BAN 673-03

Time Series Analytics

Forecasting
CVS Health Stock Price

Under the guidance of

Professor Zinovy Radovilsky

By

Kishore Kumar Nakka

Table of Contents

Summary

This is a project on Time Series Analysis and Forecasting to predict CVS Health[1] stock[3] using R Studio[2]. All the steps of the Time series forecasting methods were followed starting from data selection and exploring, visualizing the series, evaluating predictability, pre-processing of data which was not required, partitioning of time series, followed by generating some forecasting model, comparing the results of these models and then implementing the best model to forecast the future data, and then the conclusions.

The methods used for forecasting / model generation were:

1. Naive and Seasonal Naive
2. Moving Average - Trailing (with 6 different window widths as follows: 2, 4, 6, 8, 12)
3. Advanced Exponential Smoothing using Holt-Winters method
4. Regression models with (a) Linear Trend, (b) Quadratic Trend, (c) Seasonality, (d) Linear Trend and Seasonality, and (e) Quadratic Trend and Seasonality
5. Auto ARIMA.

From all the models that we developed, the best model we can use for prediction is the Regression model with Linear Trend and seasonality which has 10.261 as RMSE (Root Mean Square Error) and 11.134 as MAPE (Mean Absolute Percentage Error).

Introduction

The CVS Health stock data for four years was taken. CVS Health Corporation provides health services and plans in the United States.The company was formerly known as CVS Caremark Corporation and changed its name to CVS Health Corporation in September 2014. The company was founded in 1963 and is headquartered in Woonsocket, Rhode Island.

The stock price was $1.59 in February of 1973. On December 1st of 2020, the stock price is $67.54.

Everyday's closing price of CVS Health stock from January of 2016 through December of 2019 is taken from the website here: https://finance.yahoo.com/quote/CVS/history

In this project, I used the R Studio, a programming language to perform a time series analysis for CVS Health stock analysis. The aim is to find a good model that could be used to forecast the future values. I have used many modeling techniques for this project which will be discussed further in the paper.

Main Chapter

This is a project on time series analysis and forecasting. The steps followed were: data selection & exploring, visualizing the series, evaluating predictability, pre-processing of data, partitioning of time series, followed by generating numerous forecasting model, comparing the results of these models and then implementing the best model(s) for forecasting of data for future, and then the conclusions.

Step 1: Define goal

The goal of this project is to predict the CVS stock price. The resulting forecasts will be used to monitor CVS stock price. The forecasting models developed for this project were done via the R language.

Step 2: Get data

Everyday's closing price of CVS Health stock from January of 2016 through December of 2019 is taken from the website here: https://finance.yahoo.com/quote/CVS/history

The data had other factors too, but the relevant column was taken, saved as a csv file (CVS.csv) used as input for this analysis and forecasting.

Here is how the data looks:

```
> CVS.ts
        Jan    Feb    Mar    Apr    May    Jun    Jul    Aug    Sep    Oct    Nov    Dec
2016  96.59  97.17 103.73 100.50  96.45  95.74  92.72  93.40  88.99  84.10  76.89  78.91
2017  78.81  80.58  78.50  82.44  76.83  80.46  79.93  77.34  81.32  68.53  76.60  72.50
2018  78.69  67.73  62.21  69.83  63.39  64.35  64.86  75.24  78.72  72.39  80.20  65.52
2019  65.55  57.83  53.93  54.38  52.37  54.49  55.87  60.92  63.07  66.39  75.27  74.29
```

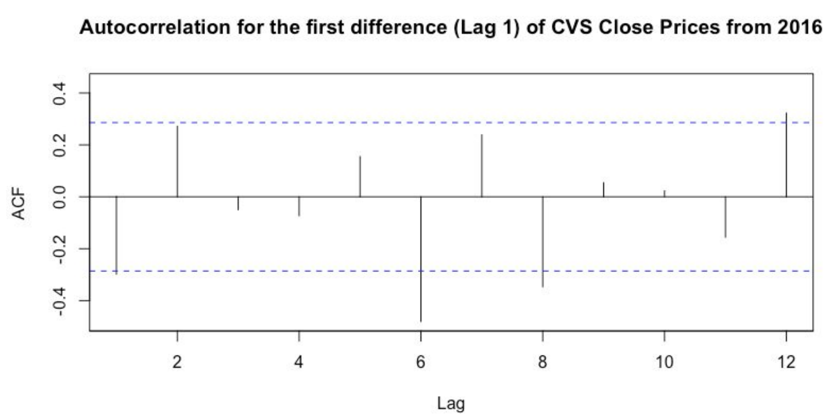
Step 3: Explore & visualize series

Firstly, let us see if the data is predictable or not. From the summary, it is seen that the ar1 value is 0.91 that is kind of close to 1. Which basically means that it might not be a random walk and the future is predictable. But, the data we are taking is stock data. So, this is common for data like this.

```
Series: CVS.ts
ARIMA(1,0,0) with non-zero mean

Coefficients:
         ar1     mean
      0.9145  78.4552
s.e.  0.0544   7.7661

sigma^2 estimated as 30.76:  log likelihood=-150.22
AIC=306.45   AICc=306.99   BIC=312.06

Training set error measures:
                     ME     RMSE      MAE       MPE     MAPE      MASE       ACF1
Training set -0.5703872 5.429707 4.230032 -1.272559 5.841641 0.3775972 -0.2549232
```

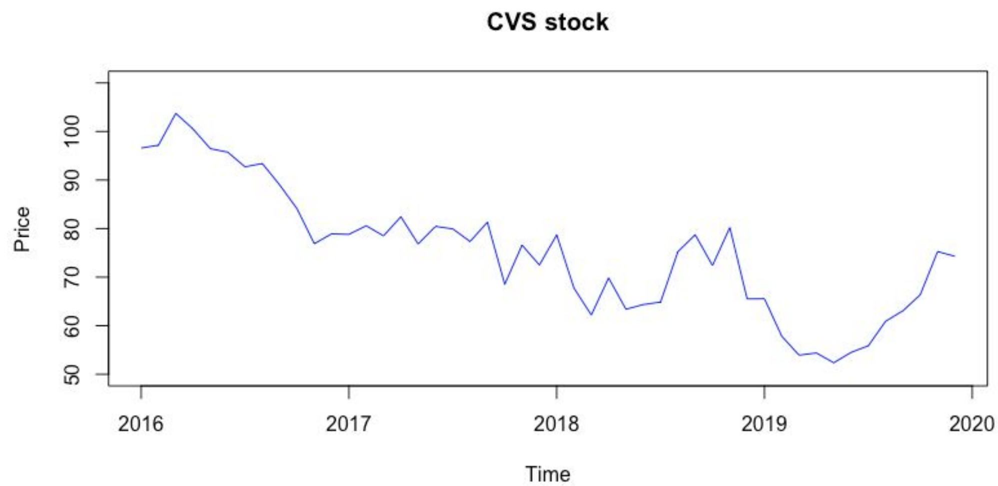
The model's equation is: $e_t = 78.45 + 0.91\ e_{t-1}$

The coefficient of the ar1 (Y_{t-1}) variable, 0.91, is below 1. Therefore, the data time series might be likely to be predictable and might not be a random walk. Let's analyse further.



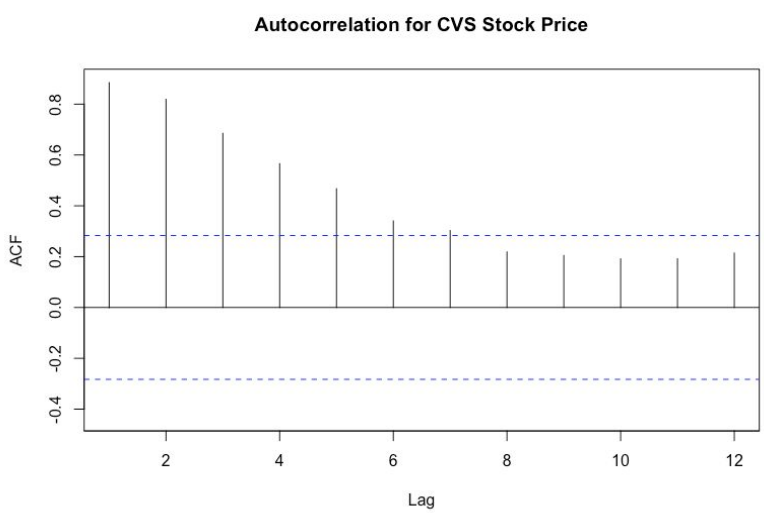
By the above chart, we can say that the data is not a random walk and the future is predictable. We see a strong negative autocorrelation at lag 6 saying that it has a half yearly seasonality.

The time series data plotted below is the CVS stock data from 2016 to 2019 which appear to have a downward trend.



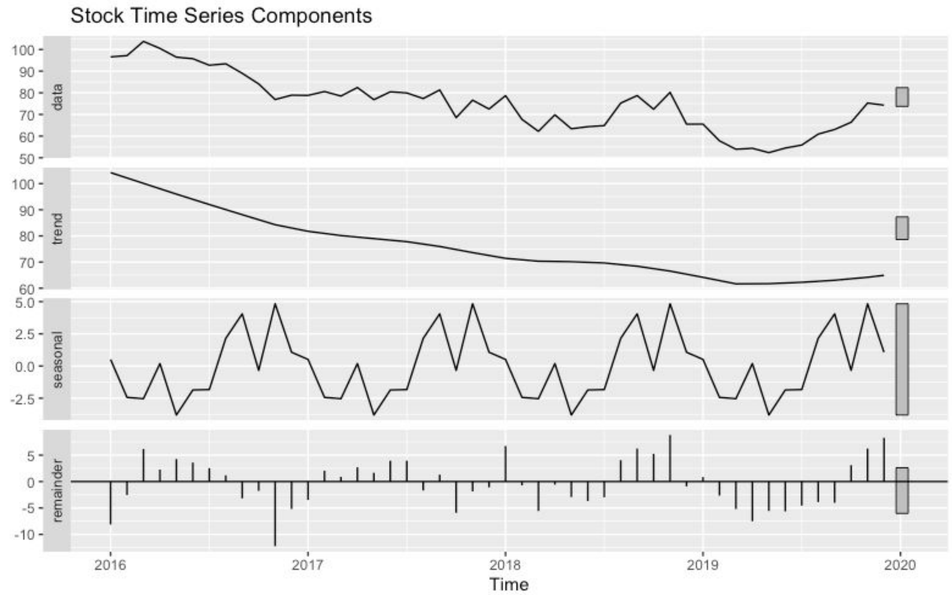
From the below auto-correlation chart and table, we see that the data is highly correlated, as the autocorrelation coefficients in all the lags are substantially higher than the horizontal threshold (significantly greater than zero).

```
> data.frame(Lag, ACF)
   Lag   ACF
1    0 1.000
2    1 0.885
3    2 0.819
4    3 0.685
5    4 0.566
6    5 0.467
7    6 0.341
8    7 0.303
9    8 0.219
10   9 0.204
11  10 0.191
12  11 0.192
13  12 0.214
```



We can also say that the auto-correlation is very high with a lag of 1 and it decreases respectively for the further lags. From this, we can visualize, it has a strong trend relationship.

Here is a plot of the time-series components which shows the trend, seasonality and noise.



The above plot shows the data has a downward trend.

Step 4: Data pre-processing

We need not do any pre-processing for this data.

Step 5: Partition series

The data was partitioned to train data and validation data.

Train data has 3 years of the data. From 2016 to 2018. It is shown as below.

```
> train.ts
        Jan    Feb    Mar    Apr    May    Jun    Jul    Aug    Sep    Oct    Nov    Dec
2016  96.59  97.17 103.73 100.50  96.45  95.74  92.72  93.40  88.99  84.10  76.89  78.91
2017  78.81  80.58  78.50  82.44  76.83  80.46  79.93  77.34  81.32  68.53  76.60  72.50
2018  78.69  67.73  62.21  69.83  63.39  64.35  64.86  75.24  78.72  72.39  80.20  65.52
```

Validation data has the year 2019. It is shown as below.

```
> valid.ts
       Jan   Feb   Mar   Apr   May   Jun   Jul   Aug   Sep   Oct   Nov   Dec
2019 65.55 57.83 53.93 54.38 52.37 54.49 55.87 60.92 63.07 66.39 75.27 74.29
```

Step 6: Apply forecasting Methods

1. Naive Forecasting

```
> round(accuracy(CVS.naive.pred$mean, valid.ts), 3)
              ME  RMSE  MAE    MPE   MAPE  ACF1 Theil's U
Test set -4.323 8.685 7.56 -8.602 12.954 0.709     2.289
```

   This shows the RMSE value of 8.685 and MAPE of 12.95

2. Seasonal Naive Forecasting

```
> round(accuracy(CVS.snaive.pred$mean, valid.ts), 3)
              ME   RMSE    MAE     MPE   MAPE  ACF1 Theil's U
Test set -9.064 11.048 10.526 -15.688 17.656 0.234     2.725
```

   This shows the RMSE value of 11.048 and MAPE of 17.656.

3. Moving Average

```
> round(accuracy(ma.trail_2, CVS.ts), 3) #Best
              ME  RMSE   MAE    MPE  MAPE   ACF1 Theil's U
Test set -0.236 2.775 2.185 -0.427 3.021 -0.298       0.5
> round(accuracy(ma.trail_4, CVS.ts), 3)
              ME  RMSE   MAE    MPE  MAPE  ACF1 Theil's U
Test set -0.901 4.648 3.695 -1.431 5.264 0.446     0.853
> round(accuracy(ma.trail_5, CVS.ts), 3)
              ME  RMSE   MAE    MPE  MAPE  ACF1 Theil's U
Test set -1.297 5.567 4.485 -2.059 6.446 0.553     1.027
> round(accuracy(ma.trail_6, CVS.ts), 3)
              ME RMSE   MAE    MPE  MAPE  ACF1 Theil's U
Test set -1.658 6.34 5.282 -2.667 7.646 0.638     1.172
> round(accuracy(ma.trail_8, CVS.ts), 3)
              ME  RMSE   MAE    MPE  MAPE  ACF1 Theil's U
Test set -2.454 7.626 6.448 -4.013 9.464 0.678     1.396
> round(accuracy(ma.trail_12, CVS.ts), 3)
              ME  RMSE   MAE   MPE   MAPE  ACF1 Theil's U
Test set -3.829 8.322 7.187 -6.29 10.766 0.602     1.483
```

   Trailing Moving Averages were generated using rollmean() function with window widths of 2, 4, 5, 6, 8, and 12. The lowest values of MAPE and RMSE are for the window width of 2. The RMSE is 2.775 and MAPE is 3.021. This is the best till now.

4. Advanced Exponential Smoothing (Holt-Winters Model)

Holt-Winters Model was used with ets() function and model = “ZZZ” to get the optimum model selected by the system for error trend and seasonality. The model is as shown below with Additive error, no trend and no seasonality (A,N,N) .

```
ETS(A,N,N)

Call:
 ets(y = train.ts, model = "ZZZ")

  Smoothing parameters:
    alpha = 0.6196

  Initial states:
    l = 97.4758

  sigma:  5.5807

     AIC     AICc      BIC
256.7396 257.4896 261.4901
```

The alpha value is 0.62. It indicates the level component of the model.

Here is the accuracy measure for the Holt-Winters Model.

```
> round(accuracy(CVS.ZZZ.pred, valid.ts), 3)
                 ME   RMSE    MAE     MPE   MAPE  MASE   ACF1 Theil's U
Training set -1.224  5.423  4.255  -1.839  5.623 0.369 -0.107        NA
Test set     -8.969 11.713 10.507 -16.303 18.358 0.910  0.709     3.147
```

This is the accuracy of this model. It has RMSE of 11.713 and MAPE of 18.358.

5. Regression based models

Below are the summaries for the regression models developed later we will compare and get the better results.

i. Regression model with linear trend

```
Call:
tslm(formula = train.ts ~ trend)

Residuals:
     Min       1Q   Median       3Q      Max 
-10.2645  -4.5973   0.2326   4.0628  14.8648 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 96.56967    2.08042  46.418  < 2e-16 ***
trend       -0.89241    0.09805  -9.101 1.23e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.112 on 34 degrees of freedom
Multiple R-squared:  0.709,	Adjusted R-squared:  0.7004 
F-statistic: 82.83 on 1 and 34 DF,  p-value: 1.229e-10
```

The Regression model with linear trend has an Adjusted R-squared value of 0.7 which says that the model accounts for 70% of the variations.

Also, the p-value is less than 0.01. So, it is statistically significant.

This regression model with linear trend has only one variable, period index (t).

The equation for this is as follows:

Y_t = 95.57 - 0.89 (t)

ii. Regression model with quadratic trend

```
Call:
tslm(formula = train.ts ~ trend + I(trend^2))

Residuals:
    Min      1Q  Median      3Q     Max 
-8.9846 -3.9857  0.6107  3.8200  8.9677 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) 104.978810   2.668076  39.346  < 2e-16 ***
trend        -2.220174   0.332515  -6.677 1.33e-07 ***
I(trend^2)    0.035885   0.008717   4.117 0.000241 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.042 on 33 degrees of freedom
Multiple R-squared:  0.8077,    Adjusted R-squared:  0.7961 
F-statistic: 69.32 on 2 and 33 DF,  p-value: 1.529e-12
```

The Regression model with linear trend has an Adjusted R-squared value of approximately 0.796 which says that the model accounts for 79.6% of the variations.

The p-value of this regression model indicates that it is statistically insignificant because it is <0.01 This regression model with linear trend has two independent variables, period index (t), and squared period index squared (t^2).

The equation for this is as follows:

Y_t = 104.98 - 2.22 (t) - 0.03 (t^2)

iii. Regression model with seasonality

```
Call:
tslm(formula = train.ts ~ season)

Residuals:
    Min      1Q  Median      3Q     Max
-19.270  -6.124  -1.493   7.223  22.250

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   84.697      7.375  11.484 3.09e-11 ***
season2       -2.870     10.430  -0.275    0.786
season3       -3.217     10.430  -0.308    0.760
season4       -0.440     10.430  -0.042    0.967
season5       -5.807     10.430  -0.557    0.583
season6       -4.513     10.430  -0.433    0.669
season7       -5.527     10.430  -0.530    0.601
season8       -2.703     10.430  -0.259    0.798
season9       -1.687     10.430  -0.162    0.873
season10      -9.690     10.430  -0.929    0.362
season11      -6.800     10.430  -0.652    0.521
season12     -12.387     10.430  -1.188    0.247
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 12.77 on 24 degrees of freedom
Multiple R-squared:  0.1025,	Adjusted R-squared:  -0.3088
F-statistic: 0.2493 on 11 and 24 DF,  p-value: 0.9899
```

The Regression model with seasonality has an Adjusted R-squared value of -0.3. And the p-value is 0.98 (greater than 0.05) which states the model is statistically insignificant.

This regression model with seasonality contains 11 seasonal variables season2 (D_2), season3 (D_3), and so on upto season12 (D_{12})

The equation for this is as follows:

$Yt = 84.697 - 2.87 (D_2) - 3.217 (D_3) - 0.44 (D_4) + \ldots.. - 6.8 (D_{11}) - 12.387 (D_{12})$

iv. Regression model with linear trend and seasonality

```
Call:
tslm(formula = train.ts ~ trend + season)

Residuals:
    Min      1Q  Median      3Q     Max 
-11.926  -3.710  -1.272   4.230  13.223 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 96.52576    4.18744  23.051  < 2e-16 ***
trend       -0.90993    0.11521  -7.898 5.34e-08 ***
season2     -1.96007    5.53137  -0.354    0.726    
season3     -1.39680    5.53497  -0.252    0.803    
season4      2.28979    5.54096   0.413    0.683    
season5     -2.16694    5.54934  -0.390    0.700    
season6      0.03632    5.56010   0.007    0.995    
season7     -0.06708    5.57321  -0.012    0.991    
season8      3.66618    5.58867   0.656    0.518    
season9      5.59278    5.60646   0.998    0.329    
season10    -1.50063    5.62654  -0.267    0.792    
season11     2.29930    5.64891   0.407    0.688    
season12    -2.37743    5.67353  -0.419    0.679    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.773 on 23 degrees of freedom
Multiple R-squared:  0.7582,	Adjusted R-squared:  0.6321 
F-statistic: 6.011 on 12 and 23 DF,  p-value: 0.0001209
```

The Regression model with seasonality has an Adjusted R-squared value of 0.63. And the p-value is 0.00012, which states the model is statistically significant.

This regression model with seasonality contains 11 seasonal variables season2 (D_2), season3 (D_3), and so on upto season12 (D_{12})

The equation for this is as follows:

$Yt = 96.525 - 0.909\ (t) - 1.96\ (D_2) - 1.396\ (D_3) - \ldots.. - 2.377\ (D_{12})$

v. Regression model with quadratic trend and seasonality.

```
Call:
tslm(formula = train.ts ~ trend + I(trend^2) + season)

Residuals:
    Min      1Q  Median      3Q     Max 
-9.6919 -2.6551  0.8163  2.4547  8.0400 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) 104.567904   3.767849  27.753  < 2e-16 ***
trend        -2.287520   0.346657  -6.599 1.23e-06 ***
I(trend^2)    0.037232   0.009058   4.110 0.000461 ***
season2      -1.587746   4.254464  -0.373 0.712575    
season3      -0.726625   4.259389  -0.171 0.866102    
season4       3.183366   4.266417   0.746 0.463479    
season5      -1.124444   4.274848  -0.263 0.794970    
season6       1.153283   4.284213   0.269 0.790289    
season7       1.049883   4.294278   0.244 0.809122    
season8       4.708680   4.305037   1.094 0.285892    
season9       6.486350   4.316714   1.503 0.147158    
season10     -0.830447   4.329755  -0.192 0.849658    
season11      2.671626   4.344828   0.615 0.544930    
season12     -2.377429   4.362816  -0.545 0.591284    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.208 on 22 degrees of freedom
Multiple R-squared:  0.8632,	Adjusted R-squared:  0.7824 
F-statistic: 10.68 on 13 and 22 DF,  p-value: 1.118e-06
```

The Regression model with seasonality has an Adjusted R-squared value of 0.78. And the p-value is less than 0.01, which states the model is statistically significant.

This regression model with seasonality contains 11 seasonal variables season2 (D_2), season3 (D_3), and so on upto season12 (D_{12})

The equation for this is as follows:

$Yt = 104.56 - 2.287 (t) - 0.037 (t^2) - 1.587 (D_2) - 0.726 (D_3) - \ldots - 2.377 (D_{12})$

Comparing all these regression models

```
> round(accuracy(train.lin.pred, CVS.ts), 3) #best2
                ME   RMSE   MAE    MPE   MAPE  MASE  ACF1 Theil's U
Training set 0.000  5.939 4.789 -0.557  6.178 0.415 0.521        NA
Test set     2.555 10.164 8.170  2.422 12.747 0.708 0.761     2.331
> round(accuracy(train.quad.pred, CVS.ts), 3)
                 ME   RMSE    MAE     MPE   MAPE  MASE  ACF1 Theil's U
Training set   0.00  4.828  4.151  -0.416  5.404 0.360 0.224        NA
Test set     -14.67 15.746 14.670 -25.352 25.352 1.271 0.598     4.204
> round(accuracy(train.season.pred, CVS.ts), 3)
                  ME   RMSE    MAE     MPE   MAPE  MASE  ACF1 Theil's U
Training set   0.000 10.430  8.278  -1.681 10.421 0.717 0.859        NA
Test set     -18.863 21.266 19.193 -33.020 33.464 1.663 0.704     5.526
> round(accuracy(train.linear.trend.season.pred, CVS.ts),3) #Best1
                ME   RMSE   MAE    MPE   MAPE  MASE  ACF1 Theil's U
Training set 0.000  5.414 4.391 -0.444  5.604 0.380 0.637        NA
Test set     2.975 10.261 7.293  3.178 11.134 0.632 0.704     2.294
> round(accuracy(train.trend.season.pred, CVS.ts),3)
                  ME   RMSE    MAE     MPE   MAPE  MASE  ACF1 Theil's U
Training set   0.000  4.072  3.320  -0.295  4.314 0.288 0.337        NA
Test set     -14.896 16.224 14.896 -25.690 25.690 1.291 0.574     4.351
```

From the above table, we can see that the RMSE and MAPE values of the regression model with linear trend and seasonality have the lowest values as 10.261 and 11.134.

The next best is the regression model with linear trend with RMSE value of 10.164 and MAPE of 12.747.

6. Auto - ARIMA

Auto-ARIMA model is the model which is used to identify optimal ARIMA model and its perspective p, d, q parameters which indicate level, trend and seasonality.

Here is the summary for the Auto-Arima model

```
Series: train.ts
ARIMA(1,1,0)

Coefficients:
          ar1
      -0.4604
s.e.   0.1633

sigma^2 estimated as 29.67:  log likelihood=-108.6
AIC=221.21   AICc=221.58   BIC=224.32

Training set error measures:
                    ME     RMSE      MAE      MPE     MAPE      MASE        ACF1
Training set -1.071767 5.293736 4.084865 -1.63162 5.406063 0.3539489 -0.01388919
```

The equation for this can be given as below:

$Y_t - Y_{t-1} = -0.46\,(Y_{t-1} - Y_{t-2})$

```
> round(accuracy(train.auto.arima.pred, valid.ts), 3)
                 ME   RMSE    MAE     MPE   MAPE  MASE   ACF1 Theil's U
Training set -1.072  5.294  4.085  -1.632  5.406 0.354 -0.014        NA
Test set     -9.073 11.740 10.617 -16.450 18.513 0.920  0.727     3.136
```

This the accuracy values of the auto - ARIMA. The RMSE is 11.740 and MAPE value is 18.513.

Step 7: Evaluate & compare performance

Below are the accuracy measures of the two best models. Regression model with linear trend, and Regression model with linear trend and seasonality

```
> round(accuracy(train.lin.pred$mean, CVS.ts), 3)
            ME   RMSE  MAE   MPE   MAPE  ACF1 Theil's U
Test set 2.555 10.164 8.17 2.422 12.747 0.761     2.331
> round(accuracy(train.linear.trend.season.pred$mean, CVS.ts),3)
            ME   RMSE   MAE   MPE   MAPE  ACF1 Theil's U
Test set 2.975 10.261 7.293 3.178 11.134 0.704     2.294
```

From these compared accuracies, we can say that both are really close in values. But, we can see that the Regression model with linear trend and seasonality has slightly lower values of the ME, MAE, ACF1 and Theil's U. So, we choose the next best one as a regression model with linear trend and seasonality. It has the RMSE value of 10.261 and MAPE of 11.134.

Step 8: Implement forecast system

We have used a Regression model with linear trend and seasonality to implement the forecast.

```
         Point Forecast     Lo 0     Hi 0    Lo 95    Hi 95
Jan 2020       54.84333 54.84333 54.84333 37.18766 72.49901
Feb 2020       50.76084 50.76084 50.76084 33.10516 68.41651
Mar 2020       49.52583 49.52583 49.52583 31.87016 67.18151
Apr 2020       51.72084 51.72084 51.72084 34.06516 69.37651
May 2020       47.19333 47.19333 47.19333 29.53766 64.84901
Jun 2020       48.69333 48.69333 48.69333 31.03766 66.34901
Jul 2020       48.27833 48.27833 48.27833 30.62266 65.93401
Aug 2020       51.65833 51.65833 51.65833 34.00266 69.31401
Sep 2020       52.95833 52.95833 52.95833 35.30266 70.61401
Oct 2020       47.78583 47.78583 47.78583 30.13016 65.44151
Nov 2020       52.17333 52.17333 52.17333 34.51765 69.82901
Dec 2020       47.73833 47.73833 47.73833 30.08266 65.39401
```

From the result above, we can see the prediction for the CVS Health of the year 2020.

Conclusion

This project on time series analysis and forecasting on **CVS Health stocks** can be predicted best using the **regression model with linear trend and seasonality**. The model has the **RMSE value of 10.261 and MAPE of 11.134**.

Although the moving average and naive models have better RMSE and MAPE values, we do not get the right prediction values for this data. Not everything can be forecast reliably, if the factors that relate to what is being forecast are known and well understood and there is a significant amount of data that can be used, very reliable forecasts can often be obtained. If this is not the case or if the actual outcome is affected by the forecasts, the reliability of the forecasts can be significantly lower. And so, we had to choose the regression model with the linear trend model.

This project was a great learning opportunity to me because I have learnt a lot by the challenges I have faced in accomplishing the goals and overcoming the challenges and understanding the subject.

Bibliography

[1] CVS Health is the name of the company that was referred in this document.

More details can be seen here: https://en.wikipedia.org/wiki/CVS_Health

[2] R Studio is the programming language mainly used for statistical analysis.

More details are here: https://en.wikipedia.org/wiki/RStudio

[3] Stock is the price of a share.

More can be known here: https://en.wikipedia.org/wiki/Stock

Appendices

1. PPT's and other study material provided in the Time Series course by **Dr. Zinovy Radivosky** at California State University, East Bay.
2. Data from the wikipedia website to know about CVS.

   Link given here: https://en.wikipedia.org/wiki/CVS_Health
3. Data used from Yahoo website to do the analysis.

   Link provided here: https://finance.yahoo.com/quote/CVS/