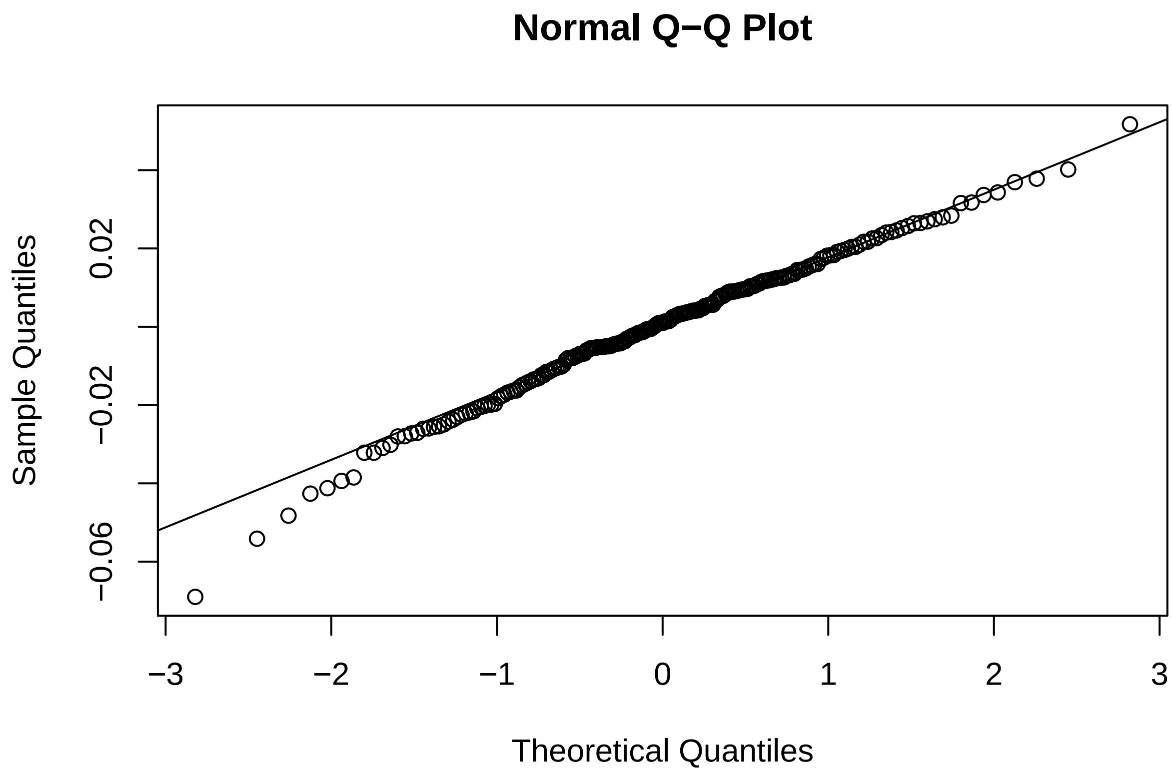
```
ts.est = auto.arima(log_price.ts, max.p = 4, max.q = 4, ic = "aic", seasonal = FALSE, stepwise = FALSE)
ts.est
```

```
## Series: log_price.ts
## ARIMA(1,1,1) with drift
##
## Coefficients:
##           ar1     ma1   drift
##       -0.8588  0.7577  0.0030
## s.e.   0.1724  0.2248  0.0012
##
## sigma^2 estimated as 0.0003453:  log likelihood=535.41
## AIC=-1062.82   AICc=-1062.62   BIC=-1049.47
```

```
tsdiag(ts.est)
```



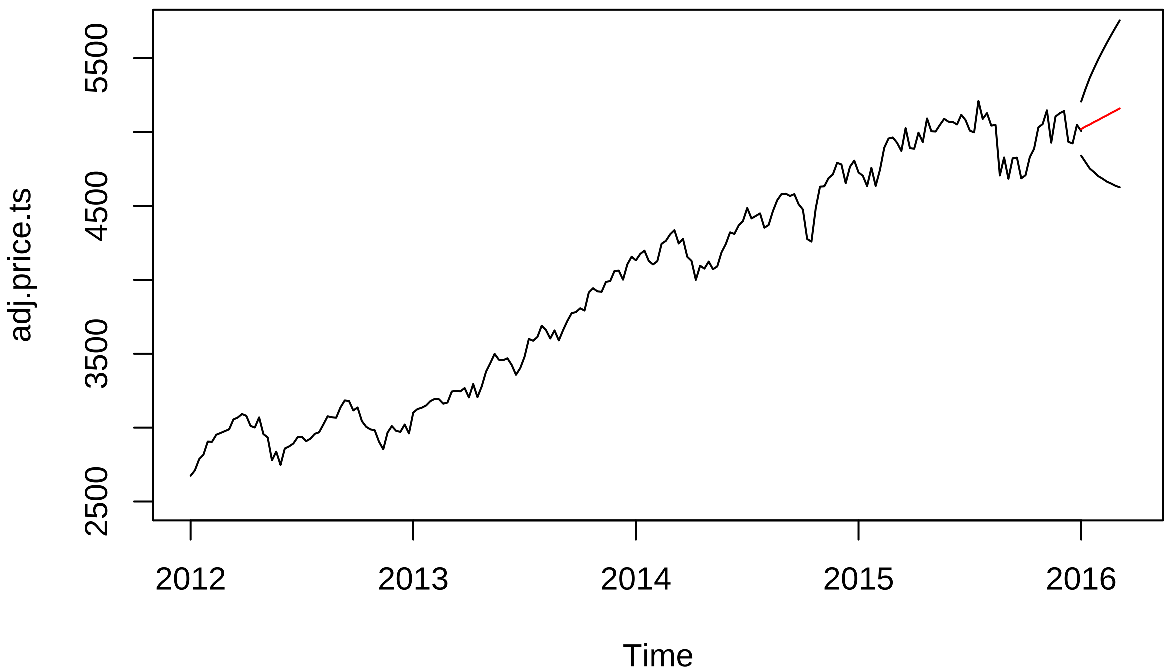

```r
source("startup.R")
myqqnorm(ts.est$residuals)
```



(c)

Based on model in (b), we do 10 step prediction on Adj. Close Price. With the model fitted to log Adj.price, we do exponetial transformation and also include 95% Confidence Interval.

```
# 10 step prediction on Adj. Close Price
forecasts = forecast(ts.est, 10)
plot(adj.price.ts, xlim = c(2012,2016.2), ylim = c(2500, 5700))
lines(seq(from = 2016, by = 1/52, length = 10), exp(forecasts$mean), col = "red")
lines(seq(from = 2016, by = 1/52, length = 10), exp(forecasts$upper[,2]))
lines(seq(from = 2016, by = 1/52, length = 10), exp(forecasts$lower[,2]))
```



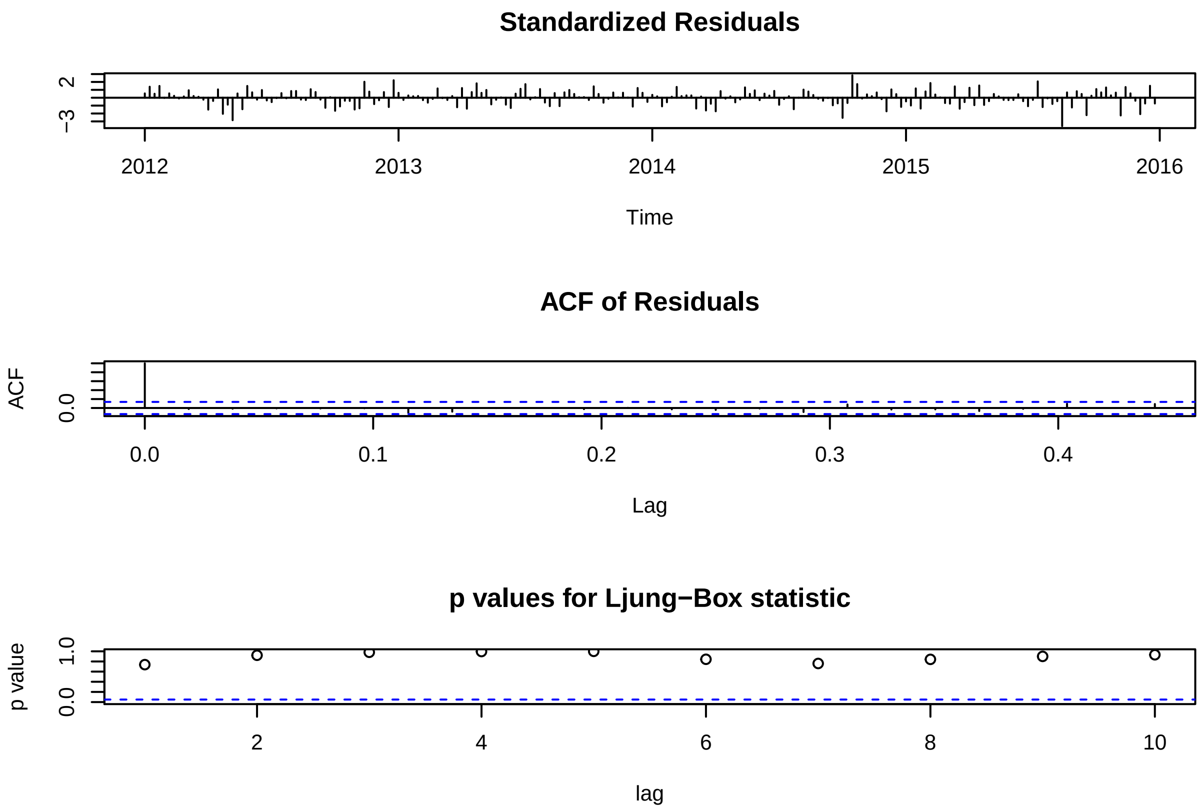
(d)

Based on model in (b), considering the Net returns, we do exponetial transformation and also include 95% Confidence Interval. The model for Net returns is basically the same, and the diagnotics shows no autocorrelation in residuals. Including the 95% confidence interval, we can show the prediction for Net Returns are as follows.

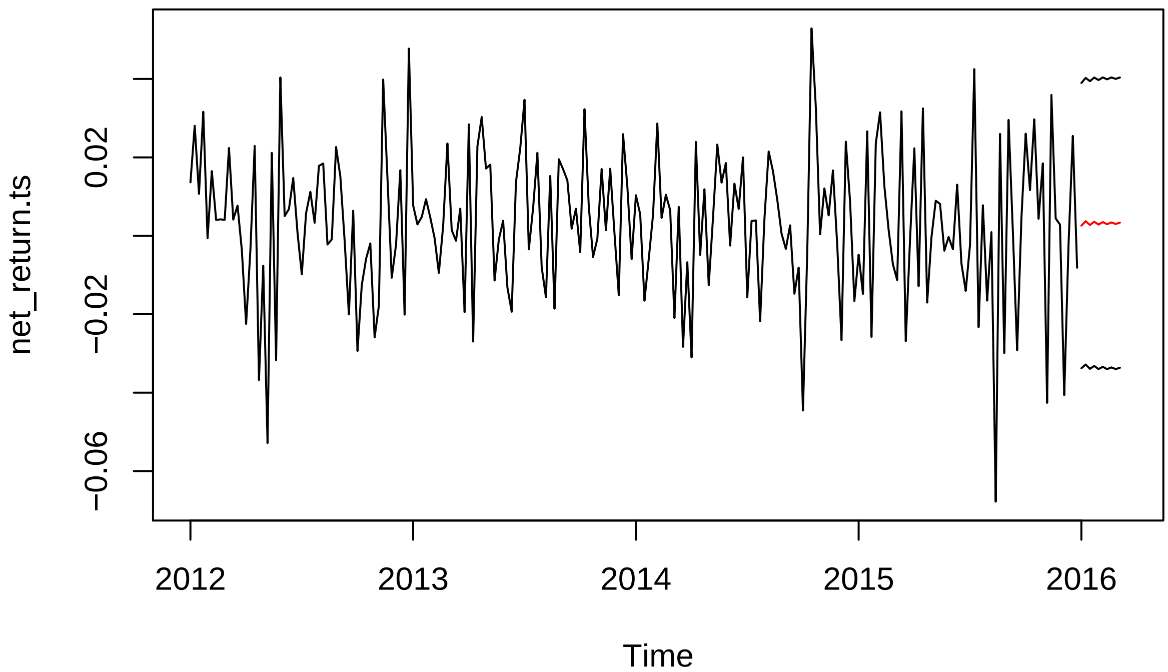
```
# 10 step prediction on Net Returns
net_return.est = auto.arima(net_return.ts, max.p = 4, max.q = 4, ic = "aic", seasonal = FALSE, stepwise
net_return.est
```

```
## Series: net_return.ts
## ARIMA(1,0,1) with non-zero mean
##
## Coefficients:
##           ar1     ma1    mean
##       -0.8641  0.7654  0.0032
## s.e.   0.1709  0.2236  0.0012
##
## sigma^2 estimated as 0.0003444:  log likelihood=535.59
## AIC=-1063.18   AICc=-1062.99   BIC=-1049.83
```

```r
tsdiag(net_return.est)
```




```r
forecasts_net = forecast(net_return.est, 10)
plot(net_return.ts, xlim = c(2012,2016.2))
lines(seq(from = 2016, by = 1/52, length = 10), forecasts_net$mean, col = "red")
lines(seq(from = 2016, by = 1/52, length = 10), forecasts_net$upper[,2])
lines(seq(from = 2016, by = 1/52, length = 10), forecasts_net$lower[,2])
```



(e)

By predict the two week ahead log adj.price, we get its mean prediction and 95% confidence interval. By assumption of normal distribution, we get standard error as 95% upper bound - 95% lower bound as 2 * 1.96 times sigma. By finding the quantile 0.005 of given mean and standard error, we get correspoding closing price at two weeks. And the Relative VaR = - (quantile adj.price - recent adj.price) - 1 = 0.056. Since from (b), we find the log_price fitting residual, we find the tail is heavier than normal distribution. The accuracy of using this model may underestimated the relative VaR.

```
forecasts_2wks = forecast(ts.est, 2) # use Arima model from (b)
mu = forecasts_2wks$mean[2]
sigma = (forecasts_2wks$upper[,2][2] - forecasts_2wks$lower[,2][2]) / (2*1.96)
quantile_adj.price = exp(qnorm(.005, mean = mu, sd = sigma, lower.tail = TRUE))
rel_VaR = - (quantile_adj.price/ adj.price.ts[209] - 1)
rel_VaR
```

```
## [1] 0.05671277
```