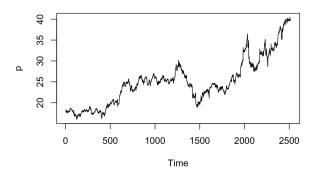
Problem Set 1: Computer Exercises

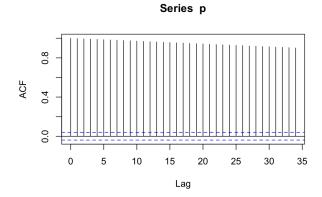
Jenny Petrova

February 6, 2025

- 6. We examine the stock returns from Walmart, Inc. from 2010 to 2019. This data is obtained from Yahoo Finance using the **quantmod** package in R.
 - (a) This data has 6 variables and 2515 observations.
 - (b) Time series plot of clos prices (**p**):



Autocorrelation Function (ACF) of **p**:

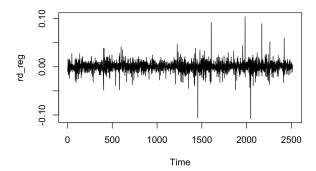


Value of first 4 lags of **p**:

Lag 0	Lag 1	Lag 2	Lag 3	Lag 4
1.000	0.997	0.994	0.991	0.988

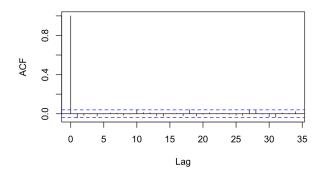
The plots above show serial dependence in the share prices. The time series plot displays an upward trend in the close prices. The ACF plot shows the lags exceed the confidence interval bounds, suggesting dependence between current and past close prices.

(c) Time series plot of daily log returns (rd):



ACF of rd:

Series rd_reg



Value of first 4 lags for rd:

Lag 0	Lag 1	Lag 2	Lag 3	Lag 4
1.000	-0.043	-0.017	-0.003	-0.024

The above plots do not show strong serial dependence in the daily log returns. In the time series plot, we see the daily log returns display a constant mean, centered at ≈ 0 . The ACF plot shows the lags remain within the confidence interval bounds at each lag, suggesting no dependence between the current and past daily log returns.

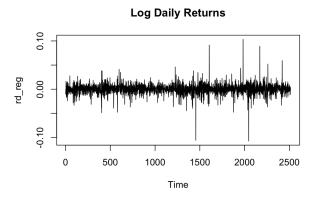
(d) First 5 observations of \mathbf{rd} :

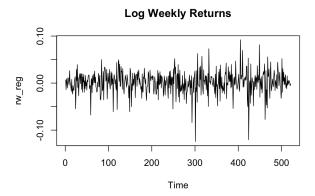
Date	Value
2010-01-05	-0.010007513
2010-01-06	-0.002237606
2010-01-07	0.000559871
2010-01-08	-0.005050052
2010-01-11	0.016366353

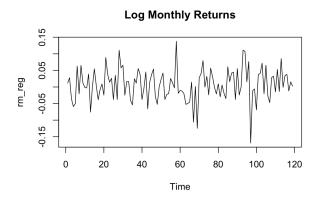
Statistical values of rd (over the entire sample period):

Mean	Median	Standard Deviation
0.0003139399	0.0005703705	0.0108949

- (e) i There are 522 observations for weekly log returns (\mathbf{rw}) and 120 observations for monthly log returns (\mathbf{rm}) .
 - ii Time series plots of \mathbf{rd} , \mathbf{rw} , and \mathbf{rm} :

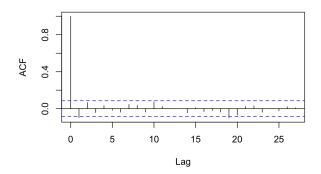






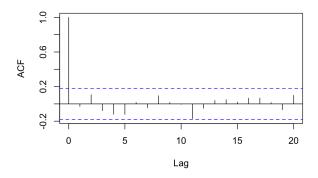
iii ACF for \mathbf{rw} :

Series rw_reg



ACF for **rm**:

Series rm_reg



```
iv Ljung-Box tests for \mathbf{rd}, \mathbf{rw}, \mathbf{rm}:
Null Hypothesis H_0 = \rho_0 = \rho_1 = \ldots = \rho_m = 0.
Alternative Hypothesis H_1: \rho_i \neq 0 for some i \in \{0, 1, \ldots, m\}

> Box.test(rd_reg, lag=10, type="Ljung-Box")

    Box-Ljung test

data: rd_reg
X-squared = 12.329, df = 10, p-value = 0.2636

> Box.test(rw_reg, lag=10, type="Ljung-Box")

    Box-Ljung test

data: rw_reg
X-squared = 15.394, df = 10, p-value = 0.1183

> Box.test(rm_reg, lag=10, type="Ljung-Box")

    Box-Ljung test

data: rm_reg
X-squared = 7.4489, df = 10, p-value = 0.6825
```

The results of the Ljung-Box tests suggest we *cannot* reject the null hypothesis for the daily, weekly, or monthly log returns. Hence there is no strong statistical evidence to suggest autocorrelation between the lags for each return.

v Examining the log returns at different frequencies, we see no trends in the mean over time, for each of the frequencies observed. This observation suggests independent returns, and is consistent with the results of the Ljung-Box tests for the daily, weekly, and monthly log returns. The time series plot for daily log returns exhibits clear stationary, with a constant mean centered around 0. For increased time periods between observations (i.e. weekly or monthly observations), though the time series plots show greater variation in the return prices, the mean remains constant over time (returns remain centered around a constant value).