Value-at-Risk of JCP Stock and Analysis of Calendar Effects

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Abstract— *This paper presents the value-at-risk (VaR) analysis of J.C. Penney Company Inc. (JCP) stock daily negative log returns between 1993 and 2018. The statistical properties of JCP are thoroughly examined and a series of diagnostic tests are conducted to check the conditions of the time series data over the two decades. The GARCH and EGARCH models with normal distribution and Student's t-distribution are used to estimate the volatility and VaR of the stock. By analyzing VaR, we show that there is currently a high risk of investing in JCP stock. In addition, this paper examines the calendar effects and seasonality of JCP stock through the fundamental properties of the data as well as the VaR. We compare the performance of the stock in four quarters which further confirms our result that JCP stock is at immense risk at this point in time. These results are valuable for anyone interested in evaluating and forecasting JCP stock. The methodology we use is applicable to any other stock that meets our test conditions and is more accurate and realistic in predicting volatility and VaR than the commonly used standard normal distribution based VaR model.*

Keywords— JCP Stock, Value-at-Risk, GARCH Model, EGARCH Model, Calendar Effect.

I. INTRODUCTION

Over the past two decades, the proliferation of the Internet has contributed to the development of e-commerce and has affected the market share of traditional retailers. Purchasing goods online as a convenient alternative to in-store shopping largely saves people's time and is increasingly popular among customers. J.C. Penney Company Inc. is a US department store chain that operates more than 1000 stores across the United States. It was founded by James Cash Penney and William Henry McManus [1] in 1902. Most J.C. Penney stores are located in shopping centers, and their business mainly includes sales of clothing, cosmetics, household items, jewelry and cookware. As J.C. Penney is one of the largest apparel and home retailers in the United States, investors are deeply concerned about the performance of J.C. Penney Company Inc. stock (NYSE: JCP). In this paper, we will investigate the risk of buying JCP stock as well as the calendar effects of the JCP stock returns. We want to provide investors with useful investment advice.

In 2017, Caroline, Emma, Madelon, Mikkel and Marc from Columbia Business School conducted a research project on J.C. Penney named *"Competing for Survival: A Turnaround of Department Store J.C. Penney"* [2]. They analyzed the company's performance from an operational perspective and provided a variety of strategies to help the company better organized. So far, we have found a lack of statistical analysis of J.C. Penney's paper. In this paper, we conducted a complete time series analysis of the JCP stock returns. We focus on the statistical characteristics of JCP stock and draw conclusions only from the statistics.

Risk management is a key process for making investment decisions. In order to control risk in an investment, we need to first determine the amount of risk involved in the investment, and then decide to either accept or alleviate the risk. Standard deviation, beta, value at risk (VaR) and expected shortfall are common measures to quantify the risk. In this paper, we use VaR as the primary tool for measuring the risk of buying stocks. Value-at-risk is a statistical indicator of the riskiness of financial entities or portfolios. It is defined as the maximum dollar amount that is expected to be lost at a predetermined confidence level for a given time frame. The stock market crash in 1987 triggered the innovation of VaR. It was developed as a systematic approach to separating extreme events from daily price changes. In 1994, it was extended by J.P. Morgan who launched the Risk Metrics and published the methodology [3]. Nowadays, VaR has become one of the most commonly used measures of market risk in the financial industry.

In order to calculate the VaR of the stock, we need to accurately predict the price of the stock. The main characteristic of a stock is its return. We model the negative log return series to derive estimates of volatility and VaR. It is well known that financial markets are highly volatile and the periods of high volatility tend to persist for some time before the market returns to a more stable environment (Tsay,2005)[4]. The autoregressive method helps to build a more accurate and reliable volatility model. The Autoregressive Conditional Heteroskedasticity (ARCH) model was originally introduced by Engle

(1982)[5]. ARCH model and its extensions such as GARCH (Bollerslov, 1986)[6] and EGARCH (Nelson, 1991) [7] are among the most popular models for forecasting market returns and volatility. See for example Vesna Bucevska (2013)[8], Zhen Yao Wong et al. (2016)[9], Julija Cerović Smolović et al. (2017)[10] and Mahsa Gorji, Rasoul Sajjad (2017) [11], who derived VaR estimation from GARCH - type models.

In terms of the organization of the paper, we analyze the basic statistical properties of the time series of negative log returns for JCP in Section 2, and test for the normality and autocorrelations of the series. In Section 3, we fit the data with GARCH and EGARCH models and estimate the VaR of the data. In Section 4, we group the data by quarter and perform time series analysis within the group, and then we analyze the results for each group to find calendar effects

II. DATA DESCRIPTION AND STATISTICAL TEST RESULTS

2.1 Data Description

In this paper, we examine the daily JCP stock price time series for a 25-year period. There were 6431 data points from January 29, 1993 to August 10, 2018. All data comes from Yahoo Finance. Let P_t denote the daily adjusted closing price of a stock, where t is an integer representing the day. We use the negative log return L_t to characterize the stock price time series. L_t is defined as:

$$L_t = -100 \cdot \log \frac{P_t}{P_{t-1}} = 100(\log P_{t-1} - \log P_t) \tag{1}$$

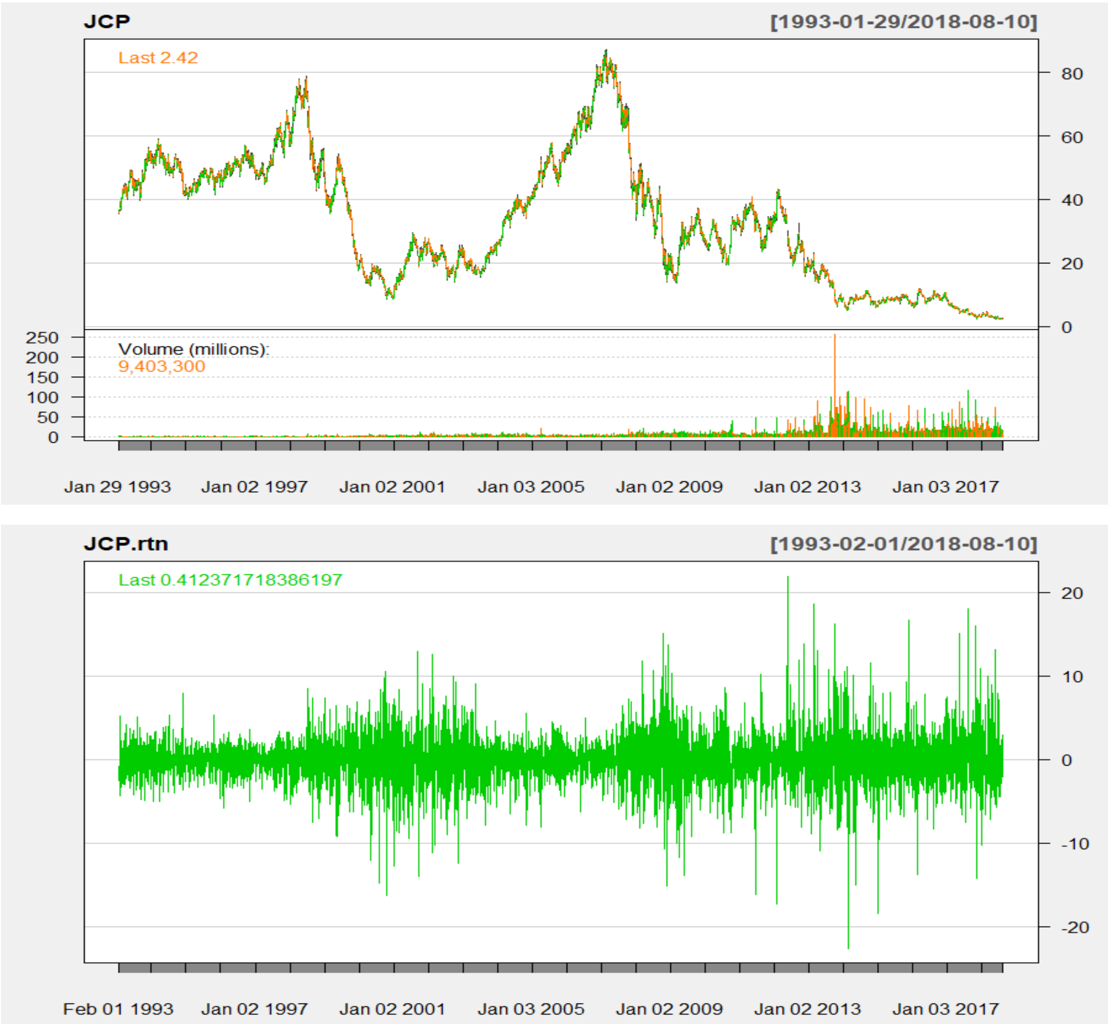


FIGURE 1: The upper panel is adjusted closing price for JCP; the lower panel is daily negative log returns

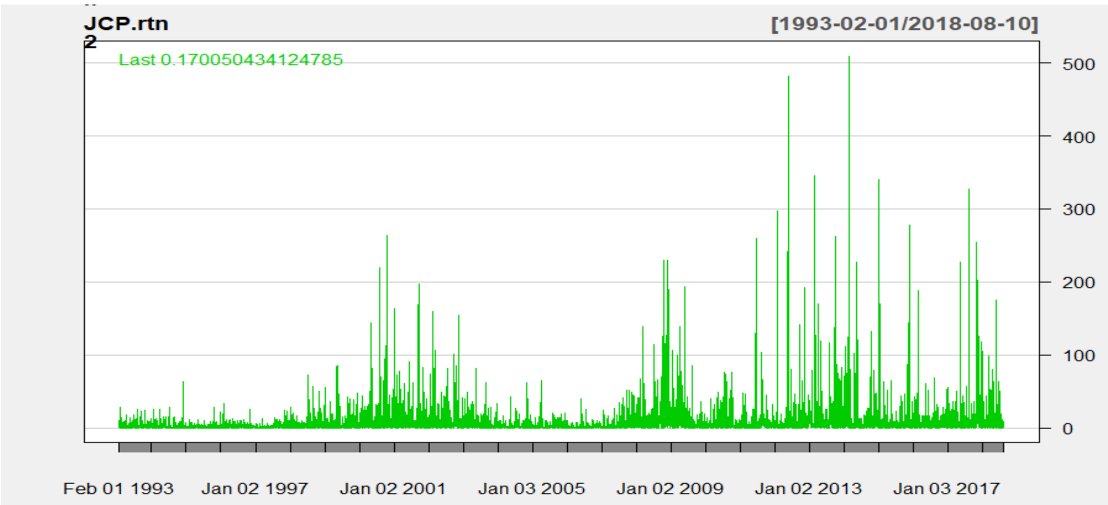


FIGURE 2: The daily squared log returns for JCP

The lower panel in Fig. 1 shows the time series plot of daily negative log returns for JCP stock. We can see from the graph that roughly from 2013 to 2018, there are more peaks in the upper half of the panel. Since we model relative loss instead of relative return, more positive peaks indicate more positive relative loss of the stock. Fig. 2 shows the time series plot of daily squared log returns of JCP stock. It can be seen that since 2011, the stock has become more volatile than before, and the stock volume shown in Fig. 1 has become higher after 2011. There are a lot of documented evidence of high stock trading volume closely related to the volatility of returns; see for example Barron, Orie E., David G. Harris, and Mary Stanford (2005[12]), K. Ravichandran, Sanjoy Bose (2012 [13]), Andrey Kudryavtsev (2017[14]).

From the price chart in Fig. 1, JCP stock reached its highest price in 2007 and then fell sharply in the following year. From 2012 to 2018, the stock price has a clear downward trend, but the trading volume tends to be higher and there are more peaks during this period. This may indicate potential activities such as stock news, analyst downgrades and insider trading.

TABLE 1
SUMMARY STATISTICS OF THE DAILY NEGATIVE LOG RETURNS FROM FEB. 1, 1993 TO AUG. 10, 2018

	Mean	Range	Std dev	Skewness	Kurtosis	Nobs
JCP	0.032	(-22.582,21.962)	2.814	0.031	5.561	6430

Table 1 summarizes the fundamental properties of daily negative log return series of JCP stock. It gives us a better view of the performance of JCP stock. It shows a positive average daily negative log return of 0.032, which indicates a positive relative loss on average.

TABLE 2
SUMMARY STATISTICS OF THE DAILY NEGATIVE LOG RETURNS GROUPED BY YEAR

Time	Mean	Range	Std dev	Skewness	Kurtosis	Nobs
1993.1.29-1998.8.10	-0.051	(-5.791,8.487)	1.588	0.006	1.606	1396
1998.8.11-2008.8.10	0.008	(-16.217,12.981)	2.707	-0.344	3.064	2514
2008.8.11-2018.8.10	0.105	(-22.582,21.962)	3.391	0.179	4.766	2518

Table 2 shows the summary statistics of the daily negative log returns for JCP stock that are grouped into three time periods. From August 11, 2008 to August 10, 2018, the average daily negative log return is 0.105 which is the highest among the three periods. It is apparent that the average daily negative log return increases at a high rate over time. In addition, in the most recent decade, the range of the daily negative log returns is the largest, from -22.582 to 21.962, with a standard deviation of 3.391, which indicates high volatility of the stock.

2.2 Test for normality

To test for the normality of the data, we use the Q-Q (quantile-quantile) plot to see if the empirical distribution of the daily negative log returns is consistent with the normal distribution.

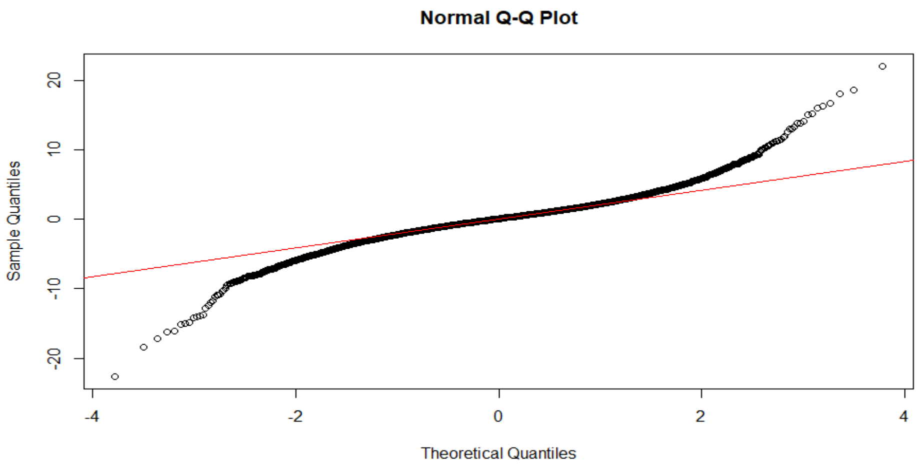


FIGURE 3: Q-Q plot of the daily negative log returns for JCP against normal distribution

Fig. 3 is a Q-Q plot of the empirical distribution of the daily negative log returns (y-axis) against normal distribution (x-axis). It can be observed from the plot that the empirical distribution of the daily negative log returns displays heavier tails than the normal distribution. Therefore, normal distribution is not an ideal fit for the negative log returns.

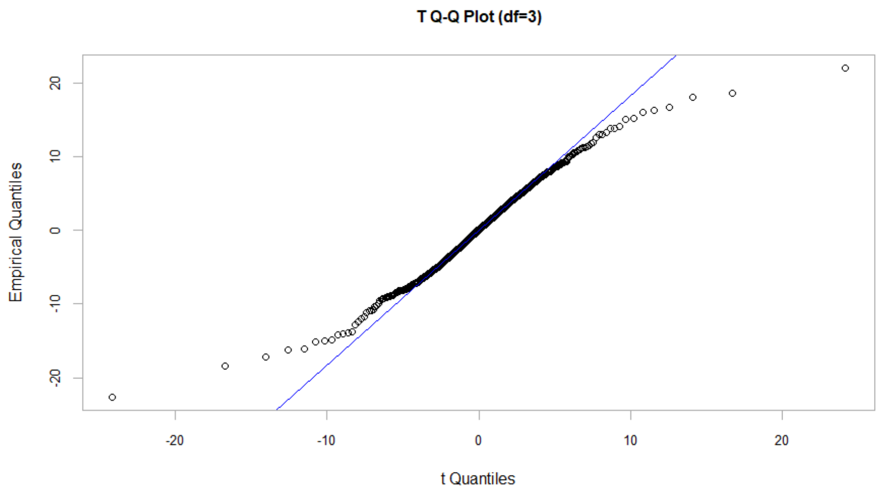


FIGURE 4: Q-Q plot of the daily negative log returns for JCP against Student's t-distribution

We also test the empirical distribution of the daily negative log returns against the Student's t-distribution using Q-Q plot. From Fig. 4, we can see that with degrees of freedom of 3, the empirical distribution of the daily negative log returns has lighter tails than the Student's t-distribution. It is apparent that the Student's t-distribution is a much better fit for the negative log returns.

To confirm our results, we perform Shapiro-Wilk normality test (1965) [15] to check for the normality of daily negative log returns for JCP. The results are shown below.

TABLE 3
SHAPIRO-WILK NORMALITY TEST OF DAILY NEGATIVE LOG RETURNS FOR JCP

Statistic	p-value	Test Result
W = 0.95186	<2.2e-16	The series does not come froma normal distribution

From Table 3, we can see that the p-value from this test is extremely small. For a significance level of 0.05, we reject the null hypothesis that the data comes from a normal distribution. This is consistent with our result from the Q-Q plot.

2.3 Test for autocorrelations

The autocorrelation coefficient (ACF) and the partial autocorrelation coefficient (PACF) are very important for us to check the specifications of the model used in analyzing the data. With the presence of autocorrelations, we can use autoregressive–moving-average (ARMA) models to fit the data. The ACF and PACF graphs for JCP negative log returns and squared log returns are shown in Fig. 5. From the graphs, we can see that the daily negative log return series exhibits weak autocorrelations, whereas the squared log return series have indication of strong autocorrelations.

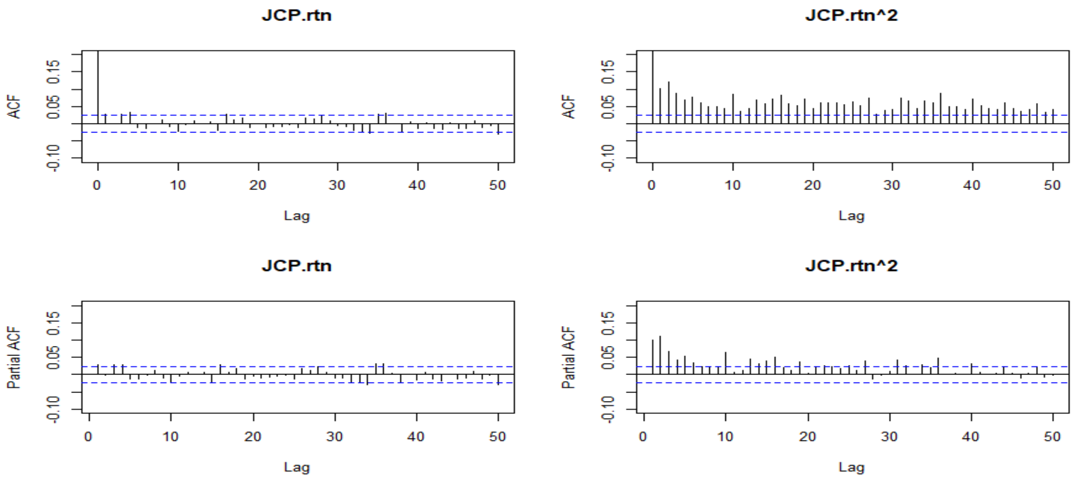


FIGURE 5: Sample ACF and PACF for JCP daily negative log returns and squared log returns

In order to confirm the results, we use the Ljung-Box test devised by Ljung and Box (1978) [16] to test the autocorrelations of the negative log return series and the squared log return series. The Ljung-Box test statistic is usually represented by Q(m), where m is the number of lags tested. If the test statistic Q(m) is greater than χ_α^2 or the p-value from the test is smaller than the significance level of α, we reject the null hypothesis that the data are independently distributed and conclude that the data exhibits autocorrelations.

The Ljung-Box test results are displayed in Table 4. The p-values are small for daily negative log returns and extremely close to zero for daily squared log returns at lags of 5, 10 and 15. At significance level of 0.05, we reject the null hypothesis and conclude that there are strong autocorrelations within our data.

TABLE 4
LJUNG-BOX TEST FOR JCP DAILY NEGATIVE LOG RETURNS AND SQUARED LOG RETURNS

	Daily Negative Log Returns		Daily Squared Log Returns	
m	χ -squared	p-value	χ -squared	p-value
5	17.287	0.003986	279.51	<2.2e-16
10	23.141	0.01024	395.42	<2.2e-16
15	26.14	0.03658	501.98	<2.2e-16

From the above statistical tests, we can see that the negative log return series $\{L_t\}$ has non-normality and relatively strong autocorrelations. For time series with these properties, a powerful test - the ARCH test was introduced by Engle (1982) to evaluate the significance of ARCH effects of the data, see [4]. Here we perform the ARCH test in Table 5. We can see that the p-values for daily negative log return series are very small at lags of 5, 10 and 15. Therefore, we reject the null hypothesis at significance level of 0.05 and conclude that there are significant ARCH effects in our data.

TABLE 5
ARCH TEST FOR JCP DAILY NEGATIVE LOG RETURNS AND SQUARED NEGATIVE LOG RETURNS

	Daily Negative Log Returns		Daily Squared Log Returns	
m	χ -squared	p-value	χ -squared	p-value
5	41.76	<2.2e-16	0.8852	0.4899
10	25.23	<2.2e-16	0.5928	0.8212
15	18.95	<2.2e-16	0.4136	0.9761

III. VALUE AT RISK WITH GARCH AND EGARCH MODEL

3.1 Methodology

ARCH model was proposed by Engle (1982) [4] to deal with the model's time-varying volatility and heteroskedasticity of the errors. It was extended by Bollerslevn (1986)[6] to the generalized autoregressive conditional heteroskedasticity (GARCH) model. The GARCH model is used to approximate conditional variance using a linear function of the past squared residuals. The model still has some shortcomings because it ignores the leverage effect of return volatility. To reflect the asymmetry of returns, we applied the EGARCH model proposed by Nelson (1991) [7], in which the volatility can react asymmetrically to positive and negative returns.

Let $\{L_t\}$ be the daily negative log returns of JCP stock as defined in Section 1 and $\{F_t\}$ be the past information about the return series up to time t. Since there is volatility and leptokurtosis in the data, we assume that the conditional mean of $\{L_t\}$ follows an autoregressive average model AR (1) and the conditional variance of $\{L_t\}$ follows an univariate GARCH model or EGARCH model. We represent $\{L_t\}$ as follow:

$$\begin{cases} L_t = \mu_t + \sigma_t \varepsilon_t \\ \mu_t = \phi_0 + \phi_1 L_{t-1} \end{cases} \tag{2}$$

the innovation $\{\varepsilon_t\}$ are white noise process with zero mean and unit variance, and we assume σ_t^2 follows a GARCH-type model. In this paper, we assume $\{\varepsilon_t\}$ to follow normal and Student's t-distribution respectively. The conditional mean μ_t is defined as: $\mu_t = E(L_t \mid F_{t-1})$, and the conditional variance σ_t is defined as: $\sigma_t^2 = Var(L_t \mid F_t)$.

The GARCH (p, q) model is given by:

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{p} \alpha_j \eta_{t-j}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 \text{ , for } p, q > 0 \tag{3}$$

where $\eta_t = \sigma_t \varepsilon_t$,p is the order of GARCH and q is the order of ARCH process, α_j and β_i are parameters and we expect their sum to be less than 1.

We use GARCH (1, 1) model and EGARCH (1, 1) model to fit the data. Petra Posedel (2005) [18], Richard A. Ashley and Douglas M. Patterson (2010)[19], Joel koima, Peter N Mwita, and Dankit K Nassiuma (2015) [20] have shown that the basic GARCH(1, 1) model is sufficiently suitable for most financial time series. From equation (3), we can easily get the equation for the GARCH (1, 1) model:

$$\sigma_t^2 = \alpha_0 + \eta_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{4}$$

The EGARCH (p, q) model is given by the following formula:

$$\log\sigma_t^2 = \alpha_0 + \sum_{j=1}^{p}[\alpha_j\eta_{t-j} + \gamma_j(|\eta_j| - E|\eta_{t-j}|)] + \sum_{i=1}^{q}\beta_i \log\sigma_{t-i}^2 \text{, for } p,q>0 \tag{5}$$

From equation (5), we derive the EGARCH (1, 1) model:

$$\log\sigma_t^2 = \alpha_0 + \eta_{t-1} + \gamma_1(|\eta_1| - E|\eta_{t-1}|) + \beta_1\log\sigma_{t-1}^2 \tag{6}$$

The results of fitting data using GARCH and EGARCH models are illustrated in Table 6. The log likelihood log(L) shows that the serial correlations in the conditional means and variances are sufficiently explained by the specified GARCH and EGARCH models. The positive coefficient γ_1 in the EGARCH model implies the presence of a leverage effect.

TABLE 6
ESTIMATION RESULTS IN GARCH AND E GARCH MODELS FOR JCP

GARCH type	GARCH Model		EGARCH Model	
Distribution	Normal	Student's t	Normal	Student's t
ϕ_0	-0.041362	0.004727	-0.000560	0.021645
ϕ_1	0.012557	0.002382	0.007003	-0.001397
α_0	0.010825	0.018960	0.009296	0.008382
α_1	0.023102	0.031519	0.046362	0.039226
β_1	0.975893	0.966760	0.996278	0.995399
γ_1			0.048972	0.065170
$log(L)$	-15080.79	-14763.57	-14995.24	-14719.55

3.2 Estimation of VaR

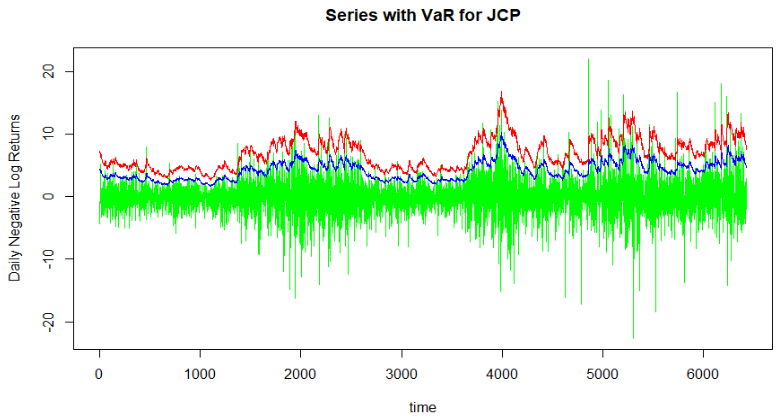
After fitting the data with GARCH and EGARCH models, we are able to predict the volatility of the daily negative log returns for JCP. We then proceed to estimate the value at risk (VaR) of the stock. As introduced in Section 1, VaR is a popular method of measuring risk of an investment, because it is easy to interpret and clearly a relevant concept in assessing the risk. It represents the maximum dollar amount that is expected to be lost at a predetermined confidence level for a specific period of time. In this study, we calculate the VaR by the quantile method. Let $\{L_t\}$ be the daily negative log returns of JCP stock and α be the confidence level. VaR_α is the α -th quantile of the distribution of the negative log returns $\{L_t\}$, and is defined by:

$$P(L_t > VaR_\alpha(L_t)) \le 1-\alpha \tag{7}$$

TABLE 7
FORECAST VALUE AT RISK IN GARCH AND E GARCH MODELS ON AUG. 13TH, 2018 FOR JCP AND SPY

	GARCH type	GARCH Model		EGARCH Model	
	Distribution	Normal	Student's t	Normal	Student's t
JCP	$VaR_{0.95}$	4.924947	4.355218	5.1341	4.523923
	$VaR_{0.99}$	6.980224	7.256845	7.26029	7.440851
	$VaR_{0.999}$	9.283975	12.66881	9.643528	12.71962
SPY	$VaR_{0.95}$	0.8465751	0.7579894	0.9715966	0.8895356
	$VaR_{0.99}$	1.237037	1.303512	1.399687	1.472815
	$VaR_{0.999}$	1.674705	2.253133	1.879532	2.443175

From the skewed property of the negative log return data, the Student's t-distribution should fit better for the distribution of white noise $\{\varepsilon_t\}$. To make comparisons, we use both normal and Student's t-distributions to test the VaR. Table 7 demonstrates the results for one-day-ahead VaR (on August 13, 2018) for JCP at quantiles 0.95, 0.99 and 0.999 respectively. To make comparisons, we also calculate one-day-ahead VaR (on August 13, 2018) for SPDR S&P 500 trust (SPY) [21] stock of which the results are shown in the same table. SPY is an exchange-traded fund (ETF) used to track the S&P 500 stock market index. It is the largest ETF in the world and represents all major sectors of the US market. From Table 7, it is clear that JCP has much higher VaR than SPY for the three quantiles.



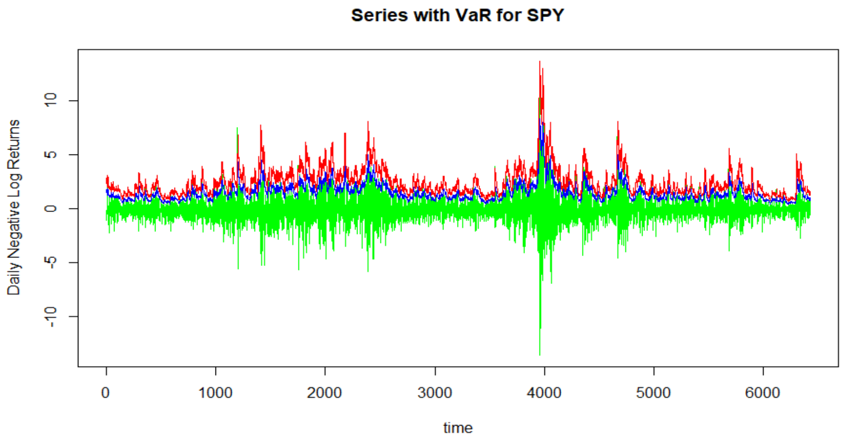


FIGURE 6: One-day-ahead VaR forecast of JCP and SPY based on the EGARCH model with Student's t-distribution at quantile 95% in blue and 99% in red

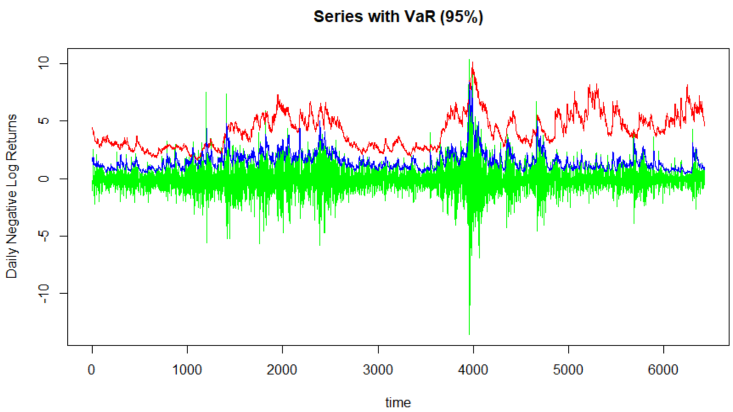


FIGURE 7: One-day-ahead VaR forecast based on the EGARCH model with Student's t-distribution at quantile 95%, with JCP in red and SPY in blue

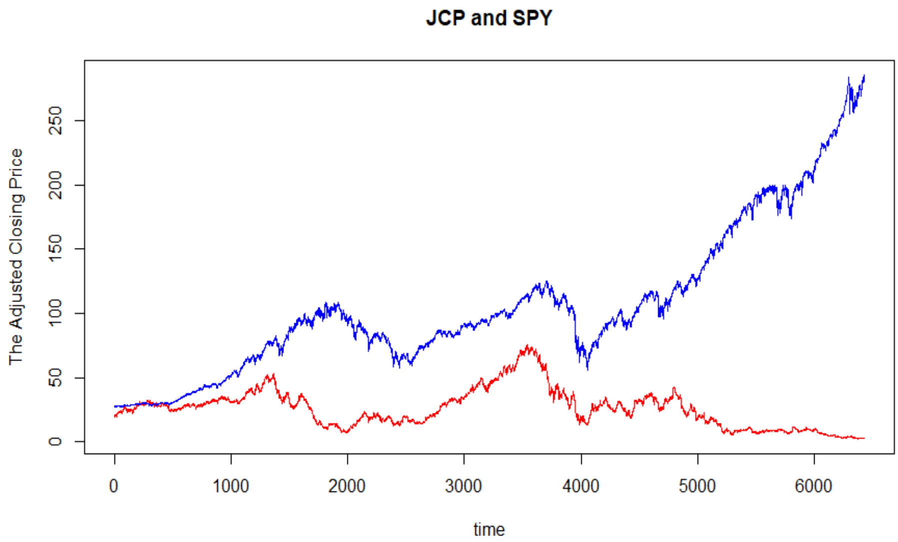


FIGURE 8: Adjusted Closing Price for JCP in red and SPY in blue

From Fig. 7, it is clear that on most of the days, JCP has much larger VaR than SPY. In addition, the VaR of JCP stock becomes higher and deviates further from the VaR of SPY in recent years. Fig. 8 shows a comparison graph of the adjusted closing price for JCP stock and SPY stock. As the price of SPY increased since 2010, the price of JCP displayed a decreasing trend. Combining the analysis of the VaR and the price plot of JCP, we find that JCP stock is highly risky for investment.

IV. CALENDAR EFFECT

A calendar effect [22] is an economic effect that seems to be associated with the calendar. If the returns of a stock vary from season to season, it is said to have seasonal tendencies and calendar effect. In order to investigate any calendar effect of JCP stock, we divide our data into four groups on a quarterly basis. Each quarter contains three months, the first quarter includes January to March expressed as Q1, the second quarter includes April to June expressed as Q2, and so on.

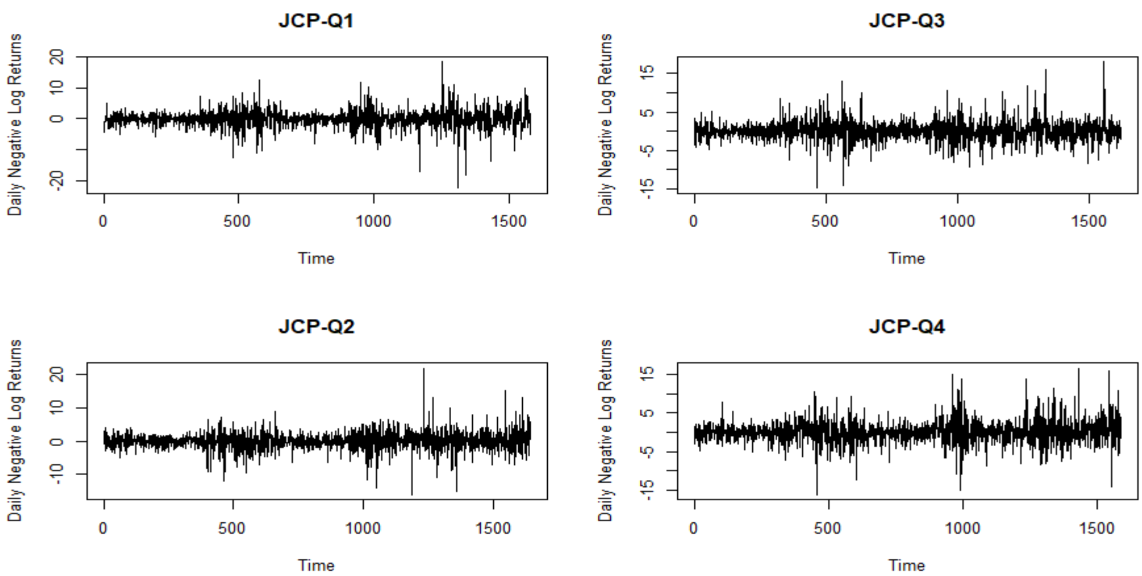


FIGURE 9: The adjusted closing price for four quarters of JCP

Fig.9 shows the time series plots of the daily negative log returns for the four quarters. From the graphs, we can see that the negative log returns of the fourth quarter Q4 are the most volatile among the four quarters. Furthermore, there are many large positive peaks in Q4, especially from time of 1200 and more, which indicates that in recent years, JCP stock experienced a lot of losses in Q4.

TABLE 9
SUMMARY STATISTICS OF THE DAILY NEGATIVE LOG RETURNS FOR JCP BY QUARTER

	Mean	Range	Std dev	Skewness	Kurtosis	Observation
Q1	-0.068	(-22.582,18.592)	2.884	-0.440	6.851	1579
Q2	-0.008	(-16.101,21.962)	2.689	0.040	6.524	1643
Q3	0.124	(-14.813,18.105)	2.663	0.342	4.904	1618
Q4	0.080	(-16.217,16.674)	3.011	0.218	3.888	1590

Table 9 shows the summary statistics of the daily negative log returns for the four quarters. From the table, we can see that in the third and fourth quarter Q3 and Q4, JCP stock has positive average daily negative log return with that in Q3 to be the largest. It indicates that JCP stock generally experiences loss in Q3 and Q4. Although the average daily negative log return in the first and second quarter Q1 and Q2 is negative, the magnitude is relatively small.

After checking the normality and autocorrelations of the data for the four quarters, we fit the data of each quarter with GARCH and EGARCH models based on normal distribution and Student's t-distribution respectively. Then we calculate one-day-ahead VaR at quantile 95% and 99% respectively of the stock negative log returns for each quarter. The results are shown in Table 10.

TABLE 10
VALUE AT RISK OF FOUR QUARTERS IN GARCH AND EGARCH MODELS FOR ONE-DAY-AHEAD PERIOD

	GARCH type	GARCH Model		EGARCH Model	
	Distribution	Normal	Student's t	Normal	Student's t
Q1	$VaR_{0.95}$	5.5055	5.1341	6.0122	5.6980
	$VaR_{0.99}$	7.8419	8.8800	8.5437	9.6957
Q2	$VaR_{0.95}$	6.3523	5.9994	7.2951	6.4139
	$VaR_{0.99}$	9.0205	10.126	10.3406	10.7452
Q3	$VaR_{0.95}$	3.6436	3.2475	3.6474	3.3087
	$VaR_{0.99}$	5.1297	5.5203	5.1112	5.5915
Q4	$VaR_{0.95}$	6.9963	6.6221	6.8536	6.5923
	$VaR_{0.99}$	9.8818	10.9387	9.6649	10.7553

From Table 10, the third quarter Q3 has the smallest VaR for both 95% and 99% quantiles, while the fourth quarter Q4 exhibits the largest VaR for both quantiles with Student's t assumption. The VaR for the first and second quarter Q1 and Q2 is large as well, despite the negative average daily negative log return in Q1 and Q2 shown in Table 9. Therefore, none of the four quarters performs well, because none of them exhibits both positive average log return and stability. Furthermore, it is an interesting phenomenon that JCP has positive average relative loss and high risk in Q4, because Q4 is usually the best season for traditional retailers to make money. It implies that JCP is not competitive with traditional retailers, which supports our previous analysis that JCP has a high investment risk.

V. CONCLUSION

In this paper, we analyze the fundamental statistics and the VaR of the daily negative log returns of JCP stock. We use GARCH and EGARCH models to fit the data with normal distribution and Student's t-distribution assumptions of white noise respectively. Based on the models, we estimate VaR of the stock at quantiles 95%, 99% and 99.9% to measure the riskiness of the stock. Comparing the VaR of JCP and SPY, we find that the VaR of JCP stock is much higher than SPY, and the price of JCP is significantly lower than SPY, especially in the past ten years. The summary statistics also indicates that the daily negative log returns of JCP averaged over ten-year period increased over time and reached the highest during the past ten years. These results help us conclude that the risk of investing in JCP stock is very high.

By analyzing the calendar effect of JCP, we find that although the returns in the four quarters are different, the performance of the stock is not good for either of the four quarters. It is surprising that Q4 has positive average daily negative log return and the highest one-day-ahead VaR among the four quarters. In general, for traditional retailers, the fourth quarter should be the most profitable, because Thanksgiving and Christmas are at the end of the year, and all goods have great discounts during the festivals. The fourth quarter is usually the quarter that Americans spend the most. However, even in the fourth quarter, J.C. Penney cannot make a profit either. It even suffered losses during Q4 and had the highest VaR in a year. It reinforces our previous conclusion that JCP is at immense risk for investment.

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