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# Analysis of Extreme Value at Risk to Amazon Stocks

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***ABSTRACT:*** The VaR of the negative log returns of E-commerce stock Amazon stock (AMZN) (during the period ofOctober 31, 1997 to October 30, 2017) are studied, and based on the statistical exam and analysis, it turns out that the returnsis a stationary, uncorrelated time series, and not normally distributed or t-distributed. Therefore, one cannot use the traditional way to compute the value at risk (VaR) of the returns based on either normal distribution or t-student distribution. How to evaluate the VaR of the returns becomes a very tricky problem. To avoid the assumption of distribution of the returns, in this paper, we use the Extreme Value Theory to approach VaR and conclude that the calendar anomalies which are the lower risk seasons are Q2 and Q3 and higher risk seasons are Q1 and Q4. But the investors should realize that the resulting principle of AMZN stock may not apply to other portfolios or stocks. Especially, comparing with empirical results of traditional portfolio SPDR S&P 500 ETF SPY (SPY), we conclude that the seasonal effect of E-commerce and traditional commerce are quite different.

***KEYWORDS:*** AMZN stocks, SPY stocks, Value-at-Risk, Extreme Value Theory, seasonal effect.

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## I. Motivation And Introduction

Throughout the 1990s, the spread of the Internet and World Wide Web has swept the world.With the increasing use of the Internet in society, companies start to look the web as a new way of doing business. Selling products through the Internet offers a variety of options and opportunities.Amazon.com Inc. is a well-known American E-commerce company and primarily a retail site, it sells almost everything including electronic products, clothes, food, games, groceries, health and personal-care items, etc. At the same time it has its own manufactures which also produce their own electronics for consumers, including the Kindle, which is an electronic reading device etc. As internet and its carriers (such as iphone, ipad, laptop and desktop) have the convenient shopping functions, in the past ten years, more and more physical stores have replaced by E-commerce companies. Nothing should be surprised to thisphenomena, shopping online has greatly saved people's time and energy, and costumers could face to a wider shopping world, have more choices for everything. As the E-commerce becomes very popular in recently, Amazon.com is the biggest E-commerce company in theyears, to study the risk of investment of E-commerce companies also becomes very important to researchers. Especial world, to study the value at risk of AMZN has typical meaning.

It is well known that the SPY is the most liquid and heavily traded security in the world, and it is the most popular ETF used to access this exposure with more than $243.3 billion in assets[1]. SPY has large institutional ownership, a robust secondary trading market has allowed SPY to establish and maintain itself as an attractive vehicle for accessing the S&P 500Index.

We introduce AMZN and SPY here, because we not only study the VaR of AMZN, but alsocompare the seasonal effect of these two stocks in this paper by using the method of value atrisk (VaR)[2][3][4], which is a measure of the risk of investments. A VaR statistic has threecomponents: a time period, a confidence level and a loss amount (or loss percentage)[5].To study the VaR of AMZN stocks, the first of all, we have to test if the log returns followthe normal distribution, if so, we can use the Variance-Covariance Method to evaluate VaRs.Unfortunately, in this paper we found the log returns of AMZN does not follow the normaldistribution or t-student distribution significantly. Therefore, we have to find another way toevaluate the VaRs of AMZN log returns.

Extreme value theory (EVT) or extreme value analysis (EVA) is a branch of statisticsdealing with the extreme deviations from the median of probability distributions. It tries toassess, from a given ordered sample of a given random variable, the probability of events thatare more extreme than any previously observed[6]. It is possible that there is no appropriate distribution for extremes, but if there is one, it must be from the Generalized ExtremeValue (GEV) family (block maxima) or the Generalized Pareto (GP) family (excesses over ahigh threshold). The two families are related. The Generalized Pareto Distribution (GPD)was introduced by Pikands III[7] and studied by E. Castillo[8][9] and others [10] [11]. Thereafter,

it is suitable to use the extreme value analysis on the tested AMZNreturns to study the seasonal effect t[12][13][14] in stock market. But all of these studies focusedon a calendar anomalies in stock returns and volatility, they did not study the seasonal effectof E-commerce and traditional commerce. However, in this paper, we use EVT to approachthe VaR of AMZN, furthermore, we also compare the VaR of seasonal effect of E-commerceAMZN and traditional commerce SPY, and discover that the seasonal effect of these two stocks are quiet different. Finally, we analyze the possible factors which caused the seasonalanomalies of these two stocks.

## II. DATA DESCRIPTION AND SOME STATISTICAL RESULTS

### A. Data Description

In this paper, we use daily adjustedclosing prices of the AMZN and SPY (from Yahoo Finance[1]) from October 31, 1997 to October 30, 2017.The adjusted closing price has formed an accurate tracking record of stock performance, furthermore, log returns of adjust closing price makes samples stable, which is used to study the VaR of a stock. Let $P_t$ represents the adjust closing price of the day t of a stock, and then the logarithmic rates of returns is determined by

$$r_t = 100(\log \frac{P_t}{P_{t-1}}) = 100(\log P_t - \log P_{t-1})$$

Fig. 1 shows a time series chart of the adjusted closing price and daily log returns of AMZN stock from 31 October 1997 to 30 October 2017. And it shows that AMZN's stock price has soared more than 200 times since 2007, and the volatility of AMZN's daily log returns is relatively stable even though we observe many peaks.

Table 1 summarizes thebasic statistical features of the AMZN stock daily log returnsseries during the test period from October 31, 1997 to October 30, 2017. The test results notice us that on one hand, there may be a possibility of time-varying variance and non-normalbehavior; on the other hand, in order to calculate the VaR properly, we need to examine stationarity and the normality of the daily log return series.

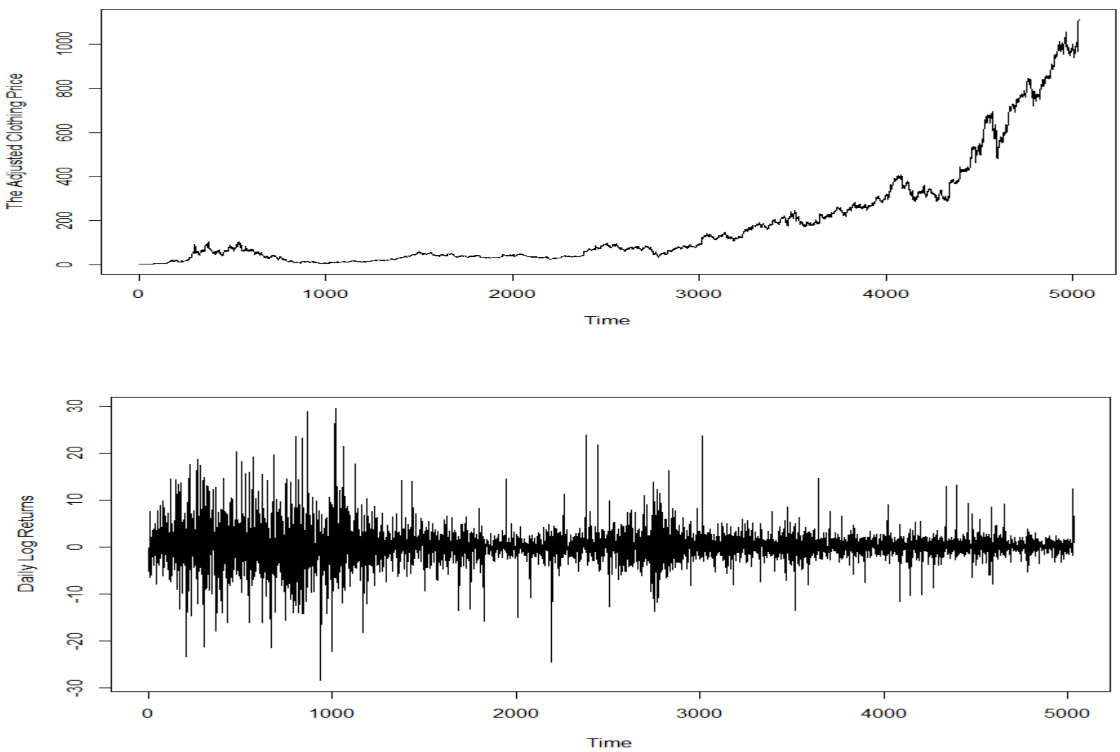


**Fig. 1:** Time plots of AMZN stock.The upper panel is for adjusted closing price, and thelower panel is for daily log returns

**Table 1:** Summary Statistics of the AMZN Daily Log Returns

| Mean | Range | Std dev | Skewness | Kurtosis | Obervation |
|---|---|---|---|---|---|
| 0.11 | (-28.46,29.62) | 3.75 | 0.43 | 8.68 | 5031 |

**Table 2:** KPSS Tests for the AMZN Daily Log Returns

| | Null Hypothesis $H_0$ | Stats | p-value | Test Result |
|---|---|---|---|---|
| KPSS test for stationary | The series is stationary arounda straight line time trend<br>The series is stationaryaround a constant. | 0.071<br><br>0.069 | 0.1<br><br>0.1 | Accept $H_0$ ,The series isstationary. |

**B. Test for Stationary Property**

For the stationarity hypothesis, the joint probability distribution of the log returnsdoesn't change when time goes. Using KPSS test [15] to examine stationarity. The hypothesis for the KPSS test is

$H_0 : \sigma_\mu^2 = 0 \quad vs \quad H_1 : \sigma_\mu^2 \neq 0$.

The rejection rule is that if the value of the KPSS statistic is more than thecritical values estimated in [15], or the p-value is less than or equal to the significancelevel $\alpha$ , we reject $H_0$, the series is non-stationary, otherwise, it is stationary.

From the above table of KPSS test in Table 2, we see that the daily log returns of AMZN is stationary during the test period.

**C. Test for Normality**

First of all, we draw a QQ-plot by the sample set of daily log returns of AMZN which against the normal distribution, and it has the fat tails, or is leptokurtic-see Fig.2.

We use the Shapiro-Wilk test [16] to verify the non-normal result. The Shapiro-Wilk test statistics is usually written as W, the value of W is between 0 and 1. If the values of W is small enough, it concludes the rejection of normality, whereas a larger value indicates the normality of data. The null hypothesis $H_0$ is W=1 which indicates the normal distribution. If the p-value of the test is less than the significance level, we reject the null hypothesis $H_0$.

From Table 3, we know that the daily log returns of AMZN are not normal during the time period of October 31, 1997 to October 30, 2017.

Fig. 3 is the T QQ-plot of empirical distribution of the daily log returns(y-axis), it isobviously not the t-student distribution even if it fits better than the normal distributioncompare to Fig. 2. The plots also show that empirical distribution of the daily log returnsof AMZN has heavier tails than the normal distribution, this means that the prior assumptionof normal distribution of the log returns is no sense.

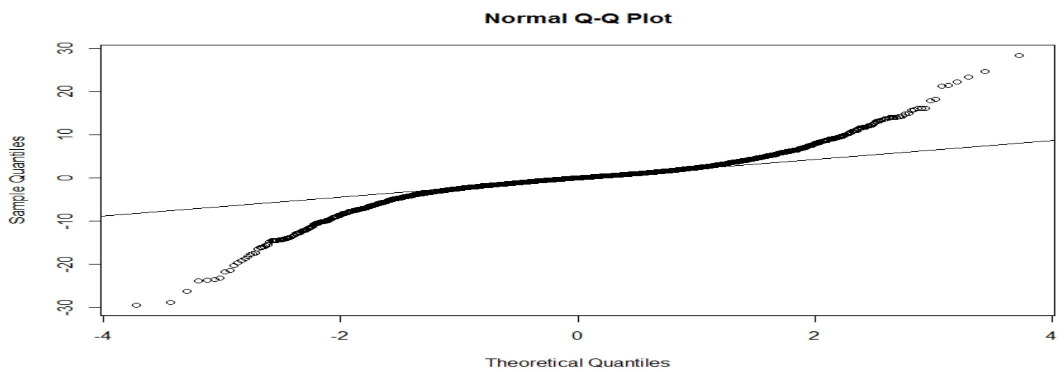


**Fig. 2:** QQ-plot of AMZN daily log returns against normal distribution

**Table 3:** Shapiro-Wilk Test for the AMZN Daily Log Returns

| | Null Hypothesis $H_0$ | Stats | p-value | Test Result |
|---|---|---|---|---|
| Shapiro-Wilk test fornormality | The series come froma normally distributed population | 0.88 | <2.2e-16 | Reject $H_0$, the series does not come from a normal distribution |

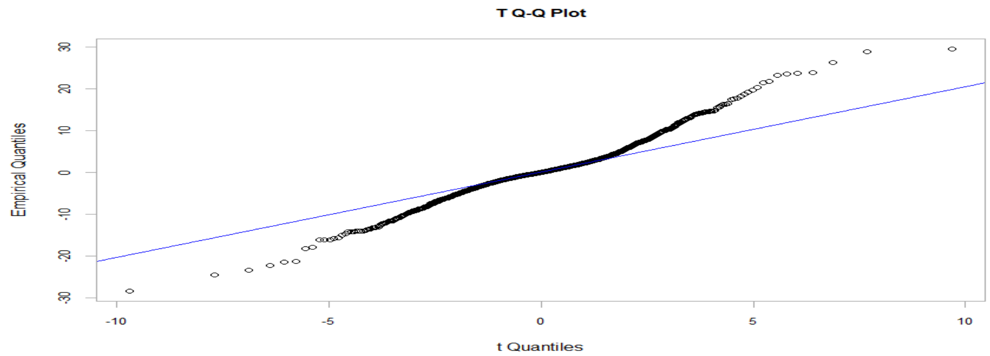


**Fig. 3:** QQ-plot of AMZN daily log returns against the t-student distribution

**D. Test for Correlations**

Autocorrelation Coefficient Function(ACF) and Partial Auto-correlation Coefficient Function (PACF) are very useful in helping us to describe randomprocesses. We plot the autocorrelation function and partial autocorrelation function of thedaily log returns $\{r_t\}$. Fig. 4 shows that the time series $\{r_t\}$ of daily log returns of AMZNdoes not have strong autocorrelations.

We can apply Ljung-Box test [17] for serial correlation of daily log returns to confirm thisresult. In this test, the null and alternative hypothesis is defined as the following,

$$H_0 : \rho_1 = \rho_2 = \cdots = \rho_m = 0 \quad vs \quad \rho_i \neq 0 \quad \text{for some } \; i \in \{1, 2, \cdots, m\}$$

where $\rho_l$ is the sample autocorrelation function at lag l, and m is the number of lags beingtested, and the Ljung-Box Q test statistics is commonly represented as Q(m).

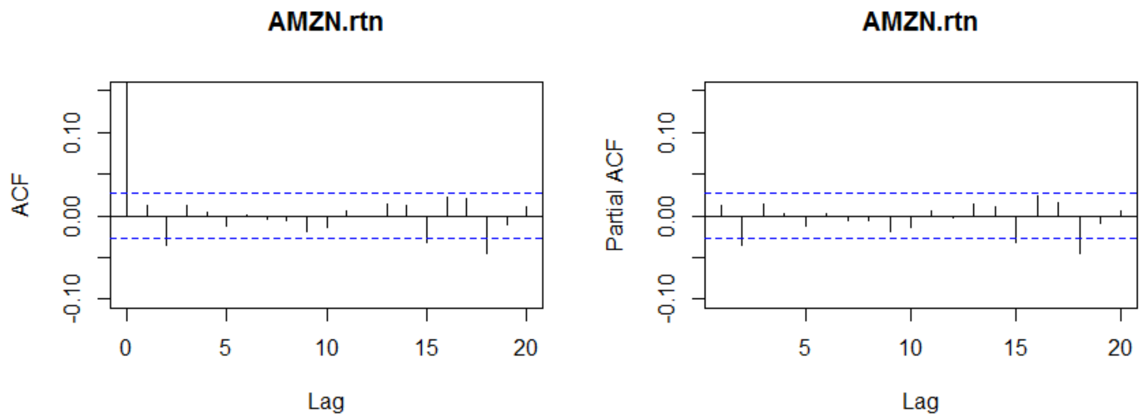


**Fig. 4:** The left panel is sample autocorrelation coefficients for AMZN log returns, the rightpanel is sample partial autocorrelation coefficients for AMZN log returns

**Table 4:**Ljung-Box Test for The AMZN Negative Daily Log Returns

| $\chi$ **-squared** | **m** | **p-value** |
|---|---|---|
| 9.0447 | 5 | 0.1073 |
| 12.08 | 10 | 0.2798 |
| 19.138 | 15 | 0.2076 |

Under the assumption of $\{r_t\}_{t=1}^{n}$ is an independent identically distributed (iid), the distribution of statistics Q(m) can be approximated as the 100(1− $\alpha$ ) the percentile of chi-squareddistribution with m degrees of freedom.

In the case of significance level $\alpha$ = 5%, if the p-value is less than 5%, then the null hypothesis that the sequence does not have autocorrelation is rejected, in other words, the series has autocorrelation; and if the p-value is more than 5%, the series does not have autocorrelation. If Q(m) > $\chi_{\alpha}^{2}$ for significance level $\alpha$ , we can also reject the null hypothesis.

The test results are shown in the Table 4: all the p-values are more than significance level5% on lag 5, 10, 15, we can determine that the daily log returns are not autocorrelation.

Based a series tests on the above, we conclude that the sample set of log returns ofAMZN is neither a normal distribution nor a t-student distribution but it is a stationary anduncorrelated time series. Therefore, the assumption of the series $\{r_t\}$ with normal distributionor t-distribution does not fit the real case even though many researchers [18] [19] have used thisassumption to compute VaR. Instead of using any of assumption to the distribution of thelog returns of AMZN, we apply the Extreme Value Theory to approach the VaR of daily logreturns.

## III. VALUE AT RISK WITH EXTREME VALUE APPROACHING

### A. VaR of a Time Series

There are extreme risks in all areas of financial investment, creditand insurance, where extreme disasters can take a large toll. Therefore, for investors and riskmanagers, the loss estimation and probability prediction of extreme loss are very important.

Extreme Value Theory (EVT)[20][21][22] is a powerful tool for the tail distribution even ifthe Historical or Monte Carlo simulation methods also does the same approach, but they arenot inefficient as EVT.

Assume a random variable X, we first fix some high threshold $\mu$ and consider the distribution of excess values Y = X − $\mu$, which is defined as:

$$F_\mu(y) = \Pr(X - \mu \le y \mid X > \mu) = \frac{F(\mu + y) - F(\mu)}{1 - F(\mu)} \qquad (2)$$

where F is the underlying distribution of X, $F_\mu$ is the conditional excess distribution function.In fact, Pickands III(1975)[7] introduced the GPD as a two parameter family of distributionsfor exceedance over a threshold $\mu$.

**Extreme Value Theory[23]** *Assume* $\{X_t\}$ *is a sequence of stationary, uncorrelated random variables with distribution F.For any* $\mu > 0$, *let* $F_\mu$ *be the conditional excess distributionfunction, for random variables defined in (2) with*

$Y_t = X_t - \mu$. *Let* $\omega_F = \sup\{x : F(x) < 1\}$, *then*

$$\lim_{\mu \to \omega_F} F_\mu(y) = H_{\sigma_{\mu,\xi}}(y)$$

Where $H_{\sigma_{\mu,\xi}}(y)$ is called GPD, specified as

$$H_{\sigma_{\mu,\xi}}(y) = 1 - (1 + \xi \frac{y}{\sigma_\mu})_+^{-1/\xi} \qquad (3)$$

The parameters of GPD are the scale parameter $\sigma_\mu$ and the shape parameter $\xi$.

Although the distribution of each random variable Xtis not known, EVT describes thetail distribution in detail. The shape parameter can reflect the tail fatness of a distribution:

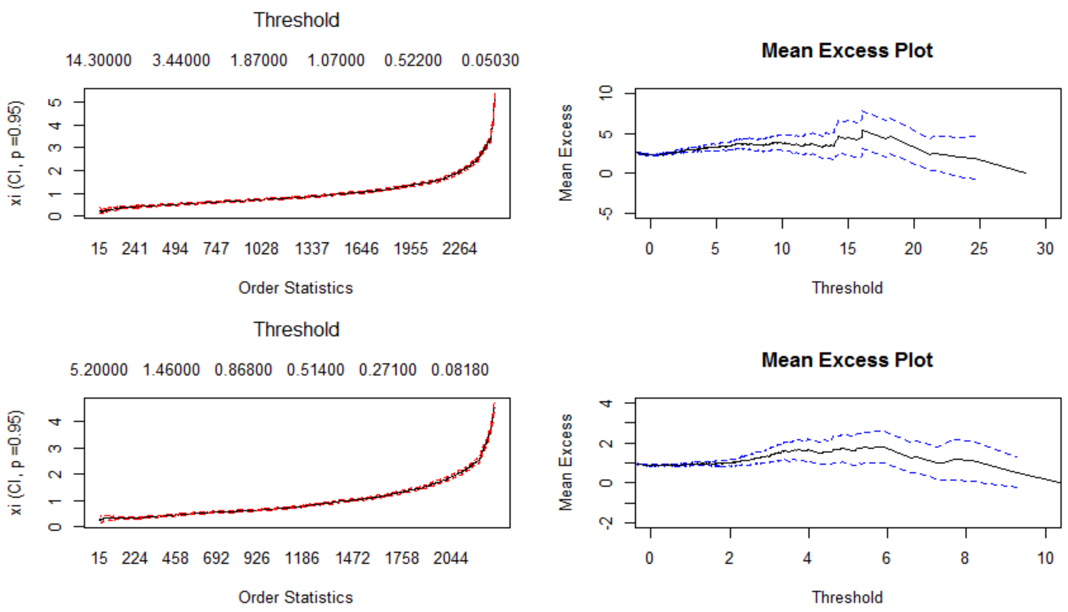


**Fig. 5:**Hill plots (left) and mean excess plots (right) for the AMZN daily negative logreturns (top) and SPY daily negativelogreturns (lower) with 95% asymptotic confidencebounds (dotted line).

- $\xi < 0$ refers to thin tails;
- $\xi = 0$ implies that the kurtosis is 3 as for a standard normal distribution;
- $\xi > 0$ implies fat tails.

The extreme value theory address that the distribution of GPD can be used to approximateall of the excess distribution function that are greater than $\mu$ if the threshold $\mu$ is larger enough.Therefore, in order to evaluate the VaR, we have to find a sufficiently large value of $\mu$, andestimate the parameters of the distribution of GPD, then use the EVT method to computethe quantile of the tail of the distribution to estimate VaR.

How to choose an optimal threshold $\mu$, that becomes a very important work for us. Herewe combine the Mean Excess plot and Hill plot together, using a graphical method to selecta reasonable threshold.

## IV. VaRAnalysis Of AMZN And SPY

### A. Modeling the Distribution of AMZN and SPY Negative Daily Log Return

We adoptOne-day-ahead VaR forecasts along with the significance level of 5%, 1% and 0.1% in theempirical investigation. For comparison, we use AMZN and SPY daily negative log returnsto compute the VaR and related statistical properties.

The daily negative log returns is defined by

$$\tilde{r}_t = -r_t \qquad (4)$$

it is the opposite of the daily log returns $r_t$.

As we have pointed out in section 3, before applying the extreme value method to the VaRon the returns, we choose a threshold $\mu$ at first by Mean Excess plot and Hill plot. Fig.5 shows, with 95% confidence interval, a reasonable threshold should around 5 and around 2for the daily negative log returns of AMZN and SPY, respectively. Assume that $\{r_t\}$ havea high enough threshold $\mu$, the number of exceedance of the threshold is $N_\mu$. For the dailynegative log returns of AMZN,

**Table 5:** GPD Tests for the AMZN Daily Negative Log Returns

| Daily negative log returns from 1997-10-31 to 2017-10-30 | AMZN | SPY |
|---|---|---|
| Threshold $\mu$ | 4.975259 | 1.918341 |
| Exceedances $N_\mu$ | 289 | 262 |
| | 0.1101152 | 0.2282867 |
| Shape parameter ML estimator $\xi$ | 2.9135830 | 0.7628415 |

| | | |
|---|---|---|
| Scale parameter ML estimator $\hat{\sigma}_{\mu}$ | | |
| VaR( T = 1 day, $\alpha$ = 5%)<br>VaR( T = 1 day, $\alpha$ = 1%)<br>VaR( T = 1 day, $\alpha$ = 0.1%) | 5.374776<br>10.592159<br>19.849102 | 1.949535<br>3.447035<br>6.815119 |

$N_{\mu}$ =289,with corresponding threshold $\mu$ =4.975259; for thedaily negative log returns of SPY, $N_{\mu}$ =262, with corresponding threshold $\mu$ =1.918341 wouldbe reasonable. See Table 5.

In order to visualize the model accurately, we use the back test method to the extremevalue of the daily negative log returns of AMZN and SPY and the fitness is summarized inFig. 6 and Fig. 7, respectively. We can see the estimates fit the given negative dailylog returns of AMZN and SPY quite well, even in the far end tail. The assumption of anunderlying heavy tailed distribution is consistent with the data is confirmed. So it seems veryreasonable for the corresponding estimate of the over of 5%, 1% and 0.1% quantile of the VaR.

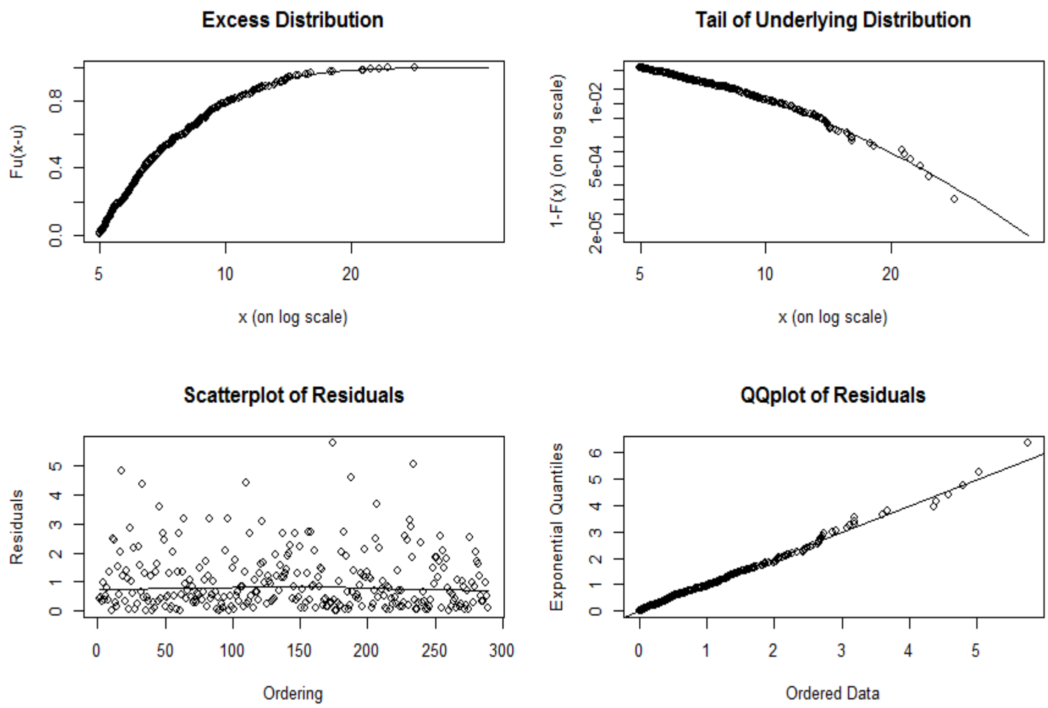


**Fig. 6:** Diagnostic plots for GPD fit to AMZN daily negative log returns

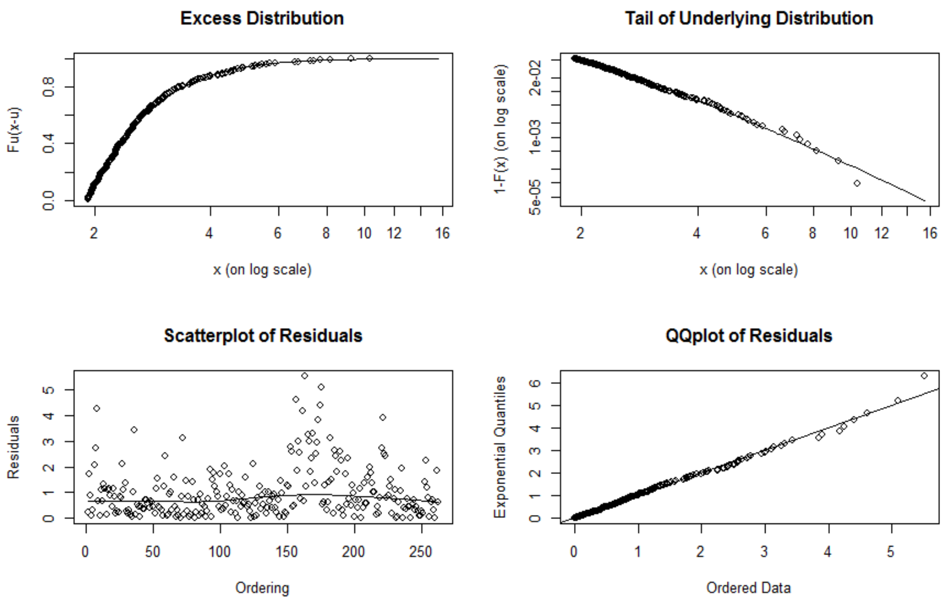


**Fig. 7:** Diagnostic plots for GPD fit to SPY daily negative log returns

**B. Seasonal Effect of AMZN and SPY**

Seasonal effects are important in determining stock performance, because the period of three-month on the financial calendar is the basisfor reporting stock returns and paying dividends. In order to study the quarterly effects of thesystem on the stock of AMZN, we divide the sample data $\{\tilde{r}_t\}$ into the following four groups:

$\{\tilde{r}_t \mid t \in Q_i\}, i = 1,2,3,4$

they are the four quarters of AMZN daily negative log returns. One-fourth of a year is aquarter and is usually expressed as Q.

Table 6 summaries the basic statistical characteristics for the four quarters of daily negativelog returns of AMZN. Next, we carry out the basic tests to examine the four quarters seasonalpattern in daily negative log returns of AMZN. Based on the Shapiro-Wilk tests, all the p-value of four quarters are less than 2.2e-16, which are less than the significant level 0.1%, soall of the four quarters have no normal distribution.

Before applying the extreme value method to the VaR on our four quarters data sets,we have to select a specific threshold to confine the estimation to those observations thatare above the given threshold. As mentioned in section 3, we choose the threshold by MeanExcess plot and Hill plot, which is the graphical procedures.

**Table 6:** Summary Statistics of AMZN Daily Negative Log Returns by Quarter

| | **Mean** | **Range** | **Std dev** | **Skewness** | **Kurtosis** | **Obs** |
|---|---|---|---|---|---|---|
| Q1 | -0.05 | (-23.57,21.29) | 3.79 | -0.61 | 6.86 | 1226 |
| Q2 | -0.17 | (-28.95,21.50) | 3.57 | -0.70 | 9.30 | 1264 |
| Q3 | -0.08 | (-21.87,28.46) | 3.66 | 0.41 | 10.36 | 1270 |
| Q4 | -0.13 | (-29.62, 22.31) | 3.97 | -0.73 | 8.20 | 1271 |

**Table 7:** Estimated GPD Parameters and VaR of AMZN Daily Negative Log Returns by Quarter

| | $\xi$ | $\sigma_\mu$ | $\mu$ | $N_\mu$ | $VaR_{0.05}$ |
|---|---|---|---|---|---|
| Q1 | 0.0036675 | 3.0436056 | 4.445176 | 91 | 5.648514 |
| Q2 | 0.1393965 | 2.5267834 | 4.054026 | 87 | 4.879855 |
| Q3 | 0.2846917 | 2.5921566 | 4.040345 | 88 | 4.040345 |
| Q4 | -0.059547 | 3.414381 | 5.142519 | 83 | 6.046996 |

**Table 8:** Estimated GPD Parameters and VaR of AMZN Daily Negative Log Returns by Quartervia the Same Threshold

$\mu$ =5.142519.

| | $\xi$ | $\sigma_{\mu}$ | $N_{\mu}$ | $VaR_{0.05}$ |
|---|---|---|---|---|
| Q1 | 0.091395 | 2.628499 | 76 | 5.713111 |
| Q2 | 0.200889 | 2.455344 | 58 | 4.933508 |
| Q3 | 0.2125037 | 3.2742714 | 57 | 4.792961 |
| Q4 | -0.059547 | 3.414381 | 83 | 6.046996 |

Next, we compute VaR on the seasonal daily negative log returns of AMZN for four quarters using themethod of extreme value theory. Table 7 and Table 8 tell us the same results, no matter we choose thedifferent thresholds via Hill plot on the four quarters or using the same threshold, the shapeparameter $\xi$ of Q3 returns is the largest returns of AMZN, which indicates the fattest tailbehavior. The over of 5% quantile VaR is the largest returns of AMZN in the fourth quarterQ4, and the third quarter Q3 is the smallest returns of the four seasons.

Using the same method, we obtain the VaR of SPY daily negative log returns of fourquarters. Table 9 and Table 10 show the results.

After the comparison of SPY returns and AMZN returns, we see that the results of SPYreturns are different from AMZN return.

## V. Conclusion

After a series tests we conclude that the daily log returns of AMZN is stable, but not normaldistributed or

**Table 9:** Estimated GPD Parameters and VaR of SPY Daily Negative Log Returns by Quarter.

| | $\xi$ | $\sigma_{\mu}$ | $\mu$ | $N_{\mu}$ | $VaR_{0.05}$ |
|---|---|---|---|---|---|
| Q1 | -0.04821617 | 0.86020868 | 1.780453 | 78 | 1.986503 |
| Q2 | 0.1148558 | 0.5779253 | 1.581727 | 77 | 1.697172 |
| Q3 | 0.2593656 | 0.7395883 | 1.944272 | 82 | 2.139780 |
| Q4 | 0.3350238 | 0.8553170 | 1.825313 | 77 | 1.994911 |

**Table 10:** Estimated GPD Parameters and VaR of SPY Daily Negative Log Returns by Quartervia the Same Threshold

$\mu$ =1.944272.

| | $\xi$ | $\sigma_{\mu}$ | $N_{\mu}$ | $VaR_{0.05}$ |
|---|---|---|---|---|
| Q1 | -0.02262276 | 0.82099745 | 65 | 1.992357 |
| Q2 | -0.01746831 | 0.78150883 | 39 | 1.565409 |
| Q3 | 0.2593656 | 0.7395883 | 82 | 2.139780 |
| Q4 | 0.3323455 | 0.9011683 | 67 | 1.992334 |

t-distributed,therefore we use extreme value theory to approach the VaR.Furthermore, we tested the seasonal effect on the negative daily log returns of AMZN andcompared its difference of seasonal effect with SPY stock. Eventually, we found that seasonalbehavior of AMZN and SPY are quite different. No matter how we choose the thresholds(the different thresholds or the same threshold), the shape parameter $\xi$ of SPY is largest inthe fourth quarter Q4, and the largest VaR over the 5% quantile is in the third quarter Q3.These are the opposite to AMZN returns. On the other hand, the smallest VaR the over of5% quantile of SPY returns happens in the second quarter Q2, but the same result does nothappen to AMZN returns.

Of course, there are many factors affected performance of stocks in financial market, forexample, tax-motivated trading, economic, government policies etc., but if we consider thesetwo stocks in the same country, so the above factors should be same affection to all of stocks,therefore, the possible explanations, for the AMZN stock, in Q1 and Q4, the VaR is larger,because there are at least two long holidays, like Thanksgiving and Christmas, there aremany coupons and discounts on E-commerce, that drives people to do the online-shoppingvery crazy. In addition, this is winter time period, people are more likely to stay at homebecause of the cold weather, so online-shopping in this case becomes favorable, that is whyAMZN stock has a larger vibration in Q1 and Q4. But for SPY stocks, its VaR is larger inQ3, mostly because the new product will be announced in this time period, it attracts morepeople's eyeball, so its VaR is larger than other three seasons.

The above conclusion is very reasonable, it also tells investors what is the good time periodto invest their money to which kind of stocks. For E-commerce, like AMZN, investors, if theywant to get a larger benefit from stock investment with higher risk, then they should investmoney in Q1 and Q4, other they should choose safe seasons, like Q2 and Q3. But if investorswant to invest stock which is not an E-commerce, like SPY, ones should be better to carryout their investment in Q3. Anyway, based on our research, there are a big difference betweenthe stock performance of E-commerce and no E-commerce, that is a basic principle which wehave concluded in this paper, investors should be very carefully to treat behaviors of stocksbetween the very modern stocks, like E-commerce AMZN and traditional stock, like SPYportfolio when they make a plan for their investments.

## ACKNOWLEDGMENT

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