CSC 425 HW 5
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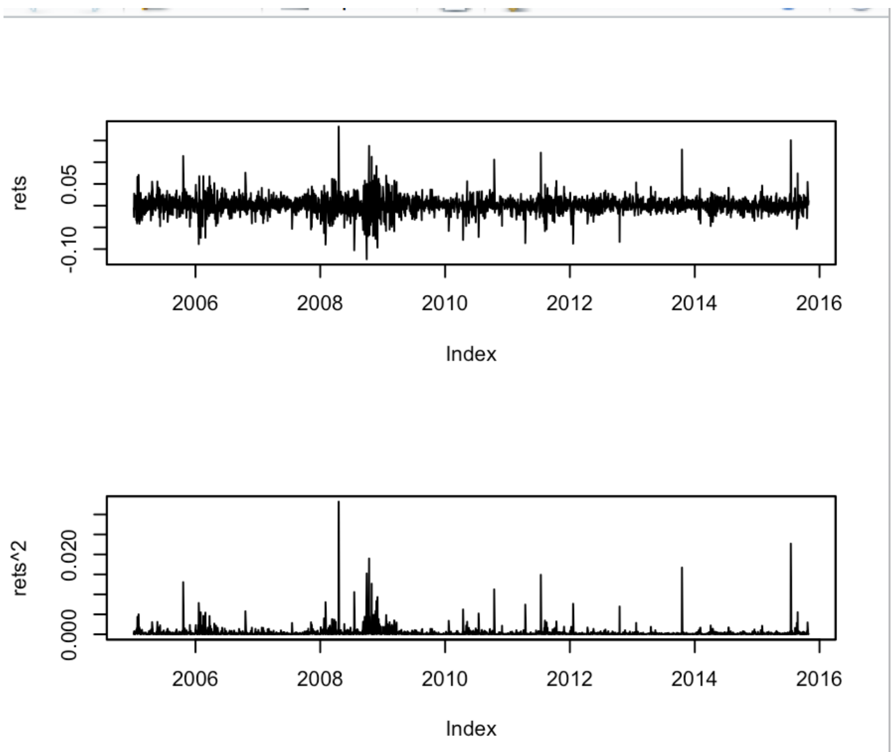
Problem 2. Analyzing Volatility of Google Stocks Data
*this data has 250 daily points for each complete year. Note: use zoo function

1. Create a variable for stock log returns X_t
   rets=log(ts/lag(ts,-1))
   retSimple=coredata(rets);

2. Create the time plot for the stock log returns and analyze the time plot.



   The time plot for returns (top, above) shows returns vary around zero, with a large spike in 2008 that appears to be a shock affect after a low return at the beginning off the year. This is followed by a high volatility period in 2009. There are also large isolated spikes in 2013 and 2015, and a few other smaller spikes. Conditional vitality is non-constant over time.

3. Are the log returns serially correlated?

   No. We have the following output for Box- Ljung tests on log returns:

Box-Ljung test
data: coredata(rets)
X-squared = 0.041901, df = 2, p-value = 0.9793

Box-Ljung test
data: coredata(rets)
X-squared = 0.54869, df = 4, p-value = 0.9686

Box-Ljung test
data: coredata(rets)
X-squared = 3.4749, df = 6, p-value = 0.7473

Because of the large p-values, we fail to reject the null hypothesis of independence. We cannot conclude the log returns are serially correlated.

4. Evidence of ARCH effects in log returns?

Yes. We have the following output for Box-Ljung tests on squared log returns:

Box-Ljung test
data: coredata(rets^2)
X-squared = 19.223, df = 2, p-value = 6.695e-05

Box-Ljung test
data: coredata(rets^2)
X-squared = 41.654, df = 4, p-value = 1.968e-08

Box-Ljung test
data: coredata(rets^2)
X-squared = 71.149, df = 6, p-value = 2.376e-13

Given such small p values, we reject the null hypothesis of no autocorrelation and conclude there is an ARCH affect.

6.