MATH 584: Homework 4

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1 Problem 1

1.1 Question A

The goal of this question was to compute the price impact coefficient, λ thanks to the following regression:

$$\Delta S_t = \lambda \Delta \hat{V} + \hat{\sigma} \eta_t \tag{1}$$

where where $\hat{V}$ is the signed traded volume, S is the midprice, η_t is a zero-mean unit-variance white noise. The regression has been realized on two tickers, MSFT and GOOG, using data from Nov 3 through Nov 26, 2014. Signed traded volumes have been obtained thanks to the vMO field. Here are the results obtained (with the price impact on top):

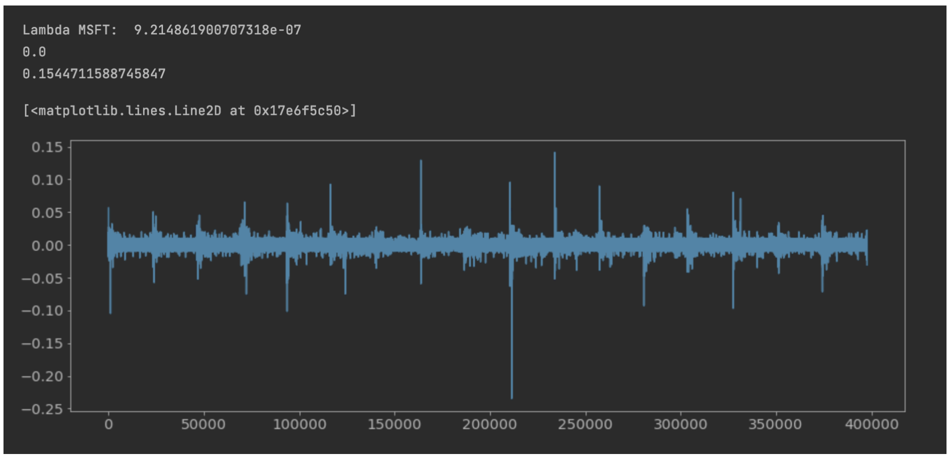

Figure 1: Results for MSFT + Residuals plot

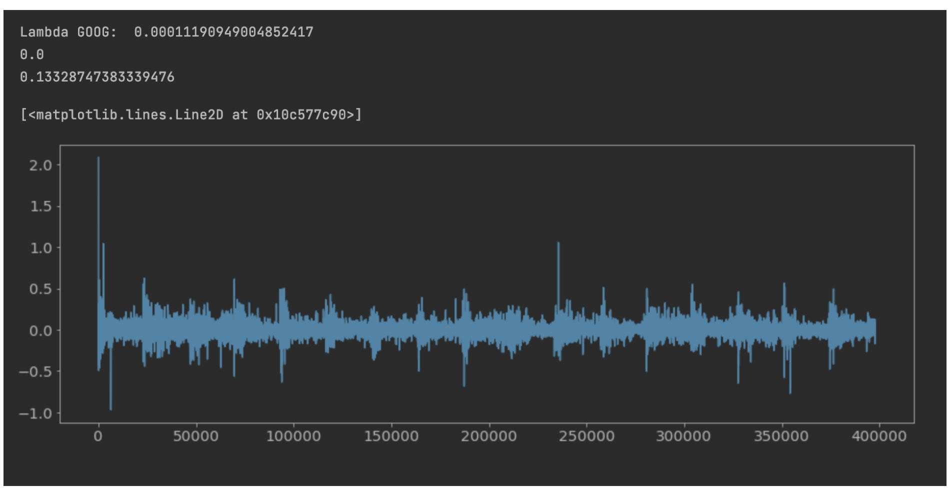

Figure 2: Results for GOOG + Residuals plot

1.2 Question B

The goal of this question was to estimate the price impact coefficient λ via LOB. To do so, the sample mean of λ_t has been computed where λ_t is defined as followed:

$$\lambda_t = \frac{1}{2}\left(\frac{1}{H_t^b} + \frac{1}{H_t^a}\right)$$

H_t^b and H_t^a are respectively the heights on the bid price and on the ask price.

$$H_t^b = \frac{1}{S_t - P_t^{b,10}} \sum_{i=1}^{10} V_t^{b,i}$$

$$H_t^a = \frac{1}{P_t^{a,10} - S_t} \sum_{i=1}^{10} V_t^{a,i}$$

```
lambda_MSFT:  1.8392754266359228e-06
lambda_GOOG:  0.0002836755634814247
```

Figure 3: Price impact estimations via LOB

The results obtained on the previous question are lower than the ones obtained with this method. This makes sense as on LOB, the number of trades/orders realized is far more important and one may not care about executing the best available trade but rather the fastest available one.
When designing a trading strategy, I would use the first method because the second method does not make any use of the market resilience.

1.3 Question C

The goal of this question was to estimate σ^2 for each ticker, GOOG and MSFT.

```
Variance of MSFT 0.002136821370666654
Variance of GOOG 0.2721184341543484
```

Figure 4: Variance for GOOG and MSFT from Nov 3 to Nov 26, 2014

What can be noticed it that the variance of Google is far greater than the one of MSFT. To make sure this phenomenon makes sense, I visualized the evolution of GOOG stock and MSFT stock over the month of November 2014 (source:Yahoo.Finance). Google stock seems to vary quite a lot over Nov 2014.

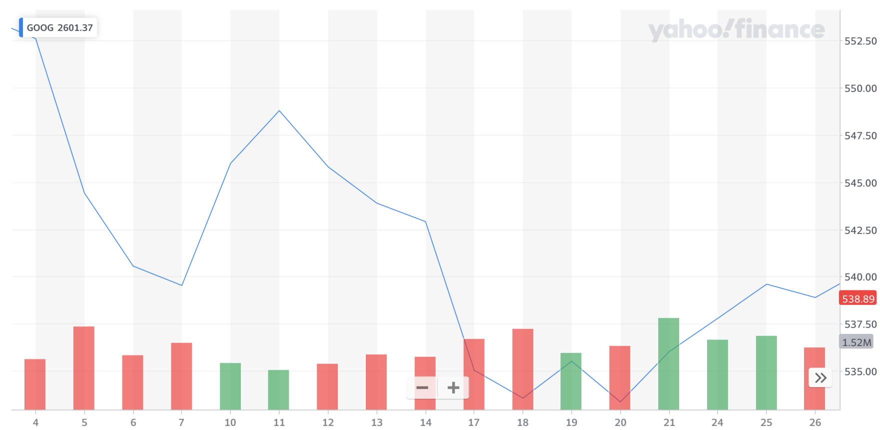

Figure 5: GOOG stock evolution from Nov 3 to Nov 26, 2014

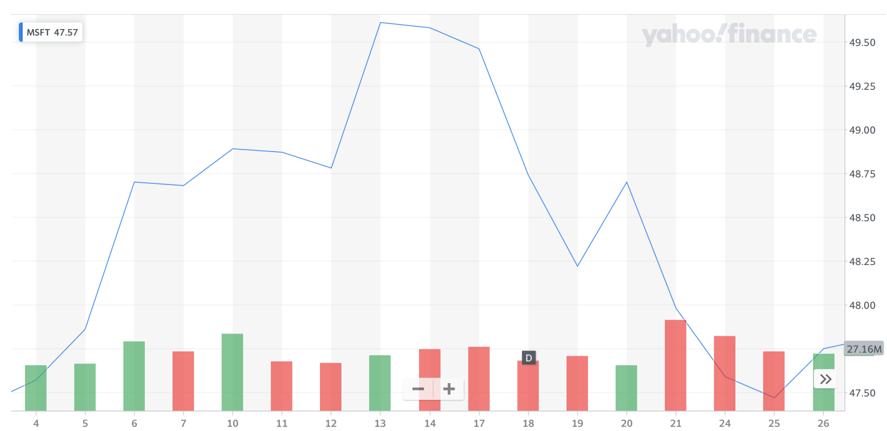

Figure 6: MSFT stock evolution from Nov 3 to Nov 26, 2014

1.4 Question D

Thanks to the values of σ^2 obtained in the previous question, we can get an estimation of the risk aversion of the market makers. Indeed, thanks to the following expression:

$$\lambda = 2\gamma\sigma^2 \tag{2}$$

We can extract the risk aversion coefficient of market makers.

```
Risk aversion obtained from MSFT data and 1A:  0.0002156207820458204
Risk aversion obtained from GOOG data and 1A:  0.0002056264405539096

Risk aversion obtained from MSFT data and 1B:  0.0004303765050005322
Risk aversion obtained from GOOG data and 1B:  0.0005212354766831434
```

Figure 7: Risk aversion coefficient estimations

When the method of question 1A is used, we get convincing results. Indeed, we get the same risk aversion for MSFT and GOOG. This makes sense as traders working for a company must have the same perception/conception of risk, dictated by the company.
On the other hand, when the method of question 1B is used, the risk aversion coefficients are close but not equal which can be explained by the value of the estimation of the price impact via LOB, that is not optimal.

2 Problem 2

I implemented the whole strategy described in the notes. I do not know why it does not behave as it should. Here is the PnL I get:

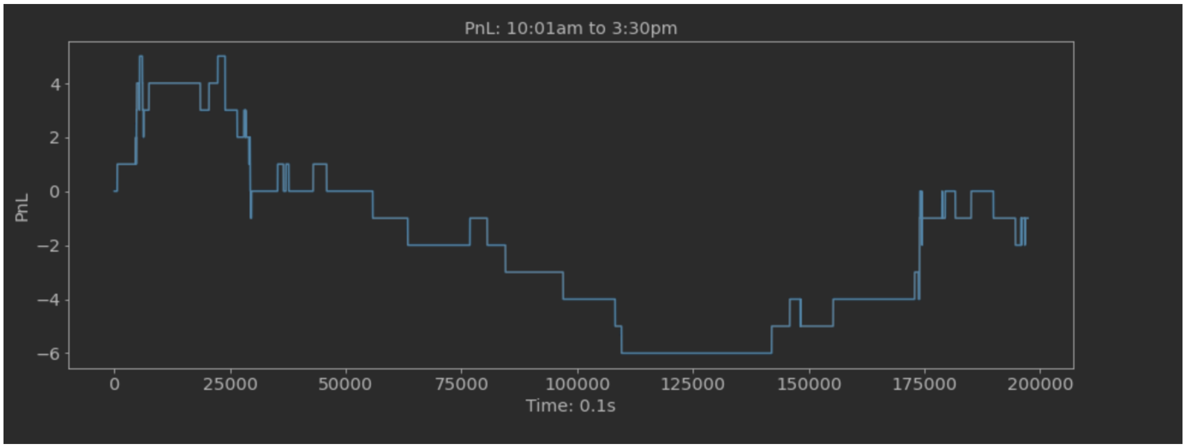

Figure 8: PnL obtained when setting $\lambda_{reg} > 0$

I have pretty much the same variations as what should be obtained. The problem is that the PnL becomes negative at one point;, so maybe I do not close the position the right way.

```
print("Shape Ratio", Sharpe_ratio)
print("Annualized Sharpe Ratio", annualized_sr)
```

```
Shape Ratio -0.0002532280403153081
Annualized Sharpe Ratio -1.7789247302951046
```

Figure 9: Annualized Sharpe Ratio

Normally, we should get an annualized Sharpe ratio close to 12.5. This great result would make sense as this means trading actively (high-frequency) using predictive factors over a year.