Prof. Dr. Natalie Packham Summer term 2021
LV-Nr. 425093

Computational Finance and FinTech – Exercises 4

Exercise 1. Load the data from the file `hprice.xls` into a data frame. The file contains data on $N = 546$ houses sold in Windsor, Canada. The dependent variable Y is the sales price of the house in Canadian dollars. The explanatory variables included in this data set are:

- the lot size of the property (in square feet)
- the number of bedrooms
- the number of bathrooms
- the number of storeys (excluding the basement)
- A dummy variable = 1 if house has a driveway (= 0 otherwise)
- A dummy variable = 1 if house has a recreation room
- A dummy variable = 1 if house has a basement
- A dummy variable = 1 if house has gas central heating
- A dummy variable = 1 if house has air conditioning
- The size of garage (number of cars it will hold)
- A dummy variable = 1 if house is in a desirable neighbourhood

Conduct a simple regression of `saleprice` on `#bedroom` and conduct a multiple regression of `saleprice` on `lot size`, `# bedroom`, `# bath` and `# stories`.

(a) What are the coefficients associated with the number of bedrooms in each regression? Can you explain why they are different?

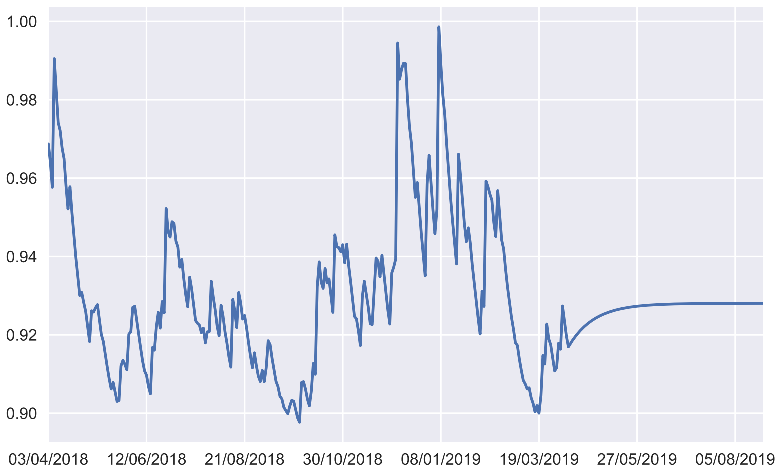
(b) What is the R^2 in the multiple regression? What is the interpretation?

(c) Are all coefficients statistically significant? Explain!

Use the data in `dax_and_spx.csv` in the following exercises. This data set contains one year of daily DAX and S&P500 index values.

Exercise 2. The goal of this exercise is to analyse the linear relationship between the DAX and the S&P 500.
Load the data set into a `DataFrame` and add columns with the log returns and create a scatter plot. Perform a linear regression of the DAX log-returns on the S&P log-returns. Comment on the ability of the model to forecast DAX returns. Is the model statistically significant?

Exercise 3. The goal of this exercise is to fit a GARCH model to the DAX and forecast DAX volatilities.
Load the data set into a `DataFrame` and add columns with the log returns and create a scatter plot. Fit a GARCH model on the DAX returns. What do the parameters of the GARCH model tell you about the variability in the DAX volatility? Next, forecast daily volatilities for 100 days and produce a plot of both the historical and the forecasted volatility. It should look similar to this:



Exercise 4. The data in `dax.csv` contains daily DAX index levels and returns from 1990 to 2016. Value-at-risk (VaR) quantifies the loss boundary that will not be exceeded with a given probability α.
Using the last 300 days as historical data, calculate one-day value-at-risk (VaR) at the level $\alpha = 0.99$ using the delta-normal, historical simulation and GARCH approaches.
The delta-normal VaR at the level α is given as:

$$\mathrm{VaR}_\alpha = -V_0 \cdot \mathrm{N}_{1-\alpha} \cdot \sigma,$$

where V_0 is the current DAX index value, $\mathrm{N}_{1-\alpha}$ is the $1-\alpha$-quantile of the standard normal distribution and σ is the volatility of the historical DAX returns. A typical level is $\alpha = 0.99$.
For historical simulation, VaR is given as

$$\mathrm{VaR}_\alpha = -V_0 \cdot \hat{Q}_{1-\alpha},$$

where $\hat{Q}_{1-\alpha}$ is the empirical $1-\alpha$-quantile
For a GARCH model, observing that conditional on the volatility forecast, returns are normally distributed, VaR is just the delta-normal VaR with the volatility replaced by the vol forecast:

$$\mathrm{VaR}_\alpha = -V_0 \cdot \mathrm{N}_{1-\alpha} \cdot \sigma_{\mathrm{GARCH}}.$$