# Forecasting Market Volatility for GBP/USD Using ‘Volatility Simulator’

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https://github.com/offgridanalytics

# What is Volatility?

“Volatility is the frequency and magnitude of price movements, ups and down. The bigger and more frequent the price swings, the more volatile the market”.

There are few factors that influence volatility:

- Timing : it can be hours or days that there will be more participants
- Sentiment: such as war
- Government policies: Announcement of Interest rate etc

Note – use APA style referencing for in-text citations (refer to link above)

# How volatility being measured?

In technical analysis there are volume reading for each candle according to each timeframe.


It can be measure in every instrument every stocks, every commodities or even every forex pairs

# How this volatility can be a problem for investor / trader ?

## Volatility and time

Your investment time frame can play a key factor in the performance of an investment portfolio. If you're planning on holding an investment for a long time, the impact of its volatility is reduced. If you are invested in the market for a very long period of time, the ups and downs are much less significant.

However, investing in the market for shorter time frames means that the potential swings are much more pronounced, and more likely to have a bigger impact on your returns. This is why investors taking a longer term view are usually more willing - and able - to hold a greater proportion of higher risk investments.

**Volatility cannot be avoided or removed from an investment, but it can be managed to make it work to the advantage of investors.**

Ref link : https://octopusinvestments.com/resources/guides/explaining-risk-and-volatility/

**Volatility cannot be avoided. But how it can be managed and considered?**

## How to take advantage of market volatility?

Volatility finds its extensive application in the domain of equity investing. Within mutual funds, the basic mechanism for price discovery happens to be volatility. Based on this, an investor decides whether he needs to go for a highly volatile fund like small caps or the moderately volatile large caps. The risk-averse usually opts for a diversified equity portfolio as against the risk-seeker who prefers a portfolio inclined towards small caps. In order to maximise returns, volatility can be extremely helpful. But how one takes it makes all the difference.

Generally, when the market is rallying, investors step-up their SIPs in order to gain from the situation. However, soon they start panicking and reducing their stakes when they see declining markets. They end up buying high-selling low. To benefit from volatility, one needs to follow behaviour moderation in tandem with the underlying goals. Considering other things to be constant, volatility is virtuous for smart investors, because volatility leads to creation of opportunity.

Closely following market valuations and instances of high volatility may help you to make wise decisions as regards diversification, asset allocation, and rebalancing. Volatility does not imply risk of loss. Volatility simply refers to the price fluctuation.

Finally if you want good returns you need to take risk just as we take it when it comes to career or for that matter many decisions in life. The mantra is, just explore the unexplored and you will find the treasure you are looking for. But do keep in mind that some investments may be more volatile while others may be less, which one to choose from is purely based on risk appetite an investor.

Ref link : https://cleartax.in/s/risk-volatility-difference

**How to take advantage of market volatility?**

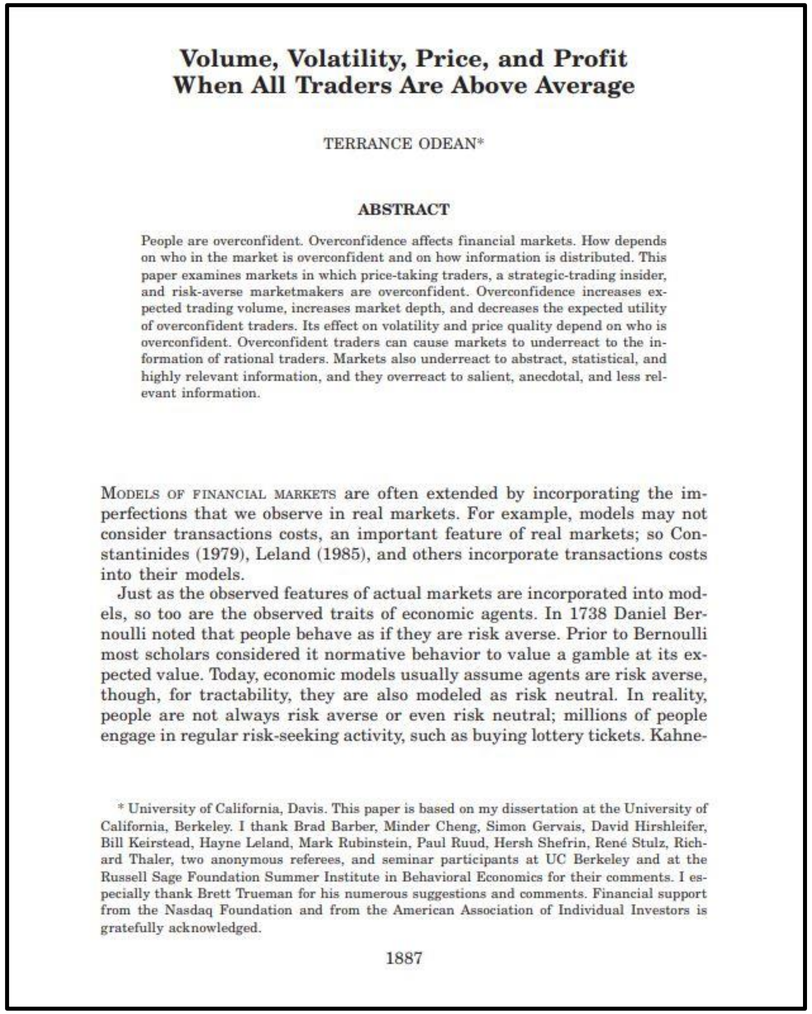
# How this volatility can be a problem for investor / trader ?

Volatility, Volume of any instrument will always affect one thing for investor or traders:

# RISK

And it need no introduction for market participants. When they talks about their Investment portfolio no matter which level they are amateur or the pros they will Always works on one thing which is to **LOWER THEIR RISK !**

**HIGHER VOLATILITY = HIGHER RISK = HARDER GAIN !**



**Volume, Volatility, Price, and Profit When All Traders Are Above Average**

TERRANCE ODEAN*

**ABSTRACT**

People are overconfident. Overconfidence affects financial markets. How depends on who in the market is overconfident and on how information is distributed. This paper examines markets in which price-taking traders, a strategic-trading insider, and risk-averse marketmakers are overconfident. Overconfidence increases expected trading volume, increases market depth, and decreases the expected utility of overconfident traders. Its effect on volatility and price quality depend on who is overconfident. Overconfident traders can cause markets to underreact to the information of rational traders. Markets also underreact to abstract, statistical, and highly relevant information, and they overreact to salient, anecdotal, and less relevant information.

MODELS OF FINANCIAL MARKETS are often extended by incorporating the imperfections that we observe in real markets. For example, models may not consider transactions costs, an important feature of real markets; so Constantinides (1979), Leland (1985), and others incorporate transactions costs into their models.

Just as the observed features of actual markets are incorporated into models, so too are the observed traits of economic agents. In 1738 Daniel Bernoulli noted that people behave as if they are risk averse. Prior to Bernoulli most scholars considered it normative behavior to value a gamble at its expected value. Today, economic models usually assume agents are risk averse, though, for tractability, they are also modeled as risk neutral. In reality, people are not always risk averse or even risk neutral; millions of people engage in regular risk-seeking activity, such as buying lottery tickets. Kahne-

* University of California, Davis. This paper is based on my dissertation at the University of California, Berkeley. I thank Brad Barber, Minder Cheng, Simon Gervais, David Hirshleifer, Bill Keirstead, Hayne Leland, Mark Rubinstein, Paul Ruud, Hersh Shefrin, René Stulz, Richard Thaler, two anonymous referees, and seminar participants at UC Berkeley and at the Russell Sage Foundation Summer Institute in Behavioral Economics for their comments. I especially thank Brett Trueman for his numerous suggestions and comments. Financial support from the Nasdaq Foundation and from the American Association of Individual Investors is gratefully acknowledged.

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Ref link : https://faculty.haas.berkeley.edu/odean/papers%20current%20versions/vvpp.pdf /

# Problem Statement

"To understand the long term volatility trend and forecast the short term volume to lower investment risk"

# This project will only focus on single forex pair data which is GBP/USD to build the model

## The Best Times to Trade the Forex Markets

By TROY SEGAL Updated February 28, 2024

Reviewed by ERIKA RASURE

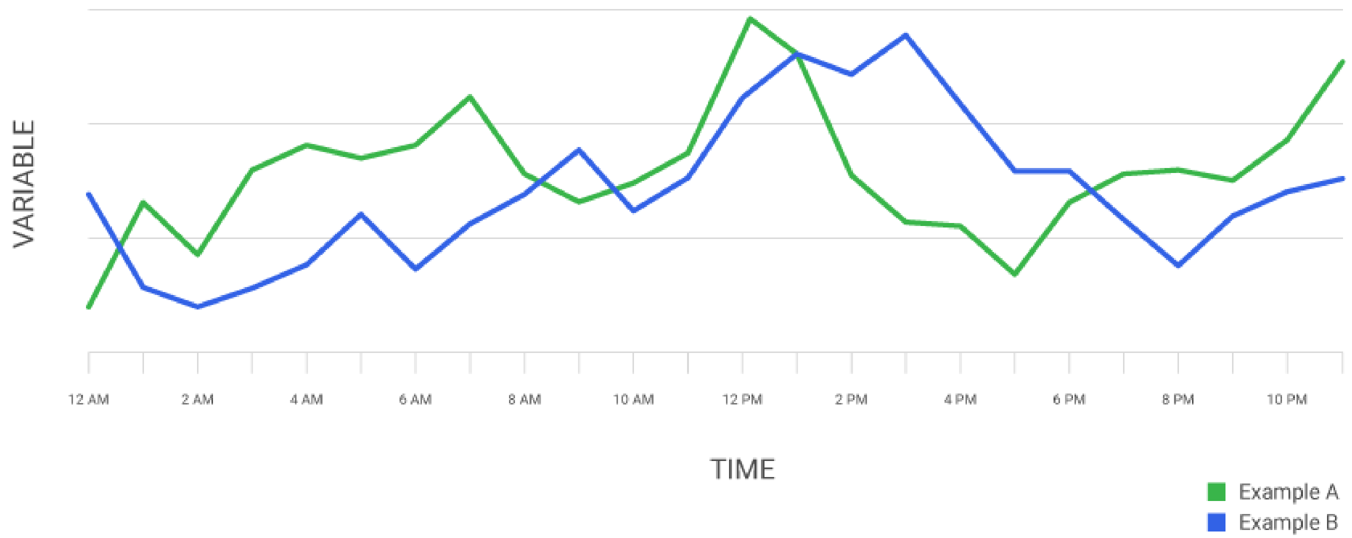
Fact checked by YARILET PEREZ

Many first-time forex traders hit the market running. They watch various economic calendars and trade voraciously on every release of data, viewing the 24-hours-a-day, five-days-a-week foreign exchange market as a convenient way to trade all day long. Not only can this strategy deplete a trader's reserves quickly, but it can burn out even the most persistent trader. Unlike Wall Street, which runs on regular business hours, the forex market runs on the normal business hours of four different parts of the world and their respective time zones, which means trading lasts all day and night.

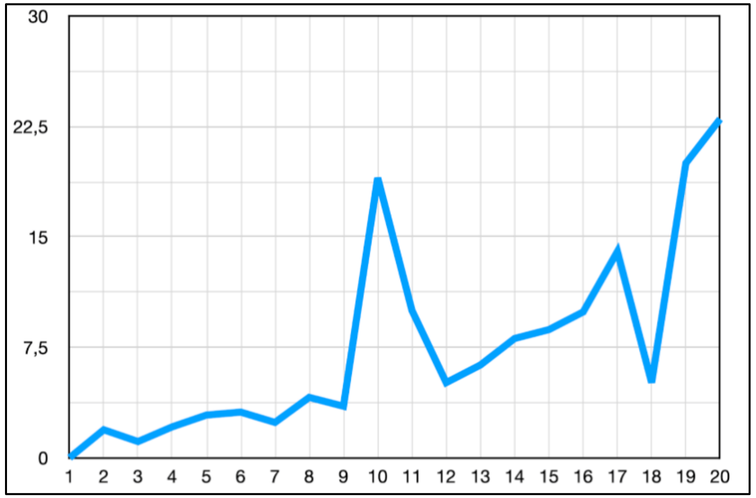
Investopedia link : https://www.investopedia.com/articles/forex/08/forex-trading-schedule-trading-times

# What is ‘Volatility Simulator’

- Basically ‘Volatility Simulator’ is a forecasting model using Time Series Analysis (TSA)
- The **aim** of this project is to develop a TSA model that could be use to check the volatility trend of any instrument in any timeframe (could be in every minutes, hourly or etc)



# The Data Sets



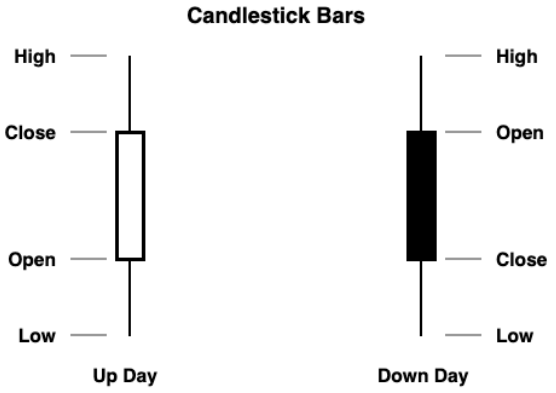

***The Data :*** Daily Recording from 2000-2023

**High Volume = High Volatility**

Data source : Kaggle

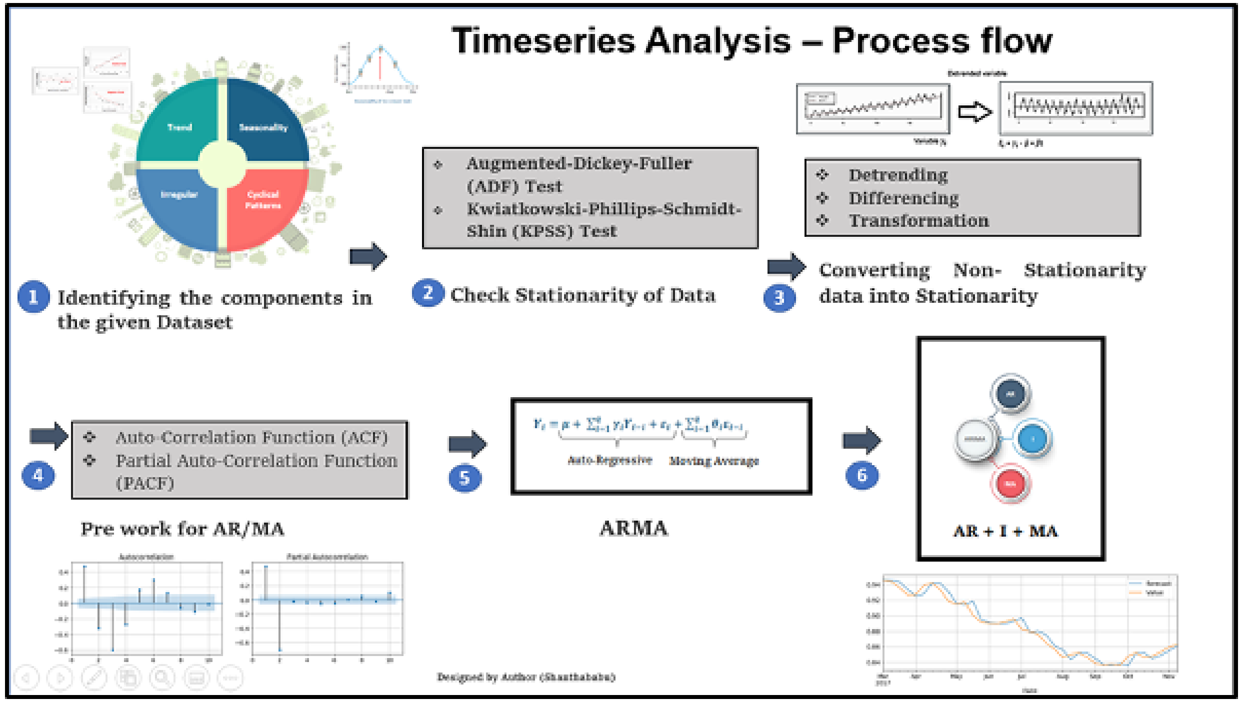
| Date | Open | High | Low | Close | Volume |
|---|---|---|---|---|---|
| **2000-01-03** | 1.6146 | 1.6400 | 1.6138 | 1.6361 | 4444 |
| **2000-01-04** | 1.6359 | 1.6415 | 1.6310 | 1.6373 | 6141 |
| **2000-01-05** | 1.6376 | 1.6450 | 1.6354 | 1.6419 | 6504 |
| **2000-01-06** | 1.6421 | 1.6511 | 1.6411 | 1.6470 | 6473 |
| **2000-01-07** | 1.6476 | 1.6499 | 1.6360 | 1.6394 | 4754 |

As mentioned earlier the volume is the readings of participant. What is OHLC:




OHLC refers to Open, High, Low Close level. However in this analysis we will not focus on that components

# Volatility Simulator = Time Series Analysis




## How we can use TSA to create the product:

1. Read data set and start the processing
2. Need to undergo ADF Test (Augmented Dickey Fuller test) to obtain the P-Value
3. Converting the nonstationary into stationary with eliminate the trend and seasonality by differencing method
4. Using ARIMA (Autoregression, Integration & Moving Average)
5. Check accuracy of forecast using accuracy metrics

# Part 1 : Exploratory Data (EDA)

**1) Data Processing**

- Importing data
- Identify components within dataset
- Set up the index

In [7]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
import matplotlib.pyplot as plt
```

In [8]:
```
# Load data
df = pd.read_csv('gbpusd.csv')
df.head()
```

Out[8]:

| | Date | Open | High | Low | Close | Volume |
|---|---|---|---|---|---|---|
| 0 | 2000.01.03 | 1.6146 | 1.6400 | 1.6138 | 1.6361 | 4444 |
| 1 | 2000.01.04 | 1.6359 | 1.6415 | 1.6310 | 1.6373 | 6141 |
| 2 | 2000.01.05 | 1.6376 | 1.6450 | 1.6354 | 1.6419 | 6504 |
| 3 | 2000.01.06 | 1.6421 | 1.6511 | 1.6411 | 1.6470 | 6473 |
| 4 | 2000.01.07 | 1.6476 | 1.6499 | 1.6360 | 1.6394 | 4754 |

In [10]:
```
# Change date column to be datetime dtype
df['Date'] = pd.to_datetime(df['Date'])
```

In [11]:
```
# Set Date to be in the index
df.set_index('Date', inplace=True)
```

In [12]:
```
df.head()
```

Out[12]:

| Date | Open | High | Low | Close | Volume |
|---|---|---|---|---|---|
| 2000-01-03 | 1.6146 | 1.6400 | 1.6138 | 1.6361 | 4444 |
| 2000-01-04 | 1.6359 | 1.6415 | 1.6310 | 1.6373 | 6141 |
| 2000-01-05 | 1.6376 | 1.6450 | 1.6354 | 1.6419 | 6504 |
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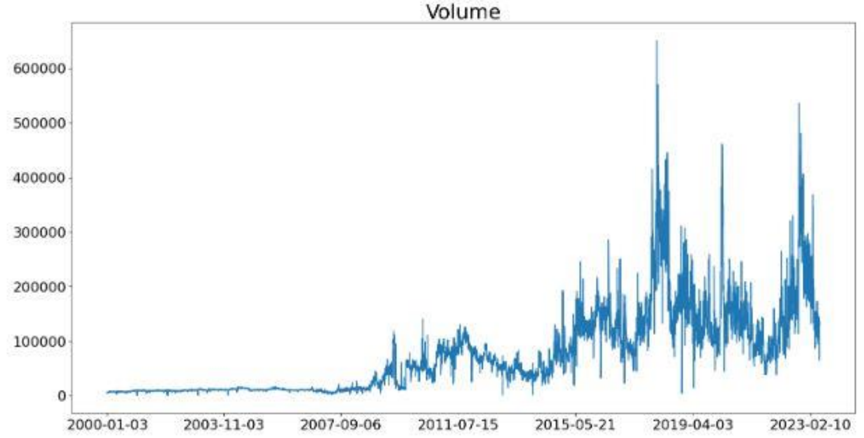
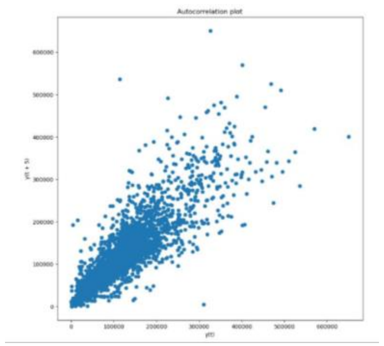
# Part 1 : Exploratory Data (EDA)

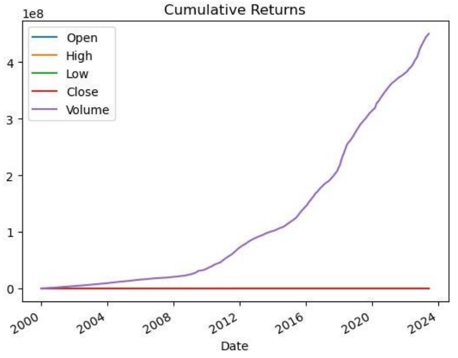
**3) Check Stationary of Data**

- Plotting the visualization of chosen variable which is 'Volume'
- Check in the visual data (mean/variance/covariance) over time
- Plot autocorrelation of the variable
- Checking on seasonality and trend

In [15]:
```
# Generate a time plot of our data.
plot_series(df, ['Volume'], title = "Volume", steps=1000)
```





# Part 1 : Exploratory Data (EDA)

## 2) Differencing

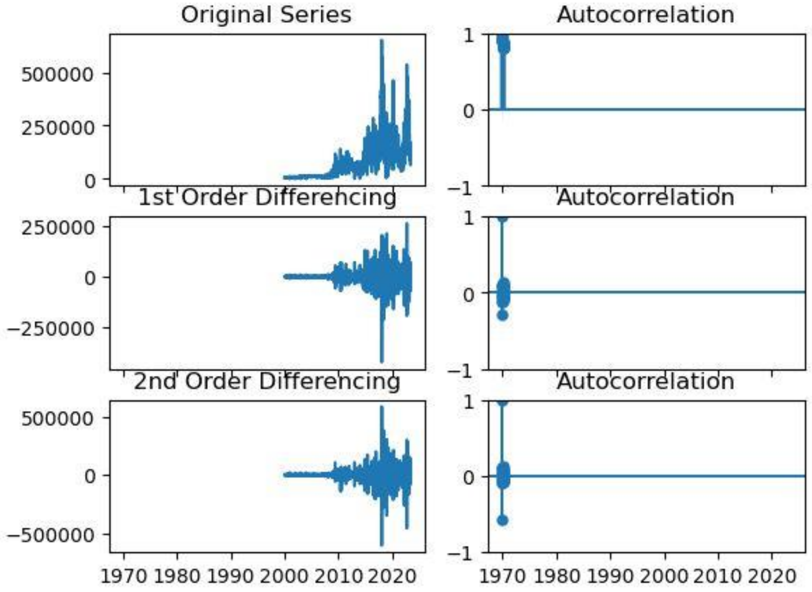
- Remove trends: Differencing helps in removing trends by subtracting the previous observation from the current one.
- Remove seasonality: If a time series exhibits seasonal patterns, differencing can help in removing these patterns by subtracting the corresponding lagged seasonal values.
- Stabilize variance: Differencing can also stabilize the variance of a time series by removing systematic changes in the scale of the data over time.

In [63]:
```
# Original Series
fig, axes = plt.subplots(3, 2, sharex=True)
axes[0, 0].plot(df['Volume']); axes[0, 0].set_title('Original Series')
plot_acf(df['Volume'], ax=axes[0, 1])

# 1st Differencing
axes[1, 0].plot(df['Volume'].diff()); axes[1, 0].set_title('1st Order Differencing')
plot_acf(df['Volume'].diff().dropna(), ax=axes[1, 1])

# 2nd Differencing
axes[2, 0].plot(df['Volume'].diff().diff()); axes[2, 0].set_title('2nd Order Differencing')
plot_acf(df['Volume'].diff().diff().dropna(), ax=axes[2, 1])

plt.show()
```



# Part 1 : Exploratory Data (EDA)

```
In [10]: # Import Augmented Dickey-Fuller test.
         from statsmodels.tsa.stattools import adfuller

         # Run ADF test on original (non-differenced!) data.

         # Import Augmented Dickey-Fuller test.
         from statsmodels.tsa.stattools import adfuller

         # Run ADF test on original (non-differenced!) data.

         adfuller(df['Volume'])

Out[10]: (-2.943655895014861,
          0.0405018542219686,
          34,
          6044,
          {'1%': -3.4314324089136767,
           '5%': -2.862018325881128З,
           '10%': -2.567024610317412},
          137339.01168246148)

In [11]: # Code written by Joseph Nelson.

         def interpret_dftest(dftest):
             dfoutput = pd.Series(dftest[0:2], index=['Test Statistic','p-value'])
             return dfoutput

In [12]: # Run ADF test on original (non-differenced!) data.
         # Run ADF test on original (non-differenced!) data.

         interpret_dftest(adfuller(df['Volume']))

Out[12]: Test Statistic    -2.943656
         p-value            0.040502
         dtype: float64
```

**2) ADF Test**

Test the models with ADF/KPSS test

- Null Hypothesis : The series has a unit root (non stationary)
- Test statistic : -2.943656
- P-Value : 0.040502
- Number of lags : 34
- Observations : 6044

Conclusion : P-Value is smaller than 0.05, we reject the null hypothesis and the series is stationary. Hence the steps as below is not compulsory and the modelling can be start.

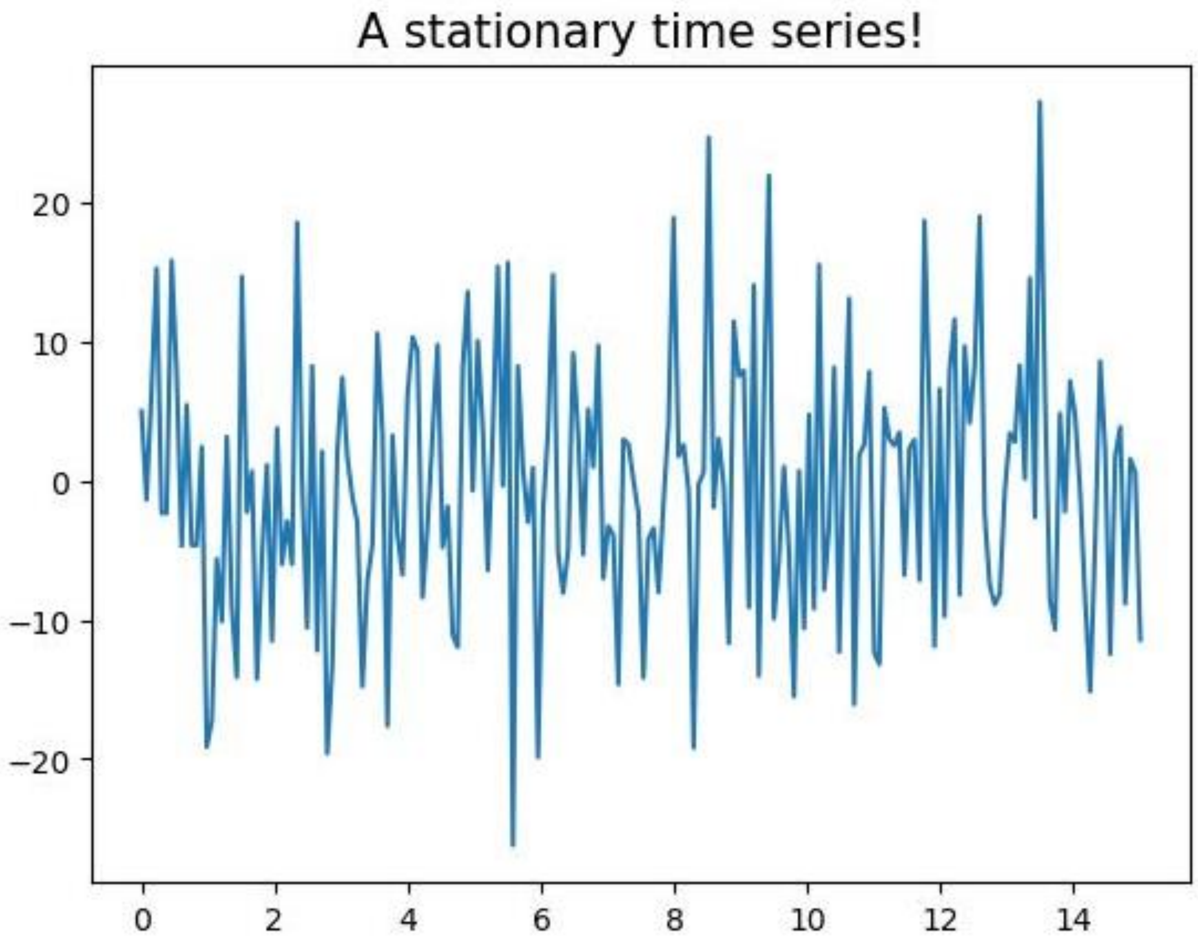
# Part 2 : Data Modelling

**Modelling  has been carried as steps below:**

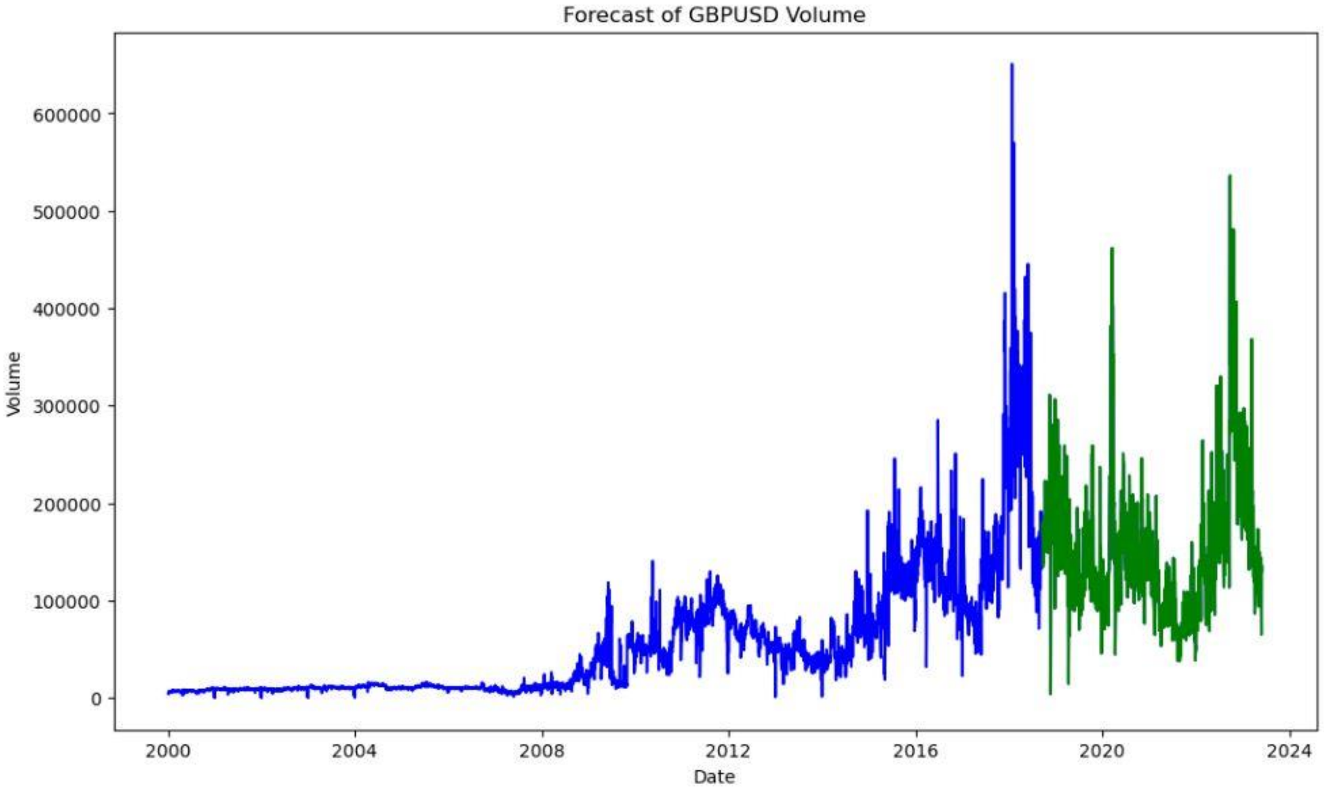
- Plot raw data
- Fitting Model
- Identify parameters
- Manual GridSearch
- Get the p,d,q value of AR1MA

```
C:\Users\fahmi\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: A date index has been provide
d, but it has no associated frequency information and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\fahmi\anaconda3\Lib\site-packages\statsmodels\tsa\statespace\sarimax.py:966: UserWarning: Non-stationary starting au
toregressive parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
C:\Users\fahmi\anaconda3\Lib\site-packages\statsmodels\tsa\statespace\sarimax.py:978: UserWarning: Non-invertible starting MA
parameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
The AIC for ARIMA(4,1,4) is: 123274.08814598958


MODEL FINISHED!
Our model that minimizes AIC on the training data is the ARIMA(4,1,4).
This model has an AIC of 123274.08814598958.
C:\Users\fahmi\anaconda3\Lib\site-packages\statsmodels\base\model.py:607: ConvergenceWarning: Maximum Likelihood optimization
failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```



# Part 2 : ARIMA




**Plotting ARIMA (where green is the prediction on volume) :**

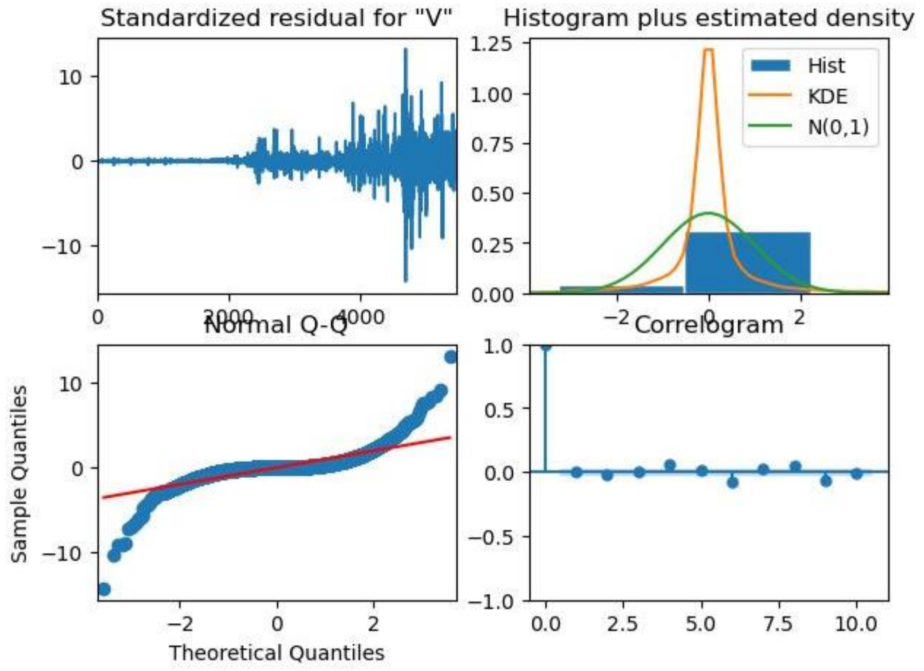
Based on manual GridSearch, we could find the the parameters and value of p-d—q.

- The series model that minimizes AIC on the training data is the ARIMA(4,1,4)
- p = 4 # Autoregressive order
- d = 1 # Differencing order
- q = 4 # Moving average order

The AIC for ARIMA 4,1,4 is; 123274.08814598958

# Part 3 : Model Evaluation (Residuals)

**Evaluation based on residuals:**




- Top left: The residual errors seem to fluctuate around a mean of zero and have a uniform variance.
- 
- Top Right: The density plot suggest normal distribution with mean zero.
- 
- Bottom left: All the dots should fall perfectly in line with the red line. Any significant deviations would imply the distribution is skewed.
- 
- Bottom Right: The Correlogram, aka, ACF plot shows the residual errors are not autocorrelated. Any autocorrelation would imply that there is some pattern in the residual errors which are not explained in the model. So you will need to look for more X's (predictors) to the model

# Part 3 : Model Evaluation (Metrics)

I have carried on few evaluation metrics to measure accuracy of this model as below:

- **Root Mean Squared Error (RMSE)**: This is the square root of the MSE and provides an interpretable measure of error in the same units as the original data.
- RMSE = sqrt(MSE)
- **RMSE: 20.73247619699088**

- **Mean Absolute Percentage Error (MAPE)**: This measures the average absolute percentage difference between the actual and predicted values, making it easy to understand the magnitude of error relative to the actual values.
- MAPE = Σ(|Actual - Predicted| / Actual) * 100 / n
- **# MAPE: 228.33332232842398**

- **Mean Absolute Error (MAE)**: This is the average of the absolute errors between the predicted values and the actual values. It provides a simple and interpretable measure of accuracy.
- MAE = Σ|Actual - Predicted| / n
- **# MAE: 49.99999601481055**

- **Mean Absolute Scaled Error (MASE)** : is a metric used to measure the accuracy of forecasts, particularly in time series forecasting, by comparing the forecast errors to a naive forecast. MASE is robust to different scales and is useful for comparing the accuracy of different forecasting methods on different datasets.
- **# MASE: 1.5584414342278614**

# Findings

- After evaluating model I can conclude that this model is not very good based on my the accuracy metrics. My scale of data is quite a big range and the RMSE is not very near to 0. I decided to also use MAPE which involves several considerations, similar to evaluating other error metrics and resulting in high percentage (considered as negative reading.
- Hence, **my problem statement cannot be answered using this model at this stage**. However, the positive positive finding of this Time Series Analysis is actually very significant which is;
- **To develop a baseline model to be the anchor for my next time series forecasting model that can be use in forecasting any financial instrument over time. With this model I can assess different future developed model to enhance accuracy.**

# Model Improvement

These are few ways to improve my next model with better accuracy:

- Data processing
- Assessing Autocorrelation
- Model Selection (SARIMA, LSTM etc)
- Parameter Tuning
- Cross Validation

By implementing these strategies and iteratively refining your models, you can improve the accuracy of your time series forecasts and make more informed decisions based on the predictions. Remember that achieving high accuracy may require a combination of data preprocessing, model selection, and careful parameter tuning.

# Significant of this TSA

- I think there's no need for introduction on the audience of financial markets.
- I to I find it very interesting to go deep into Time Series Analysis as it is a method to forecast any variables over a period of time. When I persuade this project  I can see this project might be very helpful for any investors and traders either retail or working for any professional organization.
- **However this model is still at its earliest stage to be an useful tools for those people or organization. This model can only be more useful with similar and improvise successful metric.**

# Thank you

# Appendix

https://github.com/offgridanalytics