10.3/10

Ziming Huang

Project 5

Econ 672
October 18, 2019

Exercise 1-Local Variance

(A) We can estimate local variance by using this estimator:

$$\hat{c}_{i_t}(t) = \frac{1}{2k_n + 1} \sum_{j=-k_n}^{k_n} (r^c_{i_{t+j}})^2$$

If the jump interval i_t falls in the begin or end of market hour, we can adjust our estimator as:

$$\hat{c}_{i_t}(t) = \frac{1}{J_1 - J_2 + 1} \sum_{j=-J_2}^{J_1} (r^c_{i_{t+j}})^2$$

with

$$J_2 = max(1, i - k_n)$$
$$J_1 = min(k_n + i, n)$$

where i is the number of interval intraday that jump time falls in, n is the number of daily observe interval, k_n is the half length of estimate windows.

The following is graph of the local variance estimator for PG and DIS on January 3, 2007.

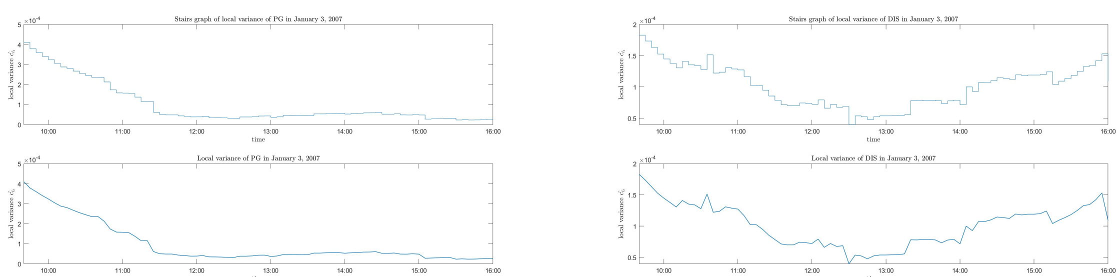


Figure 1: Estimated Local Variance of PG and DIS on January 3, 2007

From the graphs we can find the daily local variance shows a U-shape pattern (this is much more obvious in DIS' graph): at the beginning of market hour, the local variance is very high; as the deal goes on, the local variance decreases and always reach its lowest point at the middle of market hour; in the latter part of market hour, the local variance shows a increasing trend.

As for the value of local variance, we can find DIS' local variance is much larger than the PG's, which mean the volatility of DIS' log-returns will experience larger fluctuations.

(B) We use this estimator to estimate the average local variance for each interval:

$$\bar{\hat{c}}_i = \frac{1}{T}\sum_{t=1}^{T} \hat{c_i}_t$$

for $i = 1, 2, \ldots n$. The following is graph of the local variance estimator for PG and DIS on January 3, 2007.

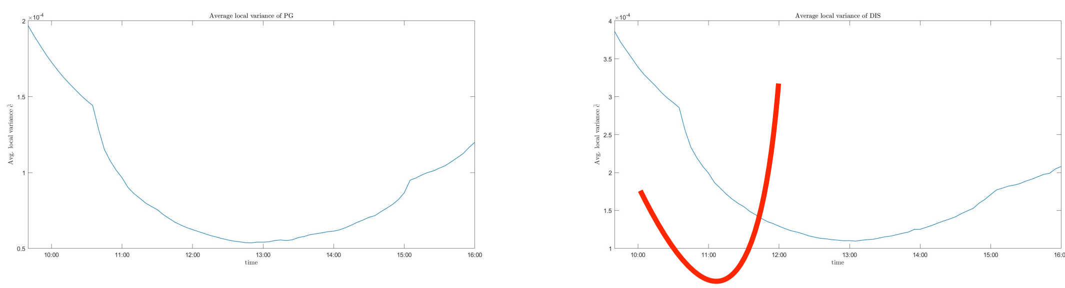


Figure 2: Estimated Average Local Variance of PG and DIS

relation to the time-of-day factor? (-0.1)

After taking average of the local variance throughout all observe time, the U-shape pattern are much clear in for PG and DIS' local variance. From the graphs we can see, the curve shape of these two stocks are very similar, the volatility of DIS is bigger than PG's.

The **MATLAB** code:

Function of Local Variance

```
function [ct] = local_var(lr_c,kn)
%lr_c is a n*T diffusive return matrix
%where n is the observation number each day and T is the number of
   observative days
n=size(lr_c,1);
T=size(lr_c,2);
ct=zeros(n,T);
for i=1:n
    j2=max(1,i-kn);
    j1=min(kn+i,n);
    ct(i,:)=sum(lr_c(j2:j1,:).^2)/((j1-j2+1)/n);
end
end
```

Scripts of Q1

```
addpath('D:\ZM—Documents\MATLAB\data','functions','scripts');
[dates_PG,lp_PG]=load_stock('PG.csv','m');
N_PG=sum(floor(dates_PG(1,1))==floor(dates_PG(:,1)));% number of observations
     per day
T_PG=size(dates_PG,1)/N_PG;
[rdates_PG,lr_PG]=log_return([dates_PG lp_PG],N_PG,1);
days_PG=unique(floor(rdates_PG));

%A1
%local variance for n*T intervals
a=5;
kn=11;
[lr_c_PG,lr_d_PG]=c_d_log_returns(lr_PG,N_PG,a);
ct_PG=local_var(lr_c_PG,kn);
%plot one day's local variance
figure;
subplot(2,1,1);
stairs(rdates_PG(:,1),ct_PG(:,1));
xlabel('time');
ylabel('local variance $\hat{c_{i_t}}$');
xlim([min(rdates_PG(:,1)),max(rdates_PG(:,1))]);
title('Stairs graph of local variance of PG in January 3, 2007');
datetick('x','keeplimits');

subplot(2,1,2);
plot(rdates_PG(:,1),ct_PG(:,1));
xlabel('time');
ylabel('local variance $\hat{c_{i_t}}$');
xlim([min(rdates_PG(:,1)),max(rdates_PG(:,1))]);
title('Local variance of PG in January 3, 2007');
datetick('x','keeplimits');

%1B
%average local variance
ct_avg_PG=mean(transpose(ct_PG));
%plot
figure;
plot(rdates_PG(:,1),ct_avg_PG);
xlabel('time');
ylabel('Avg. local variance $\bar{\hat{c}}$');
xlim([min(rdates_PG(:,1)),max(rdates_PG(:,1))]);
title('Average local variance of PG');
datetick('x','keeplimits');
```

Exercise 2-Jumps in the Variance

(A) To estimate the volatility before jump $\hat{c}^-_{i_t}$, we use:

$$\hat{c}^-_{i_t} = \frac{1}{i - J_2} \sum_{j=-J_2}^{i-1} (r^c_{i_{t+j}})^2$$

with $J_2 = max(1, i - k_n)$, $i = 2, 3, \ldots n$.

To estimate the volatility before jump $\hat{c}^+_{i_t}$, we use:

$$\hat{c}^+_{i_t} = \frac{1}{J_1 - i} \sum_{j=i+1}^{J_1} (r^c_{i_{t+j}})^2$$

with $J_1 = min(k_n + i, n)$, $i = 1, 2, \ldots n - 1$.

To measure the magnitude of the jump return, we use absolute value of jump returns:

$$M_{r^d_{t,i_t}} = |r^d_{t,i_t}|$$

with $i = 2, 3, \ldots n$.

The following is graph of $\hat{c}^-_{i_t}$, $\hat{c}^+_{i_t}$ and $|r^d_{t,i_t}|$ of PG and DIS.

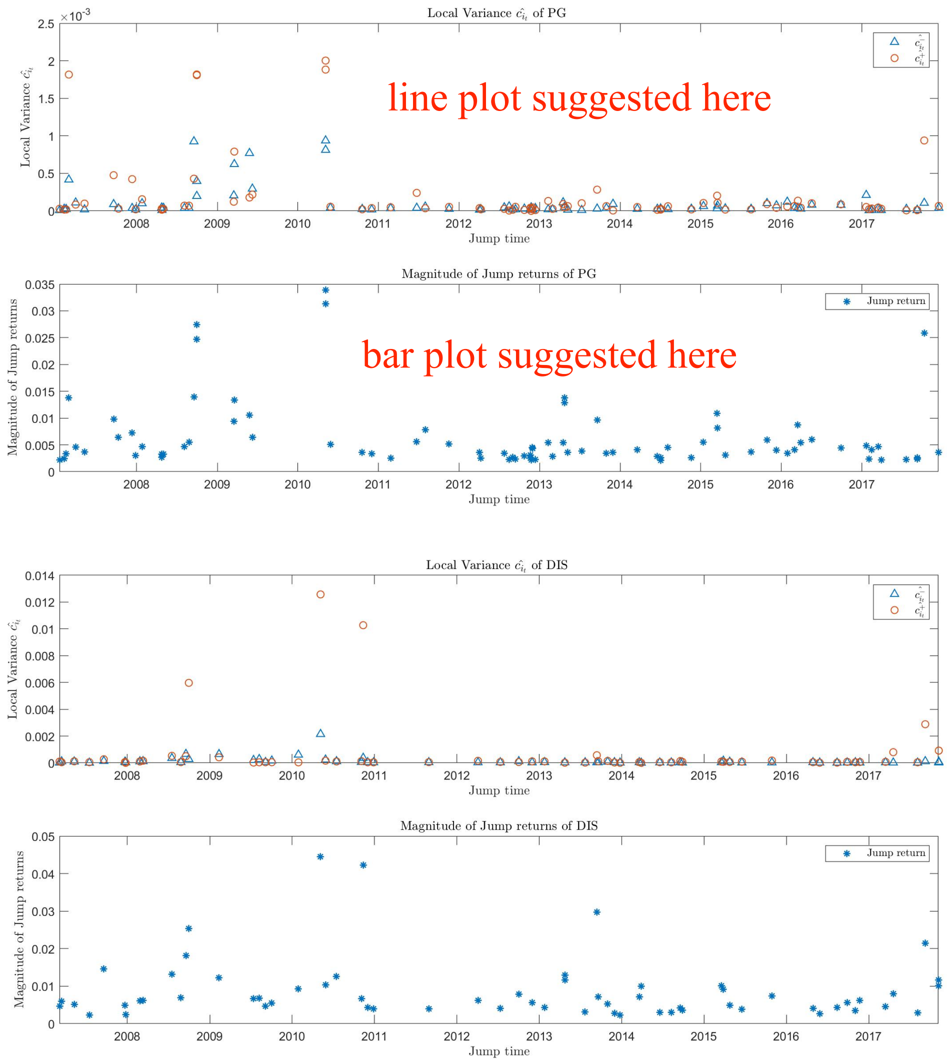


Figure 3: $\hat{c}_{i_t}^{-}$, $\hat{c}_{i_t}^{+}$ and $|r_{t,i_t}^{d}|$ of PG and DIS

From these graphs, we can detect the trading time with large magnitude of jump returns is consistent with the time when the difference of $\hat{c}_{i_t}^{-}$ and $\hat{c}_{i_t}^{+}$ is large, which indicates a jump local variance may exist. This finding may give us a method to detect the jump volatility in stock's returns: if there is a large magnitude of stock return in the stock price, then there is a high probability that the volatility is experiencing a jump.

(B) (i) To create the confidence interval of left and right local variance, we can use bootstrap method. In order to simplify the programming, we here just focus on those jumps fall in the middle of market hour. This simplification should be reasonable since about 95% jumps occur in the middle of market hour and the accuracy es-

(+0.8-0.3) 99% rather than 95% confidence interval timates for the beginning and end interval's local variance are undesirable due to limited available data.

The follows are the graphs of jump local variance and its confidence interval of PG and DIS.

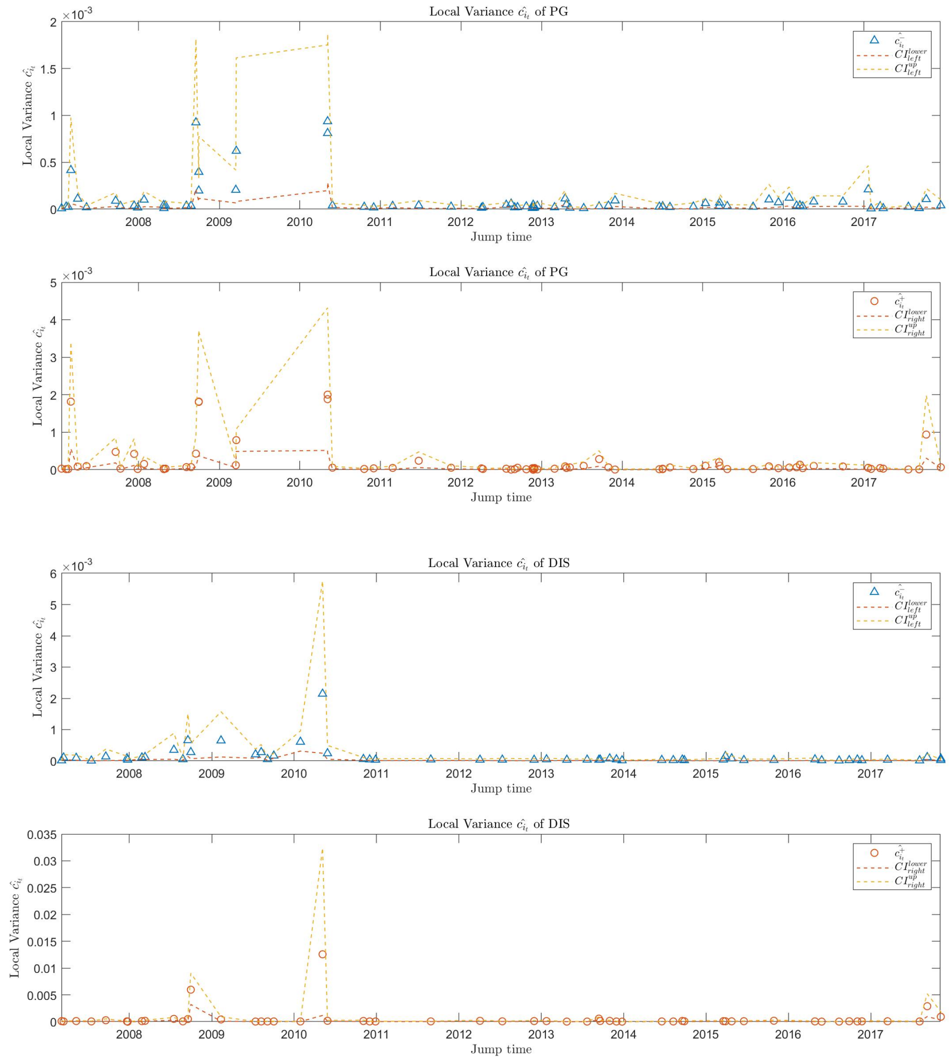


Figure 4: $\hat{c}_{i_t}^-$, $\hat{c}_{i_t}^+$ and its confidence interval of PG and DIS

The first and third graphs are the confidence interval of left limit local variance $\hat{c}_{i_t}^-$ and the second and fourth graphs are the confidence interval of left limit local variance $\hat{c}_{i_t}^+$. The blue triangles in the graphs are data estimated $\hat{c}_{i_t}^-$ and the red circle are data estimated $\hat{c}_{i_t}^+$.

From these graphs we can see, almost every data estimated values are bounded by the confidence interval upper boundary and lower boundary. Trough calculated, we find the cover rate of these bootstrap confidence interval is 100%.

(ii) To test whether the confidence interval of $\hat{c}_{i_t}^-$ and $\hat{c}_{i_t}^+$ intersect or not, we want to test whether $CI_{left}^{lower} > CI_{right}^{up}$ or $CI_{right}^{lower} > CI_{left}^{up}$.

Here are the graphs of mixed confidence interval boundary of $\hat{c}_{i_t}^-$ and $\hat{c}_{i_t}^+$.

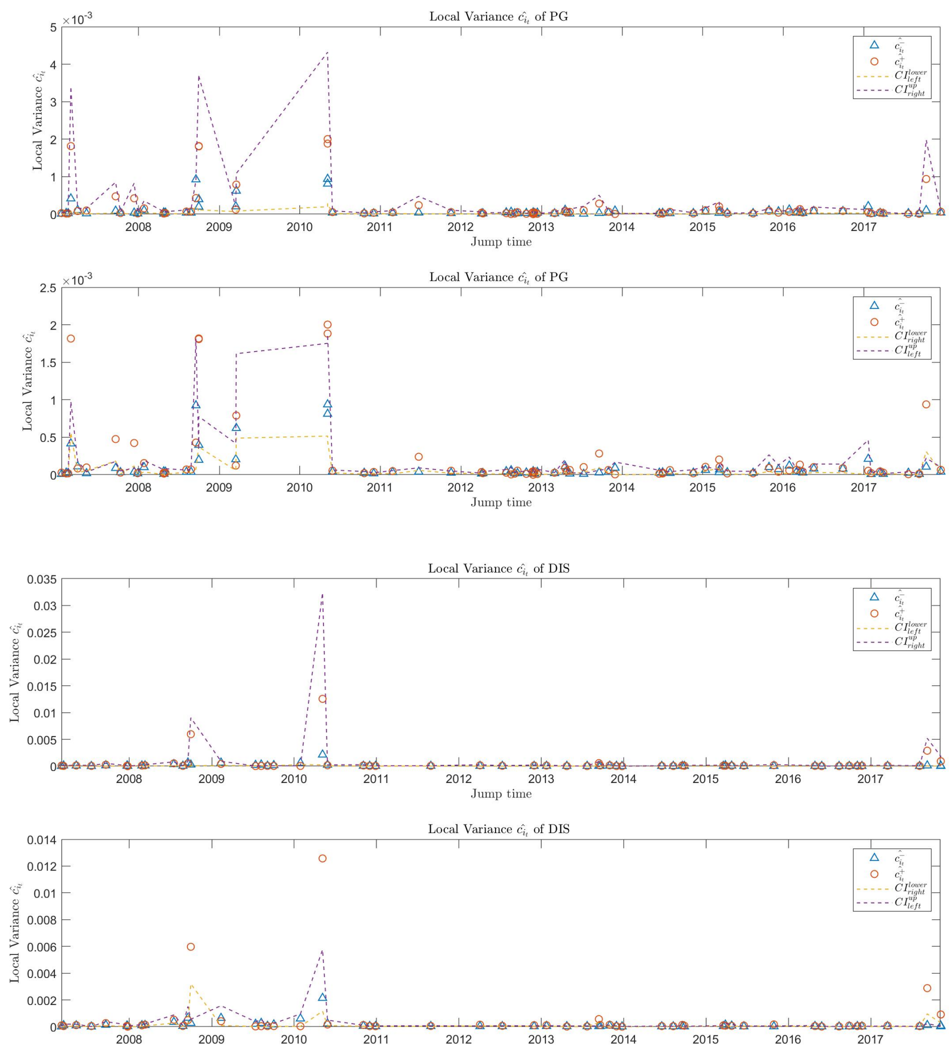


Figure 5: Mixed CI Boundary of $\hat{c}_{i_t}^-$ and $\hat{c}_{i_t}^+$ for PG and DIS

In these graphs, the purple dot lines are upper CI boundaries and the yellow dot lines are lower CI boundaries. If the lower boundaries are larger than the upper boundaries, these confidence interval of $\hat{c}_{i_t}^-$ and $\hat{c}_{i_t}^+$ will not have intersections.

From the graphs we can find, about 90% of the sample data, the lower boundaries are smaller than the upper boundaries, which indicates the confidence interval of $\hat{c}_{i_t}^-$ and $\hat{c}_{i_t}^+$ will have intersections for most of time. According to our calculations, the number and percentage of intervals that do not have intersections is 14 (17.95%) and 12 (20.69%), for PG and DIS respectively.

We can put these two confidence interval together to detect their intersections more clearly.

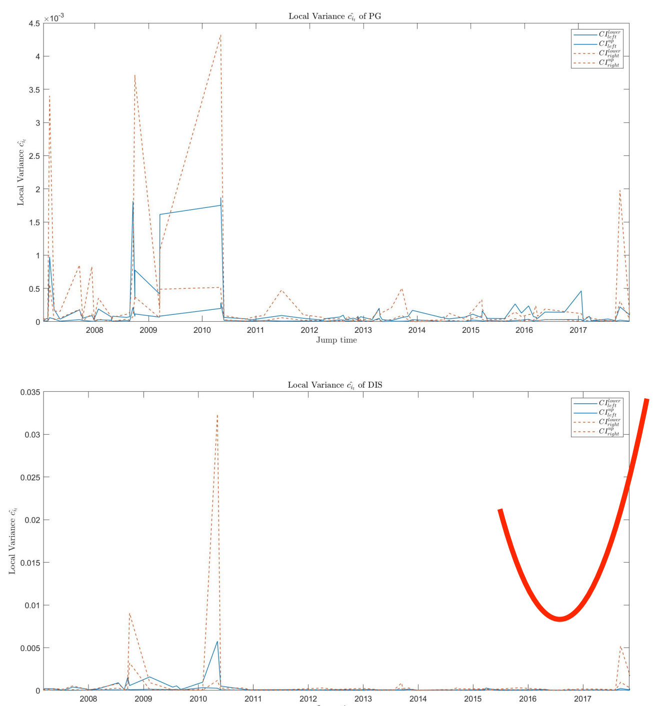


Figure 6: CI Boundary of $\hat{c}_{i_t}^-$ and $\hat{c}_{i_t}^+$ for PG and DIS

The blue lines are the confidence interval of $\hat{c}_{i_t}^-$ while the red lines are the confidence interval of $\hat{c}_{i_t}^+$. Easily to see from the figures that these two confidence intervals have intersection for most of observations.

The **MATLAB**:

Scripts of Q2

```
addpath('D:\ZM—Documents\MATLAB\data','functions','scripts');
```

```
[dates_PG,lp_PG]=load_stock('PG.csv','m');
N_PG=sum(floor(dates_PG(1,1))==floor(dates_PG(:,1)));% number of observations
     per day
T_PG=size(dates_PG,1)/N_PG;
[rdates_PG,lr_PG]=log_return([dates_PG lp_PG],N_PG,1);
days_PG=unique(floor(rdates_PG));

%2A
a=5;
[lr_c_PG,lr_d_PG]=c_d_log_returns(lr_PG,N_PG-1,a);
indi_PG=find(lr_d_PG~=0);
n=size(lr_c_PG,1);
kn=11;
%left and right limit local variance
ct1=zeros(n,T_PG);
ct2=zeros(n,T_PG);
for i=2:n-1
    j2=max(1,i-kn);%start
    j1=min(kn+i,n);%stop
    ct1(i,:)=sum(lr_c_PG(j2:i,:).^2,1)/((i-j2)/n);%left
    ct2(i,:)=sum(lr_c_PG(i:j1,:).^2,1)/((j1-i)/n);%right
end

%plot jump left and right local variance at jump return time
figure;
subplot(2,1,1);
plot(rdates_PG(indi_PG),ct1(indi_PG),'^','linewidth',0.8);
hold on;
plot(rdates_PG(indi_PG),ct2(indi_PG),'o','linewidth',0.8);

xlabel('Jump time');
ylabel('Local Variance $\hat{c_{i_t}}$');
legend('$\hat{c_{i_t}^-}$','$\hat{c_{i_t}^+}$');
xlim([min(rdates_PG(indi_PG)),max(rdates_PG(indi_PG))]);
title('Local Variance $\hat{c_{i_t}}$ of PG ');
datetick('x','keeplimits');

subplot(2,1,2);
plot(rdates_PG(indi_PG),abs(lr_d_PG(indi_PG)),'*','linewidth',1);
xlabel('Jump time');
ylabel('Magnitude of Jump returns');
legend('Jump return');
xlim([min(rdates_PG(indi_PG)),max(rdates_PG(indi_PG))]);
title('Magnitude of Jump returns of PG');
```

```
datetick('x','keeplimits');


%2B
%To simplify the program ,we here just consider the jumps fall in the
%middle intervals
indi_PG=find(lr_d_PG~=0);
a1=find(indi_PG.*(mod(indi_PG,77)<=11));
a2=find(indi_PG.*(mod(indi_PG,77)>=66));
a=[a1; a2];
indi_PG(a)=[];
j1_PG=indi_PG-11;
j2_PG=indi_PG+11;

left_sample_PG=zeros(11,size(indi_PG,1));
right_sample_PG=zeros(11,size(indi_PG,1));
for i=1:size(indi_PG,1)
left_sample_PG(:,i)=lr_c_PG(j1_PG(i):indi_PG(i)-1);
right_sample_PG(:,i)=lr_c_PG(indi_PG(i)+1:j2_PG(i));
end

%bootstrap sample

r=1000;
sct1_PG=zeros(r,size(indi_PG,1));
sct2_PG=zeros(r,size(indi_PG,1));
parfor i=1:r
    newsample1=sbsample(left_sample_PG,kn,size(indi_PG,1));
    newsample2=sbsample(right_sample_PG,kn,size(indi_PG,1));
   sct1_PG(i,:)=sum(newsample1.^2,1)/(kn/n);%left
   sct2_PG(i,:)=sum(newsample2.^2,1)/(kn/n);%right
end
ct1_low_PG = quantile(sct1_PG, 0.025);
ct1_up_PG = quantile(sct1_PG, 0.975);
ct2_low_PG = quantile(sct2_PG, 0.025);
ct2_up_PG = quantile(sct2_PG, 0.975);

Notinter_PG=sum((ct1_low_PG>ct2_up_PG)|(ct1_up_PG<ct2_low_PG));


%
% num_in_PG_d=sum(CI_low_PG <=TV_PG & CI_up_PG >=TV_PG);
% cover_rate_PG_d=num_in_PG_d/T_PG;
figure;
```

```
subplot(2,1,1);
plot(rdates_PG(indi_PG),ct1(indi_PG),'^','linewidth',0.8);
hold on;
%plot(rdates_PG(indi_PG),ct2(indi_PG),'linewidth',0.8);
hold on;
plot(rdates_PG(indi_PG),ct1_low_PG,'--');
hold on;
plot(rdates_PG(indi_PG),ct1_up_PG,'--');
hold off;

xlabel('Jump time');
ylabel('Local Variance $\hat{c_{i_t}}$');
legend('$\hat{c_{i_t}^-}$','$CI_{left}^{lower}$','$CI_{left}^{up}$');
xlim([min(rdates_PG(indi_PG)),max(rdates_PG(indi_PG))]);
title('Local Variance $\hat{c_{i_t}}$ of PG ');
datetick('x','keeplimits');

%------right
subplot(2,1,2);
plot(rdates_PG(indi_PG),ct2(indi_PG),'o','linewidth',0.8,'color',[0.8500 0.3250 0.0980]);
hold on;
%plot(rdates_PG(indi_PG),ct2(indi_PG),'linewidth',0.8);
hold on;
plot(rdates_PG(indi_PG),ct2_low_PG,'--');
hold on;
plot(rdates_PG(indi_PG),ct2_up_PG,'--');
hold off;


xlabel('Jump time');
ylabel('Local Variance $\hat{c_{i_t}}$');
legend('$\hat{c_{i_t}^+}$','$CI_{right}^{lower}$','$CI_{right}^{up}$');
xlim([min(rdates_PG(indi_PG)),max(rdates_PG(indi_PG))]);
title('Local Variance $\hat{c_{i_t}}$ of PG ');
datetick('x','keeplimits');

%put together
figure;
subplot(2,1,1);
plot(rdates_PG(indi_PG),ct1(indi_PG),'^','linewidth',0.8);
hold on;
plot(rdates_PG(indi_PG),ct2(indi_PG),'o','linewidth',0.8);
hold on;
```

```
plot(rdates_PG(indi_PG),ct1_low_PG,'--');
hold on;
plot(rdates_PG(indi_PG),ct2_up_PG,'--');
hold off;

xlabel('Jump time');
ylabel('Local Variance $\hat{c_{i_t}}$');
legend('$\hat{c_{i_t}^-}$','$\hat{c_{i_t}^+}$','$CI_{left}^{lower}$','$CI_{
    right}^{up}$');
xlim([min(rdates_PG(indi_PG)),max(rdates_PG(indi_PG))]);
title('Local Variance $\hat{c_{i_t}}$ of PG ');
datetick('x','keeplimits');

%-----right
subplot(2,1,2);
plot(rdates_PG(indi_PG),ct1(indi_PG),'^','linewidth',0.8);
hold on;
plot(rdates_PG(indi_PG),ct2(indi_PG),'o','linewidth',0.8);
hold on;
plot(rdates_PG(indi_PG),ct2_low_PG,'--');
hold on;
plot(rdates_PG(indi_PG),ct1_up_PG,'--');
hold off;

xlabel('Jump time');
ylabel('Local Variance $\hat{c_{i_t}}$');
legend('$\hat{c_{i_t}^-}$','$\hat{c_{i_t}^+}$','$CI_{right}^{lower}$','$CI_{
    left}^{up}$');
xlim([min(rdates_PG(indi_PG)),max(rdates_PG(indi_PG))]);
title('Local Variance $\hat{c_{i_t}}$ of PG ');
datetick('x','keeplimits');

%CI together
figure;
plot(rdates_PG(indi_PG),ct1_low_PG,'-','color',[0 0.4470 0.7410]);
hold on;
plot(rdates_PG(indi_PG),ct1_up_PG,'-','color',[0 0.4470 0.7410]);
hold on;
plot(rdates_PG(indi_PG),ct2_low_PG,'--','color',[0.8500 0.3250 0.0980]);
hold on;
plot(rdates_PG(indi_PG),ct2_up_PG,'--','color',[0.8500 0.3250 0.0980]);
hold off;

xlabel('Jump time');
```

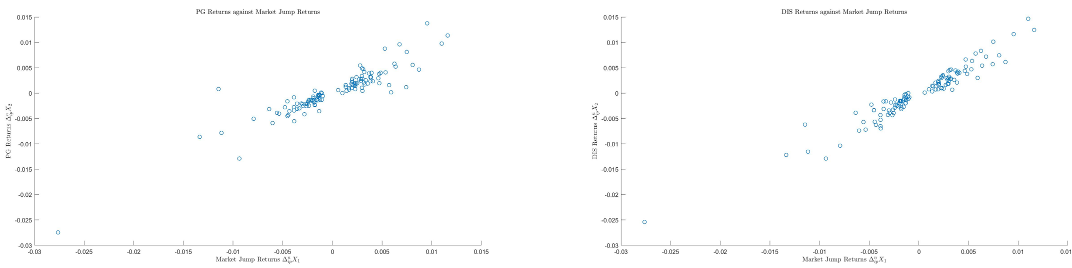
```
ylabel('Local Variance $\hat{c_{i_t}}$');
legend('$CI_{left}^{lower}$','$CI_{left}^{up}$','$CI_{right}^{lower}$','$CI_{
    right}^{up}$');
xlim([min(rdates_PG(indi_PG)),max(rdates_PG(indi_PG))]);
title('Local Variance $\hat{c_{i_t}}$ of PG ');
datetick('x','keeplimits');
```

Exercise 3-Jump Regression(Jump Beta)

(A) By using detector $I'_n \equiv \{i : |\Delta_i^n X_1| > \alpha \Delta_n^{0.49} \sqrt{\tau_i BV_t}\}$, we detect there are total 116 jumps in market log-returns. Here is the summary table sheet for jump times and return magnitude from year 2007 to 2017.

Stock	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
#Jump	11	5	7	8	4	17	9	14	8	18	15
Avg.Size	0.0047	0.0095	0.0063	0.0051	0.0067	0.0034	0.0045	0.0024	0.0040	0.0027	0.0019

(B) Here is the scatter plot of PG(and DIS)'s log-returns against the market jump returns.



wrong caption here...

Figure 7: $\hat{c}_{i_t}^-$, $\hat{c}_{i_t}^+$ and $|r_{t,i_t}^d|$ of PG and DIS

We can see, the data mostly concentrate around the origin point $(0, 0)$ and the linear relationship between individual stock's log-return and market jump log-return is obvious in these figures.

(C) We can get the estimator of jump beta by using the OLS regression:

$$\hat{\beta} \equiv \frac{\sum_{p=1}^{Pn} \Delta_{i_p}^n X_1 \Delta_{i_p}^n X_2}{\sum_{p=1}^{Pn} (\Delta_{i_p}^n X_1)^2}$$

The estimate jump beta of PG and DIS:

Stock	$\hat{\beta}$
PG	0.8269
DIS	0.9942

Having the value of $\hat{\beta}$, we can use this regression relation to estimate out stock's returns when there is a jump in the market return:

$$Y_{stock_{ip}} = \hat{\beta}_{stock} X_{market_{ip}} + \epsilon_{ip}$$

where i_p is the detected jump time of market. The larger the β is, the bigger jump will occur at stock's return.

For PG, $\hat{\beta} = 0.8269$, which means when the market return jumps for 1%, we will expected PG's return will also experience a jump and the jump size is $\hat{\beta}$%=0.8269%.

For DIS, $\hat{\beta} = 0.9942$, which means when the market return jumps for 1%, we will expected DIS' return will also experience a jump and the jump size is $\hat{\beta}$%=0.9942%.

(D) These are the plots of stocks returns against market return with estimated regression lines.

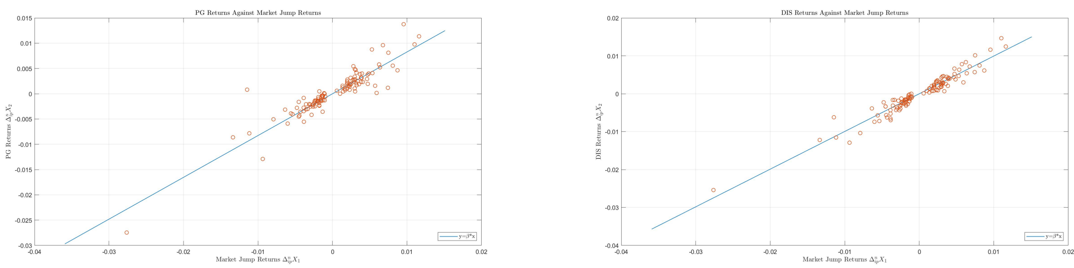


Figure 8: Stock Return v.s. Market return and Regression Line

According to the graph, we can easily see the this linear regression is good since most of our data fall on or near the regression line.

(E) We use this estimator to estimate the local variance for jump beta of PG and DIS:

$$\hat{V}_\beta = \frac{\sum_{p=1}^{Pn} (\Delta_{i_p}^n X_1)^2 \hat{c}_{e,t_p}}{(\sum_{p=1}^{Pn} (\Delta_{i_p}^n X_1)^2)^2}$$

The estimated value of $\sqrt{\Delta_{i_p}^n \hat{V}_\beta}$ for PG and DIS:

Stock	$(\Delta_{i_p}^n \hat{V}_\beta)^{\frac{1}{2}}$
PG	0.0393
DIS	0.0505

(F) We can create a 95% confidence interval of jump beta by using it asymptotic distribution and the confidence interval can be represented as:

$$CI_{low} = \hat{\beta} - c * \sqrt{\Delta_{i_p}^n \hat{V}_\beta}$$

$$CI_{up} = \hat{\beta} + c * \sqrt{\Delta^n_{i_p} \hat{V}_\beta}$$

where $c = 1.96$ for a 95% confidence level interval.

The estimated 95% confidence interval of PG and DIS.

Stock	Estimated beta	CI lower bound	CI upper bound
PG	0.8296	0.7499	0.9039
DIS	0.9942	0.8952	1.0932

For PG, the confidence interval is $CI_{\hat{\beta}_{PG}} = [0.7499, 0.9003]$, which means when there is a 1% jump in market log-return, we will expect at lease 0.7499% jump and at most0.9003% jump in PG's return.

For DIS, the confidence interval is $CI_{\hat{\beta}_{DIS}} = [0.8952, 1.9032]$, which means when there is a 1% jump in market log-return, we will expect at lease 0.8952% jump and at most 1.9032% jump in PG's return. Notice that $CI_{\hat{\beta}_{DIS}}$ includes the value of 1, which indices PG might perfectly co-movement with the market.

(G) Assume you expect the market price will jump down by 1% and V_{stock} is the value of existing portfolio, V_{mkt} is the value of market future index you plan to short sell, then we can use a table to show how to create a hedge strategy.

Asset	Position Value at t_0	Position Value at t_1	Cost of Position	P&L
Stock	V_{stock}	$(1 - \beta_{stock}\%)V_{stock}$	V_{stock}	$-\beta_{stock}\%V_{stock}$
Future	0	V_{mkt}	$(1 - 1\%)V_{mkt}$	$1\%V_{mkt}$

According to this table, if you want to perfectly hedge your current position, you need to short sell market index future for $V_{mkt} = \beta_{stock}V_{mkt}$, so that the P&L for your position at time t_1 will equal to zero.

Here is the estimated short sell value confidence interval of PG and DIS:

Stock	estimated value	Value lower bound	Value upper bound
PG	165.3727	149.9728	180.7726
DIS	198.8345	179.0336	218.6354

(H) The estimated jump beta and beta variance of PG and DIS.

Stock	β_1	β_2	$\hat{V}_{\beta 1}$	$\hat{V}_{\beta 2}$
PG	0.7573	0.9827	0.2784	0.0474
DIS	0.9520	1.0957	0.4510	0.0468

(I) We can create a 95% confidence interval of $\hat{\beta}_1 - \hat{\beta}_2$ by using it asymptotic distribution and the confidence interval can be represented as:

$$CI_{low} = \hat{\beta}_1 - \hat{\beta}_2 - c * \sqrt{\Delta^n_{i_p} \hat{V}_\beta}$$

$$CI_{up} = \hat{\beta}_1 - \hat{\beta}_2 + c * \sqrt{\Delta^n_{i_p} \hat{V}_\beta}$$

where $c = 1.96$ for a 95% confidence level interval.

The estimated 95% confidence interval of PG and DIS:

Stock	$\hat{\beta}_1 - \hat{\beta}_2$	CI lower bound	CI upper bound
PG	-0.2255	-0.3530	-0.0979
DIS	-0.1437	-0.3013	0.0139

not contain zero in PG (-0.1)

According to the table, PG's confidence interval contains zero, which means there is of 95% probability that $\hat{V}_{\beta 1}$ and $\hat{V}_{\beta 2}$ are not equal.

DIS' confidence interval contains zero, which means there is a probability that DIS' $\hat{V}_{\beta 1}$ and $\hat{V}_{\beta 2}$ are equal.

This result cannot be a strong evidence to against or support our assumption of jump beta is constant.

The **MATLAB**: Scripts of Q3

```
addpath('D:\ZM-Documents\MATLAB\data','functions','scripts');
[dates_PG,lp_PG]=load_stock('PG.csv','m');
N_PG=sum(floor(dates_PG(1,1))==floor(dates_PG(:,1)));% number of observations
    per day
T_PG=size(dates_PG,1)/N_PG;
[rdates_PG,lr_PG]=log_return([dates_PG lp_PG],N_PG,1);
days_PG=unique(floor(rdates_PG));

[dates_SPY,lp_SPY]=load_stock('SPY.csv','m');
N_SPY=sum(floor(dates_SPY(1,1))==floor(dates_SPY(:,1)));% number of
    observations per day
T_SPY=size(dates_SPY,1)/N_SPY;
[rdates_SPY,lr_SPY]=log_return([dates_SPY lp_SPY],N_SPY,1);
days_SPY=unique(floor(rdates_SPY));
```

```
a=5;
kn=11;
n=77;
[lr_c_PG,lr_d_PG]=c_d_log_returns(lr_PG,N_PG-1,a);
[lr_c_SPY,lr_d_SPY]=c_d_log_returns(lr_SPY,N_SPY-1,a);

%Q3
%A
%find the jump time index In'
Pn=find(lr_d_SPY~=0); %focus on jumps
num_jump=size(Pn,1);
jd_PG=datetime(rdates_PG(Pn),'ConvertFrom','datenum');
times_PG=zeros(11,1);%jump times per year
size_PG=zeros(11,1);
for i=1:11
   times_PG(i)=sum(jd_PG.Year==i+2006);
   k=abs(lr_d_SPY(Pn)).*(jd_PG.Year==i+2006);
   size_PG(i)=mean(k(k~=0));%average magnitude
end
%B plot x1 and x2(stock)
figure;
scatter(lr_SPY(Pn),lr_PG(Pn));
xlabel('Market Jump Returns $\Delta_{ip}^n X_1$');
ylabel('PG Returns $\Delta_{ip}^n X_2$');
title('PG Returns against Market Jump Returns');
%C
beta_hat_PG=sum(lr_PG(Pn).*lr_SPY(Pn))/sum(lr_SPY(Pn).^2);
%D
x=linspace(1.3*min(lr_SPY(Pn)),1.3*max(lr_SPY(Pn)),200);
y=beta_hat_PG*x;
figure;
plot(x,y);
hold on;
scatter(lr_SPY(Pn),lr_PG(Pn));
grid on;
xlabel('Market Jump Returns $\Delta_{ip}^n X_1$');
ylabel('PG Returns $\Delta_{ip}^n X_2$');
legend('y=$\beta$*x','Location','southeast');
title('PG Returns Against Market Jump Returns');
%E
et_PG=lr_PG-beta_hat_PG*lr_SPY;%local residual
V_beta_PG=beta_var(lr_SPY,lr_PG,n,a,kn);
sd_beta_PG=sqrt((1/n)*V_beta_PG);
```

```
%F
%CI by asym distribution
c=-norminv(0.025);
CI_l_beta_PG=beta_hat_PG-c*sqrt((1/n)*V_beta_PG);
CI_u_beta_PG=beta_hat_PG+c*sqrt((1/n)*V_beta_PG);

%G
V_PG=beta_hat_PG*200;
Vl_PG=CI_l_beta_PG*200;
Vu_PG=CI_u_beta_PG*200;

%H
daytime=datetime(rdates_PG,'ConvertFrom','datenum');
Y=sum(daytime(:).Year<=2011);

[V_beta1_PG,beta1_PG]=beta_var(lr_SPY(1:Y),lr_PG(1:Y),77,5,11);
[V_beta2_PG,beta2_PG]=beta_var(lr_SPY(Y+1:end),lr_PG(Y+1:end),77,5,11);

%I
V12_PG=V_beta1_PG+V_beta2_PG;
beta12_PG=beta1_PG-beta2_PG;
CI_l_PG=(beta1_PG-beta2_PG)-1.96*sqrt(V12_PG/n);
CI_u_PG=(beta1_PG-beta2_PG)+1.96*sqrt(V12_PG/n);
```