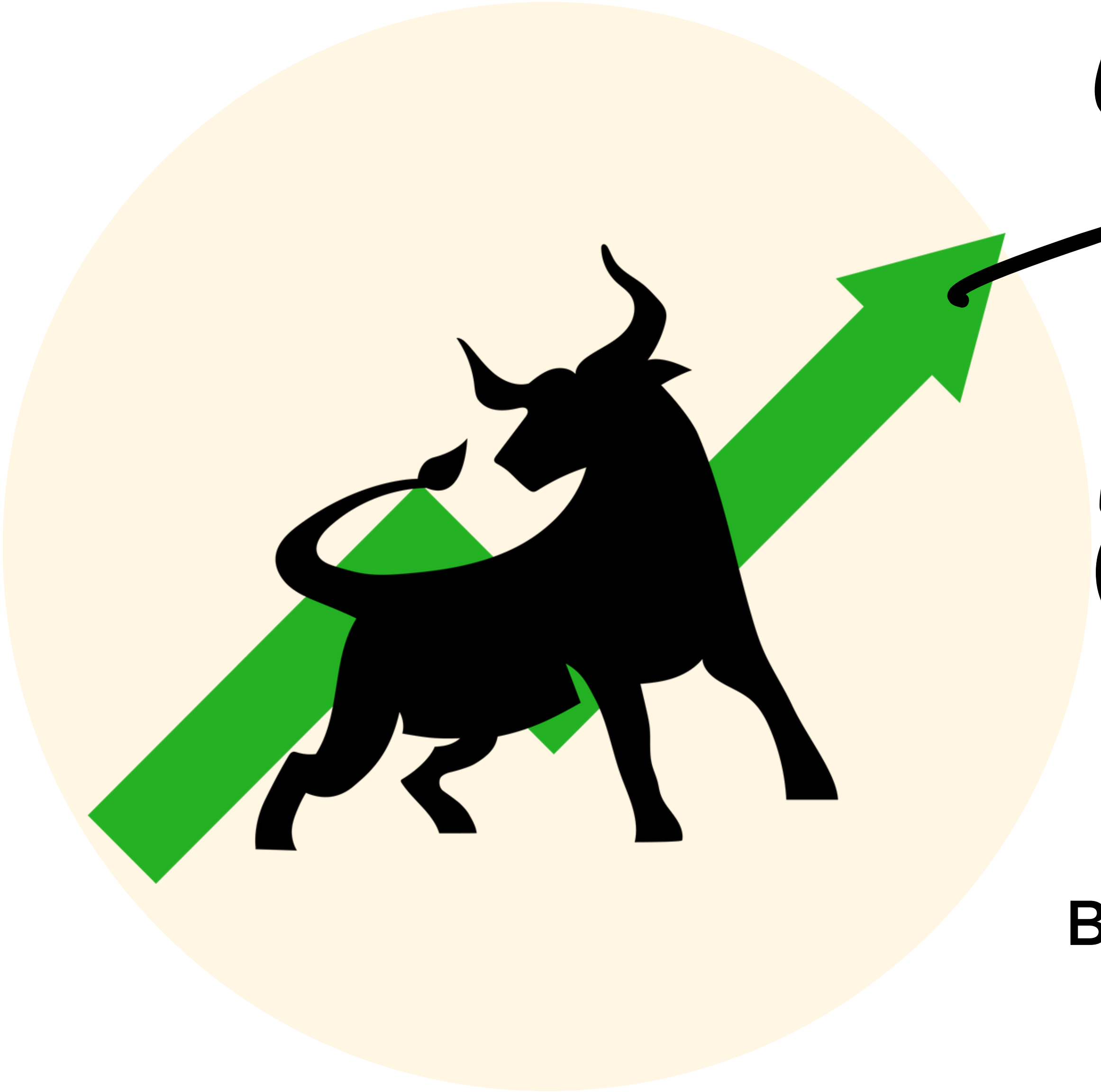


Hackrush'24

QUANTITATIVE FINANCE

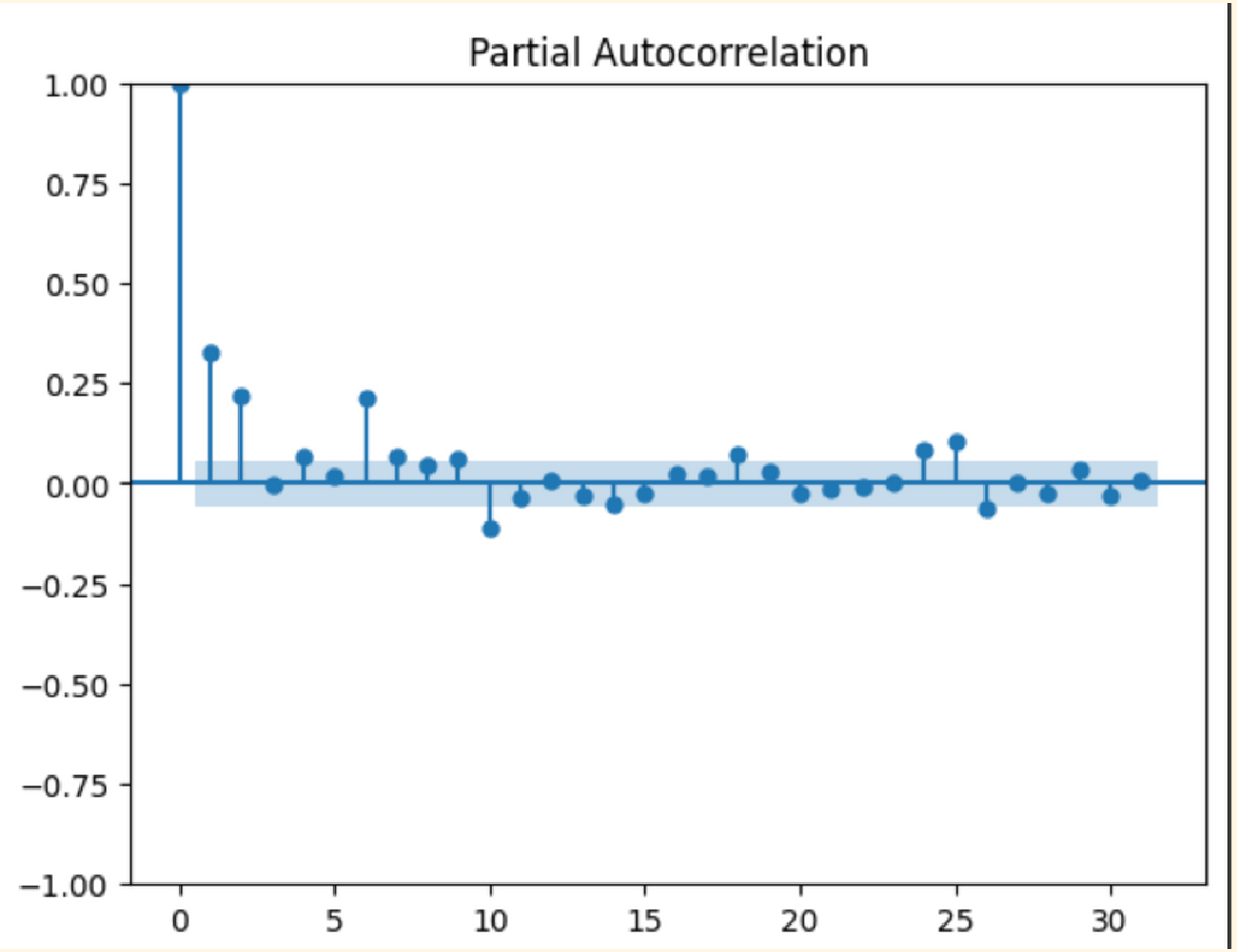
By Disha Chopra

MODEL FOR VOLATILITY FORECASTING

GARCH: Generalized Autoregressive Conditional Heteroskedasticity.

An upgradation of ARCH.

GARCH models are well-suited for capturing the phenomenon of volatility clustering, where periods of high volatility tend to cluster together, followed by periods of low volatility. By modeling the conditional variance as a function of past squared residuals, GARCH models can effectively capture this clustering behavior.



Volatility Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
omega	1.0837	0.142	7.649	2.021e-14	[0.806, 1.361]
alpha[1]	0.2306	9.020e-02	2.557	1.056e-02	[5.385e-02, 0.407]
alpha[2]	0.2209	6.587e-02	3.354	7.976e-04	[9.180e-02, 0.350]
alpha[3]	0.2166	9.146e-02	2.368	1.787e-02	[3.736e-02, 0.396]

AR(1)

at= phi * a(t-1) + epsilon t

ARMA(1,1)

at= beta * a(t-1) + phi* epsilon (t-1)+ epsilon t

ARCH(1) (Bursty curves)

at=epsilon t* squareRoot(alpha+ alpha1* a(t-1)^2)

=epsilon t * sigma t

GARCH(1,1)

at=epsilon t* squareRoot(alpha+ alpha1* a(t-1)^2+

beta* sigma(t-1)^2)

=epsilon t * sigma t

next volatility is also affected by the previous

volatility i.e sigma(t-1)

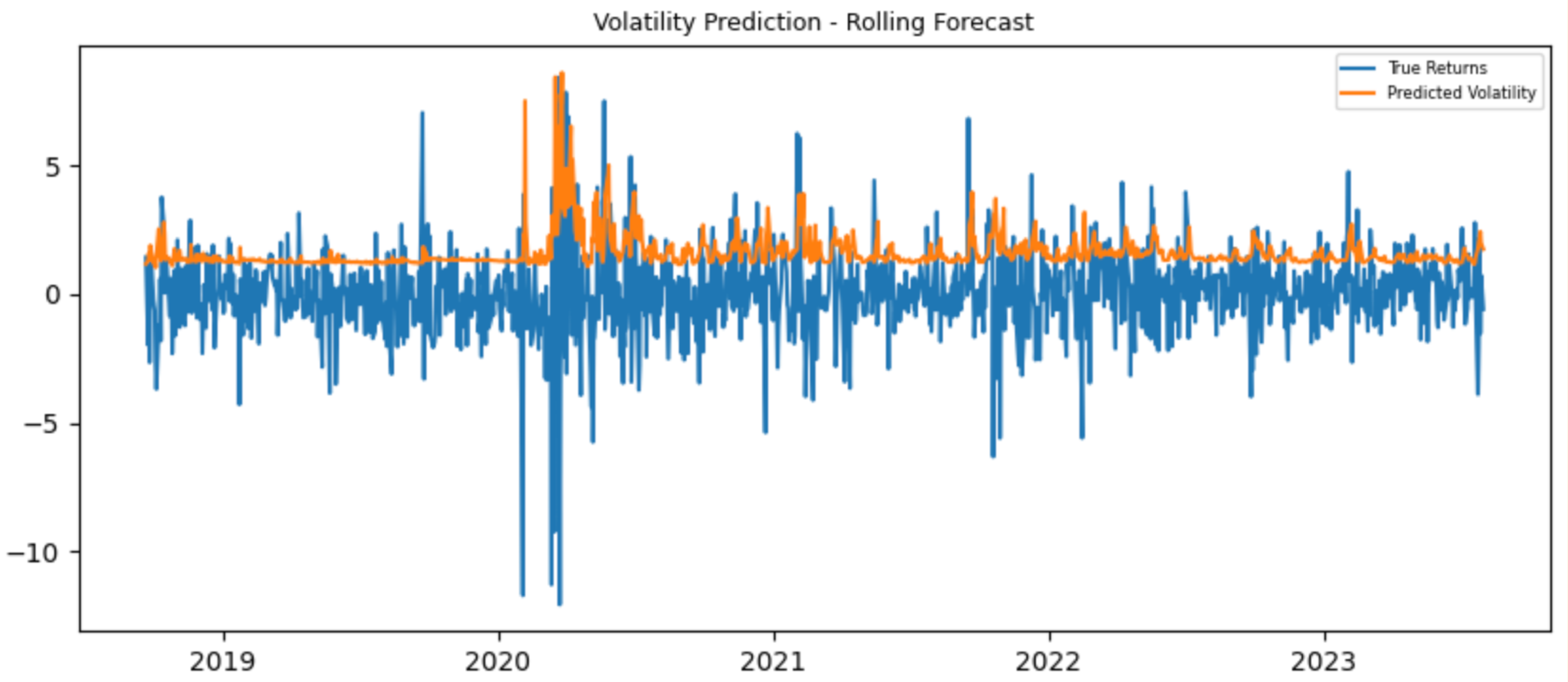
GARCH model is applied for each of 20 stocks. Best p and q values are found by partial autocorelation graphs.

Plot for ITC stock

```
def plot_volatility_pred(returns, p, q):
    rolling_predictions = []
    test_size = 1200

    for i in range(test_size):
        train = returns[:-(test_size-i)]
        model = arch_model(train, p=p, q=q)
        model_fit = model.fit(disp='off')
        pred = model_fit.forecast(horizon=1)
        rolling_predictions.append(np.sqrt(pred.variance.values[-1,:][0]))
    rolling_predictions = pd.Series(rolling_predictions, index=returns.index[-1200:])

    plt.figure(figsize=(10,4))
    true, = plt.plot(returns[-1200:])
    preds, = plt.plot(rolling_predictions)
    plt.title('Volatility Prediction - Rolling Forecast', fontsize=9)
    plt.legend(['True Returns', 'Predicted Volatility'], fontsize=6)

    return rolling_predictions
```

Plot for ITC stock

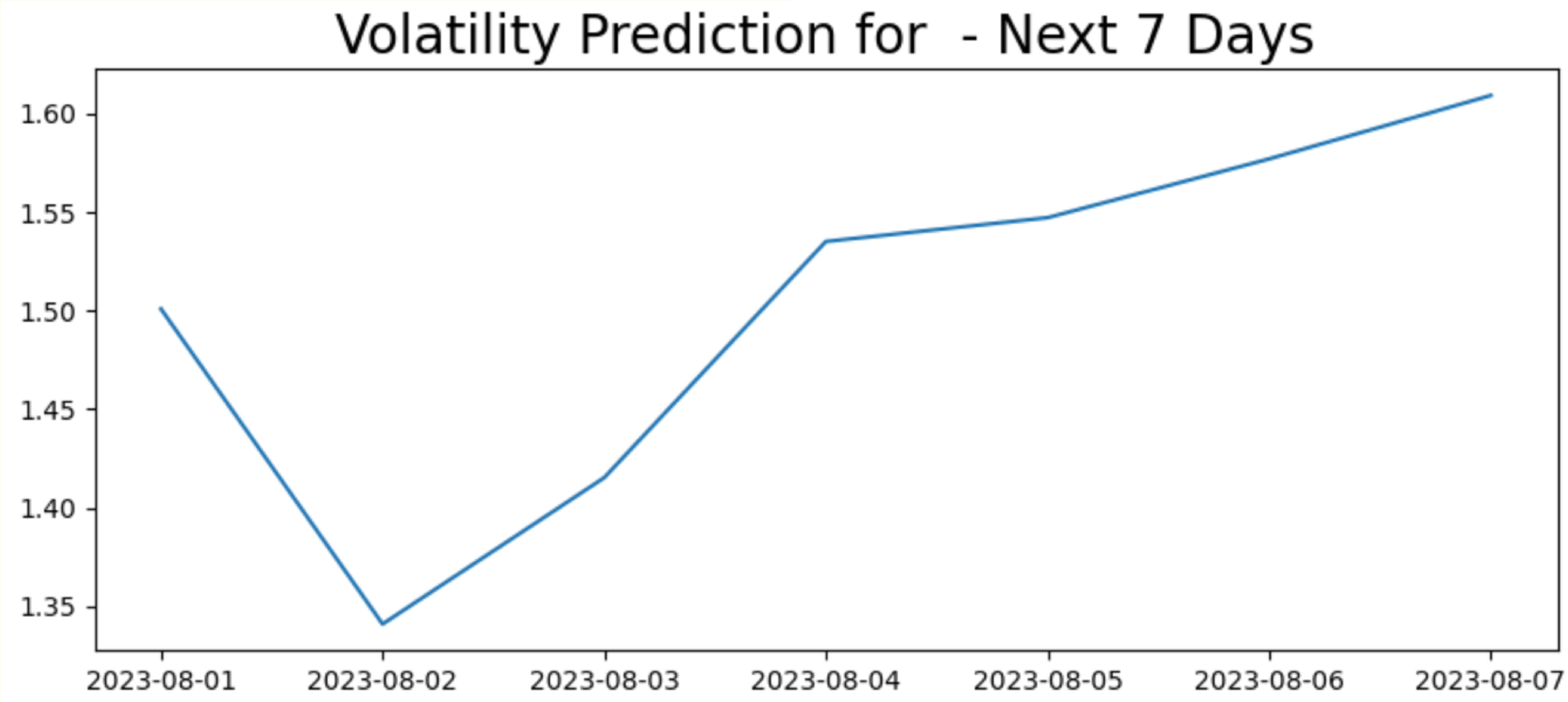
.




```
high_vol_threshold = np.percentile(rolling_predictions, 90)
low_vol_threshold = np.percentile(rolling_predictions, 10)
```

Now we can use the above model to predict future volatility.

Volatility for ITC stock for next 7 days after 1st August 2023



Using the volatillity data, divided the set of 20 stocks into 3 categories:

- Low Volatility
- Middle volatility
- High Volatity

Low	**Middle**	**High**
REL	TCS	ONGC
ADANI	HDFC	HINDULIVER
KOTAK	INFY	MARUTI
NTPC	AXIS	TATASTEEL
ICICI	SBIN	ITC
INDUS	SUNPHARMA	LT
	BHARTI	
	IOC	

We weight the stocks according to their position in this table

Lower volatile stocks would be given higher weights compared to middle, which further will be given higher weights compared to High.

Weights for each are in ratio: 10:5:2

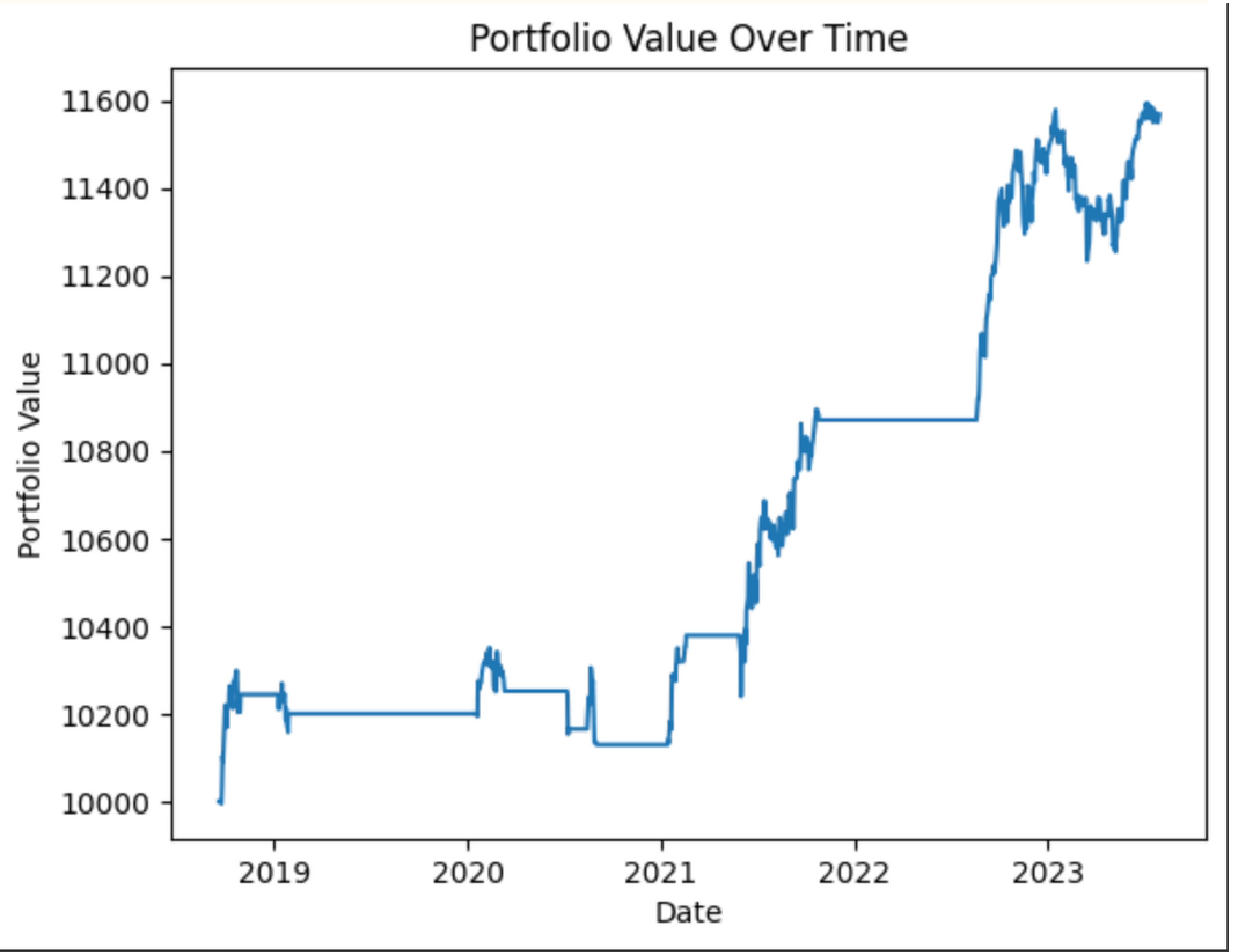
TRADING STRATEGY

Hypothesis:

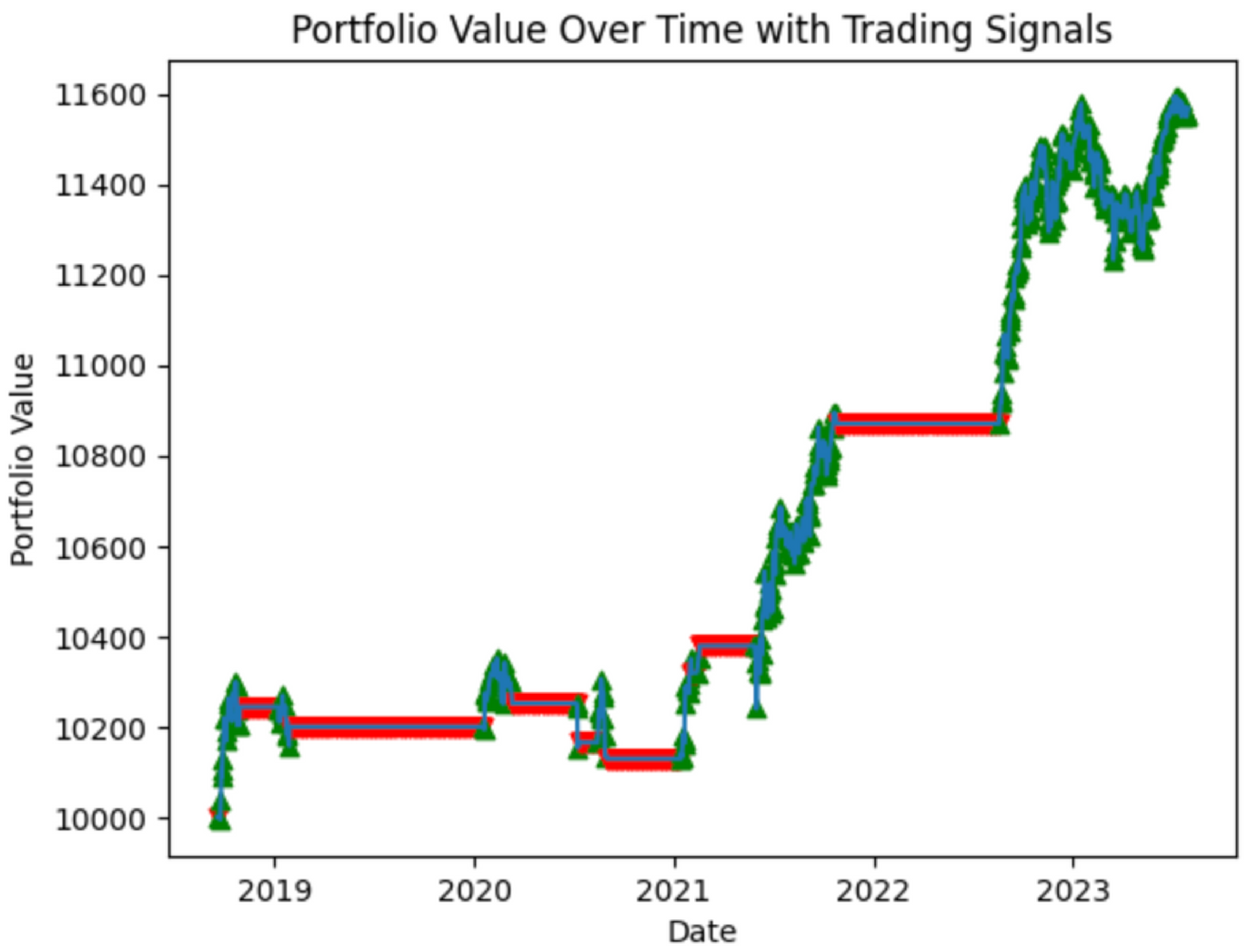
When the predicted volatility of the market is low, it may be a good time to buy (go long) financial assets, and when the predicted volatility is high, it may be a good time to sell (exit long positions) or stay out of the market.

For every stock taking in account weights, this strategy is being applied and returns are calculated.

FOR ICICI STOCK
(ON INITIAL CAPITAL OF $10000)




```
Final Portfolio Value: $ 11568.460780348969
```




```
Sharpe Ratio: -0.4123255452395395
Turnover: 339.44873269346135 %
```

*didn’t calculate sharpe ratio and turnover for all stocks.

NET PROFIT

Capital invested for all 3 categories of stocks is summed up, return gained are summed up.
Net profit percentage is calculated by= (Return Amount - Invested Amount) / Invested Amount) * 100

which comes out to be:

8.697%

	Stock Name	Invested Amount	Return Amount	Return Percentage
0	dis	2000	1973.68	-1.3160
1	tcs	5000	5019.51	0.3902
2	rela	10000	11898.73	18.9873
3	hdfc	5000	5230.98	4.6196
4	infy	5000	5192.81	3.8562
5	adani	10000	11928.04	19.2804
6	icici	10000	11568.46	15.6846
7	kotak	10000	11079.59	10.7959
8	lt	2000	1925.32	-3.7340
9	axis	5000	5315.37	6.3074
10	sbin	5000	5039.29	0.7858
11	ioc	5000	5325.98	6.5196
12	bharti	5000	5063.26	1.2652
13	ongc	2000	1946.03	-2.6985
14	hindul	2000	1862.56	-6.8720
15	ntpc	10000	10281.99	2.8199
16	maruti	2000	2055.56	2.7780
17	sunpharma	5000	5098.94	1.9788
18	tatasteel	2000	1916.79	-4.1605
19	indus	10000	12018.50	20.1850

total profit is 8.697669642857129

THANK YOU.