AMA488 Simulation

Individual Project Report

Topic: Amazon Stock Price Prediction

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Abstract

The project purposes analyze and forecast Amazon stock prices. The global economy was affected disruptively due to the COVID-19 outbreak. The reason why the technology sector especially Amazon performed much better than other industries in the unstable period is noteworthy. To predict the stock prices, the Monte Carlo simulation was adopted in the project. In the prediction result, we figured out the stock price increase and keep stable under the COVID-19 pandemic. The reasons behind this could be because of the changes in customer behavior and company policies.

Keywords

Amazon, Big tech, stock price, analyze, forecast, COVID-19

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1. Introduction

1.1. Background

Since the COVID-19 pandemic, the global economy was affected disruptively. The study by Fernandes (2020) pinpointed that the high stock market volatility caused by COVID-19 and pointed out that the global stock market volatility was above or similar to the 2008–09 level of volatility. Regarding the stock returns for different sectors in 2020, the worst performers were the energy, travel, and aerospace sector respectively. These stock market outcomes corroborate with the findings of the economic impact of COVID-19 on general markets (Fernandes 2020). In addition, under the global pandemic impact, COVID-19 are having an apparent impact on the technology sector, affecting raw materials supply, disrupting the electronics value chain, and causing an inflationary risk on products. However, to consider the stock price, figure 1 showed the trend of big tech stock prices, which include Apple, Amazon, Facebook, Google, and Microsoft in the period of 4 April 2019 to 30 April 2021. It overall performed satisfied especially Amazon and Google. This is unexpected that information technology sectors performed better than others during the outbreak of the COVID-19 (Al-Awadhi et al. 2020). In my opinion, the performance of the technology stocks in the future is noteworthy.

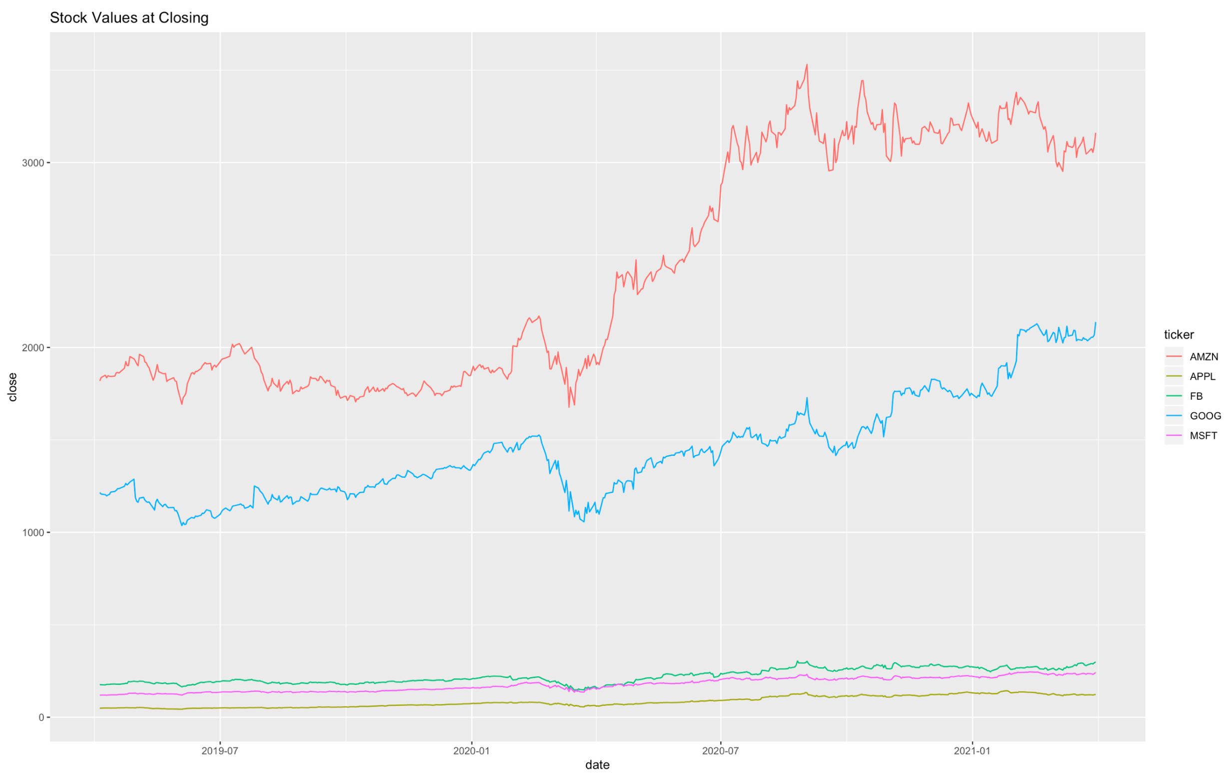

Figure 1 The graph shows the big tech stock closing prices in the period of 4 April 2019 to 30 April 2021

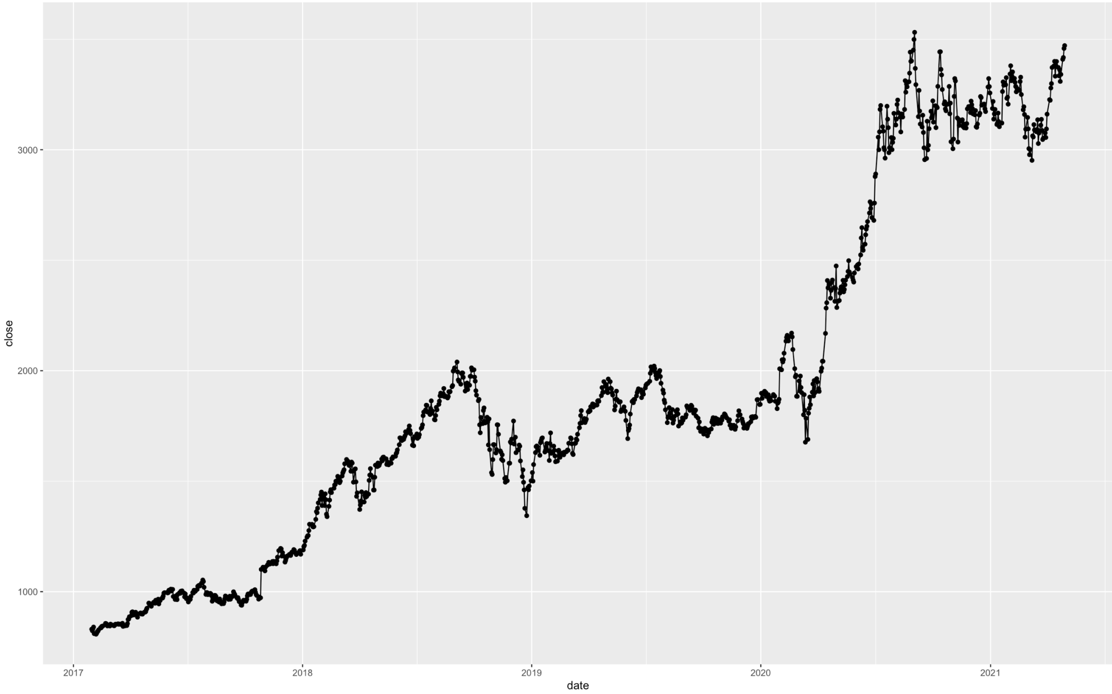

Figure 2 Amazon stock closing prices in the period of 29 January 2017 to 29 April 2021

1.2. Aim

This report focuses on Amazon due to its biggest growth among the big tech. The historical stock price of Amazon during 30 January 2017 to April 2021 adopt in this project. I will focus on analyzing how the COVID-19 pandemic affected Amazon's stock price and forecast the Amazon's future trends within an unstable atmosphere. The report will first introduce which approaches be used in the data analysis report, followed by figuring out the key findings by evidence and discuss their cause and effect.

2. Methodology

2.1. Data source

The data adopted in this project is Amazon's historical stock price in the period of 30 January 2017 to 30 April 2021, which was extracted from Yahoo Finance. The organization provides open historical stock price data for everyone to download. R language, which will be used in this project, has a big literature, packages and functions developed, help to conduct stock price analysis. The data extracted from Yahoo Finance using the package called quantmod. Quantmod is a well-known package used for quantitative financial modeling. After installing and loading the packages, using the function getSymbols is to download and treat the data to get them in the best possible format for the analysis.

2.2. Analysis methods

The prediction approach adopted in this project is Monte Carlo simulations, which was used to simulate an experiment with probabilistic components of a system, by which random numbers are being generated in order to assign values to the components of a system (Render, Stair and Hanna, 2012).

Monte Carlo simulation was found effective when stock returns were created from continuous and discrete returns, according to Arnaut-Berilo, Zaimović, and Turbo-Merdan (2019). The Monte Carlo simulation model is being derived from the Markov process, Wiener process and Brownian motion. The model can be presented as follows when we analyze discrete

$$\Delta S = \mu S \Delta t + \sigma S \epsilon \sqrt{\Delta \mathrm{t}}$$

where symbols represent
ΔS – Change in stock price,
μ – Stock return,
Δt – Time in which stock price is being observed (day, month, year or similar),
S – Initial stock price or price from the last observed period,
σ – Standard deviation,
ϵ – Random component.

In above equation, $\mu \Delta t$ is expected return, while $\sigma \epsilon \sqrt{\Delta \mathrm{t}}$ is a stochastic component of return (Hull, 2012). Random component ϵ simulates Markov process, meaning that selected samples of ϵ should be independent from each other.

2.3. Steps in data analysis

Importing the packages and data was the first step of the analysis. The package quantmod is used to extract the data from Yahoo Finance. In order to get them in the best possible format for the analysis, I downloaded the data using the function getSymbols. After installing the data, the package lubridate is used to parse date-time data in a fast and userfriendly way. The function pbapply was utilized in processing the possibly leveraging parallel. The grey shows the coding part and the additional comment is after the symbols of "#".

```
require(quantmod)
require(lubridate)
require(pbapply)

ticker <- "AMZN"
stock <- getSymbols(ticker,
          auto.assign = FALSE,
          from = '2017-01-30',
          to = Sys.Date())
```

The second step is needed to call in the current stock quote using the function GetQuote and calculated the return using the ROC function and found its mean and standard deviation.

```
tail(stock)
tmp <- getQuote(ticker)
stock <- rbind(stock,
xts(cbind(tmp$Open,tmp$High,tmp$Low,tmp$Last,tmp$Volume,tmp$Last), order.by =
Sys.Date()))
tail(stock) # today data
tmp <- Ad(stock) # store the adjusted price
rets <- ROC(tmp,type="discrete") # calculate the returns
rets[is.na(rets)]<-0
mean(rets)
sd(rets)
```

The third step is to build a function that passes in the stock price and the number periods in order to predict the mean and standard deviation and it is going to return the summary of predicted price using quantile function.

```
stk_ret = function(STK_PRC, N, MEAN, STDEV) # N is the period try to predict
{
  delta_t = 1/N # for 1 period
  for(i in seq(N))
  {
    epsilon <- runif(n=1,min=0,max=1) # random probability from 0 to 1
    STK_PRC <- STK_PRC * (1 + qnorm(epsilon, MEAN*delta_t, STDEV*sqrt(delta_t))) #
use qnorm along epsilon prob, mean, sd
  }
  STK_PRC
}

last(tmp) # the close price on this day
simulations <- 1000 # simulation times
N = 20 # look back 20 days to see the predict stock price for today
```

```
STK_PRC <- as.numeric(coredata(tmp[Sys.Date() - days(20)]))
MEAN = mean(rets)
STDEV = sd(rets)

stock_prices <- c() # empty vector to store the stock prices
for(i in seq(simulations))
{
  stock_prices <- c(stock_prices,stk_ret(STK_PRC = STK_PRC,
N=N,MEAN=MEAN,STDEV=STDEV))
}

stock_prices # predictions for today's closing price
quantile(stock_prices) # summary
```

The fourth step is to predict the closing prices every month by the Monte Carlo Simulation. Before simulating, the mean and standard deviation for each of the options expiration dates are needed to calculate. The Monte Carlo function do the simulation 10000 times.

```
EXPIRY <- tmp[options.expiry(tmp)] # monthly options expiration dates along with the
close of that day
EXPIRY <- EXPIRY["2007::"]
IDX <- index(EXPIRY)
NEXT.EXPIRY <- as.Date("2021-5-30")
IDX <- c(IDX,NEXT.EXPIRY)

MEAN = function(calculateUNTIL)
{
  tmp <- tmp[paste0("::",calculateUNTIL)]
  tmp <- ROC(tmp,type="discrete")
  tmp[is.na(tmp)]<-0
  mean(tmp)
}

STDEV = function(calculateUNTIL)
{
  tmp <- tmp[paste0("::",calculateUNTIL)]
  tmp <- ROC(tmp,type="discrete") # calculate the return
  tmp[is.na(tmp)]<-0
  sd(tmp)
}

# calculate the mean and sd for each of the options expiration dates
means <- do.call(rbind,lapply(as.list(IDX), MEAN))
stdevs <- do.call(rbind,lapply(as.list(IDX), STDEV))
```

```
days = as.numeric(diff(IDX)) # calculate the difference of days in between the options
expiration dates

# pass the number of simulations, or iteration, if's the last iteration
MONTE.CARLO = function(sim,iter,LastIter)
{
  simulations <- sim
  N <- days[iter]
  STK_PRC <- as.numeric(EXPIRY[iter])
  MEAN <- means[iter]
  STDEV <- stdevs[iter]
  stock_prices <- c()

  # do simulation
  for(i in seq(simulations))
  {
    stock_prices <- c(stock_prices, stk_ret(STK_PRC =
STK_PRC,N=N,MEAN=MEAN,STDEV=STDEV))
  }

  # data frame
  # store opening price and closing price
  START <- as.data.frame(round(STK_PRC,2))
  START.DATE = index(EXPIRY[iter])
  PROBS = as.data.frame(t(round(quantile(stock_prices,probs = seq(0,1,0.05)),2)))

  if(iter == LastIter)
  {
    END <- as.data.frame(NA)
    END.DATE = as.data.frame(NA)
  }else{
    END <- as.data.frame(as.numeric(round(EXPIRY[iter+1],2)))
    END.DATE = index(EXPIRY[iter+1])
  }
  all <- cbind(START,START.DATE,PROBS,END,END.DATE)
  colnames(all) <-
c("START.PRC","START.DATE","0%","5%","10%","15%","20%","25%","30%","35%","4
0%","45%","50%","55%",

"60%","65%","70%","75%","80%","85%","90%","95%","100%","END.PRC","END.DATE
")
  all
}
```

```
p <- pblapply(as.list(1:length(days)), function(x){
  MONTE.CARLO(sim=10000,iter = x, LastIter = length(days))
})

p <- do.call(rbind,p)
```

The sixth step is to visualize the result. To create the graph, I plot the line of ending prices and the lowest and the highest possible stock price of that months. The numbers of times it closes price above 0% and 100% will be calculated.

```
# plot the ending prices along with the prob
plot(p$END.PRC, type="l", main="The ending prices along with the probability of zero and
one hundred percent",
     ylab="close")
lines(p$`0%`, col='red')
lines(p$`100%`,col='green')
legend("topleft", inset=.02, legend=c("zero percent","one hundred percent"),
       col=c("red","green"), lty=1:1, cex=0.6, box.lty=0)

# number of months
nMo <- nrow(p)

# numbers of times it closes above 100%
sum(as.numeric(na.omit(ifelse(p$END.PRC > p$`100%`,1,0))))/nMo

# numbers of times it closes below 0%
sum(as.numeric(na.omit(ifelse(p$END.PRC < p$`0%`,1,0))))/nMo

write.csv(p,"Amazon.csv")
```

The final step is to calculate the accuracy to check whether the model is good enough. The project adopted mean absolute percentage error and symmetric mean absolute percentage error to test the model accuracy. These methods can be presented as follows

$$MAPE = \frac{100\%}{n} \Sigma_{i=1}^{n} \left| \frac{\hat{y}_i - y_i}{y_i} \right|$$

$$SMAPE = \frac{100\%}{n} \Sigma_{i=1}^{n} \frac{\hat{y}_i - y_i}{(|\hat{y}_i| + |y_i|)/2}$$

where symbols represent

$\hat{y}_i$ – predict ending prices,

y_i – closing price of a specified date.

```
y_true <- p$END.PRC[1:49]
y_pred <- p$`100%`[1:49]

# MAPE
MAPE <- mean(abs((y_pred - y_true) / y_true)) * 100
```

```
MAPE

# SMAPE
SMAPE <- mean(abs(y_pred - y_true) / (abs(y_pred) + abs(y_true))/2) * 100
SMAPE

row1 <- c("Mean Absolute Percentage Error (MAPE)","Symmetric Mean Absolute
Percentage Error (SMAPE)")
row2 <- c(MAPE,SMAPE)
x <- cbind(row1,row2)
colnames(x) <- c("Forecast Accuracy Method", "Accuracy")
x
```

2.4. Advantages

Compare with a deterministic and single-point estimate analysis, the Monte Carlo simulation has many advantages. To begin with, the Monte Carlo simulation can produce probabilistic outcomes. The results indicate not just what might happen, but also how likely each outcome is to occur.

Second, a high sensitivity analysis. The deterministic regression makes it difficult to determine which variables have the greatest effect on the outcome in a few cases. In Monte Carlo simulation, however, determining the inputs had the greatest impact on bottom-line outcomes is much easier.

Finally, there is the capability of scenario analysis. It is hard to model various combinations of values for different inputs in deterministic models to see the results of truly different scenarios. Analysts may see precisely which inputs had which values together when those outcomes happened using Monte Carlo simulation. This is extremely useful for further research.

3. Results

3.1. Stock Price Prediction

By predicting the stock prices in the period of 30 January 2017 to 30 May 2021 using the Monte Carlo simulation model, we generated the table with the information of the starting price for our starting date for each options expiration, the probabilities of where the start will be for the next options expiration date, and the ending price and ending expiration date as shown as figure 3.

	START.PRC	START.DATE	0%	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%	55%	60%	65%	70%	75%	80%	85%	90%	95%	100%	END.PRC	END.DATE
1	845.07	17/2/2017	808.62	830.1	833.57	835.91	837.82	839.33	840.82	842.11	843.35	844.63	845.83	847.1	848.4	849.8	851.15	852.59	854.31	856.23	858.56	862.13	883.65	852.31	17/3/2017
2	852.31	17/3/2017	825.66	841.25	843.96	845.68	847.08	848.22	849.23	850.29	851.24	852.2	853.18	854.03	854.89	855.77	856.81	857.86	859.08	860.48	862.08	864.63	880.36	898.53	21/4/2017
3	898.53	21/4/2017	870.02	886.69	889.53	891.43	892.96	894.31	895.48	896.61	897.72	898.75	899.77	900.81	901.85	902.88	903.98	905.26	906.61	908.17	910.12	913.2	932.99	959.84	19/5/2017
4	959.84	19/5/2017	927.87	947.06	950.4	952.54	954.26	955.63	956.97	958.19	959.38	960.52	961.67	962.76	963.88	964.98	966.31	967.69	969.36	971.11	973.3	976.81	994.41	987.71	16/6/2017
5	987.71	16/6/2017	949.09	973.58	976.98	979.12	981.08	982.74	984.07	985.49	986.73	988.18	989.47	990.67	991.91	993.25	994.58	996.02	997.66	999.72	1002.19	1005.79	1028.65	1025.67	21/7/2017
6	1025.67	21/7/2017	989.2	1010.75	1014.5	1016.79	1018.71	1020.46	1021.97	1023.27	1024.55	1025.91	1027.26	1028.58	1029.92	1031.29	1032.74	1034.25	1035.84	1037.8	1040.38	1044.29	1068.65	958.47	18/8/2017
7	958.47	18/8/2017	919.16	942.91	946.33	948.89	950.8	952.4	953.89	955.32	956.72	958.07	959.36	960.62	961.88	963.28	964.77	966.29	968.1	970.11	972.93	976.7	998.66	986.79	15/9/2017
8	986.79	15/9/2017	951.01	970.66	974.52	977.02	979.01	980.8	982.38	983.79	985.13	986.48	987.78	989.15	990.43	991.86	993.48	995.06	996.9	998.88	1001.34	1005.22	1025.75	982.91	20/10/2017
9	982.91	20/10/2017	945.75	967.45	971.21	973.57	975.5	977.17	978.67	980.12	981.43	982.78	984.05	985.37	986.67	987.99	989.36	990.75	992.54	994.48	996.94	1000.68	1029	1129.88	17/11/2017
10	1129.88	17/11/2017	1070.45	1107.02	1111.79	1115.59	1118.55	1121.11	1123.35	1125.57	1127.46	1129.36	1131.34	1133.21	1135.15	1137.25	1139.36	1141.92	1144.38	1147.49	1151.27	1157.16	1192.28	1179.14	15/12/2017
11	1179.14	15/12/2017	1120.27	1154.7	1160.19	1164.18	1167.36	1170.12	1172.44	1174.85	1177.05	1179.19	1181.22	1183.08	1185.17	1187.36	1189.6	1192.03	1194.8	1197.91	1202.19	1208.03	1247.81	1294.58	19/1/2018
12	1294.58	19/1/2018	1232.48	1269.24	1275.25	1279.11	1282.5	1285.19	1287.95	1290.48	1292.66	1294.95	1297.11	1299.2	1301.32	1303.54	1306.16	1308.6	1311.6	1315.19	1319.44	1325.74	1359.95	1448.69	16/2/2018
13	1448.69	16/2/2018	1358.74	1417.92	1425.61	1430.83	1434.86	1438.1	1441.11	1443.96	1446.54	1449.08	1451.68	1454.26	1456.94	1459.79	1462.51	1465.83	1469.48	1473.35	1478.36	1486.22	1538.12	1571.68	16/3/2018
14	1571.68	16/3/2018	1487.93	1539.27	1546.91	1552.09	1556.24	1559.73	1562.98	1565.97	1568.98	1571.61	1574.47	1577.26	1580.36	1583.29	1586.43	1589.78	1593.36	1597.55	1602.63	1610.68	1660.95	1527.49	20/4/2018
15	1527.49	20/4/2018	1446.65	1492.11	1500.26	1505.97	1510.3	1514.05	1517.47	1520.78	1523.75	1526.83	1529.9	1532.8	1535.95	1539.36	1542.72	1546.32	1550.51	1555.14	1561.15	1569.28	1619.11	1574.37	18/5/2018
16	1574.37	18/5/2018	1476.23	1537.98	1546.76	1552.57	1557.05	1560.8	1564.39	1567.98	1571.01	1574.27	1577.39	1580.55	1583.64	1587.05	1590.65	1594.13	1598.42	1603.61	1609.65	1618.4	1667.13	1715.97	15/6/2018
17	1715.97	15/6/2018	1625.63	1677.04	1686.12	1692.48	1698.12	1702.33	1706.07	1709.61	1713.03	1716.36	1719.65	1722.98	1726.18	1729.47	1733.29	1736.84	1741.27	1746.31	1752.36	1762.56	1817.3	1813.7	20/7/2018
18	1813.7	20/7/2018	1722.13	1773.76	1783.42	1789.77	1794.63	1799.37	1803.35	1807.19	1810.75	1814.28	1817.6	1820.84	1824.37	1827.73	1831.35	1835.36	1840.1	1845.62	1852.33	1862.87	1933.48	1882.22	17/8/2018
19	1882.22	17/8/2018	1779.78	1840.99	1850.99	1857.81	1863.25	1867.59	1871.66	1875.36	1878.89	1882.48	1886.03	1889.57	1893.31	1896.92	1901	1905.09	1909.79	1915.05	1922.37	1933.3	2004.96	1915.01	21/9/2018
20	1915.01	21/9/2018	1815.82	1872.78	1882.72	1890.36	1895.7	1900.09	1904.26	1908.24	1912.1	1915.68	1919.1	1922.76	1926.34	1929.97	1933.62	1937.92	1942.8	1948.3	1955.33	1966.61	2032.92	1764.03	19/10/2018
21	1764.03	19/10/2018	1662.19	1724.31	1733.2	1739.79	1745.18	1749.23	1753.46	1756.93	1760.35	1763.93	1767.27	1770.65	1773.99	1777.56	1781.3	1785.43	1789.83	1795.07	1801.96	1812.01	1869.25	1593.41	16/11/2018
22	1593.41	16/11/2018	1493.42	1551.53	1561.26	1567.84	1573.28	1577.32	1581.59	1585.38	1589	1592.64	1596.01	1599.16	1602.96	1606.74	1610.96	1615.22	1619.44	1624.83	1631.28	1641.44	1701.94	1377.45	21/12/2018
23	1377.45	21/12/2018	1292.45	1337.64	1347.46	1353.47	1358.02	1362.02	1365.83	1369.32	1372.6	1375.77	1379.1	1382.27	1385.46	1388.61	1391.96	1396.09	1400.25	1404.95	1411.72	1421.9	1474.46	1696.2	18/1/2019
24	1696.2	18/1/2019	1560.13	1646.17	1657.26	1665.37	1671.79	1676.97	1681.67	1686.12	1690.32	1694.21	1698.11	1702.01	1706.63	1710.72	1715.36	1719.87	1725.57	1732.09	1740.2	1751.48	1832.27	1607.95	15/2/2019
25	1607.95	15/2/2019	1485.44	1560.24	1570.55	1577.82	1583.93	1588.99	1593.4	1597.66	1601.85	1605.98	1609.91	1613.91	1617.87	1622.05	1626.71	1631.39	1637.03	1642.97	1650.86	1662.28	1729.3	1712.36	15/3/2019
26	1712.36	15/3/2019	1602.47	1661.75	1673.48	1681.26	1687.32	1692.81	1697.77	1701.95	1705.9	1710.21	1714.69	1718.58	1722.47	1726.64	1731.04	1736.25	1742.06	1748.2	1756.51	1768.08	1834.53	1869	17/5/2019
27	1869	17/5/2019	1743.96	1815.99	1828.1	1836.69	1842.87	1848.63	1853.78	1858.6	1863.42	1867.82	1871.93	1876.19	1880.72	1885.42	1890.58	1895.72	1900.95	1907.68	1916.63	1929.5	2020.26	1911.3	21/6/2019
28	1911.3	21/6/2019	1789.71	1856.57	1868.96	1877.68	1884.18	1889.93	1895	1900.21	1904.73	1908.97	1913.38	1917.59	1922.17	1926.79	1931.86	1937.05	1943.01	1949.91	1958.44	1971.28	2051.87	1964.52	19/7/2019
29	1964.52	19/7/2019	1835.09	1907.92	1921.47	1929.88	1936.62	1942.52	1948.05	1953.14	1958.34	1962.67	1967.32	1971.89	1976.37	1981.03	1986.12	1991.17	1997.63	2004.52	2013.69	2027.57	2133.72	1792.57	16/8/2019
30	1792.57	16/8/2019	1676.19	1741.43	1753.05	1760.6	1766.94	1772.62	1777.51	1782.37	1786.29	1790.61	1794.68	1798.9	1802.82	1807.3	1811.88	1816.72	1821.99	1828.72	1836.89	1848.8	1935.09	1794.16	20/9/2019
31	1794.16	20/9/2019	1681.3	1743.46	1755.04	1763.37	1768.96	1774.63	1779.71	1784.28	1788.58	1792.67	1796.67	1800.71	1804.77	1808.8	1813.16	1818.22	1823.97	1830.59	1838.64	1850.33	1911.66	1757.51	18/10/2019
32	1757.51	18/10/2019	1646.88	1707.63	1718.89	1726.85	1732.8	1738.01	1742.78	1747.15	1751.2	1755.04	1759.28	1762.88	1767.1	1771.27	1775.89	1780.66	1785.82	1792.09	1799.99	1812.09	1874.35	1739.49	15/11/2019
33	1739.49	15/11/2019	1637.45	1690.75	1701.13	1708.81	1714.78	1720.39	1724.79	1729.11	1732.89	1736.82	1740.54	1744.29	1747.99	1752.03	1756.47	1761.46	1766.69	1772.91	1780.66	1792.64	1851.25	1786.5	20/12/2019
34	1786.5	20/12/2019	1664.68	1737.71	1748.64	1756.04	1762.07	1767.15	1771.69	1775.86	1779.96	1784.13	1787.79	1791.98	1796.12	1800.21	1804.71	1809.76	1815.13	1821.41	1829.62	1840.81	1919.31	1864.72	17/1/2020
35	1864.72	17/1/2020	1741.5	1814.5	1826.1	1833.88	1839.88	1844.9	1849.9	1854.73	1858.95	1862.88	1866.8	1870.73	1874.81	1878.97	1883.43	1888.18	1893.63	1900.1	1908.05	1919.46	1991.73	2095.97	21/2/2020
36	2095.97	21/2/2020	1950.43	2039.76	2051.75	2060.56	2068.12	2074.24	2079.83	2084.96	2089.71	2093.95	2098.52	2103.36	2107.87	2112.69	2117.95	2123.55	2129.65	2136.32	2145.4	2159.39	2236.9	1846.09	20/3/2020
37	1846.09	20/3/2020	1715.22	1792.74	1805.29	1812.98	1819.22	1825.25	1830.55	1835.38	1839.95	1844.03	1848.37	1852.8	1857.22	1861.8	1866.22	1871.06	1876.51	1883.21	1892.01	1903.78	1983.85	2375	17/4/2020
38	2375	17/4/2020	2222.03	2305.03	2321.36	2331.63	2340.52	2347.76	2354.7	2361.02	2366.97	2372.72	2378.61	2384.12	2389.73	2395.59	2402.12	2408.7	2416.28	2424.81	2435.29	2451.97	2604.31	2409.78	15/5/2020
39	2409.78	15/5/2020	2236.91	2338.9	2354.28	2365.18	2373.98	2381.16	2387.95	2394.94	2400.68	2406.57	2411.97	2417.95	2423.48	2429.61	2435.95	2442.87	2450.7	2459.94	2471.46	2488.2	2591.17	2675.01	19/6/2020
40	2675.01	19/6/2020	2490.66	2596.67	2614.26	2626.3	2635.82	2644.63	2652.16	2658.91	2665.61	2672.33	2678.47	2684.83	2691.38	2697.68	2704.94	2712.96	2721.19	2731	2743.55	2763.12	2883.66	2961.97	17/7/2020
41	2961.97	17/7/2020	2778.11	2875.86	2895.89	2909.49	2920.38	2929.61	2938.05	2945.55	2953	2960.95	2968.32	2975.4	2982.6	2989.68	2997.12	3005.97	3014.55	3024.91	3038.77	3058.9	3198.17	3284.72	21/8/2020
42	3284.72	21/8/2020	3036.59	3189.18	3209.32	3224.76	3237.86	3247.66	3256.57	3264.99	3272.9	3281.18	3288.82	3296.9	3305.23	3313.45	3322.18	3332.29	3342.73	3355.23	3370.76	3392.99	3535.62	2954.91	18/9/2020
43	2954.91	18/9/2020	2777.6	2867.46	2887.17	2901.25	2911.7	2921.4	2929.71	2937.23	2944.49	2952.3	2958.97	2966.45	2973.89	2981.47	2989.19	2997.64	3006.9	3017.89	3031.62	3053.23	3211.22	3272.71	16/10/2020
44	3272.71	16/10/2020	3061.29	3176.27	3197.49	3212.32	3223.86	3234.34	3243.46	3252.42	3260.65	3268.79	3277.63	3284.97	3293.45	3302.08	3311.23	3321.16	3331.87	3344.04	3360.56	3384.21	3549.59	3099.4	20/11/2020
45	3099.4	20/11/2020	2866.79	3002.95	3024.25	3039.45	3051.38	3061.37	3071.05	3079.45	3087.03	3094.92	3103	3110.99	3118.69	3126.79	3135.49	3144.5	3155.61	3167.17	3182.15	3204.3	3400.13	3201.65	18/12/2020
46	3201.65	18/12/2020	2981.8	3107.36	3128.62	3143.59	3155.57	3166.02	3175.34	3184.36	3192.63	3200.14	3207.08	3215.7	3223.71	3231.44	3240.1	3249.23	3260.2	3271.92	3287.82	3312.16	3476.19	3104.25	15/1/2021
47	3104.25	15/1/2021	2888.42	3012.76	3033.02	3046.76	3058.17	3068.31	3076.72	3084.55	3092.72	3100.32	3107.87	3115.36	3123.15	3131.47	3140.46	3149.13	3159.32	3170.69	3185.79	3206.7	3345.27	3249.9	19/2/2021
48	3249.9	19/2/2021	3011.15	3154.13	3175.14	3190.16	3202.83	3213.06	3222.27	3231.09	3239.19	3247.22	3255.03	3262.36	3270.49	3279.36	3288.18	3296.9	3307.31	3319.73	3335.65	3359.74	3475.07	3074.96	19/3/2021
49	3074.96	19/3/2021	2868	2981.93	3002.09	3017.67	3029.47	3038.74	3047.64	3055.55	3063.58	3071.12	3078.21	3085.67	3093.25	3100.84	3109.32	3118.73	3128.62	3140.07	3155.67	3177.47	3336.05	3399.44	16/4/2021
50	3399.44	16/4/2021	3158.29	3297.09	3320.32	3335.33	3348.59	3359.74	3369.85	3377.62	3386.17	3395.11	3403.46	3412.35	3420.6	3428.9	3438.15	3448.17	3460.66	3473.36	3490.18	3514.99	3639.14	NA	NA

Figure 3 The CSV table show the predicted stock prices using the Monte Carlo simulation model

In figure 4, the data in the last three months is extracted to analyze the result. From examining the data from 19 February 2021 to 19 March 2021, the one hundred per cent predicted stock price on 19 March 2021 is 3475.07 is far from the exact stock price of 3074.96. There is a difference of 400.11. From 19 March 2021 to 16 April 2021, the one hundred per cent predicted stock price is 3336.05 on 16 April 2021, which is much closer to the exact stock price of 3399.44. Besides, on 13 May 2021, one hundred per cent predicted stock price is 3639.14 respectively.

	START.PRC	START.DATE	0%	25%	50%	75%	100%	END.PRC	END.DATE
48	3249.9	19/2/2021	3011.15	3213.06	3255.03	3296.9	3475.07	3074.96	19/3/2021
49	3074.96	19/3/2021	2868	3038.74	3078.21	3118.73	3336.05	3399.44	16/4/2021
50	3399.44	16/4/2021	3158.29	3359.74	3403.46	3448.17	3639.14	NA	NA

Figure 4 The extracted data of the last three-months

Regarding the accuracy of the prediction model, mean absolute percentage error (MAPE) and symmetric mean absolute percentage error (SMAPE) are calculated. As you can see, in figure 5, the accuracy rate are 6.9441% and 1.6695%. The accuracy rate more closer with zero percentage, the more higher accuracy because the range of error is from zero to infinite. Therefore, the prediction model is quite well.

	Forecast Accuracy Method	Accuracy
[1,]	"Mean Absolute Percentage Error (MAPE)"	"6.94407943213984"
[2,]	"Symmetric Mean Absolute Percentage Error (SMAPE)"	"1.66947450356813"

Figure 5 The table shows the accuracy of two prediction models

3.2. Trend Analysis

Figure 6 displayed the ending prices along with the probability of zero and one hundred per cent. Overall, after August 2018, the line of ending prices was always between the green line and the red line. The one hundred per cent predicted stock prices are always higher than the exact price and the zero percentage is lower. In addition, it is apparent that there are two periods where show a trend from decline to rise, respectively on August 2018 and February 2020. More importantly, under the impact of the COVID-19 pandemic, the rise in March 2020 rises suddenly until the end of the year 2020. From the end of the year 2020 to now, the stock price fluctuates constantly.

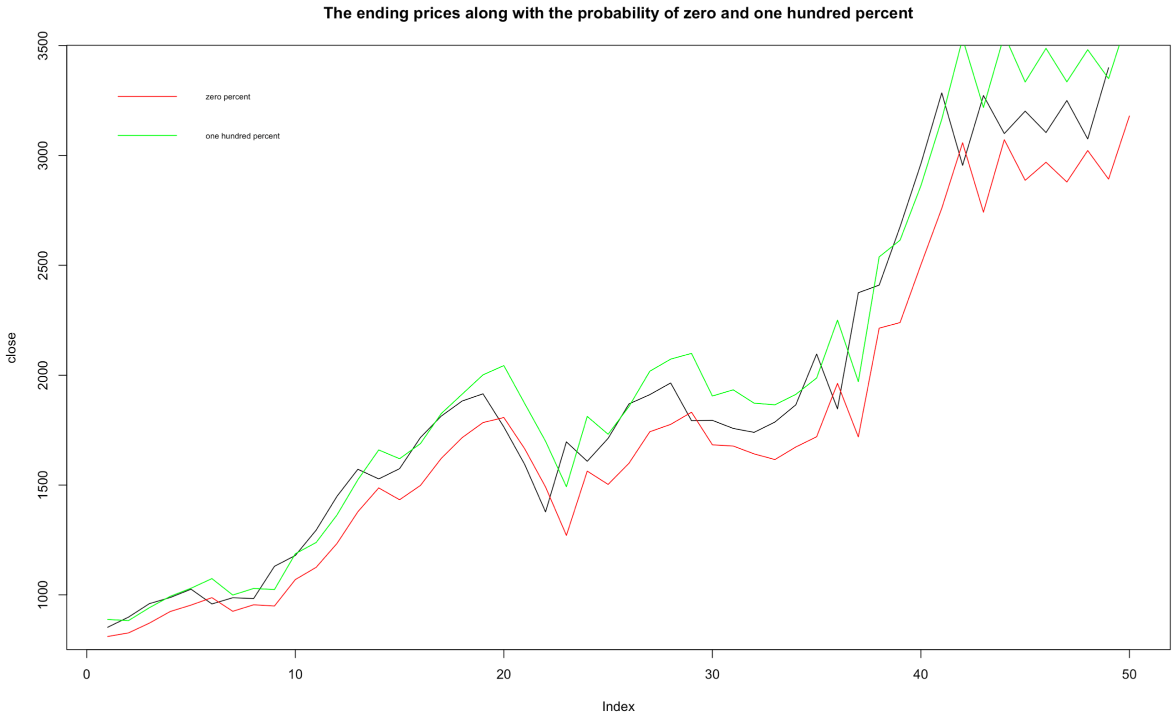

Figure 6 The predicted ending prices along with the probability of zero and one hundred per cent

4. **Discussion**

As a result of the study, overall, the predicted ending stock price increased continuously and maintained stability in the past half-year. Amazon stock hit record high amid coronavirus gloom. The increasing stock price during the COVID-19 pandemic could be because of the change in customer behavior and effective company policies.

The COVID-19 pandemic has had major effects on customer behaviors, who tend to rely on online shopping to reduce contact with others. Due to the high demand for groceries, traditional supermarkets might have trouble restocking those products, which could lead to scarcity. The severity of the pandemic and shortage in supplies made Amazon increase in sales. According to Forbes (2021), in the first quarter of 2020, Amazon's gross sales increased by 26%. Amazon web services-led sales growth with a 33% year-over-year, while North American retail revenue increased by 29% y-o-y. The reason is that people are staying at home to reduce the risks of getting infected. Therefore, ordering the needed products online has become a common habit. During the pandemic, anti-epidemic products, home exercise equipment, and home entertainment are showing increasing in search terms on Amazon. Thus, the change of customer behavior enhances the profits on Amazon.

Since the beginning of 2020, the COVID-19 pandemic has posed significant challenges to the global supply chain. Several countries have slowed or stopped the movement of raw materials and finished goods, causing manufacturing to be disrupted. Millions of customers in the United States and abroad are moving to online marketplaces to meet their basic needs including groceries, clothing, toiletries, and drugs as a result of global supply chain disturbances, Amazon has benefited in recent months. Moreover, Amazon instituted crucial strategies to boost its productivity. In these turbulent days where businesses are cutting pay and jobs, Amazon has increased pay and recruited over 100,000 warehouses and distribution staff, with plans to recruit more as it struggles to meet the massive, unforeseen increase in demand. Therefore, Amazon's policies stabilize the entire operating model under the COVID-19 crisis.

5. Conclusions

The Monte Carlo simulation shows high accuracy in predicting ending stock prices on Amazon. As the result of this study, the predicted stock prices of Amazon increased continuously and maintained stability in the past half-year. Surprisingly, Amazon had incredible growth during the COVID-19 pandemic. The analysis result could be because of the change in customer behavior and effective company policies. People tended to online shopping instead of traditional supermarkets since there is a risk of infection. In addition, the policies adopted in Amazon stabilize the operating model under the COVID-19 crisis.

According to Arnaut-Berilo, Zaimović, and Turbo-Merdan (2019), the Monte Carlo simulation has an advantage in predicting stock prices in longer periods of time (21 days). There is a need for a more accurate model to predict in short periods. In potential future work, I would like to utilize the ARIMA model for predicting short periods of time. When determining whether to buy or sell stocks, investors could use a combination of these results, and the Monte Carlo simulation could be used to determine which stock to sell short.

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