final_exam report

November 27, 2019

Empirical Method in Financial Econometrics: Final Exam

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Exercise 0

Stock	Ticker
1	DIS
2	PG
3	SPY
Option File	20150102_48.csv

Exercise 1

A

[58]:
```
import numpy as np
```

[59]:
```
from scipy.stats import norm
def BLS_price(s,k,T,r,q,sigma):
    d1 = (np.log(s/k)+(r-q+ sigma ** 2/2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma * np.sqrt(T)
    put_price = k * np.exp(-r*T) * norm.cdf(-d2) - s*np.exp(-q*T)*norm.cdf(-d1)
    return put_price
```

[60]:
```
spy = 50
strike = 42.5
rf = 0.013
tenor = 90/365
sigma = 0.4
q = 0.025
p = BLS_price(spy,strike,tenor,rf,q,sigma)
print(p)
```

```
1.085929065393616
```

[61]:
```
strike = 44
p = BLS_price(spy,strike,tenor,rf,q,sigma)
```

```
print(p)
```

```
1.4883511391847986
```

[62]:
```
strike = 48
p = BLS_price(spy,strike,tenor,rf,q,sigma)
print(p)
```

```
3.0046350891369116
```

[63]:
```
strike = 50
p = BLS_price(spy,strike,tenor,rf,q,sigma)
print(p)
```

```
4.011079195608197
```

[64]:
```
strike = 52
p = BLS_price(spy,strike,tenor,rf,q,sigma)
print(p)
```

```
5.176198098753648
```

[65]:
```
strike = 55
p = BLS_price(spy,strike,tenor,rf,q,sigma)
print(p)
```

```
7.193553964886185
```

[73]:
```
def HW_price(s,k,T,r,q,sigma_hat):
    d1 = (np.log(s/k)+(r-q+ sigma_hat ** 2/2)*T)/(sigma_hat*np.sqrt(T))
    d2 = d1 - sigma_hat * np.sqrt(T)
    put_price = np.mean(k * np.exp(-r*T) * norm.cdf(-d2) - s*np.exp(-q*T)*norm.
↪cdf(-d1))
    return put_price
```

[74]:
```
z = np.random.randn(1,1000)
V = np.exp(np.log(40)-(1.2*1.2/2)+1.2*z)
sigma_hat = V/100

strike = 42.5
p = HW_price(spy,strike,tenor,rf,q,sigma_hat)
print(p)
```

```
1.7669018189205485
```

[75]:
```
strike = 44
p = HW_price(spy,strike,tenor,rf,q,sigma_hat)
print(p)
```

2.025220419501628

[76]:
```
strike = 48
p = HW_price(spy,strike,tenor,rf,q,sigma_hat)
print(p)
```

3.037069327726387

[77]:
```
strike = 50
p = HW_price(spy,strike,tenor,rf,q,sigma_hat)
print(p)
```

3.9088048488475646

[78]:
```
strike = 52
p = HW_price(spy,strike,tenor,rf,q,sigma_hat)
print(p)
```

5.235822143079598

[79]:
```
strike = 55
p = HW_price(spy,strike,tenor,rf,q,sigma_hat)
print(p)
```

7.63134798393759

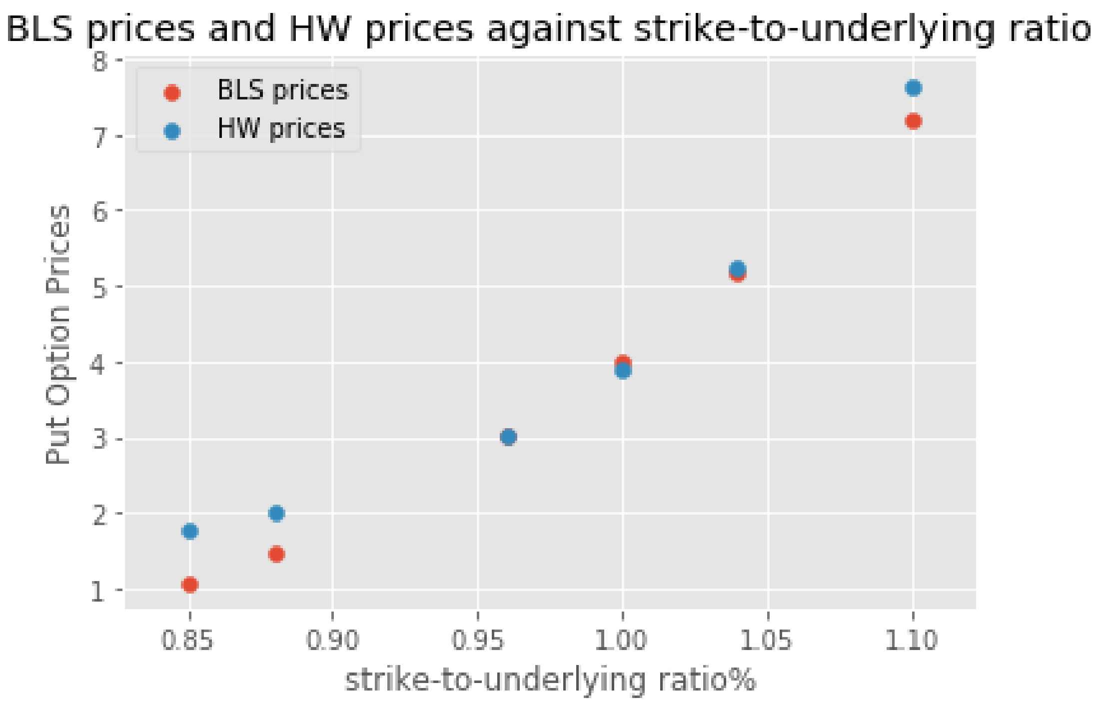
		Put Price implied by
K	Black-Scholes	Hull-White
42.5	1.085929065393616	1.7669018189205485
44	1.4883511391847986	2.025220419501628
48	3.0046350891369116	3.037069327726387
50	4.011079195608197	3.9088048488475646
52	5.176198098753648	5.235822143079598
55	7.193553964886185	7.63134798393759

B

[92]:
```
strike = np.array([42.5,44,48,50,52,55])
spy = np.array([50,50,50,50,50,50])
ratio = strike/spy
BLS_p = np.array([1.085929065393616,1.4883511391847986,3.0046350891369116,4.
 ↪011079195608197,5.176198098753648,7.193553964886185])
HW_p = np.array([1.7669018189205485,2.025220419501628,3.037069327726387,3.
 ↪9088048488475646,5.235822143079598,7.63134798393759])
```

[94]:
```
import matplotlib.pyplot as plt
import matplotlib.legend
```

```
with plt.style.context("ggplot"):
    line1 = plt.scatter(ratio,BLS_p)
    line2 = plt.scatter(ratio,HW_p)
    plt.legend(['BLS prices','HW prices'])
    plt.xlabel("strike-to-underlying ratio%")
    plt.ylabel("Put Option Prices")
    plt.title("BLS prices and HW prices against strike-to-underlying ratio")
```



Interpret: It is clear to see that the Hull-White put prices are higher than the Black-Scholes put prices generally. I think the reason lies in the difference of these two models, which is the sigma chosen. Black-Scholes put prices are created by a simple constant volatility. However, the volatility in Hull-White model includes stochastic process, which is more accurate than the Black-Scholes model. I think the random volatility in the Hull-White model can help explain the under-pricing by the Black-Scholes model, because the estimated prices match the market prices better when adding the random volatility in the model.

C

[444]:
```
import os
os.chdir("/Users/zhouxijie/python/final exam/datas")
```

[96]:
```
def load_data(filename,columns=0):
    data = np.loadtxt(filename,delimiter = ',',usecols = columns)
    return data
```

[99]:
```
data = load_data("20150102_48.csv",(0,2,3,4,5,6,7))
print(option_data[0])
```

```
[2.0150102e+07 2.0541000e+02 2.0000000e-02 2.2098000e+00 3.6500000e-01
 1.7000000e+02 4.9000000e+01]
```

[138]:
```
dates,spy,rf,q,put,strike,tenor = (
    data[:,0],
    data[:,1],
    data[:,2]/100,
    data[:,3]/100,
    data[:,4],
    data[:,5],
    data[:,6]/365)
```

[123]:
```
def get_return(fileaddress):
    date, time, price = np.loadtxt(fileaddress, delimiter = ',', unpack = True)
    N = sum(date == date[0])
    T = len(date)//N
    returns = np.diff((np.reshape(np.log(price), (N,T), order = 'F')), axis = 0)
    return returns, date
```

[124]:
```
r, date = get_return('/Users/zhouxijie/python/final exam/datas/SPY.csv')
```

[125]:
```
day = np.where(date == 20150102)[0][0]//78
```

[126]:
```
def realized_var(returns):
    RV = sum(returns**2)
    return RV
```

[127]:
```
RV = np.sqrt(realized_var(r[:,2014])*252)*100
print(RV)
```

```
12.494961571074171
```

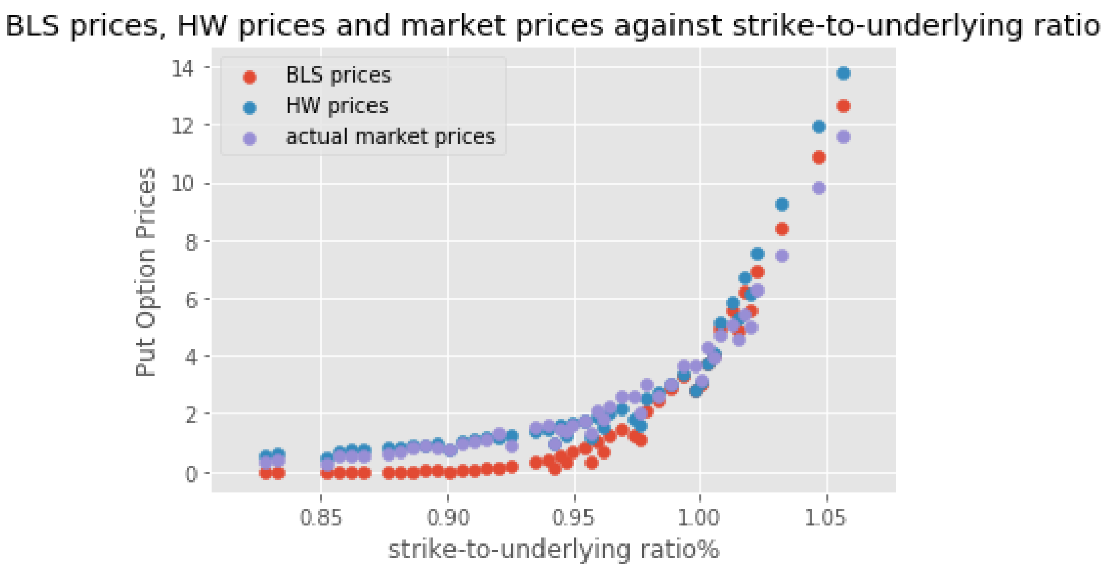
[309]:
```
BLS_p = BLS_price(spy,strike,tenor,rf,q,RV/100)
```

[186]:
```
z = np.random.randn(1,1000)
V = np.exp(np.log(RV)-(1.2*1.2/2)+1.2*z)
sigma_hat = V/100
```

[200]:
```
HW_p = []
for i in range(0,48):
    HW_p.append(HW_price(spy[i],strike[i],tenor[i],rf[i],q[i],sigma_hat))
HW_p = np.array(HW_p)
```

[199]:
```
ratio = strike/spy
```

```
[198]: import matplotlib.pyplot as plt
import matplotlib.legend
with plt.style.context("ggplot"):
    line1 = plt.scatter(ratio,BLS_p)
    line2 = plt.scatter(ratio,HW_p)
    line3 = plt.scatter(ratio,put)
    plt.legend(['BLS prices','HW prices','actual market prices'])
    plt.xlabel("strike-to-underlying ratio%")
    plt.ylabel("Put Option Prices")
    plt.title("BLS prices, HW prices and market prices against␣
 ↪strike-to-underlying ratio")
```




```
[203]: Average_BLS_p = np.mean(BLS_p)
Average_HW_p = np.mean(HW_p)
print(Average_BLS_p)
print(Average_HW_p)
```

```
2.1168462997109367
2.800789038410361
```

Interpret: The file I use is “20150102_48”. The average price from the Black-Scholes model is 2.1168; The average price from the Hull-White model is 2.8008. From the figure above, we can see that the pricing of OTM puts by the Hull-White model is much better than the Black-Scholes model. I think the stochastic volatility truely help with pricing out-of-the-money put options. When the strike-to-underlying ratio is from 0.98-1.02, the differences that the models compare to the market price is the least.

Exercise 2

A

[507]:
```
r_1, date_1 = get_return('/Users/zhouxijie/python/final exam/datas/DIS.csv')
```

[508]:
```
r_2, date_2 = get_return('/Users/zhouxijie/python/final exam/datas/PG.csv')
```

[509]:
```
realized_beta_1 = []
for i in range(0,2769):
    realized_beta_1.append(np.sum((r[:,i]*r_1[:,i]))/np.sum(r[:,i]*r[:,i]))
```

[510]:
```
realized_beta_2 = []
for i in range(0,2769):
    realized_beta_2.append(np.sum((r[:,i]*r_2[:,i]))/np.sum(r[:,i]*r[:,i]))
```

[511]:
```
Average_rb1 = np.mean(realized_beta_1)
print(Average_rb1)
Average_rb2 = np.mean(realized_beta_2)
print(Average_rb2)
```

```
0.9372810762752267
0.5454156664249717
```

[512]:
```
Min_rb1 = np.min(realized_beta_1)
print(Min_rb1)
Min_rb2 = np.min(realized_beta_2)
print(Min_rb2)
```

```
-1.0811145134104991
-0.4166602658009185
```

[513]:
```
Per_25_1 = np.percentile(realized_beta_1,25)
print(Per_25_1)
Per_25_2 = np.percentile(realized_beta_2,25)
print(Per_25_2)
```

```
0.7757819580852029
0.3778622648870579
```

[514]:
```
Per_50_1 = np.percentile(realized_beta_1,50)
print(Per_50_1)
Per_50_2 = np.percentile(realized_beta_2,50)
print(Per_50_2)
```

```
0.9468146700941424
0.5348547035059938
```

[515]:
```
Per_75_1 = np.percentile(realized_beta_1,75)
print(Per_75_1)
Per_75_2 = np.percentile(realized_beta_2,75)
print(Per_75_2)
```

```
1.1089788490175745
0.7070440738738019
```

[516]:
```
Max_rb1 = np.max(realized_beta_1)
print(Max_rb1)
Max_rb2 = np.max(realized_beta_2)
print(Max_rb2)
```

```
3.134483648417962
2.042069465609289
```

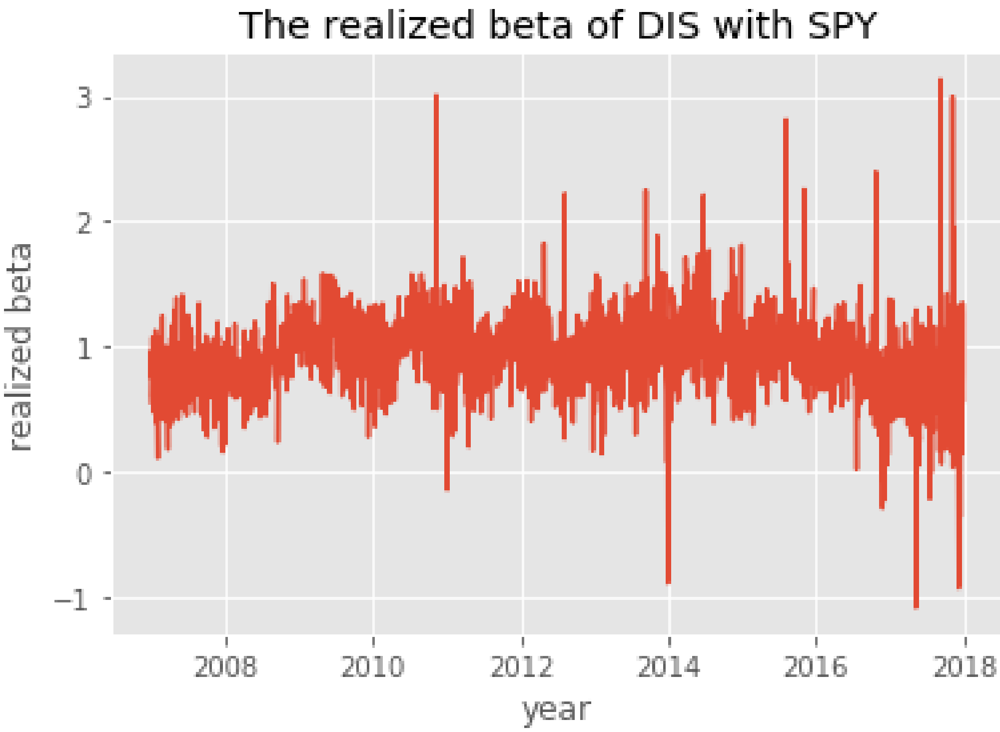
	$R\beta_{Stock1,Market}$	$R\beta_{Stock2,Market}$
Average	0.9372810762752267	0.5454156664249717
Minimum	-1.0811145134104991	-0.4166602658009185
25% Percentile	0.7757819580852029	0.3778622648870579
50% Percentile	0.9468146700941424	0.5348547035059938
75% Percentile	1.1089788490175745	0.7070440738738019
Maximum	3.134483648417962	2.042069465609289

[517]:
```
N = sum(date_1 == date_1[0])
T = len(date_1)//N
dates=np.reshape(date_1,(N,T),order = 'F')
```

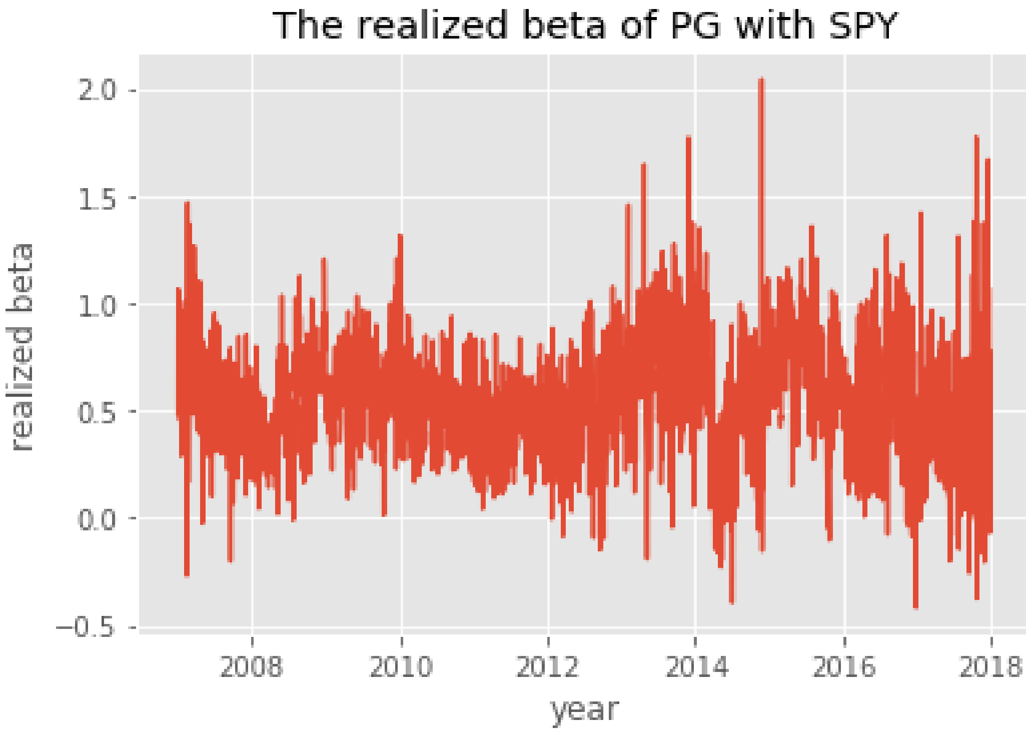
[518]:
```
strdate = []
for i in dates[1,:]:
    strdate.append(str(int(i)))
```

[519]:
```
dates = []
for i in range(len(strdate)):
    dates.append(datetime.strptime(strdate[i], '%Y%m%d'))
```

[520]:
```
from datetime import datetime
with plt.style.context("ggplot"):
    plt.plot(dates,realized_beta_1)
    plt.xlabel('year')
    plt.ylabel('realized beta')
    plt.title('The realized beta of DIS with SPY')
```



[521]:
```
with plt.style.context("ggplot"):
    plt.plot(dates,realized_beta_2)
    plt.xlabel('year')
    plt.ylabel('realized beta')
    plt.title('The realized beta of PG with SPY')
```



Interpret: The plots of DIS fluctuated around 0.9 generally and the plots of PG fluctuated around 0.5 generally, so the stock returns of PG is not so close to the market return, which is represented by SPY here. In general, when the scale of realized beta is between 0 and 1, it means that the stock return is less than the market income; when it is less than 0, it indicates that the stock not only has no income, but a loss; when it is greater than 1, it shows that the stock returns are more than the market income.

B

[536]:
```
rv_1 = np.sqrt(252*realized_var(r_1))*100
rv_2 = np.sqrt(252*realized_var(r_2))*100
```

[537]:
```
Average_rv_1 = np.mean(rv_1)
Average_rv_2 = np.mean(rv_2)
print(Average_rv_1)
print(Average_rv_2)
Min_rv_1 = np.min(rv_1)
Min_rv_2 = np.min(rv_2)
print(Min_rv_1)
print(Min_rv_2)
Per_25_rv_1 = np.percentile(rv_1,25)
Per_25_rv_2 = np.percentile(rv_2,25)
print(Per_25_rv_1)
```

```
print(Per_25_rv_2)
Per_50_rv_1 = np.percentile(rv_1,50)
Per_50_rv_2 = np.percentile(rv_2,50)
print(Per_50_rv_1)
print(Per_50_rv_2)
Per_75_rv_1 = np.percentile(rv_1,75)
Per_75_rv_2 = np.percentile(rv_2,75)
print(Per_75_rv_1)
print(Per_75_rv_2)
Max_rv_1 = np.max(rv_1)
Max_rv_2 = np.max(rv_2)
print(Max_rv_1)
print(Max_rv_2)
```

```
18.327885197254957
13.357460282810921
5.681423418887914
4.825248283116661
11.720755941935643
9.07685105629298
15.019035530425818
11.364598799912011
20.745396216715775
14.894888013837887
165.66328353148913
121.56429909053088
```

[538]:
```
ind = r_1>=0
r_1_p = r_1*ind
rv_1_p = np.sqrt(252*realized_var(r_1_p))*100

ind = r_2>=0
r_2_p = r_2*ind
rv_2_p = np.sqrt(252*realized_var(r_2_p))*100


Average_rv_1_p = np.mean(rv_1_p)
Average_rv_2_p = np.mean(rv_2_p)
print(Average_rv_1_p)
print(Average_rv_2_p)
Min_rv_1_p = np.min(rv_1_p)
Min_rv_2_p = np.min(rv_2_p)
print(Min_rv_1_p)
print(Min_rv_2_p)
Per_25_rv_1_p = np.percentile(rv_1_p,25)
Per_25_rv_2_p = np.percentile(rv_2_p,25)
print(Per_25_rv_1_p)
```

```
print(Per_25_rv_2_p)
Per_50_rv_1_p = np.percentile(rv_1_p,50)
Per_50_rv_2_p = np.percentile(rv_2_p,50)
print(Per_50_rv_1_p)
print(Per_50_rv_2_p)
Per_75_rv_1_p = np.percentile(rv_1_p,75)
Per_75_rv_2_p = np.percentile(rv_2_p,75)
print(Per_75_rv_1_p)
print(Per_75_rv_2_p)
Max_rv_1_p = np.max(rv_1_p)
Max_rv_2_p = np.max(rv_2_p)
print(Max_rv_1_p)
print(Max_rv_2_p)
```

```
12.881831322420995
9.44658926794523
3.159627093141045
2.730986283659158
8.148802054041987
6.305368713558153
10.589108275187007
7.952222854538945
14.440848754608268
10.544654271462077
128.2541802903802
95.45315697077751
```

[539]:

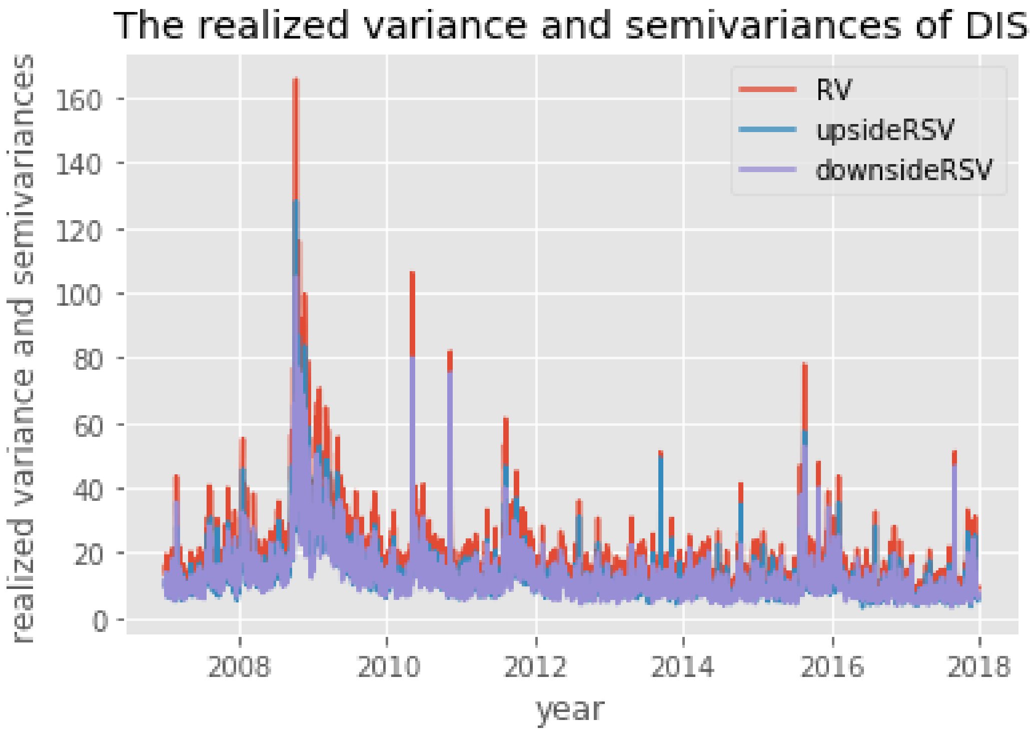
```
ind = r_1<0
r_1_n = r_1*ind
rv_1_n = np.sqrt(252*realized_var(r_1_n))*100

ind = r_2<0
r_2_n = r_2*ind
rv_2_n = np.sqrt(252*realized_var(r_2_n))*100

Average_rv_1_n = np.mean(rv_1_n)
Average_rv_2_n = np.mean(rv_2_n)
print(Average_rv_1_n)
print(Average_rv_2_n)
Min_rv_1_n = np.min(rv_1_n)
Min_rv_2_n = np.min(rv_2_n)
print(Min_rv_1_n)
print(Min_rv_2_n)
Per_25_rv_1_n = np.percentile(rv_1_n,25)
Per_25_rv_2_n = np.percentile(rv_2_n,25)
print(Per_25_rv_1_n)
print(Per_25_rv_2_n)
```

```
Per_50_rv_1_n = np.percentile(rv_1_n,50)
Per_50_rv_2_n = np.percentile(rv_2_n,50)
print(Per_50_rv_1_n)
print(Per_50_rv_2_n)
Per_75_rv_1_n = np.percentile(rv_1_n,75)
Per_75_rv_2_n = np.percentile(rv_2_n,75)
print(Per_75_rv_1_n)
print(Per_75_rv_2_n)
Max_rv_1_n = np.max(rv_1_n)
Max_rv_2_n = np.max(rv_2_n)
print(Max_rv_1_n)
print(Max_rv_2_n)
```

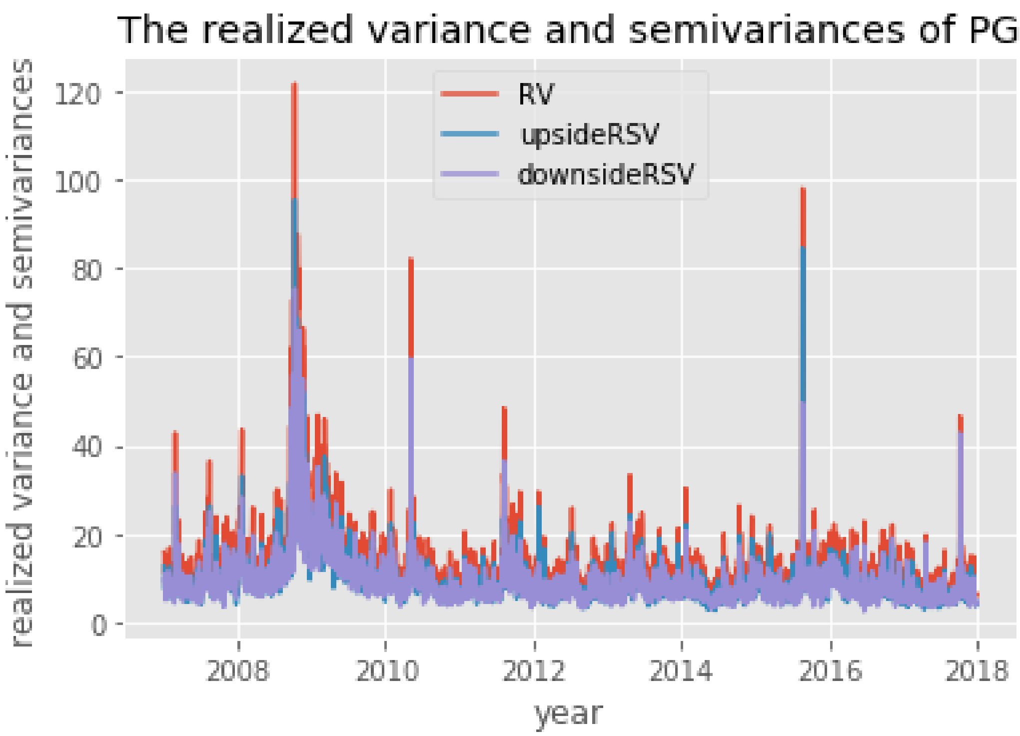
```
12.830355097818842
9.304824525657896
3.133739902899201
2.4570531833069778
7.925145256504812
6.1849527968023805
10.51683112867519
7.882630783902718
14.784952262068881
10.482437620738986
104.85794556673906
75.27664735948433
```

	Stock 1			Stock 2		
	$RV_t\%$	$RV_t^+\%$	$RV_t^-\%$	$RV_t\%$	$RV_t^+\%$	$RV_t^-\%$
Average	18.33	12.88	12.83	13.36	9.45	9.30
Minimum	5.68	3.16	3.13	4.83	2.73	2.46
25% Percentile	11.72	8.15	7.93	9.08	6.31	6.18
50% Percentile	15.02	10.59	10.52	11.36	7.95	7.88
75% Percentile	20.75	14.44	14.78	14.89	10.54	10.48
Maximum	165.66	128.25	104.86	121.56	95.45	75.28

[540]:
```
with plt.style.context("ggplot"):
    line1 = plt.plot(dates,rv_1)
    line2 = plt.plot(dates,rv_1_p)
    line3 = plt.plot(dates,rv_1_n)
    plt.legend(['RV','upsideRSV','downsideRSV'])
    plt.xlabel('year')
    plt.ylabel('realized variance and semivariances%')
    plt.title('The realized variance and semivariances of DIS')
```



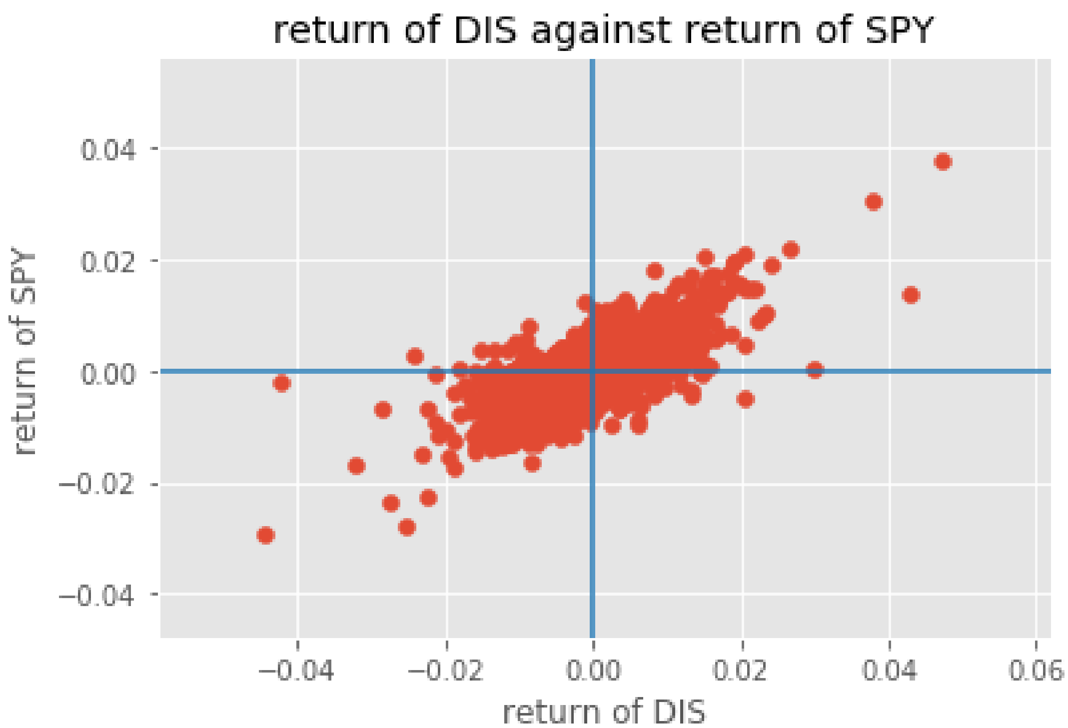
[541]:
```
with plt.style.context("ggplot"):
    line1 = plt.plot(dates,rv_2)
    line2 = plt.plot(dates,rv_2_p)
    line3 = plt.plot(dates,rv_2_n)
    plt.legend(['RV','upsideRSV','downsideRSV'])
    plt.xlabel('year')
    plt.ylabel('realized variance and semivariances%')
    plt.title('The realized variance and semivariances of PG')
```



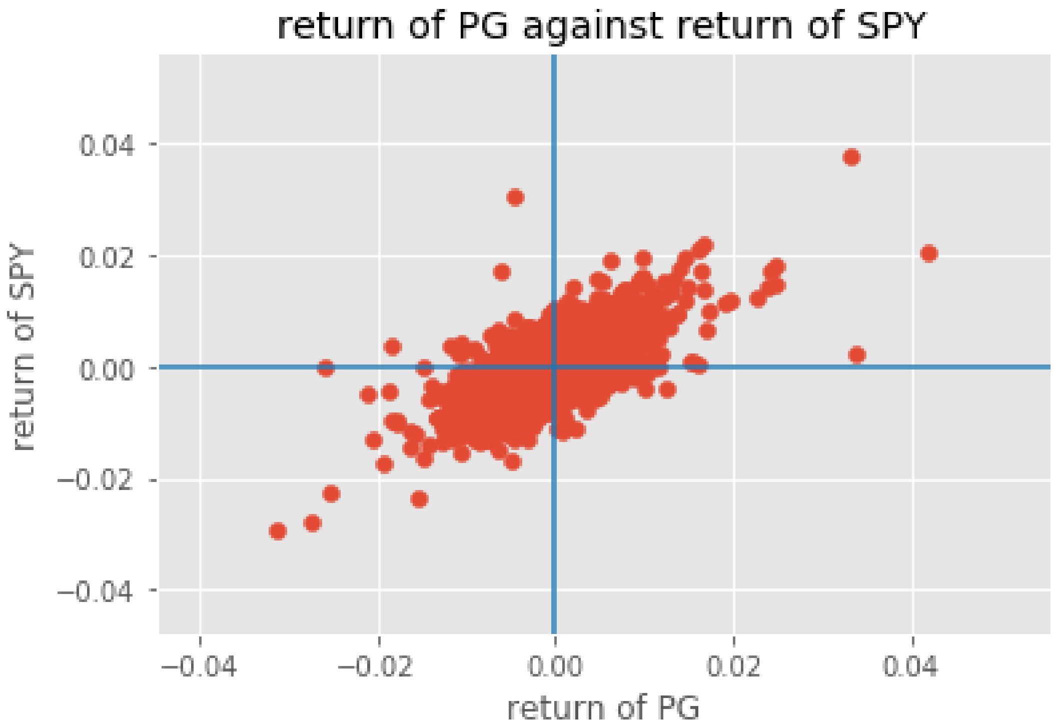
Interpret: As we can be seen from the plots, upside and downside realized semivariance follow the simillar pattern with the realized variance. Notice that the upside realizde variance is mostly higher when there is huge volatility, but still can not match the realized variance completely. Focus on data around 2008 crisis (actuall on 2009), the pattern of semivariance still similar to the realized variance. At the same time, a higher volatility in market happened.

C

[528]:
```
with plt.style.context("ggplot"):
    plt.scatter(r_1,r)
    plt.xlabel("return of DIS")
    plt.ylabel("return of SPY")
    plt.title("return of DIS against return of SPY")
    plt.axhline()
    plt.axvline()
```



[529]:
```
with plt.style.context("ggplot"):
    plt.scatter(r_2,r)
    plt.xlabel("return of PG")
    plt.ylabel("return of SPY")
    plt.title("return of PG against return of SPY")
    plt.axhline()
    plt.axvline()
```



Interpret: First of all, both sotcks returns tend to move positively with the direction of the market returns. For market returns are below 0, there are only a few instances (lower right quadrant) where the stock returns are positive, with the majority of stock returns being negative (lower left quadrant). For market returns are higher than 0, there are only a few instances (upper left quadrant) where the stock returns are negative, with the majority of stock returns being positive (upper right quadrant).

D

Interpret: If the stock moves in the same direction as the market, investors will need higher expected returns to hold the stock. Because the stock cann't hedge risk. On the contrary, if a stock moves adversely in the direction of the market, it means that the asset's beta is negative. When investors add this asset to their portfolio, the overall risk of the portfolio will be hedged. Investors will not require high expected returns on holding assets in their portfolios. Based on my solution, my stocks comove positively with the market. I hope my stocks could have high risk premiums, because it means the higher chance of high profits.

E

[530]:
```
ind = r>=0
r_p = r*ind

ind = r<0
r_n = r*ind
```

[531]:
```python
rb_1_pp = []
for i in range(0,2769):
    rb_1_pp.append(np.sum((r_p[:,i]*r_1_p[:,i]))/np.sum(r[:,i]*r[:,i]))

rb_1_pn = []
for i in range(0,2769):
    rb_1_pn.append(np.sum((r_p[:,i]*r_1_n[:,i]))/np.sum(r[:,i]*r[:,i]))

rb_1_np = []
for i in range(0,2769):
    rb_1_np.append(np.sum((r_n[:,i]*r_1_p[:,i]))/np.sum(r[:,i]*r[:,i]))

rb_1_nn = []
for i in range(0,2769):
    rb_1_nn.append(np.sum((r_n[:,i]*r_1_n[:,i]))/np.sum(r[:,i]*r[:,i]))
```

[532]:
```python
rb_2_pp = []
for i in range(0,2769):
    rb_2_pp.append(np.sum((r_p[:,i]*r_2_p[:,i]))/np.sum(r[:,i]*r[:,i]))

rb_2_pn = []
for i in range(0,2769):
    rb_2_pn.append(np.sum((r_p[:,i]*r_2_n[:,i]))/np.sum(r[:,i]*r[:,i]))

rb_2_np = []
for i in range(0,2769):
    rb_2_np.append(np.sum((r_n[:,i]*r_2_p[:,i]))/np.sum(r[:,i]*r[:,i]))

rb_2_nn = []
for i in range(0,2769):
    rb_2_nn.append(np.sum((r_n[:,i]*r_2_n[:,i]))/np.sum(r[:,i]*r[:,i]))
```

[542]:
```python
Average_rb_1_pp = np.mean(rb_1_pp)
Average_rb_1_pn = np.mean(rb_1_pn)
Average_rb_1_np = np.mean(rb_1_np)
Average_rb_1_nn = np.mean(rb_1_nn)
print(Average_rb_1_pp)
print(Average_rb_1_pn)
print(Average_rb_1_np)
print(Average_rb_1_nn)

Average_rb_2_pp = np.mean(rb_2_pp)
Average_rb_2_pn = np.mean(rb_2_pn)
Average_rb_2_np = np.mean(rb_2_np)
Average_rb_2_nn = np.mean(rb_2_nn)
print(Average_rb_2_pp)
print(Average_rb_2_pn)
```

```
print(Average_rb_2_np)
print(Average_rb_2_nn)
```

```
0.5527766894271416
-0.08195783306741487
-0.07683115464629818
0.543293374561798
0.37285569019613046
-0.0911586795611272
-0.08918364556970317
0.35290230135967177
```

[543]:

```
Min_rb_1_pp = np.min(rb_1_pp)
Min_rb_1_pn = np.min(rb_1_pn)
Min_rb_1_np = np.min(rb_1_np)
Min_rb_1_nn = np.min(rb_1_nn)
print(Min_rb_1_pp)
print(Min_rb_1_pn)
print(Min_rb_1_np)
print(Min_rb_1_nn)

Min_rb_2_pp = np.min(rb_2_pp)
Min_rb_2_pn = np.min(rb_2_pn)
Min_rb_2_np = np.min(rb_2_np)
Min_rb_2_nn = np.min(rb_2_nn)
print(Min_rb_2_pp)
print(Min_rb_2_pn)
print(Min_rb_2_np)
print(Min_rb_2_nn)
```

```
0.05127519061899447
-1.1849176268078934
-1.4838945583378844
0.06738366254880157
0.06256245281510617
-1.268049710714106
-0.8667662539188542
0.04567104816113811
```

[544]:

```
Per_25_rb_1_pp = np.percentile(rb_1_pp,25)
Per_25_rb_1_pn = np.percentile(rb_1_pn,25)
Per_25_rb_1_np = np.percentile(rb_1_np,25)
Per_25_rb_1_nn = np.percentile(rb_1_nn,25)
print(Per_25_rb_1_pp)
print(Per_25_rb_1_pn)
print(Per_25_rb_1_np)
print(Per_25_rb_1_nn)
```

```
Per_25_rb_2_pp = np.percentile(rb_2_pp,25)
Per_25_rb_2_pn = np.percentile(rb_2_pn,25)
Per_25_rb_2_np = np.percentile(rb_2_np,25)
Per_25_rb_2_nn = np.percentile(rb_2_nn,25)
print(Per_25_rb_2_pp)
print(Per_25_rb_2_pn)
print(Per_25_rb_2_np)
print(Per_25_rb_2_nn)
```

```
0.40458167041328186
-0.1007742133727276
-0.0940433600817832
0.40680129284810845
0.2505129919041556
-0.11718503783712385
-0.11339229512390292
0.24261983081668745
```

[545]:

```
Per_50_rb_1_pp = np.percentile(rb_1_pp,50)
Per_50_rb_1_pn = np.percentile(rb_1_pn,50)
Per_50_rb_1_np = np.percentile(rb_1_np,50)
Per_50_rb_1_nn = np.percentile(rb_1_nn,50)
print(Per_50_rb_1_pp)
print(Per_50_rb_1_pn)
print(Per_50_rb_1_np)
print(Per_50_rb_1_nn)

Per_50_rb_2_pp = np.percentile(rb_2_pp,50)
Per_50_rb_2_pn = np.percentile(rb_2_pn,50)
Per_50_rb_2_np = np.percentile(rb_2_np,50)
Per_50_rb_2_nn = np.percentile(rb_2_nn,50)
print(Per_50_rb_2_pp)
print(Per_50_rb_2_pn)
print(Per_50_rb_2_np)
print(Per_50_rb_2_nn)
```

```
0.5198779231022732
-0.05076867453047529
-0.04777163885120527
0.5200142208896111
0.3403516289303669
-0.06150430416543107
-0.06322360634882052
0.33004350733527155
```

[546]:
```
Per_75_rb_1_pp = np.percentile(rb_1_pp,75)
Per_75_rb_1_pn = np.percentile(rb_1_pn,75)
Per_75_rb_1_np = np.percentile(rb_1_np,75)
Per_75_rb_1_nn = np.percentile(rb_1_nn,75)
print(Per_75_rb_1_pp)
print(Per_75_rb_1_pn)
print(Per_75_rb_1_np)
print(Per_75_rb_1_nn)

Per_75_rb_2_pp = np.percentile(rb_2_pp,75)
Per_75_rb_2_pn = np.percentile(rb_2_pn,75)
Per_75_rb_2_np = np.percentile(rb_2_np,75)
Per_75_rb_2_nn = np.percentile(rb_2_nn,75)
print(Per_75_rb_2_pp)
print(Per_75_rb_2_pn)
print(Per_75_rb_2_np)
print(Per_75_rb_2_nn)
```

```
0.6646882841606637
-0.02477208756913299
-0.024984782745866373
0.654965619823472
0.4623674914760752
-0.03210443362671408
-0.033371830403132595
0.43270988074591393
```

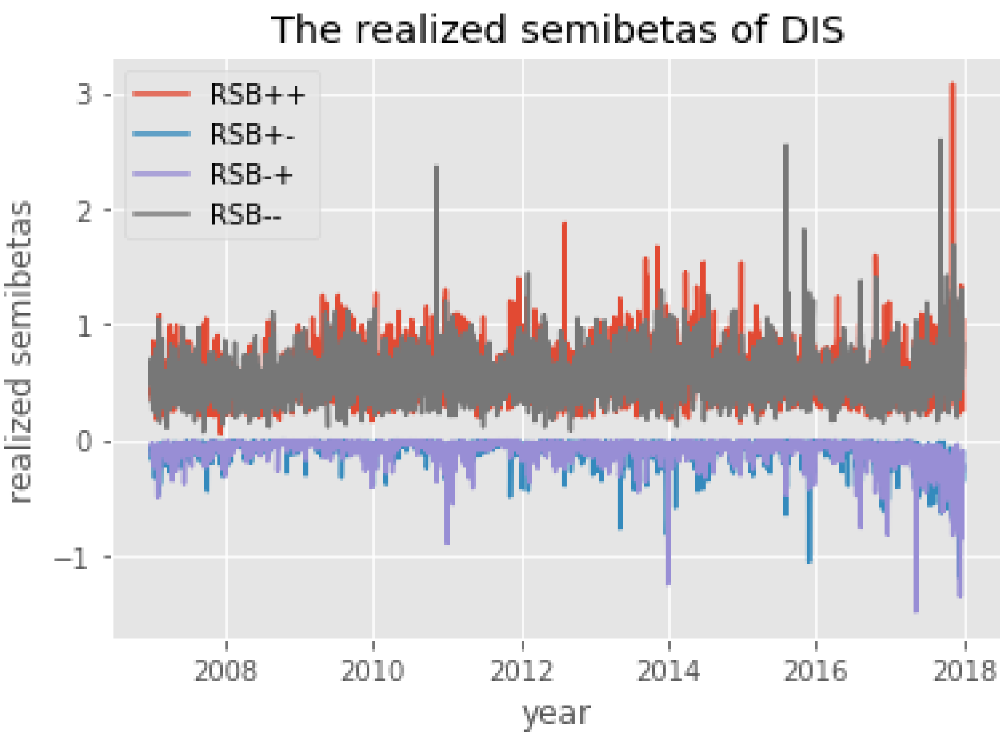
[547]:
```
Max_rb_1_pp = np.max(rb_1_pp)
Max_rb_1_pn = np.max(rb_1_pn)
Max_rb_1_np = np.max(rb_1_np)
Max_rb_1_nn = np.max(rb_1_nn)
print(Max_rb_1_pp)
print(Max_rb_1_pn)
print(Max_rb_1_np)
print(Max_rb_1_nn)

Max_rb_2_pp = np.max(rb_2_pp)
Max_rb_2_pn = np.max(rb_2_pn)
Max_rb_2_np = np.max(rb_2_np)
Max_rb_2_nn = np.max(rb_2_nn)
print(Max_rb_2_pp)
print(Max_rb_2_pn)
print(Max_rb_2_np)
print(Max_rb_2_nn)
```

```
3.0760018744112974
0.0
0.0
```

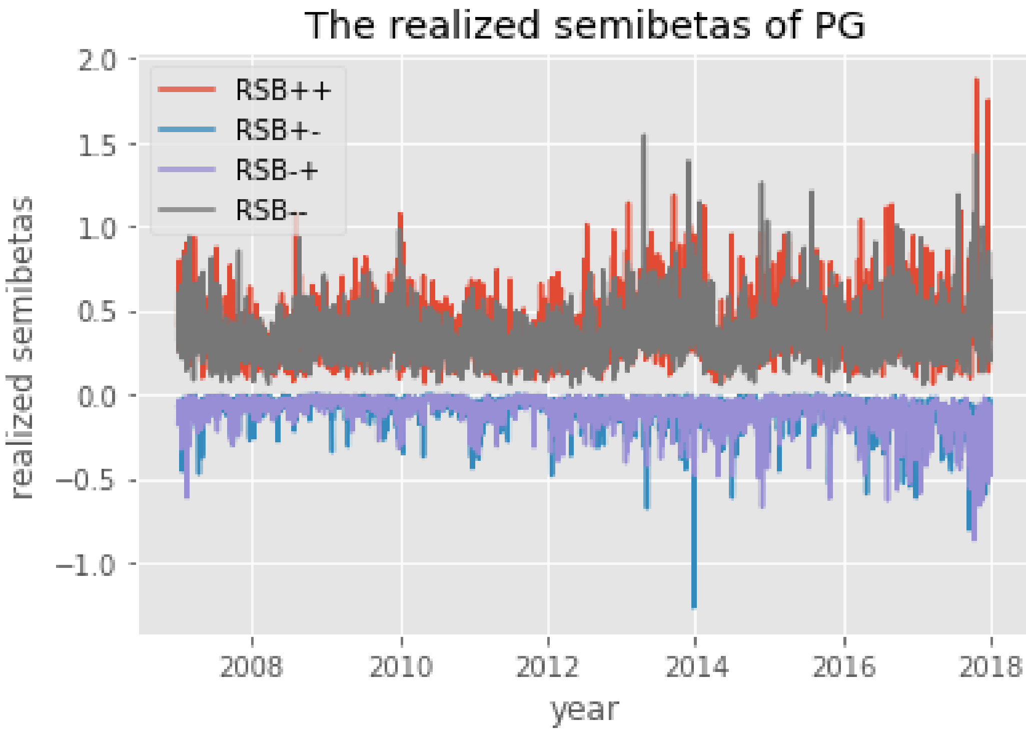
```
2.589068487173038
1.8723696852704312
-0.0005221473201412088
-0.0010052193156259792
1.5394607097494466
```

	Stock 1	and	Market	Index	Stock 2	and	Market	Index
	$R\beta_t^{+,+}$	$R\beta_t^{+,-}$	$R\beta_t^{-,+}$	$R\beta_t^{-,-}$	$R\beta_t^{+,+}$	$R\beta_t^{+,-}$	$R\beta_t^{-,+}$	$R\beta_t^{-,-}$
Average	0.55	-0.08	-0.08	0.54	0.37	-0.09	-0.09	0.35
Minimum	0.05	-1.18	-1.48	0.07	0.06	-1.27	-0.87	0.05
25% Percentile	0.40	-0.10	-0.09	0.41	0.25	-0.12	-0.11	0.24
50% Percentile	0.52	-0.05	-0.05	0.52	0.34	-0.06	-0.06	0.33
75% Percentile	0.66	-0.02	-0.02	0.65	0.46	-0.03	-0.03	0.43
Maximum	3.08	0.00	0.00	2.59	1.87	-0.00	-0.00	1.54

[534]:
```
with plt.style.context("ggplot"):
    line1 = plt.plot(dates,rb_1_pp)
    line2 = plt.plot(dates,rb_1_pn)
    line3 = plt.plot(dates,rb_1_np)
    line4 = plt.plot(dates,rb_1_nn)
    plt.legend(['RSB++','RSB+-','RSB-+','RSB--'])
    plt.xlabel('year')
    plt.ylabel('realized semibetas')
    plt.title('The realized semibetas of DIS')
```



[535]:
```
with plt.style.context("ggplot"):
    line1 = plt.plot(dates,rb_2_pp)
    line2 = plt.plot(dates,rb_2_pn)
    line3 = plt.plot(dates,rb_2_np)
    line4 = plt.plot(dates,rb_2_nn)
    plt.legend(['RSB++','RSB+-','RSB-+','RSB--'])
    plt.xlabel('year')
    plt.ylabel('realized semibetas')
    plt.title('The realized semibetas of PG')
```



Interpret: It is clear to see that the realized semibetas (RSB) fluctuated over time. We can see the RSB++, RSB– are above 0, while RSB+-, RSB-+ are below 0. And the RSB++, RSB– fluctuated more dramatically than the other two RSB. The two realized betas when market returns are negative combined gives the risk measure of the stock which an investor who only cares about downside risks concerns, that is, the magnitudes of RSB-+ and RSB– suggest the degree of my stocks risk premium.