RETURN ANALYSIS OF FMCG STOCKS

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INTRODUCTION TO MARKOV CHAIN

- A Markov chain is a stochastic process containing random variables transitioning from one state to another depending only on certain assumptions and definite probabilistic rules

- The Markov property is a simple statement where we say: given the present, the future is independent of the past

- It is a property belonging to a memoryless process as it is solely dependent on the current state and the randomness of transitioning to the next states

MARKOV CHAIN MODEL

The discrete-time process X_k, k = 0, 1, 2, . . . is a Markov chain if $\forall$i, j, k, . . . , m, we have

$$P[X_k = j | X_{k-1} = i, X_{k-2} = n, \ldots, X_0 = m] = P[X_k = j | P[X_{k-1} = i] = p_{ij(k)}$$

where $p_{ij(k)}$ is called the state-transition probability, which is the conditional probability that the process will be in state j at time k immediately after the next transition, given that it is in state i at time k-1. A Markov chain that follows the preceding rule is called a non homogenous Markov chain. This work uses the homogenous Markov chain, that is a Markov chain, that is independent of time. And we have

$$P[X_k = j | X_{k-1} = i, X_{k-2} = n, \ldots, X_0 = m] = P[X_k = j | P[X_{k-1} = i] = p_{ij}$$

THERE ARE THREE MEASURES WE NEED TO BE AWARE OF SO WE MAY CONSTRUCT A MARKOV CHAIN:

- **States:** All the states (occurrences) within the state-space ‘s’ of the dynamical system.
- **The initial state distribution:** The initial probability distribution of the starting state at time t = 0.
- **State transition probabilities:** transition probability of moving from one state to another. It is encoded into an s-by-s matrix denoted as ‘P’.

TRANSITION PROBABILITY MATRIX

- The matrix describing the Markov chain is called the transition matrix. It is the most important tool for analysing Markov chains.
- The transition matrix is usually given the symbol P = p_{ij}

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1r} \\ p_{21} & p_{22} & \cdots & p_{2r} \\ \vdots & \vdots & \vdots & \vdots \\ p_{r1} & p_{r2} & \cdots & p_{rr} \end{bmatrix}.$$

Note that $p_{ij} \geq 0$, and for all i, we have

$$\begin{aligned} \sum_{k=1}^{r} p_{ik} &= \sum_{k=1}^{r} P(X_{m+1} = k | X_m = i) \\ &= 1. \end{aligned}$$

STEADY STATE PROBABILITY

The n-step state-transition probability $p_{ij}^{(n)}$ is the conditional probability that the system will be in state j after exactly n transitions, given that it is presently in state i.

The n-step transition probability can be obtained by multiplying the transition probability matrix by itself n times.

For the class of Markov chains in which the limit exists, we define the limiting-state

probabilities as:

$$lim_{n\to\infty} P[X(n) = j] = \pi_j; n = 1, 2, \ldots, N$$

ASSUMPTIONS OF MARKOV CHAIN

The probabilities of moving from a state to all row sum to one.

The probabilities apply to all system participants.

The probabilities are constant over time.

APPLICATIONS OF MARKOV CHAIN

- Frequently used to describe consumer behavior
- Sales Forecasting
- Useful in the prediction of brand switching and their effects on individual's market share
- Brand loyalty and consumer behavior can be analyzed

STOCK MARKET

It is a place where shares of public listed companies are traded. The primary market is where companies float shares to the general public in an initial public offering (IPO) to raise capital.

MARKOV CHAIN AND STOCK MARKET

- Markov Chain is used to show when a stock has moved into an overbought or oversold position.
- Stock prices are stochastic processes in discrete time which take only discrete values due to the limited measurement scale. Nevertheless, stochastic processes in continuous time are used as models since they are analytically easier to handle than discrete models, e.g. the binomial or trinomial process.

RETURN ANALYSIS OF FMCG STOCKS

MOTIVATION TO PICK THIS TOPIC

- Stock prices change and fluctuate every second. Therefore the concept of markov chain could be applied to study the trend and future probabilities.
- Stochastic modeling predicts outcomes that account for certain levels of unpredictability or randomness just like a stock price in a stock market

OVERVIEW OF THE PROJECT

- Return analysis of FMCG stocks

Companies under study: Britannia Industries Ltd
Jubilant Foodworks Ltd
Nestle India Ltd

Secondary data source: https://in.finance.yahoo.com/

Time frame considered: 5-Year monthly data of closing prices
(Jan'16 - Jan'21)
2-Year daily data of closing prices
(Mar'19 - Mar'21)

SPECIFIC OBJECTIVES

- Return analysis of FMCG stocks

1

Objective 1:

- Finding Transition Probability Matrix (TPM)

2

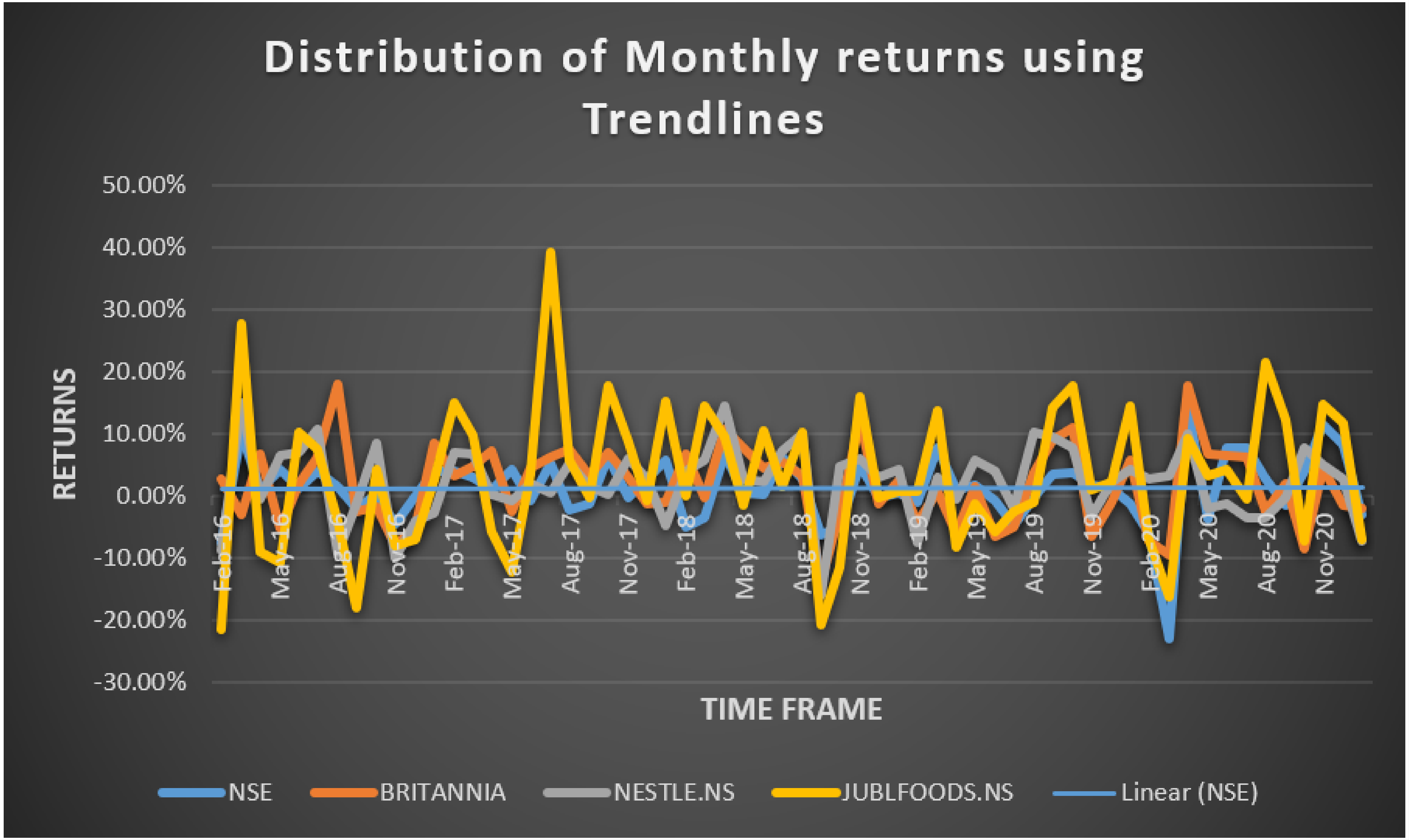
Objective 2:

- Short Run Expected Returns
- Long Run Expected Returns

3

Objective 3:

- Expected Returns using Capital Asset Pricing Model


Distribution of Monthly returns using Trendlines
50.00%
40.00%
30.00%
20.00%
10.00%
0.00%
-10.00%
-20.00%
-30.00%
RETURNS
Feb-16
May-16
Aug-16
Nov-16
Feb-17
May-17
Aug-17
Nov-17
Feb-18
May-18
Aug-18
Nov-18
Feb-19
May-19
Aug-19
Nov-19
Feb-20
May-20
Aug-20
Nov-20
TIME FRAME
NSE
BRITANNIA
NESTLE.NS
JUBLFOODS.NS
Linear (NSE)

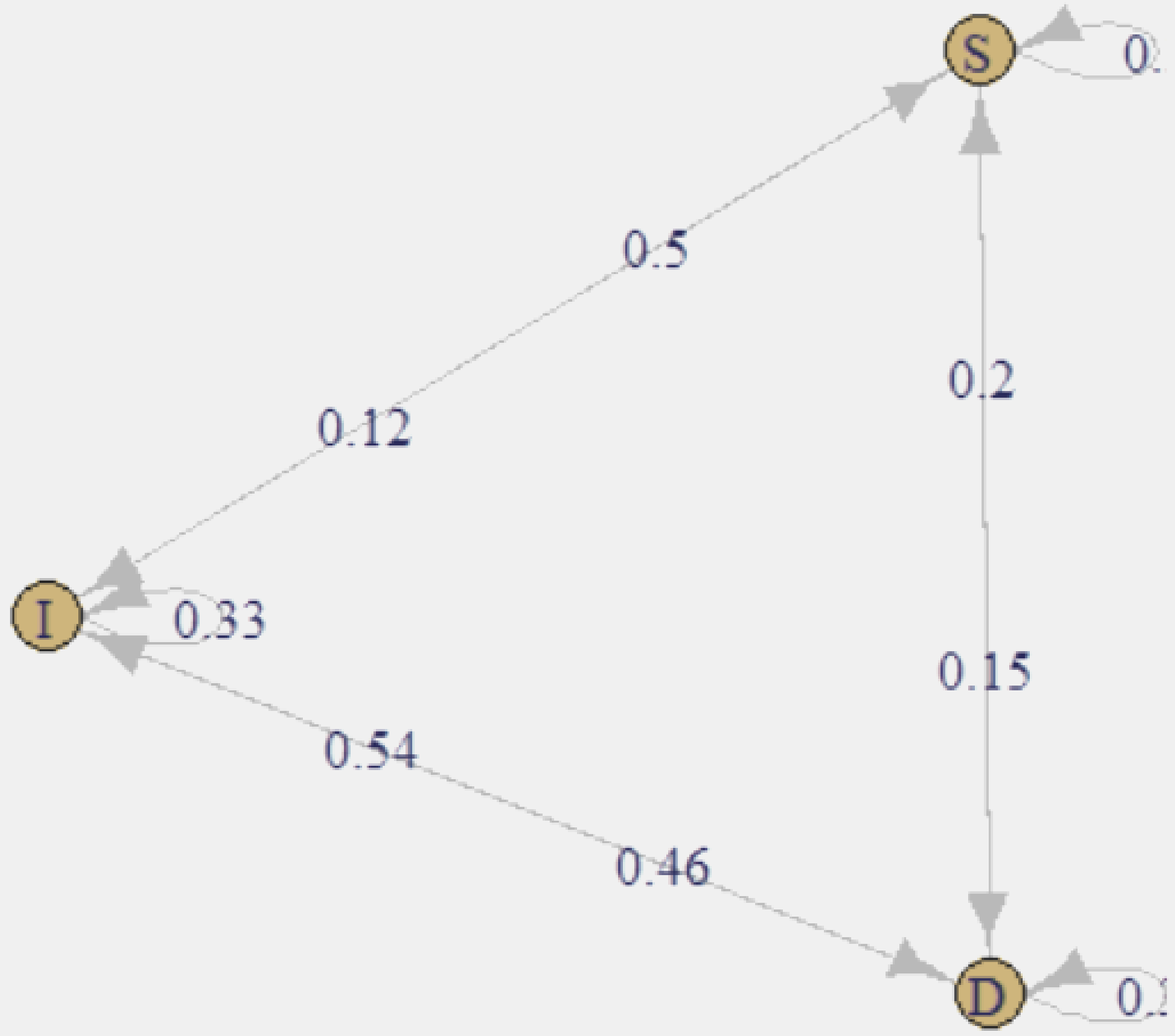
ANALYSIS

BRITANNIA

$$\begin{array}{cc} & \begin{array}{ccc} D & I & S \end{array} \\ \begin{array}{c} D \\ I \\ S \end{array} & \begin{bmatrix} 0.4 & 0.4 & 0.2 \\ 0.34 & 0.54 & 0.12 \\ 0.78 & 0.22 & 0 \end{bmatrix} \end{array}$$

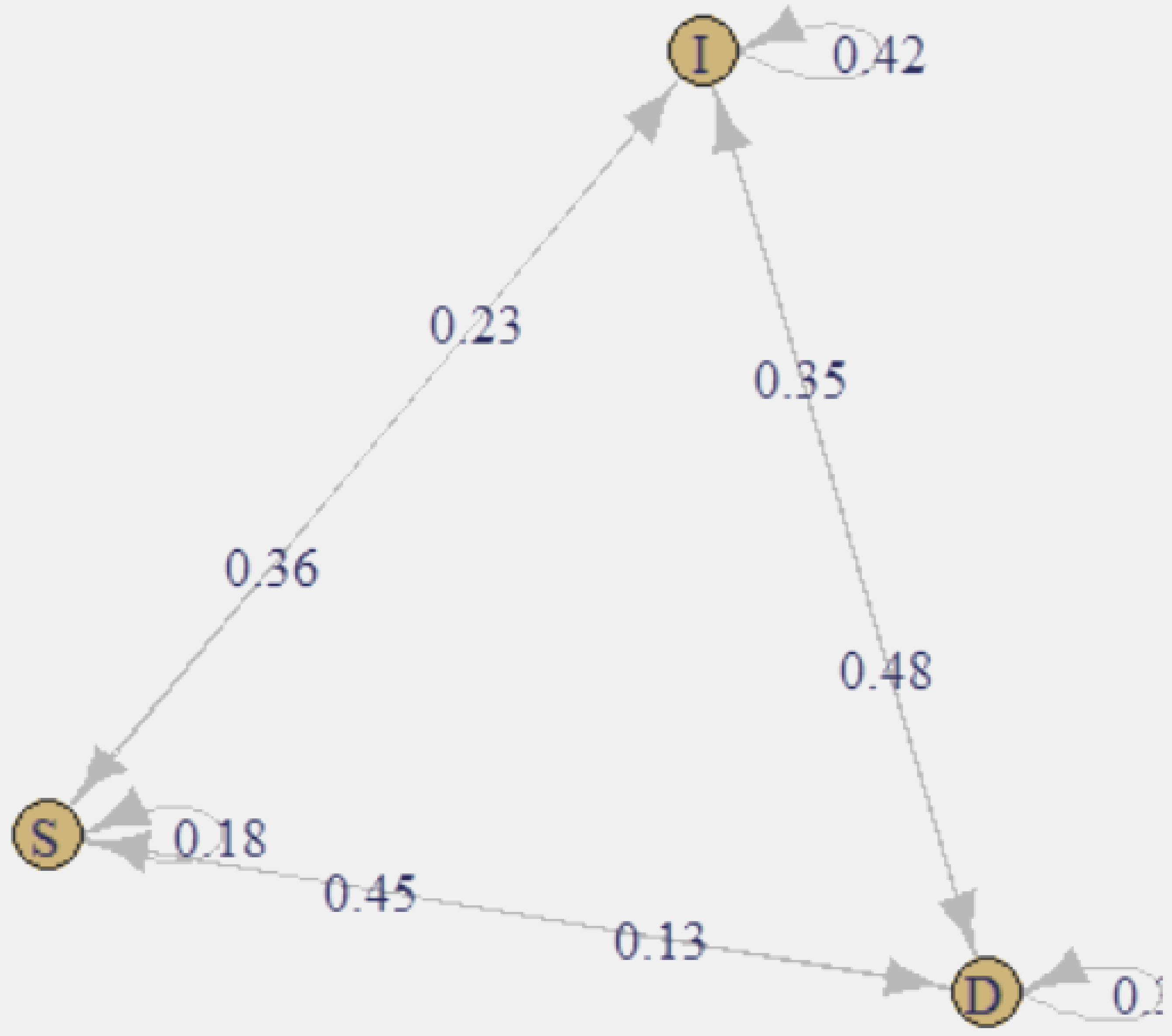
JUBILANT

$$\begin{array}{cc} & \begin{array}{ccc} D & I & S \end{array} \\ \begin{array}{c} D \\ I \\ S \end{array} & \begin{bmatrix} 0.39 & 0.46 & 0.15 \\ 0.54 & 0.34 & 0.12 \\ 0.2 & 0.5 & 0.3 \end{bmatrix} \end{array}$$



NESTLE

$$\begin{array}{c|ccc} & D & I & S \\ \hline D & 0.39 & 0.48 & 0.13 \\ I & 0.35 & 0.42 & 0.23 \\ S & 0.46 & 0.36 & 0.18 \end{array}$$



Expected short run return -

$$E_r = P^n * \mu_i$$

Expected long run return -

$$E_R = \pi_j * \mu_i$$

Where P^n = Limiting Probability

μ_i = Mean Return of each State

π_j = Steady State Probability

CAPITAL ASSET PRICING MODEL

It is used to calculate the predicted rate of return of any risky asset. It compares the relationship between systematic risk and expected return.

Expected return using CAPM -

$$E(r) = rf + \beta(R_m - rf)$$

Where rf = Risk Free Rate

R_m = Market Return

β = Riskiness of the stock

TPM for monthly data of Nestle, t = Feb, Mar, Apr…

t = 1

$$\begin{array}{c c} & \begin{array}{ccc} D & I & S \end{array} \\ \begin{array}{c} D \\ I \\ S \end{array} & \begin{bmatrix} 0.39130 & 0.47826 & 0.13043 \\ 0.34615 & 0.42308 & 0.23077 \\ 0.45455 & 0.36364 & 0.18182 \end{bmatrix} \end{array}$$

t = 2

$$\begin{array}{c c} & \begin{array}{ccc} D & I & S \end{array} \\ \begin{array}{c} D \\ I \\ S \end{array} & \begin{bmatrix} 0.37796 & 0.43692 & 0.18512 \\ 0.38680 & 0.42846 & 0.18474 \\ 0.38638 & 0.43735 & 0.17626 \end{bmatrix} \end{array}$$

t = 3

$$\begin{array}{c c} & \begin{array}{ccc} D & I & S \end{array} \\ \begin{array}{c} D \\ I \\ S \end{array} & \begin{bmatrix} 0.38328 & 0.43293 & 0.18378 \\ 0.38364 & 0.43344 & 0.18292 \\ 0.38270 & 0.43392 & 0.18337 \end{bmatrix} \end{array}$$

$$\begin{array}{c c} & \begin{array}{ccc} D & I & S \end{array} \\ \begin{array}{c} D \\ I \\ S \end{array} & \begin{bmatrix} 0.38338 & 0.43330 & 0.18332 \\ 0.38330 & 0.43338 & 0.18332 \\ 0.38331 & 0.43330 & 0.18339 \end{bmatrix} \end{array}$$

t = 4

$$\begin{array}{c c} & \begin{array}{ccc} D & I & S \end{array} \\ \begin{array}{c} D \\ I \\ S \end{array} & \begin{bmatrix} 0.38333 & 0.43333 & 0.18333 \\ 0.38333 & 0.43333 & 0.18333 \\ 0.38333 & 0.43333 & 0.18333 \end{bmatrix} \end{array}$$

t = 5

Short run return for monthly data of Nestle where t = Feb, Mar, Apr...

	State	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 8	t = 9	t = 10
Short Run Returns	D	0.02309	0.02320	0.02318	0.02318	0.02318	0.02318	0.02318	0.02318	0.02318	0.02318
	I	0.02336	0.02317	0.02318	0.02318	0.02318	0.02318	0.02318	0.02318	0.02318	0.02318
	S	0.02293	0.02316	0.02318	0.02318	0.02318	0.02318	0.02318	0.02318	0.02318	0.02318

Overall Average Return = 0.02088

For 5 Year Monthly Data of the three stocks
(Sample size - 60 rows)

Britannia	
Exp.Long Run Return =	0.01928085
Exp. Return (CAPM) =	0.00607103
Average Return =	0.01813172
Value =	Underpriced

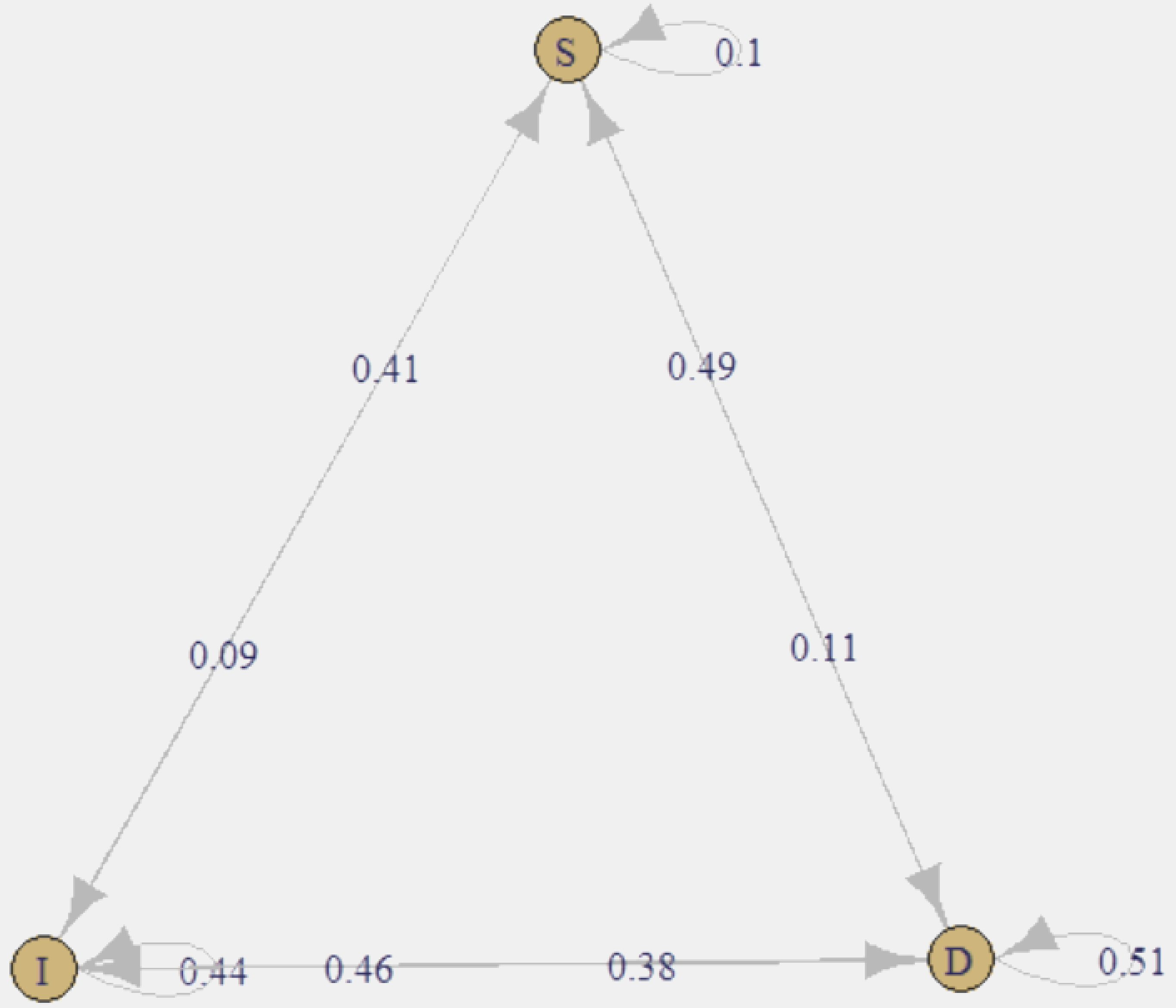
Jubilant	
Exp.Long Run Return =	0.033423478
Exp. Return (CAPM) =	0.004956173
Average Return =	0.030279114
Value =	Underpriced

Nestle	
Exp.Long Run Return =	0.02317759
Exp. Return (CAPM) =	0.00540441
Average Return =	0.02087694
Value =	Underpriced

Meaningful conclusions could not be derived because of limited data. Hence, we further used daily data of closing prices considering the same three stocks.

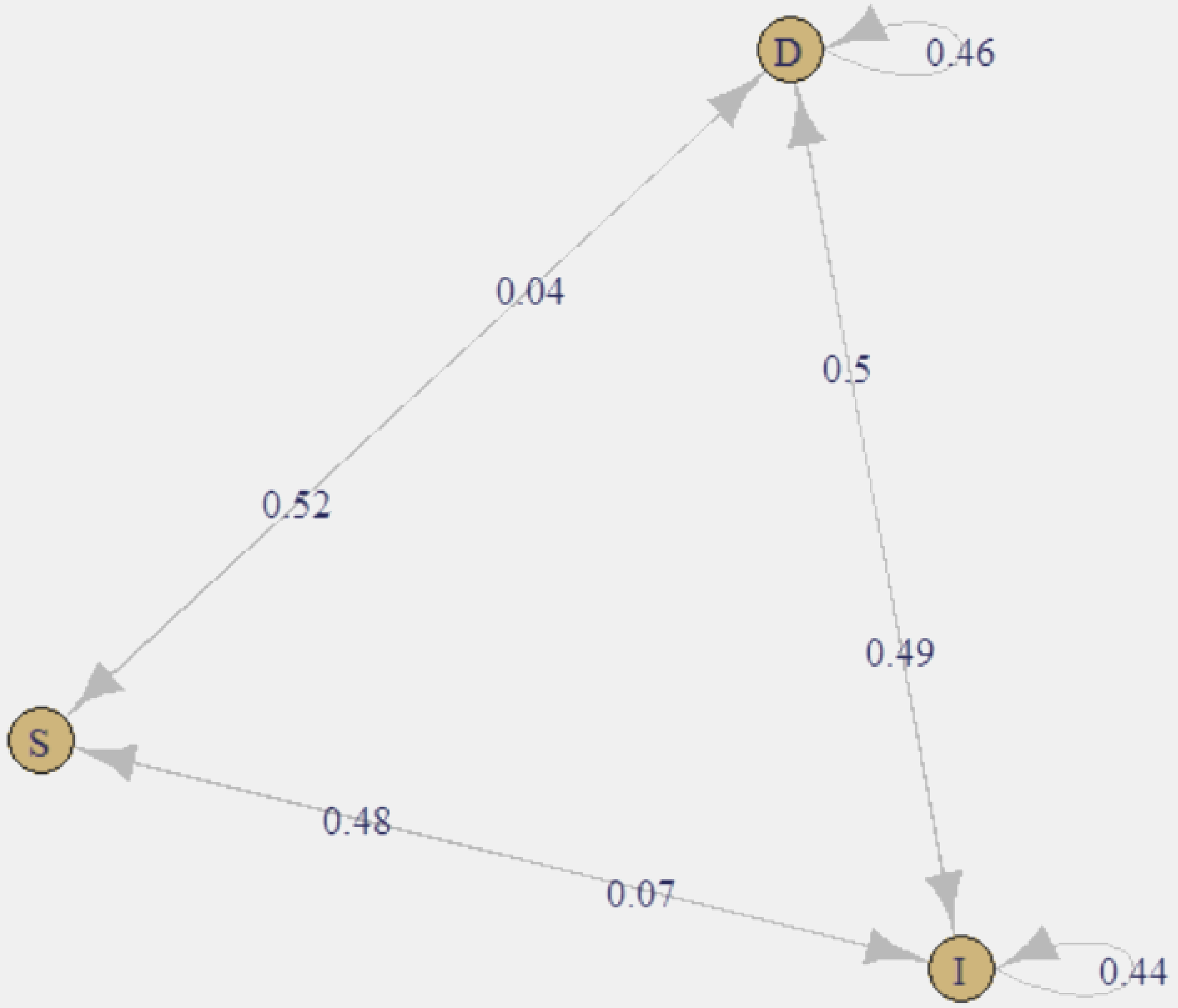
BRITANNIA

$$
\begin{array}{c}
\\ D \\ I \\ S
\end{array}
\begin{array}{c}
\begin{array}{ccc} \quad D & \quad I & \quad S \end{array} \\
\left[\begin{array}{ccc}
0.51 & 0.38 & 0.11 \\
0.46 & 0.44 & 0.09 \\
0.49 & 0.41 & 0.10
\end{array} \right]
\end{array}
$$



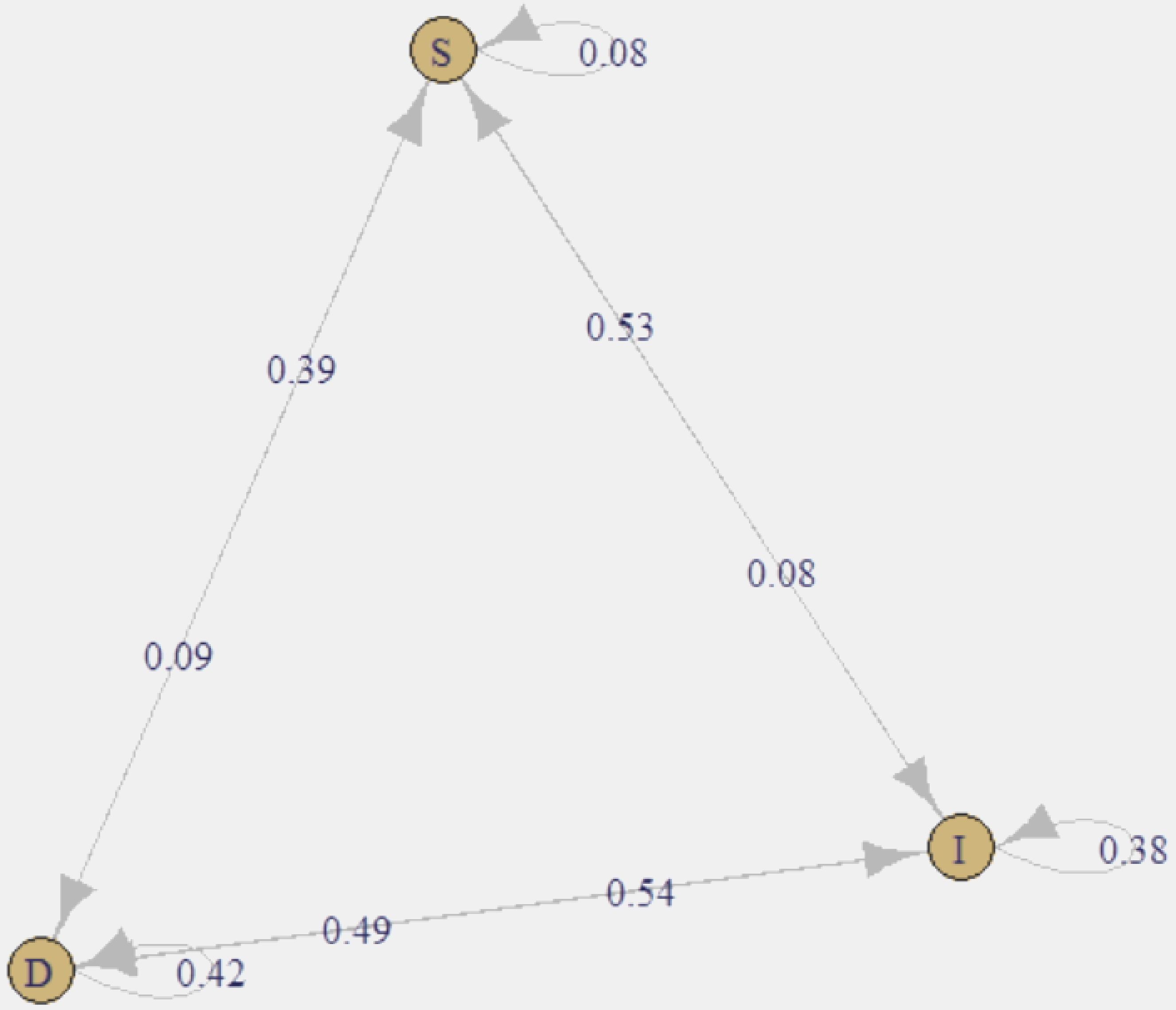
JUBILANT

$$
\begin{array}{c c}
 & \begin{array}{ccc} D & I & S \end{array} \\
\begin{array}{c} D \\ I \\ S \end{array} & \begin{bmatrix} 0.46 & 0.5 & 0.04 \\ 0.49 & 0.44 & 0.07 \\ 0.52 & 0.48 & 0 \end{bmatrix}
\end{array}
$$



NESTLE

$$
\begin{array}{c c}
 & \begin{array}{ccc} D & I & S \end{array} \\
\begin{array}{c} D \\ I \\ S \end{array} & \begin{bmatrix} 0.43 & 0.49 & 0.08 \\ 0.54 & 0.38 & 0.08 \\ 0.39 & 0.53 & 0.08 \end{bmatrix}
\end{array}
$$



Return Analysis for daily data of britannia where t = 27^{th} Mar′21, 28^{th} Mar′21 …

	State	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 8	t = 9	t = 10
Short run returns of the states	D	0.0004277	0.0004287	0.0004288	0.0004288	0.0004288	0.0004288	0.0004288	0.0004288	0.0004288	0.0004288
	I	0.0004301	0.0004288	0.0004288	0.0004288	0.0004288	0.0004288	0.0004288	0.0004288	0.0004288	0.0004288
	S	0.0004286	0.0004288	0.0004288	0.0004288	0.0004288	0.0004288	0.0004288	0.0004288	0.0004288	0.0004288

Long run return = 0.0004288

Exp. return (CAPM) =	0.0012299
Overall average return =	0.0004191

Return analysis for daily data of jubilant where t = $27^{\text{th}}\ \text{Mar}'21, 28^{\text{th}}\ \text{Mar}'21 \ldots$

	States	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 8	t = 9	t = 10
Short run returns of the states	D	0.001618	0.001619	0.001619	0.001619	0.001619	0.001620	0.001620	0.001620	0.001620	0.001620
	I	0.001618	0.001619	0.001619	0.001619	0.001619	0.001620	0.001620	0.001620	0.001620	0.001620
	S	0.001630	0.001619	0.001619	0.001619	0.001619	0.001620	0.001620	0.001620	0.001620	0.001620

Long run return =	0.001620045

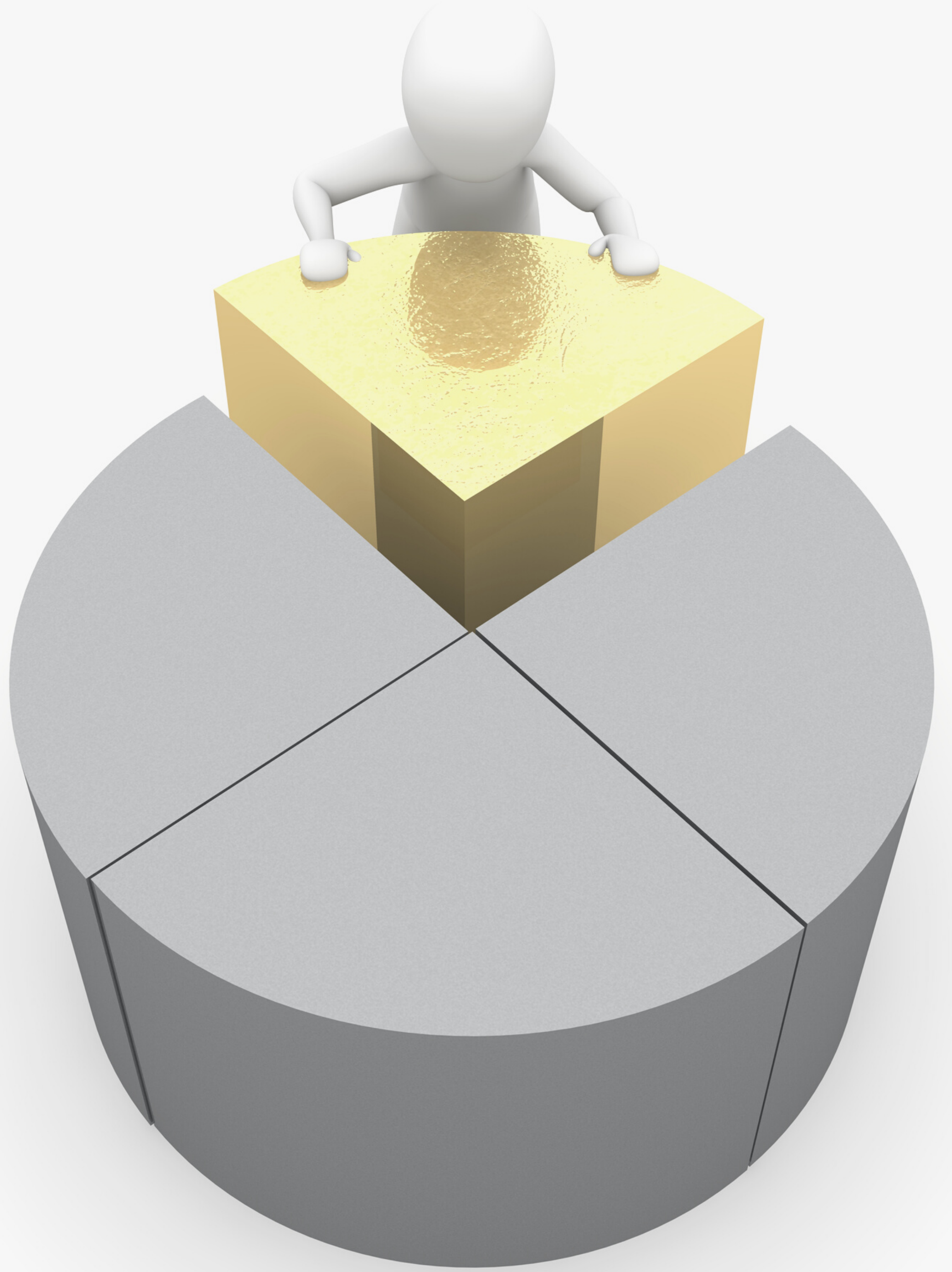
Exp. return (CAPM) =	0.00120
Overall average return =	0.00160

Return analysis for daily data of nestle where t = $27^{\text{th}}\ \text{Mar}'21, 28^{\text{th}}\ \text{Mar}'21 \ldots$

	State	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 8	t = 9	t = 10
Short run returns of the states	**D**	0.0009928	0.0009906	0.0009908	0.0009908	0.0009908	0.0009936	0.0009936	0.0009936	0.0009936	0.0009936
	I	0.0009884	0.0009909	0.0009908	0.0009908	0.0009908	0.0009936	0.0009936	0.0009936	0.0009936	0.0009936
	S	0.0009905	0.0009907	0.0009908	0.0009908	0.0009908	0.0009936	0.0009936	0.0009936	0.0009936	0.0009936

Long run return =	0.000993563

Exp. return (CAPM) =	0.00123492
Overall average return =	0.00099963



CONCLUSION

1 **Britannia** - regardless of the present state of return, the expected return of the CAPM will not be realized in the long run. This hints that the stock was overpriced by Capital asset pricing model. **Hence it indicates that an investor will not realize a positive return in the long run.**

2 **Jubilant** - regardless of the present state of return, the expected return of the CAPM will be realized in the long run. This hints that the stock was not overpriced by Capital asset pricing model. **Hence it indicates that an investor will realize a positive return in the long run.**

3 **Nestle** - regardless of the present state of return, the expected return of the CAPM will not be realized in the long run. This hints that the stock was overpriced by Capital asset pricing model. **Hence it indicates that an investor will not realize a positive return in the long run.**

ANNEXURE

R Code for confidence interval -

```
B<- read.xlsx ("C:/Users/HP/Desktop/Project/Britannia data.xlsx")
B
#Confidence interval : #
yB = mean (B$ChangeXn,na.rm = T)
yB
zB = qt(0.95, df =  59)
zB
wB = sd(B$ChangeXn,na.rm = T)/sqrt(60)
wB
lB = zB*wB
lB
limitB<-c(yB-lB,yB+lB)
limitB
```

R OUTPUT -

```
> yB = mean(B$ChangeXn,na.rm = T)
> yB
[1] 0.01813172
> zB = qt(0.95, df = 59)
> zB
[1] 1.671093
> wB = sd(B$ChangeXn,na.rm = T)/sqrt(60)
> wB
[1] 0.008245518
> lB = zB*wB
> lB
[1] 0.01377903
> limitB<-c(yB-lB,yB+lB)
> limitB
[1] 0.004352689 0.031910743
>
```

R Code for matrix formation -

```
transitionmatrixB = table(B$StateXn,B$StateXn1)
print(transitionmatrixB)
initialprobmatrixB = matrix(data = rowSums(transitionmatrixB)/60, nrow = 1,ncol = 3,byrow = T)
initialprobmatrixB
transprobmatrixB = transitionmatrixB/rowSums(transitionmatrixB)
transprobmatrixB
```

R output -

```
> transitionmatrixB = table(B$StateXn,B$StateXn1)
> print(transitionmatrixB)

     D  I  S
  D 10 10  5
  I  9 14  3
  S  7  2  0
> initialprobmatrixB = matrix(data = rowSums(transitionmatrixB)/60, nrow = 1,ncol = 3,byrow = T)
> initialprobmatrixB
          [,1]      [,2] [,3]
[1,] 0.4166667 0.4333333 0.15
> transprobmatrixB = transitionmatrixB/rowSums(transitionmatrixB)
> transprobmatrixB

            D         I         S
  D 0.4000000 0.4000000 0.2000000
  I 0.3461538 0.5384615 0.1153846
  S 0.7777778 0.2222222 0.0000000
> 
```

R code for markov chain -

```
matrixobjTPMB<-unclass(transprobmatrixB)
markovobjTPMB <- new("markovchain", states = c("D","I","S"), byrow = T, transitionMatrix = matrixobjTPMB, name =
"TPMB")
markovobjTPMB
plot(markovobjTPMB)
steadyStates(markovobjTPMB)
```

R output -

```
> matrixobjTPMB<-unclass(transprobmatrixB)
> markovobjTPMB <- new("markovchain", states = c("D","I","S"), byrow = T, transitionMatrix = matrixobjTPMB, name = "TPMB")
> markovobjTPMB
TPMB
 A  3 - dimensional discrete Markov Chain defined by the following states:
 D, I, S
 The transition matrix  (by rows)  is defined as follows:

          D         I         S
  D 0.4000000 0.4000000 0.2000000
  I 0.3461538 0.5384615 0.1153846
  S 0.7777778 0.2222222 0.0000000

> plot(markovobjTPMB)
> steadyStates(markovobjTPMB)
             D         I        S
[1,] 0.4278523 0.4362416 0.135906
>
```

LIMITATIONS

- The number of decimal places considered for the analysis majorly affects the results and hence it also justifies the minute difference between the return values
- Unfortunately, Markov analysis is not very useful for explaining events. Yes, it is relatively easy to estimate conditional probabilities based on the current state. However, that often tells one little about why something happened

FUTURE SCOPE

- Further research be carried out using a portfolio consisting of different stocks or on other instruments like gold and foreign exchange returns
- Also since this work focuses on daily and monthly returns, more work can be done by analyzing smaller or larger interval of returns
- There should be more work done to determine suitability of different threshold for different instruments, as the choice of threshold is usually decided by the researcher

ACKNOWLEDGEMENT

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https://medium.com/swlh/exploring-markov-chains-in-stock-market-trends-48e1a4951193

Thank you!