

SFU

Beedie School of Business BUS 865 Market Risk Management

Back Testing:

VaR and ES Backtesting For Nintendo

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Company Introduction



- 34.858B MKT CAP
- Multinational consumer electronics and video game company
- Switch; Zelda, Super Mario



Methodology For Backtest

Select Estimation/Test Window



Estimate ARMA/GARCH models



Simulate Paths for 1-day VaR for Each Test



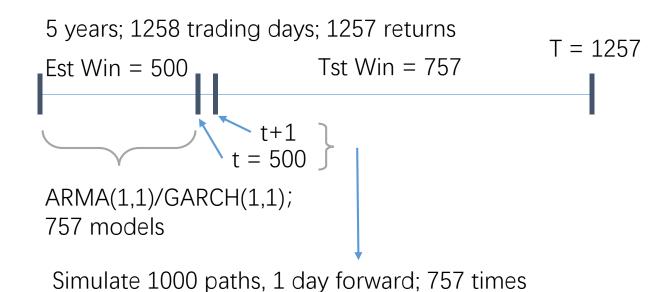
Compute 95% VaR/ES for Each Test



Find Violations; Compute VR, Std ES, Ave Std ES



Test the Significance of VR



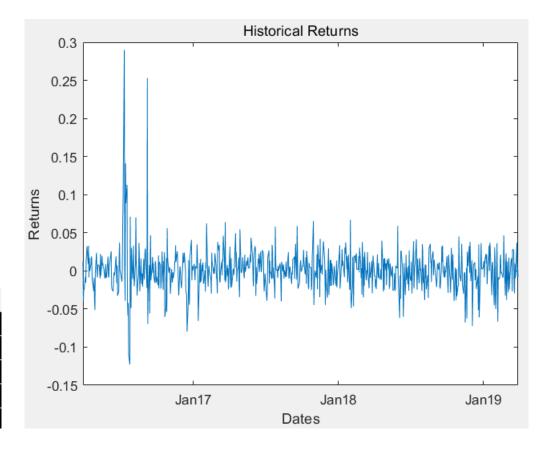
- Compute Violation Ratio/Standardized ES
- Mean of the Standardized ES
- Bernoulli coverage test/Independence of the Violations

Data Source/Processing

- Download & import 5-year historical daily data from Yahoo Finance.
- Convert adjusted closing price into returns.
- Plot the returns

```
data = readtable('NTDOY.csv');
ninR = price2ret(data.AdjClose);
%%
plot(data.Date(2:end),ninR);
xlabel('Dates');ylabel('Returns');title('Historical Returns');
datetick('x',12);xlim([dates(1) dates(end)]);
```

Date	Open	High	Low	Close	AdjClose	Volume
2014-04-02	14.6600	14.6600	14.5500	14.6100	13.8791	26400
2014-04-03	14.4900	14.5000	14.3600	14.3900	13.6701	41600
2014-04-04	14.4500	14.4500	14.2200	14.2500	13.5371	28800
2014-04-07	14.2500	14.3500	14.2500	14.2800	13.5656	15600
2014-04-08	13.9600	14.0900	13.9600	14.0400	13.3376	36700



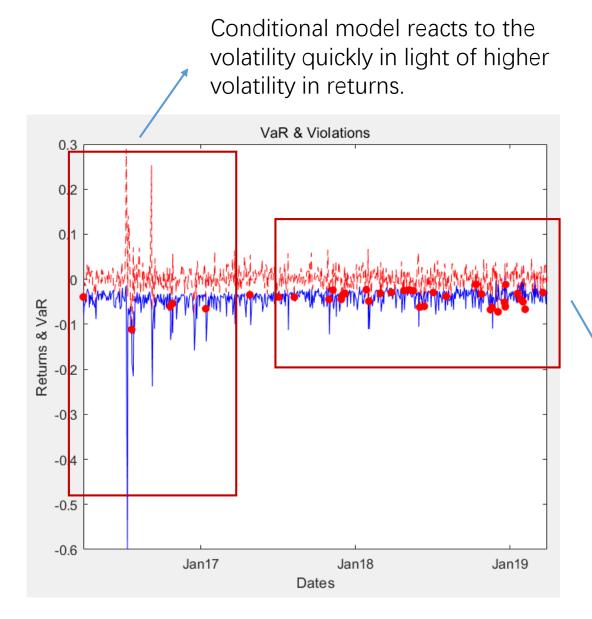
Define Variables & Compute VaR/ES

- Set up ARMA(1,1)-GARCH(1,1) model; Define other variables
- For loop to estimate each estimation window and simulate 1-day forward returns
- Cal and record VaR&ES for each tests.

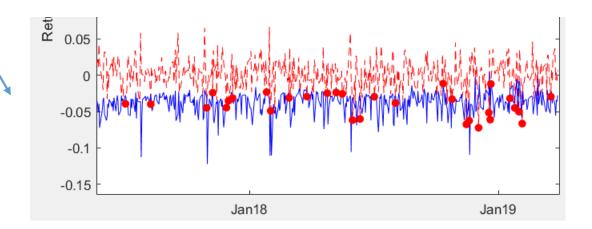
```
%%
%%
                                                                for t = EstWin + 1:T
MdI = arima('ARLags',1,'MALags',1,'Variance',garch(1,1));
                                                                   try
T = length(ninR);
                                                                      EstMdl = estimate(Mdl,ninR(t-EstWin:t-1));
EstWin = 500;
                                                                      [Innovations, Variances] = infer(EstMdl, ninR(t-EstWin:t-1));
p = 0.05;
                                                                      Simu(t,:) = simulate(EstMdl,NumObs,'NumPaths',NumPaths,...
NumObs = 1;
                                                                        'E0',Innovations,'V0',Variances);
NumPaths = 1000:
                                                                     VaR(t) = min(prctile(Simu(t,:), 5));
VaR = NaN(T,1);
                                                                      ES(t) = mean(prctile(Simu(t,:),1:5));
ES = NaN(T,1);
                                                                   catch
Simu = NaN(T,NumPaths);
                                                                     VaR(t) = min(prctile(ninR, 5));
                                                                      ES(t) = mean(prctile(ninR,1:5));
                                                                   end
```

end

Plot VaRs & Corresponding Violations



```
dates = data.Date(EstWin + 1:T);
figure(1)
plot(dates,ninR_TstWin,'r--', dates, VaR_TstWin,'b');
hold on
plot(dates(index),ninR_TstWin(index),'r.','markersize',20)
xlabel('Dates');ylabel('Returns & VaR');title('VaR &
Violations');
datetick('x',12);xlim([dates(1) dates(end)]);
```



Calculate Violation Ratio & Significance Test

VR = length(find(index))/(p *(T - EstWin));% **Violation Ratio** s = std(VaR(EstWin + 1:T));% **Volatility** ber = bern_test(p,v); % **p** is significant level,5%; v is 0-logical vector indicating violations ind = ind_test(v);

- Violation Ratio is close to 1.
 This indicates the model performs well in capturing extreme outcomes.
- For a 95% significant level, the statistics should be greater than 3.84 based on a Chi^2(1)

Violaiton Ratio	0.9775
Volatility	0.0298

With no comparison, we can not conclude if it is high or low. But from the previous plot, we can see a higher volatility in VaR corresponding to higher volatile returns.

	Coverage Tesi		
ARMA(1,1)-	Test Statistic	P-value	
GARCH(1,1)	0.0202	0.8869	

Coverage Test

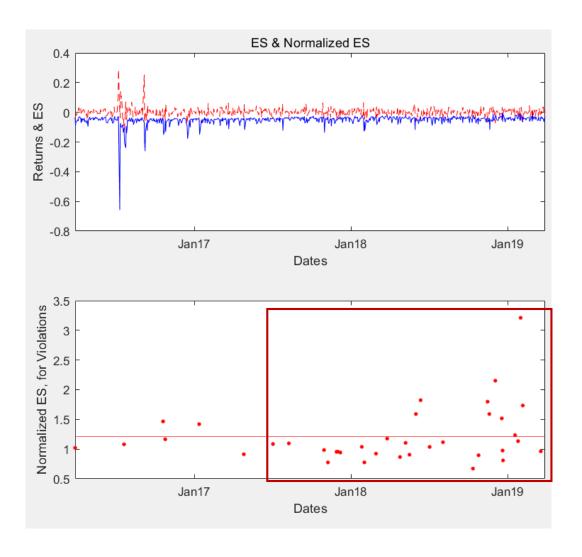
7	Eest Statistic	P-value
	0.4251	0.5144

Independence Test

- Bernoulli coverage test is not significant.
 We can not reject the hypothesis of VaR
 = 1 at 5% for this model.
- Independence test is not significant. We can not reject the hypothesis that VaR is dependent on the volatility of 1-day before for this model.

$$VR = \frac{\text{Observed number of violations}}{\text{Expected number of violations}} = \frac{v_1}{p \times W_T}.$$

Plot ESs & Standardized ESs for Violations



$$NS_t = \frac{y_t}{ES_t}$$

Average Standardized ES = 1.2139

- This model slightly underestimate the ES for violations, which in hypothethis should have an expectation of 1.
- The Standardized ES for violations are more clustered in recent years.
- It also shows a wider range.

Conclusions & Improvements

- ARMA(1,1)-GARCH(1,1) model captures extreme results quite well as indicated by the 0.9775 VR.
- By testing, we can not reject VR = 1.
- More violations clusters in recent years.
- VaRs calculated from conditional model show a simultaneous volatility with the returns.
- There is a slightly underestimation for ES as shown in Ave Std ES > 1.

- The returns of Nintendo is relatively steady without many breaks. It remains unknown if this model applicable for other assets.
- There are more violations clustering in recent years. We can choose these years as a separate back testing dataset to see if this model still works well.



Thank you!

Q & A

