Final Project Report

Time Series Analysis – Google- Alphabet

"GOOGL"



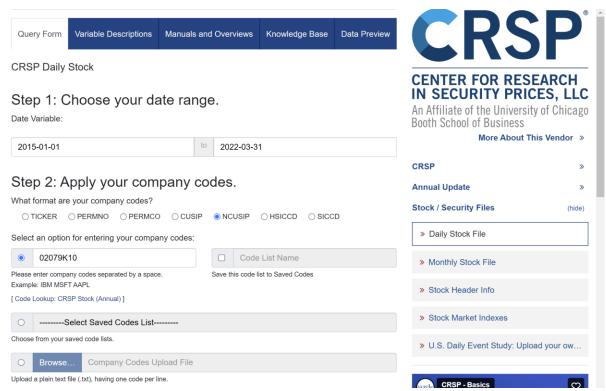
FE-511-A/WS- Introduction to Bloomberg & Thomson-Reuters

Abhishek Hasmukh Rathod

Fall 2022 Semester

December 16, 2022

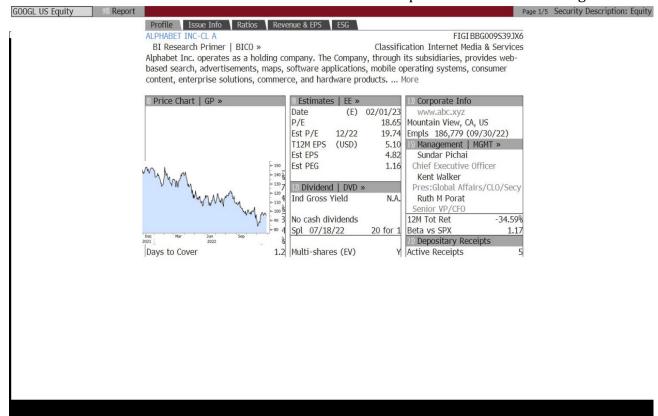
For the stock analysis of GOOGL - ALPHABET, I have collected data from the Wharton Research Data Services



	Date	Low	High	Volume	Close	Open
0	1/2/2015	524.09998	531.27002	1446662	524.67999	529.01001
1	1/5/2015	513.06000	524.33002	2054238	513.85999	523.26001
2	1/6/2015	501.04999	516.17499	2891950	501.60999	515.00000
3	1/7/2015	499.64999	507.24399	2059366	501.07999	507.00000
4	1/8/2015	491.00000	503.48001	3344395	502.67999	497.98999
1820	3/25/2022	2793.98999	2839.18994	959918	2830.34009	2835.08008
1821	3/28/2022	2796.56274	2839.53003	1182975	2838.50000	2813.68994
1822	3/29/2022	2849.67993	2883.25000	1427189	2864.60010	2863.20996
1823	3/30/2022	2843.36011	2869.61011	1045617	2852.65991	2857.39990
1824	3/31/2022	2792.37988	2852.88989	1464785	2792.23999	2848.96997

1825 rows × 6 columns

Alphabet – INC -CL A is basically a holding company that provides web-based search. Where one can find any data like advertisement, maps, software's etc. It acts like a search engine. Here, I have extracted data to show linear regression among them.



DES- Extracted consolidated financial information for Alphabet – INC -CL A through DES

Company Description

Alphabet Inc. is an American multinational technology conglomerate holding company headquartered in Mountain View, California. It was created through a restructuring of Google on October 2, 2015 and became the parent company of Google and several former Google subsidiaries.

OVERVIEW

Alphabet is the world's third-largest technology company by revenue and one of the world's most valuable companies. The establishment of Alphabet Inc. was prompted by a desire to make the core Google business "cleaner and more accountable" while allowing greater autonomy to group companies that operate in businesses other than Internet services. Founders Larry Page and Sergey Brin announced their resignation from their executive posts in December 2019, with the CEO role to be filled by Sundar Pichai, also the CEO of Google. This growth has transformed Alphabet into one of the largest companies in the world, with a market capitalization of nearly \$1.9 trillion. The company has trailing 12-month (TTM) net income of \$62.9 billion and TTM revenue of \$220.3 billion.

Operations

The parent also is involved on a broad array of businesses, including cloud computing, software and hardware, advertising services, and mobile and desktop applications.

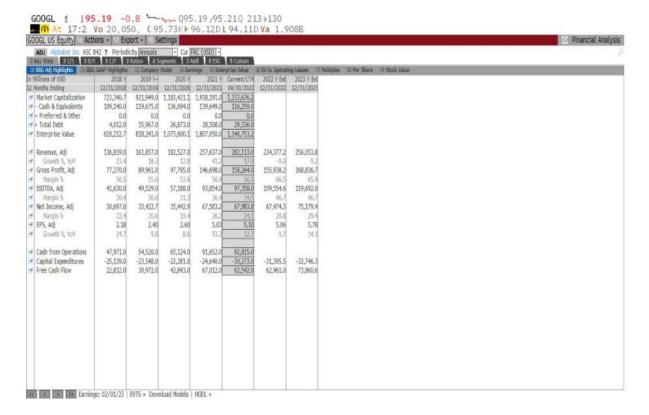
Alphabet Inc. has a diverse set of operations representing various products. As a result, productivity criteria vary, depending on the subsidiary and the goods or services involved. Some of the productivity criteria applicable to Google's operations management are as follows:

- Rate of software error or bug correction This criterion measures the productivity of software development personnel and their teams.
- Rate of release of mobile app updates This productivity criterion matches current information technology trends, and measures Alphabet's operations management effectiveness in supporting product development and rollout.
- Rate of installation of Google Fiber connections This factor measures the productivity of Alphabet's Google Fiber teams in satisfying market demand for Internet connection service.

Company Background

The establishment of Alphabet was prompted by a desire to become a technology conglomerate which makes the core Google internet services business "cleaner and more accountable" while allowing greater autonomy to group companies that operate in businesses other than Internet services. The company is engaged in the business of acquisition and operation of different companies.

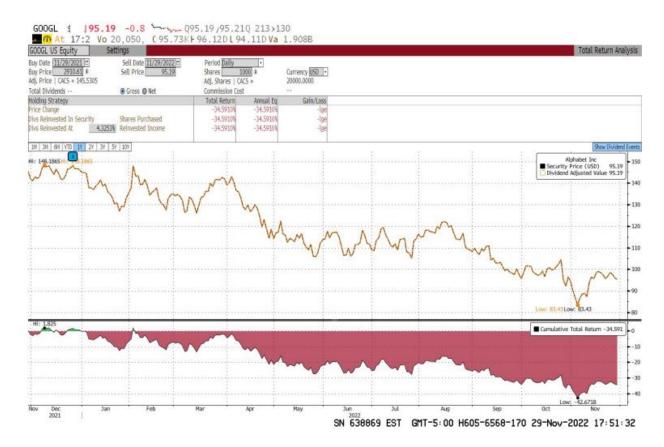
FA – Extracted the Company Fundamentals through FA function.



Through fundamentals, we see that the market capitalization of BRK-A has increased from \$723,340.7M USD in 2018 to \$1,233,676.2M USD currently. Total debt in 2018 was \$4012M USD and currently, the debt has marginally increased to \$29336M USD. The latest EPS or the earnings per share has been \$5.10 USD with a growth of 133% YOY. The net income in 2018 was \$30697M USD and currently, it is \$67983.8M USD. The cash from operations has increased marginally from \$47971M USD to \$92815M USD, still, GOOGL has a ton of money and more than some countries' GDP. The stock is trading at a P/E ratio of 18.9. Normally its P/E ratio ranges from 18-25.

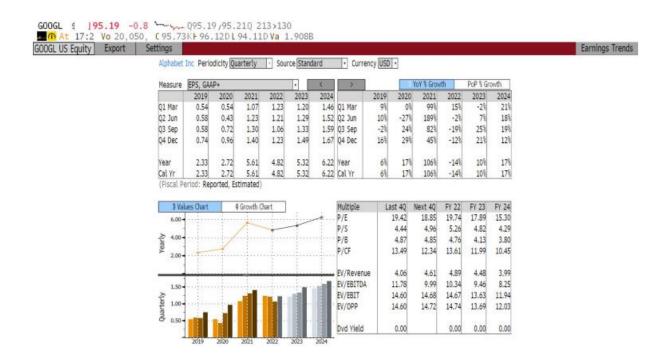
TRA- Total Return Analysis (TRA) function provides a rich set of options for calculating returns between a start date and an end date.

The company's cumulative total return is -34.59% which is not great looking at the magnitude of the company. The daily volumes are very low 20-30shares are traded daily. The security price is 95.19 which is the same as the dividend adjusted value. The Divs reinvested at 4.325%



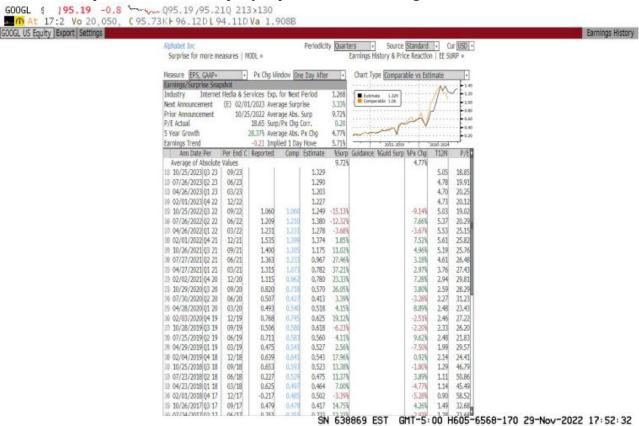
EM - Emerging market equity funds offer investors access to countries and regions that are undergoing economic transition.

We see that quarterly projected EPS for the Q1 Mar 2023 is 1.20 and for Q1 2024 is 1.46. For Q2 June 2023 projected EPS is 1.29 and for Q2 Jun 2024 projected EPS is 152. For Q3 Sept 2023 projected EPS is 1.33 and for Q3 Sept 2024 projected EPS is 1.59. For Q4 Dec 2023 projected EPS is 1.49 and for Q4 Dec 2024 projected EPS is 1.67.



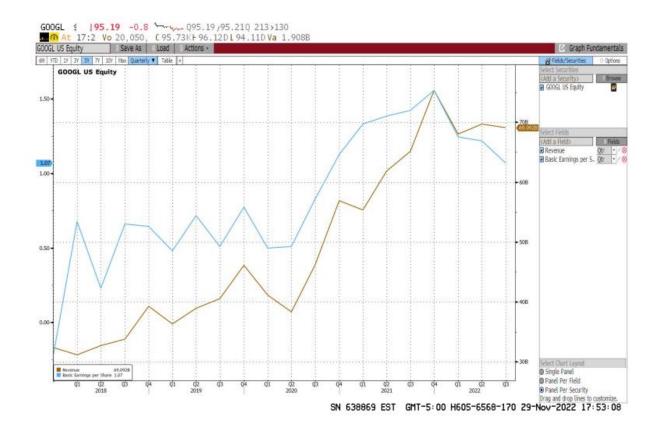
SURP- Surprise Analysis was used to analyze historical data on earnings surprisesand share price changes

Most of the times, we see a positive surprise in GOOGL results. In Q1 2021, we saw a nearly +37.21% surprise when the company reported 1.315 beating the street estimates of 1.073



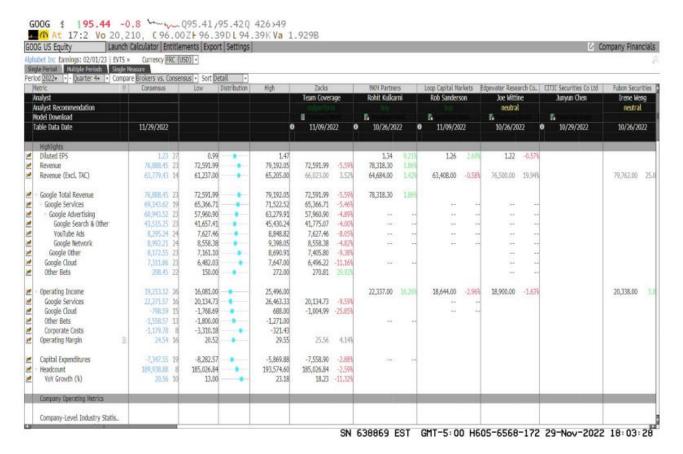
GF - Graph Fundamentals

In this graph, the brown line represents Revenues, and the blue line represents Earnings per share over the 5-year time period. We see that at most of the times the earnings per share is higher as compared to the revenue. We could notice that during Q4 of 2021 both were equivalent.



Modl – It provides all the reported data across regions. MODL combines detailed disclosures with analyst expectations and models.

Here we can see Google Total Revenue as 76,888.45 and there are different services that comes under google are also shown below. Its operating income is 19,213.12. It has a diluted EPS of 1.23



Firstly, Alphabet's Google Search & Other business performed very well in Q2 2022 notwithstanding macroeconomic challenges, and this bodes well for the long-term outlook for the company and its core business.

According to its Q2 2022 10-Q filing, revenue for the Google Search & Other service grew by +13.5% YoY from \$35.9 billion in Q2 2021 to \$40.7 billion for Q2 2022. Alphabet's actual Q2 2022 revenue for the Google Search & Other business also beat the market's consensus forecast by approximately +1% as per *S&P Capital IQ* data.

Google Search & Other is the most important business for Alphabet, as it is the company's largest revenue contributor accounting for 58% of its top line FY 2021. At its Q2 2022 earnings briefing, Alphabet stressed that the company's strategy is to provide products and services that are "helpful to people and businesses during uncertain moments" and "for the long term" as well. Specifically, GOOG highlighted that Google Search serves the purpose of enabling people "to find anything from anywhere."

Financial Performance

Alphabet spent approximately \$15.2 billion on share buybacks in Q2 2022, and this means that it has allocated around \$28.5 billion to share buybacks in 2H 2022, this will work out o be a decent annualized share buyback yield of 4%

TIME SERIES ANALYSIS USING Python

Time Series Analysis - Google.ipynb

Abhishek Hasmukh Rathod 2022-12-16

DATA PREPROCESSING

```
[] import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
%matplotlib inline
```

1.

[] data=pd.read_csv("/content/sefanqmfc1oq41t3.csv")

D data

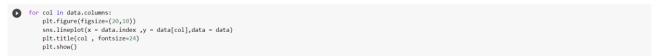
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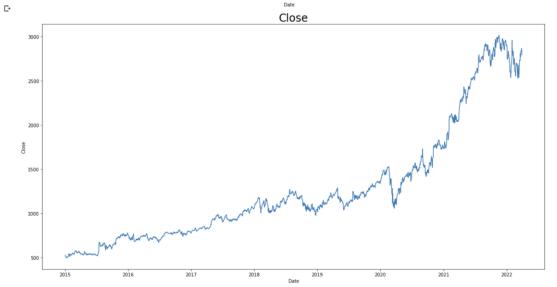
	Date	Low	High	Volume	Close	0pen
0	1/2/2015	524.09998	531.27002	1446662	524.67999	529.01001
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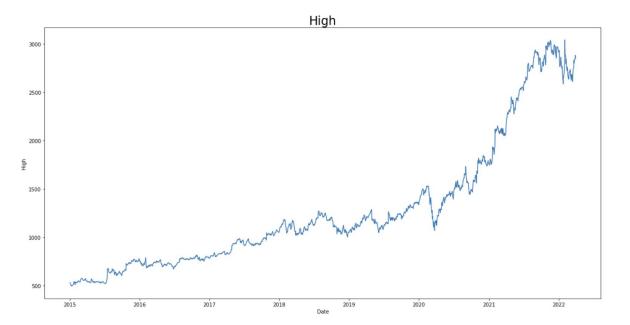
1825 rows × 6 columns

data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1825 entries, 0 to 1824
Data columns (total 6 columns):
Column Non-Null Count Dtype
-----0 Date 1825 non-null object
1 Low 1825 non-null float64
2 High 1825 non-null float64
3 Volume 1825 non-null int64
4 Close 1825 non-null float64
5 Open 1825 non-null float64
dtypes: float64(4), int64(1), object(1)
memory usage: 85.7+ KB







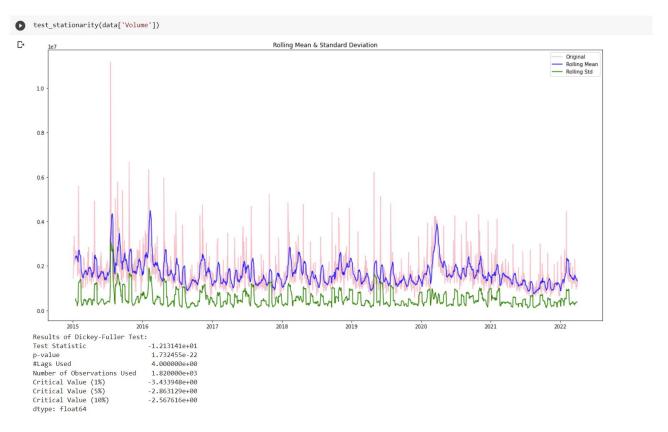
- Likewise for all Volume, Low and Open graphs are present in the notebook.
- It's clear from the plots that there is an overall increase in the trend, with some seasonality in above plot

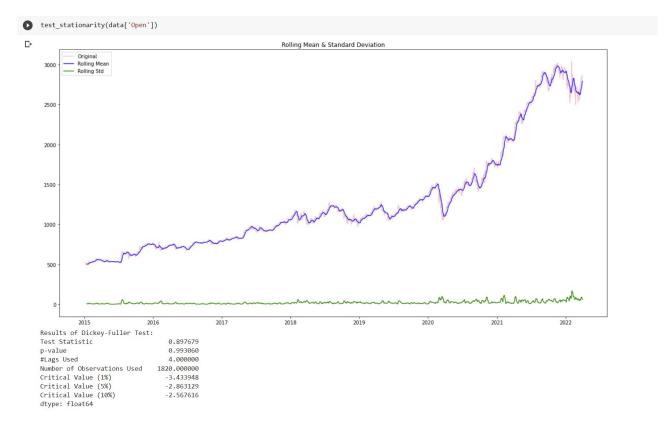
STATIONARITY

This is a very important concept in Time Series Analysis. In order to apply a time series model, it is important for the Time series to be stationary; in other words all its statistical properties (mean, variance) remain constant over time.

```
from statsmodels.tsa.stattools import adfuller
def test_stationarity(timeseries):
    #Determing rolling statistics
    MA = timeseries.rolling(window = 10).mean()
    MSTD = timeseries.rolling(window = 10).std()
    #Plot rolling statistics:
    plt.figure(figsize=(20,10))
    orig = plt.plot(timeseries, color='pink',label='Original')
    mean = plt.plot(MA, color='b', label='Rolling Mean')
    std = plt.plot(MSTD, color='g', label = 'Rolling Std')
    plt.title('Rolling Mean & Standard Deviation')
    plt.legend(loc='best')
    plt.show()
    #Perform Dickey-Fuller test:
    print('Results of Dickey-Fuller Test:')
    dftest = adfuller(timeseries, autolag='AIC')
    dfout = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags Used','Number of Observations Used'])
    for key,value in dftest[4].items():
        dfout['Critical Value (%s)'%key] = value
    print(dfout)
```

The most used is the Dickey-fuller Test: This is one of the statistical tests for checking stationarity. First, we consider the null hypothesis: the time series is non- stationary. The result from the rest will contain the test statistic and critical value for different confidence levels. The idea is to have Test statistics less than critical value, in this case we can reject the null hypothesis and say that this Time series is indeed stationary.





This is not stationary because:

- mean is increasing even though the std is small.
- Test stat is > critical value.
- Note: the signed values are compared and the absolute values.

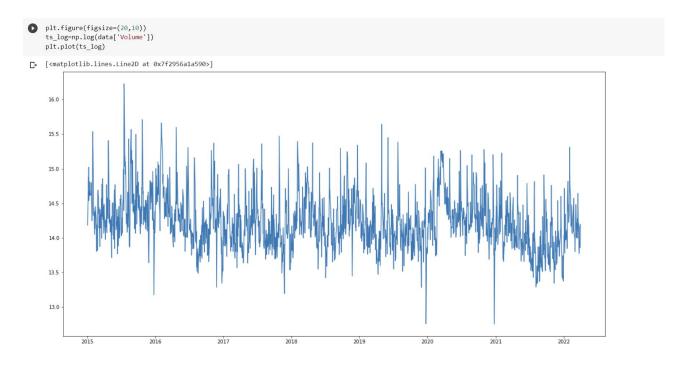
Transformation There are two major factors that make a time series non-stationary. They are:

- Trend: non-constant mean
- Seasonality: Variation at specific time-frames

Trend The first step is to reduce the trend using transformation, as we can see here that there is a strong positive trend. These transformation can be log, sq-rt, cube root etc. Basically it penalizes larger values more than the smaller. In this case we will use the logarithmic transformation.

[] data.info()

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1825 entries, 2015-01-02 to 2022-03-31
Data columns (total 5 columns):
    Column Non-Null Count Dtype
0
    Low
            1825 non-null
                            float64
    High
            1825 non-null
                            float64
    Volume 1825 non-null
                            int64
            1825 non-null
                            float64
    Close
            1825 non-null
                            float64
    0pen
dtypes: float64(4), int64(1)
memory usage: 150.1 KB
```

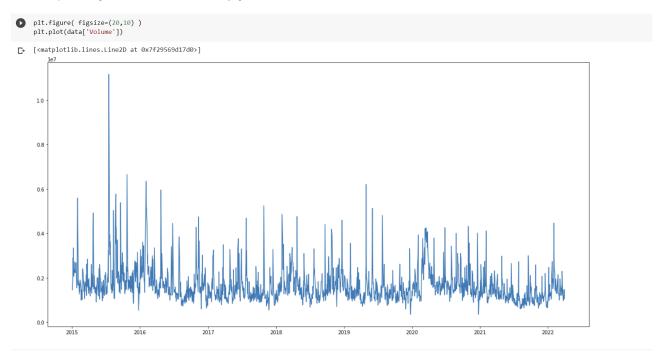


There is some noise in realizing the forward trend here. There are some methods to model these trends and then remove them from the series. Some of the common ones are:

- Smoothing: using rolling/moving average
- Aggression: by taking the mean for a certain time period (year/month)

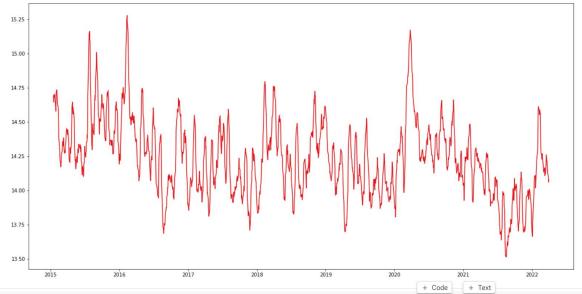
Smoothing of a time series may be useful in:

Reducing the effect of noise in a signal get a fair approximation of the noise-filtered series. The smoothed version of series can be used as a feature to explain the original series itself. Visualize the underlying trend better



plt.figure(figsize=(20,10)) moving_averge=ts_log.rolling(window = 10).mean() plt.plot(moving_averge , color='red')

[→ [<matplotlib.lines.Line2D at 0x7f2956b48790>]



[] moving_avg_diff= ts_log-moving_averge moving_avg_diff

Date 2015-01-02 2015-01-05 2015-01-06 2015-01-07 2015-01-08 NaN NaN NaN NaN NaN -0.358172 -0.124892 0.068094 2022-03-25 2022-03-28 2022-03-29 2022-03-30 2022-03-31

0 test_stationarity(moving_avg_diff)

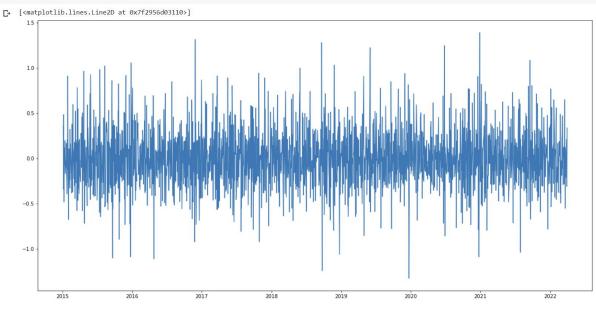
-0.201026 0.115921



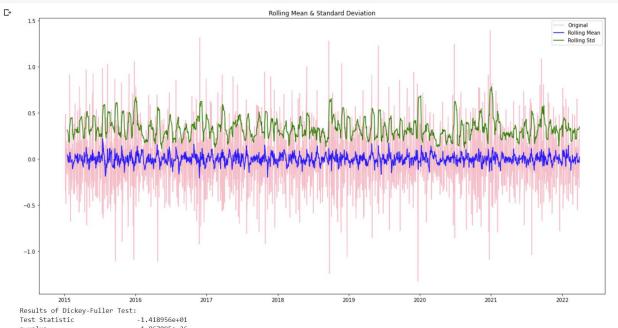
Results of Dickey-Fuller Test: Test Statistic -1.387652e+01 Test Statistic
p-value
#Lags Used
Number of Observations Used
Critical Value (1%)
Critical Value (5%)
Critical Value (10%)
dtype: float64 6.323734e-26 2.100000e+01 1.794000e+03 -3.434000e+00 -2.863152e+00 -2.567628e+00 Seasonality (along with Trend) Previously we saw just trend part of the time series, now we will see both trend and seasonality. Most Time series have trends along with seasonality. There are two common methods to remove trend and seasonality, they are:

- · Differencing: by taking difference using time lag
- Decomposition: model both trend and seasonality, then remove them

plt.figure(figsize=(20,10))
ts_log_diff=ts_log-ts_log.shift()
plt.plot(ts_log_diff)







Results of Dickey-Fuller Test:
Test Statistic -1.418956e+01
p-value 1.867095e-26
#Lags Used 2.400000e+01
Number of Observations Used 7.715ical Value (1%) -3.433990e+00
Critical Value (5%) -2.863148e+00
Critical Value (10%) -2.567626e+00
dtype: float64

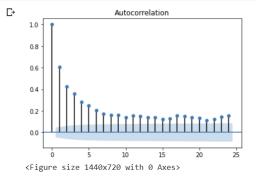
Modelling Now let's check out on how we can figure out what value of p and q to use. We use two popular plotting techniques; they are:

- Autocorrelation Function (ACF): It just measures the correlation between two consecutive (lagged version). example at lag 4, ACF will compare series at time instance t1...t2 with series at instance t1-4...t2-4
- · Partial Autocorrelation Function (PACF): is used to measure the degree of association between y(t) and y(t-p).

Autocorrelation Function (ACF)

Use the autocorrelation function (ACF) to identify which lags have significant correlations, understand the patterns and properties of the time series, and then use that information to model the time series data. From the ACF, you can assess the randomness and stationarity of a time series. You can also determine whether trends and seasonal patterns are present.

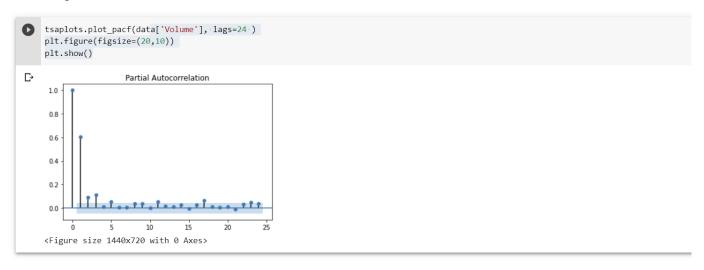
```
from statsmodels.graphics import tsaplots
# Display the autocorrelation plot of your time series
tsaplots.plot_acf(data['Volume'], lags=24 )
plt.figure(figsize=(20,10))
plt.show()
```



In an ACF plot, each bar represents the size and direction of the correlation. Bars that extend across the red line are statistically significant.

Partial Autocorrelation Function (PACF)

The partial autocorrelation function is similar to the ACF except that it displays only the correlation between two observations that the shorter lags between those observations do not explain. For example, the partial autocorrelation for lag 3 is only the correlation that lags 1 and 2 do not explain. In other words, the partial correlation for each lag is the unique correlation between those two observations after partialling out the intervening correlations.



ARIMA Auto Regressive Integrated Moving Average(ARIMA) — It is like a liner regression equation where the predictors depend on parameters (p,d,q) of the ARIMA model

Let's explain these dependent parameters:

- $\bullet p: This is the number of AR (Auto-Regressive) terms . Example \\ if p is 3 the predictor for y(t) will be y(t-1), y(t-2), y(t-3). \\$
- $\bullet \ q : This \ is \ the \ number \ of \ MA \ (Moving-Average) \ terms \ . \ Example if \ p \ is \ 3 \ the \ predictor \ for \ y(t) \ will \ be \ y(t-1), y(t-2), y(t-3).$
- · d :This is the number of differences or the number of non-seasonal differences .



/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:583: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting. 'ignored when e.g. forecasting.', ValueWarning)

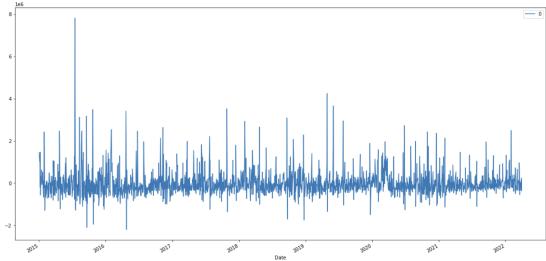
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:583: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.'
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/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_model.py:583: ValueWarning: A date index has been provided, but it has no associated frequency information and so will be ignored when e.g. forecasting.'
ignored when e.g. forecasting.'
ignored when e.g. forecasting.'
ignored when e.g. forecasting.'
SARIMWA Results

		SAI	THMX Kesu	105			
Dep. Variable:		Vo	lume No.	Observations:		1825	
Model:		ARIMA(1, 1	, 2) Log	Likelihood		-26967.789	
Date: Wed		d, 30 Nov 3	2022 AIC			53943.579	
Time: 18:		18:1	8:46 BIC			53965.614	
Sample:			0 HQI	C		53951.707	
		- 1	1825				
Covariance	Type:		opg				
	coef	std err	Z	P> z	[0.025	0.975]	
ar.L1	0.6310	0.035	17.932	0.000	0.562	0.700	
ma.L1	-1.1083	0.040	-27.674	0.000	-1.187	-1.030	
ma.L2	0.1272	0.037	3.439	0.001	0.055	0.200	
sigma2	4.348e+11	1.18e-13	3.68e+24	0.000	4.35e+11	4.35e+11	
							===
Ljung-Box (L1) (Q):		0.04	Jarque-Bera	(JB):	27747	.26	
Prob(Q):			0.84	Prob(JB):		0	.00
Heteroskedasticity (H):			0.48	Skew:		2	.73

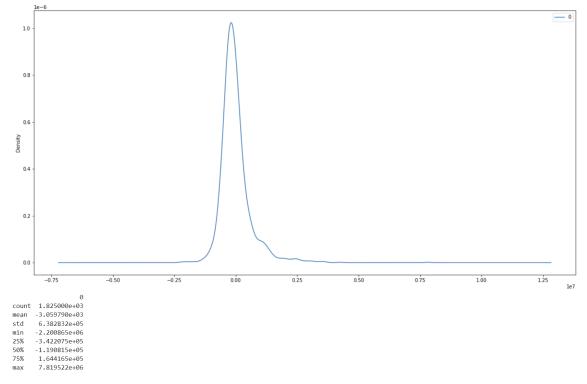
Covariance Type:			opg					
	coef	std err	Z	P> z	[0.025	0.975]		
ar.L1	0.6310	0.035	17.932	0.000	0.562	0.700		
ma.L1	-1.1083	0.040	-27.674	0.000	-1.187	-1.030		
ma.L2	0.1272	0.037	3.439	0.001	0.055	0.200		
sigma2	4.348e+11	1.18e-13	3.68e+24	0.000	4.35e+11	4.35e+11		
Ljung-Box (L1) (Q):			0.04	Jarque-Bera	(JB):	27747.	26	
Prob(Q):			0.84	Prob(JB):		0.	00	
Heteroske	dasticity (H):	:	0.48	Skew:		2.	73	
Prob(H) (two-sided):			0.00	Kurtosis:		21.	31	

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 2.84e+39. Standard errors may be unstable.







Conclusion:

We were successfully able to evaluate Time Series analysis of GOOG over a certain period. It helped us to understand better about the stocks.