SRI VENKATESWARA INTERNSHIP PROGRAM
FOR RESEARCH IN ACADEMICS
(SRI-VIPRA)

SRI-VIPRA

Project Report of 2025: SVP-2510

“Leveraging Markov Chain Models to Enhance Stock Selection in Portfolio Optimization”

IQAC
Sri Venkateswara College
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SRIVIPRA PROJECT 2024

Title : Leveraging Markov Chain Models to Enhance Stock Selection in Portfolio Optimization

Name of Mentor: Prof. Veena Budhraja **Name of Department:** Statistics **Designation:** Professor	**Photo** 

List of students under the SRIVIPRA Project

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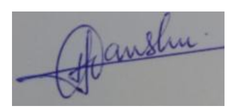
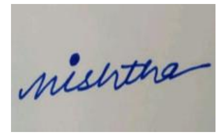
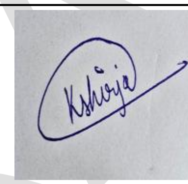
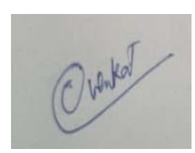
1		Hiyanshi	1824010	B.Sc. (H) Physics	
2		Uday Jadoun	1723014	B.Sc. (H) Mathematics	

3		Nishtha Malhotra	0523039	B.A. (H) Economics	
4		Kshirja Queera	0523059	B.A. (H) Economics	
5		Tarini Korla	1923045	B.Sc. (H) Statistics	
6		Nipun	1923010	B.Sc. (H) Statistics	
7		C.Venkat Ganapathi	0524053	B.A. (H) Economics	

8		Ananya Singh	0522003	B.A. (H) Economics	
9		Gritwik Sharma	1922008	B.Sc. (H) Statistics	
10		Udit Bansal	1924043	B.Sc. (H) Statistics	

Signature of Mentor

Certificate of Originality

This is to certify that the aforementioned students from Sri Venkateswara College have participated in the summer project SVP-2510 titled "Leveraging Markov Chain Models to Enhance Stock Selection in Portfolio Optimization". The participants have carried out the research project work under my guidance and supervision from 1st July, 2025 to 30th September 2025. The work carried out is original and carried out in an offline mode.

Signature of Mentor

Acknowledgements

We are very grateful to our mentor Prof. Veena Budhraja, Department of Statistics, Sri Venkateswara College, University of Delhi, for guiding us and giving us valuable suggestions and ideas throughout the project.

We would also like to extend our deepest gratitude to our college Principal, Professor Vajala Ravi for providing this platform to learn and gain skills under the guidance of our mentor.

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Abstract
This study applies Markov chain modelling to examine the dynamics of stock price movements within a diversified portfolio comprising ten stocks selected from distinct sectors including consultancy, automobiles, fast-moving consumer goods (FMCG), information technology, financial services, health care, commodities, ETF's etc. Daily closing price data over a one-year period are analysed to construct transition probability matrices (TPMs) under both two-state (gain vs loss) and multi-state (varying magnitudes of gains and losses) frameworks. Stationary distributions and mean recurrence times are computed for each constituent stock. The analysis reveals that sectoral stocks demonstrate heterogeneous behaviour. Furthermore, stocks with relatively higher stationary probabilities of gains and shorter recurrence times are identified as comparatively more efficient. The adequacy of the Markov models is validated through chi-square tests. The findings contribute to the literature on stochastic financial modelling by highlighting cross-sectoral efficiency and offering insights for investors seeking to optimize diversification strategies.

Key Words: Markov Chain, Stationary Distribution, Transition Probability Matrix, Multi-state framework, Heterogeneous Behaviour, Chi-Square test, Stochastic Financial Modelling

Introduction
The prediction of stock market movements remains one of the most challenging yet essential pursuits in financial research and investment practice. Market fluctuations are influenced by a confluence of factors, including macroeconomic conditions, global events, and sector-specific dynamics. Consequently, researchers and practitioners have long sought robust quantitative frameworks capable of capturing such complexities. Among these, Markov chain models have emerged as a useful tool, as they provide a probabilistic approach to studying state-dependent transitions and long-run equilibrium behaviour in financial time series. The Markov chain is relatively simple since it only requires the information of the present state to predict the future states.

Previous studies have primarily applied Markov chain analysis to major stock indices, such as the Sensex or Dow Jones, or to portfolios concentrated within a few dominant firms. These studies demonstrate that indices tend to exhibit stable stationary distributions and interpretable recurrence properties, thereby aiding investors in developing predictive strategies. However, there is limited research on the application of Markov models to diversified, sector-based portfolios, which may provide deeper insights into cross-sectoral behaviour and relative efficiency of individual stocks.

This study seeks to address this gap by constructing a portfolio of ten stocks drawn from heterogeneous sectors, including health care, consultancy, automobiles, fast-moving consumer goods (FMCG), information technology, financial services, commodities, ETF's, etc. Using daily closing price data over a one-year period, we develop Markov chain models under both binary (gain/loss) and multi-state categorizations. Transition probability matrices are derived for both the models of individual stocks, followed by the computation of stationary distributions and mean recurrence times. To ensure methodological robustness, chi-square tests are employed to assess the goodness of fit of the models.

The objectives of this research are threefold:
1. To analyse the stochastic behaviour of a diversified ten-stock portfolio using Markov chain models.
2. To identify the most efficient stocks across sectors based on stationary probabilities and recurrence metrics.
3. To evaluate the applicability and stability of Markov chain modelling in the context of sectoral diversification.

In our analysis, a random sample of 50 trading days was selected from the full set of population data spanning over a year. The transition probability matrices (TPMs) derived from this sample showed a close resemblance to those derived from the complete dataset. This indicates that the sampling method was both representative and reliable, and that the results are able to capture the essential market dynamics over the period of study.
By analysing the probabilities of different market states and the relative efficiency of individual stocks, the framework provides investors with information that can support In making informed decisions and potentially leading to higher returns. At the same time, the work contributes to financial research by presenting a practical application of stochastic models in stock market forecasting. In this way, the study adds to academic discussion while also offering investors an analytical tool as well as a practical guide to navigate and manage the complexities of market behaviour.

Literature Review

The application of Markov models in financial economics has been considerably used to study the stochastic character of stock prices and returns. The foundation of these models is that transitions between states depend only on the current state and not on the series of the past states, as embedded in the early work of Markov (1906). These models are suitable for modeling the dynamics of stock markets, where regimes are characterized by high and low noise components, because of their memoryless property. The mathematical formulation of finite Markov chains for further practical applications in economics and finance was developed by Kemeny and Snell (1976).

Two-state Markov models are commonly used as the easiest and simple to comprehend framework. They are used to capture binary regimes such as bullish versus bearish markets, or periods of low versus high volatility while requiring relatively few parameters to estimate. One of the most famous contributions is that of Hamilton's (1989) regime-switching model which demonstrates how two-state Markov processes explain periodic patterns in macroeconomic and financial data. Further studies in the field have used two-state models to study exchange rate movements (Engel & Hamilton, 1990), characterize interest rate regimes (Ang & Bekaert, 2002), Two-state models are useful in nature but fail to capture the complexity of the financial time series. Different stock markets frequently display multiple phases of volatility and return patterns that cannot be precisely defined by a binary classification. To cater to this, multi-state Markov models like the six-state have been found. Models like these allow finer granules by distinguishing between different levels of market operations, ranging from extreme volatility to stable intermediate states. For example, Gray (1996) used a multi-state Markov switching process to account for the persistence in volatility, while Bulla and Bulla (2006) applied hidden multi-state models to explain facts of financial returns such as heavy tails and volatility clustering. Likewise, Zivot and Wang (2006) highlighted the edge of multi-state approaches in capturing cycles of growth, decline, and the upcoming stagnation in the financial markets

The preference between the two-state and multi-state models eventually depends on the research question and kind of data. The two-state framework uncovers paramount market cycles, while the six-state model unveils more granular patterns in stock price changes. The literature gaps found in the existing studies of Markov chain models show that the financial markets often rely on simplified two state frameworks that limit their ability to capture the finer dynamics of stock price changes. Most research studies assume that the states achieve stationarity ignoring the fact that financial markets are unpredictable. Finally, the memoryless property of these models fails to account for any exogenous shocks.

Methodology

1)The Markov Chain model: A random walk is said to exhibit the Markov property if the position of the walk at time n depends only upon the position of the walk at time $n - 1$. If we call our random variable Xn, then:

$$P(Xn = j | Xn-1 = i) = p_{ij} \qquad (1)$$

is independent of $Xn-2$, $Xn-3$, …, $X1$ so that the state of X at time n depends only upon the state of X at step $n - 1$. Here each p_{ij} for j = 1,2, … is a probability row vector describing every possible transition from state i to any other available state in the system.

$$\sum_{j=1}^{m} pij = 1 \ \forall\ i \qquad (2)$$

Thus,

$$P\ (X_{n+1} = i_{n+1}\ | X_n = i_n\ , X_{n-1} = i_{n-1} . . .) = P\ (X_{n+1} = i_{n+1} | X_n = i_n) \qquad (3)$$

And $pij^{(m)} = P\ (X_n = j | X_{n-m} = i) \qquad (4)$

indicates m-step transition.

The process of moving from one state of the system to another with the associated probabilities of each transition is known as the chain. It is said that every step taken in a chain possessing the Markov property depends only upon the immediately preceding step.

It can easily be seen how calculating probabilities of a series, or chain, of events in a Markov system is greatly simplified due to this Markov property. Instead of concerning ourselves with the entire path a random variable might have taken to arrive at its current state, we need only consider its state directly before a given point of interest.

2)Transition Matrix:

The transition probabilities form an $m \times m$ transitional probability matrix

T, where: $T = [pij] = \begin{bmatrix} p11 & \cdots & p1m \\ \vdots & \ddots & \vdots \\ pm1 & \cdots & pmm \end{bmatrix}$

Each row of T is the probability distribution relating to a transition from state i to state j.

States i and j are said to communicate if there exists a path between them. It must be true that i is reachable from j in a finite number of transitions and also that j is reachable from i in a finite number of transitions for any two states i and j to communicate. A state i is said to be periodic if all paths leading from state i back to i have a length that is a multiple of some integer k, such that $k > 0$ for the smallest possible k. If all states of a chain communicate and are not periodic, then the chain is said to be ergodic.

Model Specification

Under this study, two models have been developed:

1. **Model 1- Probabilities of a specific portfolio of stocks moving up or down.**

   State 1: Portfolio's value is the same or higher than that of the previous day.

   State 2: Portfolio’s value drops below the previous day's closing figure.

2. **Model 2- Probabilities of a specific portfolio of stocks moving between partitions of possible gains and losses.**

   - Large Jump Up/Down:

   Up: Greater than $\mu + 1.96\sigma$. This captures changes that are significantly higher than the average, falling in the top 2.5% of all changes (assuming normal distribution).

   Down: Less than $\mu - 1.96\sigma$. This represents changes significantly lower than the average, also in the bottom 2.5%.

   - Moderate Jump Up/Down:

   Up: Between $\mu + 1\sigma$ and $\mu + 1.96\sigma$. These changes are above average but not as extreme as the large jumps.

   Down: Between $\mu - 1\sigma$ and $\mu - 1.96\sigma$. These are below average but not to the extent of large jumps.

   - Small Jump Up/Down:

   Up: Between μ and $\mu + 1\sigma$. These are slight increases, within the range of what's typically expected.

   Down: Between μ and $\mu - 1\sigma$. These are slight decreases, again within the range of normal fluctuations.

The transition matrices were estimated based on transitions obtained from closing values of different stocks over a time frame of a year.

The closing values were categorized using Microsoft Excel.

3)Stationary Distribution:

The probability distribution $\{vj\}$ is called stationary distribution of a Markov Chain with transition probabilities pjk if

$v_k = \sum_j v_j p_{jk}$ such that $v_j \geq 0$ and $\sum v_j = 1$

i.e., whether a Markov System regardless of the initial state j, reaches a stable state after a large number of transitions.

A chain is said to have a steady state distribution if there exists a vector v such that given a transition matrix T,

$vT = v$

If a chain is ergodic then we are guaranteed the existence of this steady state vector v. This steady state vector can be viewed as the distribution of a random variable in the long run. This steady state probability vector v of an m state random walk can also be obtained

The test for goodness of fit was used to test the null hypothesis that the steady-state probabilities are stable and consistent.as:

$$\text{Lim}_{n\to\infty} T^n = \begin{bmatrix} v1 & \cdots & vm \\ \vdots & \ddots & \vdots \\ v1 & \cdots & vm \end{bmatrix}$$

4)Recurrent property:

Consider a state that is arbitrary but fixed, i, and define an integer n ≥ 1; then,

$fii(n) = \{X_n = i, X_j \neq i, j = 1,2,..,n-1 | X_0 = i\}$ (7)

It implies that $fii(n)$ is the likelihood that the first return to state i, from state i, happens at the nth transition. However, given that

$pii^n = \sum fii^{(k)} pii^{(n-k)} = 0, n \geq 1$ (8)

If state i is aperiodic, then

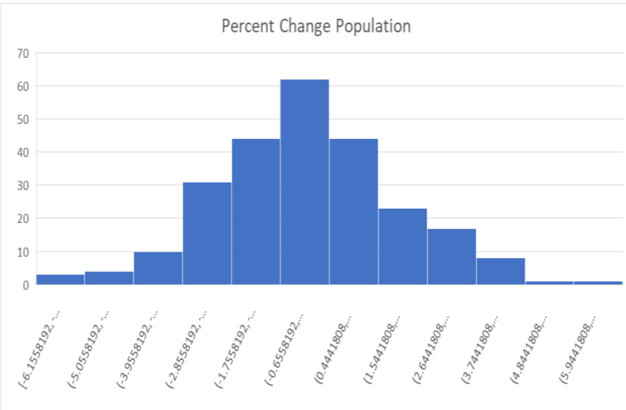
$p_{ii}^{(n)} \rightarrow 1/\mu_{ii}, \text{ as } n \rightarrow \infty.$

5)The Chi-square Test:

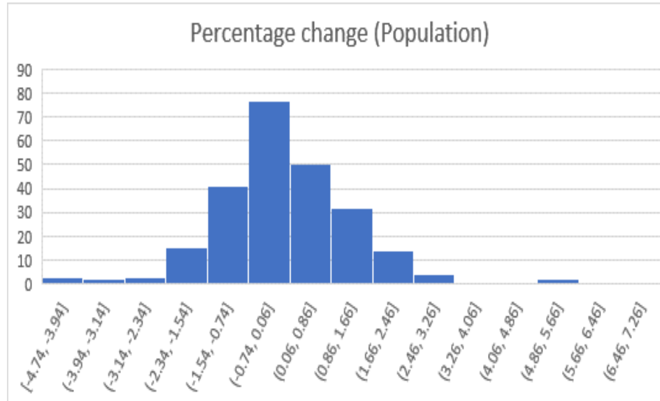
The test for goodness of fit was used to test the null hypothesis that the steady-state probabilities are stable and consistent.

Estimation of Results:

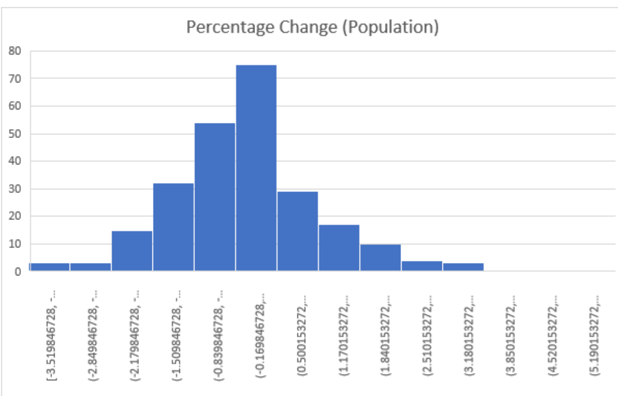
1. **Histogram of individual stocks for the population data**



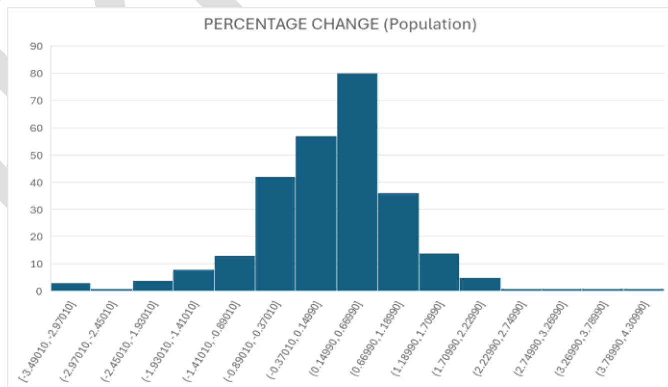
ABCapital Equity



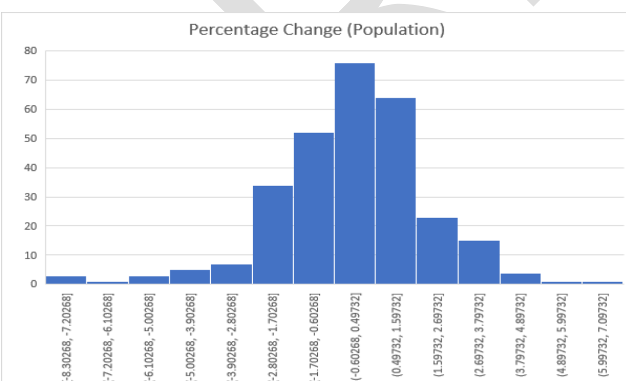
MARUTI SUZUKI Equity



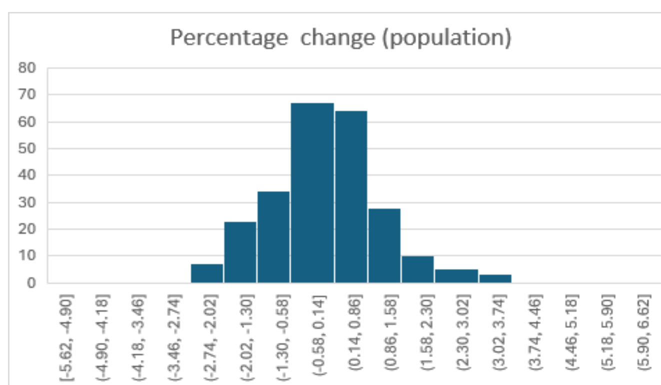
ITC Equity



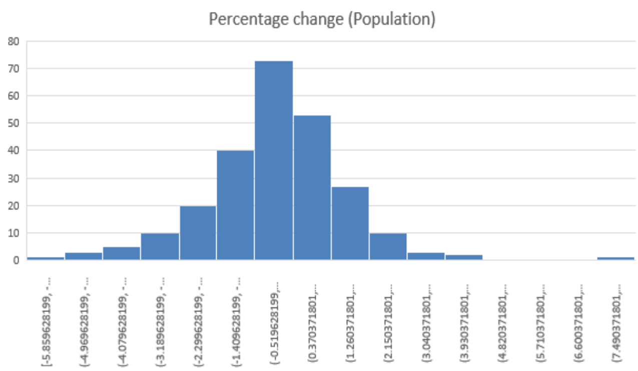
Nippon India ETF Gold BeES Equity



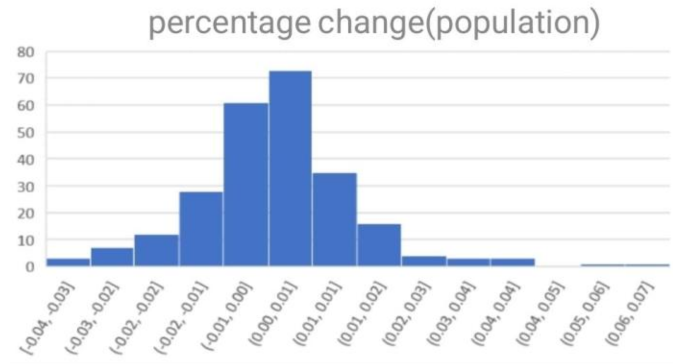
Tata Motors Equity



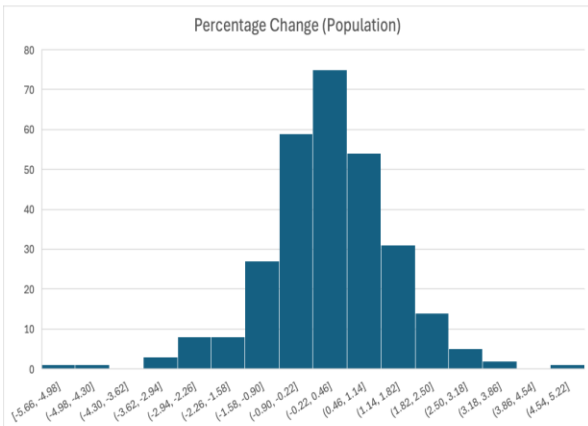
HUL Equity



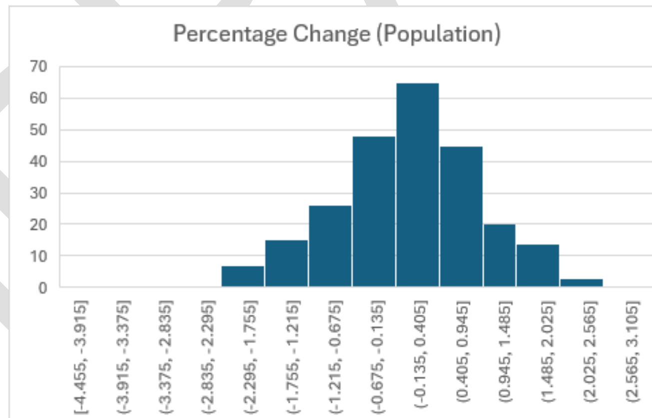
Infosys equity histogram



TCS equity histogram

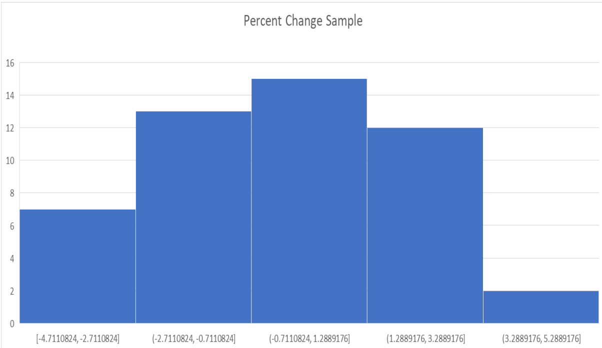


HDFC Bank Equity

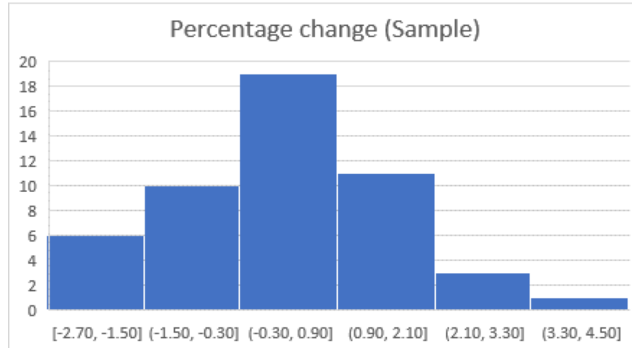


ICICI Bank Equity

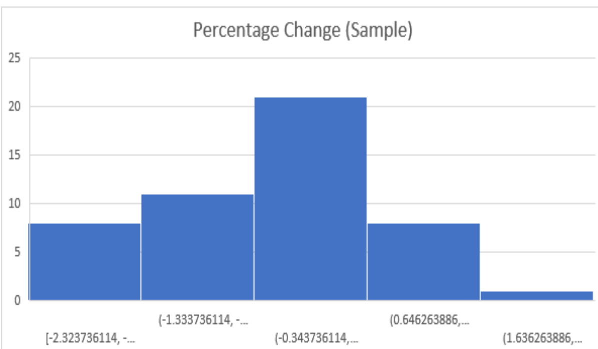
2.Histogram of individual stocks for the sample data



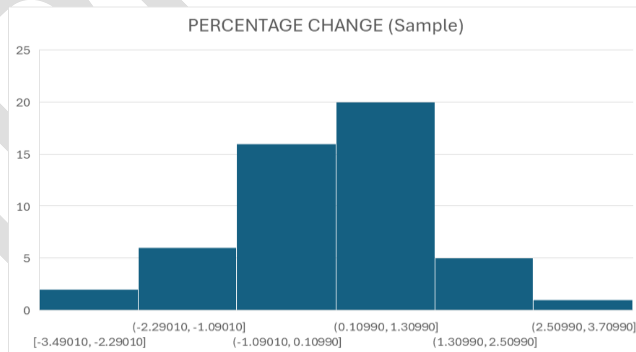
ABCapital Equity



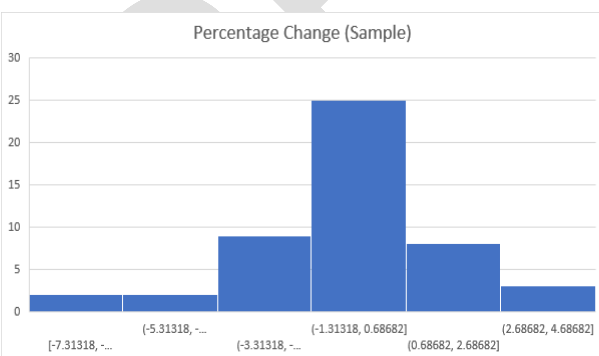
MRTI Equity



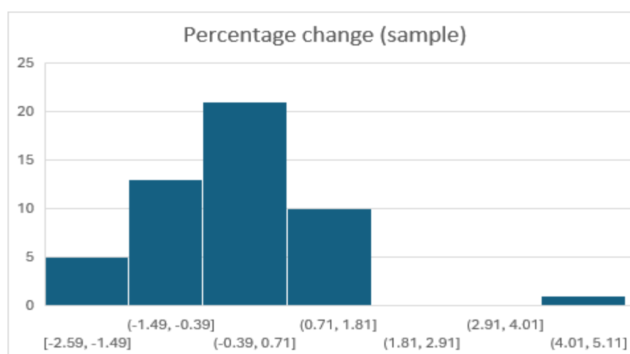
ITC Equity



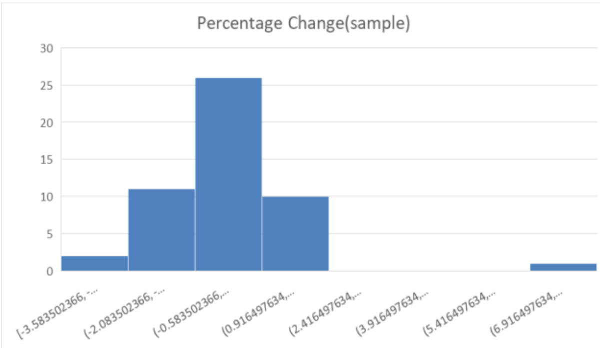
Nippon India ETF Gold BeES Equity



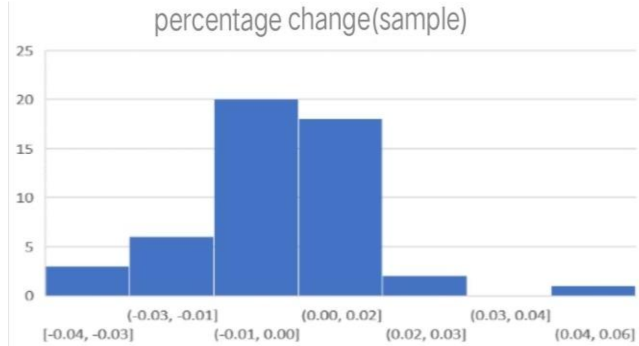
Tata motors equity



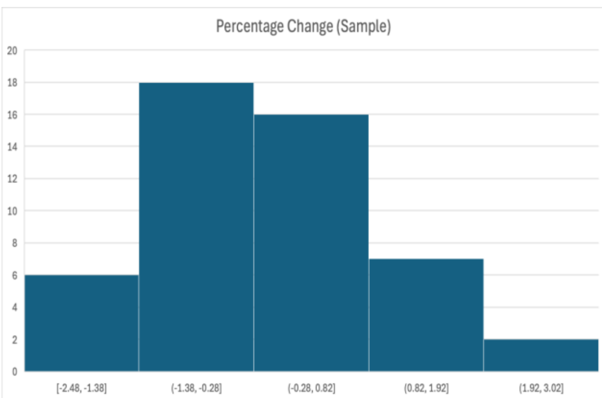
HUL Equity



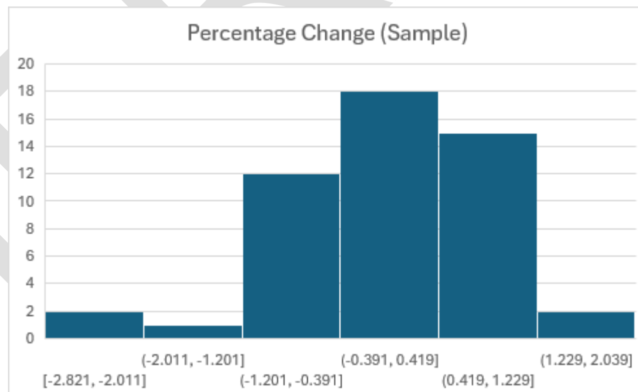
Infosys Equity



TCS Equity



HDFC Bank Equity



ICICI Bank Equity

3. Transition Probabilities Matrix for individual stocks

NIPPON GOLD ETF

POPULATION:

$$P = \begin{pmatrix} 0.589 & 0.411 \\ 0.596 & 0.404 \end{pmatrix}$$

STATE 1

$$P^3 = \begin{pmatrix} 0.592 & 0.408 \\ 0.592 & 0.408 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.000 & 0.111 & 0.111 & 0.556 & 0.222 & 0.000 \\ 0.000 & 0.143 & 0.381 & 0.381 & 0.095 & 0.000 \\ 0.054 & 0.076 & 0.315 & 0.489 & 0.054 & 0.010 \\ 0.025 & 0.059 & 0.364 & 0.449 & 0.068 & 0.034 \\ 0.000 & 0.100 & 0.300 & 0.350 & 0.150 & 0.100 \\ 0.143 & 0.143 & 0.571 & 0.143 & 0.000 & 0.000 \end{pmatrix}$$

STATE 2

$$P^7 = \begin{pmatrix} 0.034 & 0.079 & 0.341 & 0.445 & 0.075 & 0.026 \\ 0.034 & 0.079 & 0.341 & 0.445 & 0.075 & 0.026 \\ 0.034 & 0.079 & 0.341 & 0.445 & 0.075 & 0.026 \\ 0.034 & 0.079 & 0.341 & 0.445 & 0.075 & 0.026 \\ 0.034 & 0.079 & 0.341 & 0.445 & 0.075 & 0.026 \\ 0.034 & 0.079 & 0.341 & 0.445 & 0.075 & 0.026 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 2)

SAMPLE:

$$P = \begin{pmatrix} 0.500 & 0.500 \\ 0.636 & 0.364 \end{pmatrix}$$

STATE 1

$$P^6 = \begin{pmatrix} 0.560 & 0.440 \\ 0.560 & 0.440 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.000 & 0.000 & 0.000 & 0.750 & 0.250 & 0.000 \\ 0.000 & 0.000 & 0.333 & 0.500 & 0.167 & 0.000 \\ 0.143 & 0.214 & 0.214 & 0.357 & 0.071 & 0.000 \\ 0.056 & 0.056 & 0.389 & 0.278 & 0.111 & 0.111 \\ 0.000 & 0.200 & 0.200 & 0.400 & 0.000 & 0.200 \\ 0.333 & 0.333 & 0.333 & 0.000 & 0.000 & 0.000 \end{pmatrix}$$

STATE 2

$$P^{10} = \begin{pmatrix} 0.080 & 0.120 & 0.280 & 0.360 & 0.010 & 0.060 \\ 0.080 & 0.120 & 0.280 & 0.360 & 0.010 & 0.060 \\ 0.080 & 0.120 & 0.280 & 0.360 & 0.010 & 0.060 \\ 0.080 & 0.120 & 0.280 & 0.360 & 0.010 & 0.060 \\ 0.080 & 0.120 & 0.280 & 0.360 & 0.010 & 0.060 \\ 0.080 & 0.120 & 0.280 & 0.360 & 0.010 & 0.060 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 2)

HUL(Hindustan Unilever)

POPULATION:

$$P = \begin{pmatrix} 0.480 & 0.520 \\ 0.537 & 0.462 \end{pmatrix}$$

STATE 1

$$P^6 = \begin{pmatrix} 0.508 & 0.491 \\ 0.508 & 0.491 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.166 & 0.166 & 0.333 & 0.166 & 0.166 & 0.000 \\ 0.040 & 0.160 & 0.240 & 0.520 & 0.040 & 0.000 \\ 0.022 & 0.122 & 0.322 & 0.411 & 0.088 & 0.033 \\ 0.021 & 0.093 & 0.443 & 0.350 & 0.072 & 0.021 \\ 0.000 & 0.055 & 0.333 & 0.555 & 0.055 & 0.000 \\ 0.000 & 0.142 & 0.428 & 0.428 & 0.000 & 0.000 \end{pmatrix}$$

STATE 2

$$P^8 = \begin{pmatrix} 0.025 & 0.111 & 0.365 & 0.403 & 0.074 & 0.020 \\ 0.025 & 0.111 & 0.365 & 0.403 & 0.074 & 0.020 \\ 0.025 & 0.111 & 0.365 & 0.403 & 0.074 & 0.020 \\ 0.025 & 0.111 & 0.365 & 0.403 & 0.074 & 0.020 \\ 0.025 & 0.111 & 0.365 & 0.403 & 0.074 & 0.020 \\ 0.025 & 0.111 & 0.365 & 0.403 & 0.074 & 0.020 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 2)

SAMPLE:

$$P = \begin{pmatrix} 0.263 & 0.737 \\ 0.437 & 0.563 \end{pmatrix}$$

STATE 1

$$P^7 = \begin{pmatrix} 0.372 & 0.627 \\ 0.372 & 0.627 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.000 & 0.000 & 0.100 & 0.000 & 0.000 & 0.000 \\ 0.143 & 0.000 & 0.285 & 0.571 & 0.000 & 0.000 \\ 0.000 & 0.157 & 0.263 & 0.315 & 0.210 & 0.052 \\ 0.000 & 0.187 & 0.437 & 0.312 & 0.062 & 0.000 \\ 0.000 & 0.200 & 0.600 & 0.200 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.500 & 0.500 & 0.000 & 0.000 \end{pmatrix}$$

STATE 2

$$P^7 = \begin{pmatrix} 0.020 & 0.143 & 0.379 & 0.336 & 0.101 & 0.019 \\ 0.020 & 0.143 & 0.379 & 0.336 & 0.101 & 0.019 \\ 0.020 & 0.143 & 0.379 & 0.336 & 0.101 & 0.019 \\ 0.020 & 0.143 & 0.379 & 0.336 & 0.101 & 0.019 \\ 0.020 & 0.143 & 0.379 & 0.336 & 0.101 & 0.019 \\ 0.020 & 0.143 & 0.379 & 0.336 & 0.101 & 0.019 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 2)

TATA MOTORS

POPULATION:

$$P = \begin{pmatrix} 0.342 & 0.658 \\ 0.717 & 0.283 \end{pmatrix}$$

STATE 1

$$P^{16} = \begin{pmatrix} 0.522 & 0.478 \\ 0.522 & 0.478 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.000 & 0.167 & 0.500 & 0.333 & 0.000 & 0.000 \\ 0.062 & 0.062 & 0.438 & 0.344 & 0.312 & 0.062 \\ 0.009 & 0.103 & 0.364 & 0.411 & 0.103 & 0.009 \\ 0.027 & 0.108 & 0.342 & 0.396 & 0.081 & 0.045 \\ 0.000 & 0.182 & 0.364 & 0.364 & 0.045 & 0.045 \\ 0.000 & 0.182 & 0.545 & 0.091 & 0.000 & 0.182 \end{pmatrix}$$

STATE 2

$$P^{10} = \begin{pmatrix} 0.021 & 0.111 & 0.374 & 0.381 & 0.076 & 0.038 \\ 0.021 & 0.111 & 0.374 & 0.381 & 0.076 & 0.038 \\ 0.021 & 0.111 & 0.374 & 0.381 & 0.076 & 0.038 \\ 0.021 & 0.111 & 0.374 & 0.381 & 0.076 & 0.038 \\ 0.021 & 0.111 & 0.374 & 0.381 & 0.076 & 0.038 \\ 0.021 & 0.111 & 0.374 & 0.381 & 0.076 & 0.038 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 2)

SAMPLE:

$$P = \begin{pmatrix} 0.423 & 0.577 \\ 0.636 & 0.364 \end{pmatrix}$$

STATE 1

$$P^{14} = \begin{pmatrix} 0.524 & 0.476 \\ 0.524 & 0.476 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.000 & 0.000 & 0.000 & 0.100 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.500 & 0.500 & 0.000 & 0.000 \\ 0.043 & 0.087 & 0.478 & 0.304 & 0.043 & 0.043 \\ 0.000 & 0.111 & 0.389 & 0.444 & 0.056 & 0.000 \\ 0.000 & 0.000 & 0.500 & 0.000 & 0.000 & 0.500 \\ 0.000 & 0.000 & 0.100 & 0.000 & 0.000 & 0.000 \end{pmatrix}$$

STATE 2

$$P^{12} = \begin{pmatrix} 0.020 & 0.080 & 0.460 & 0.360 & 0.040 & 0.040 \\ 0.020 & 0.080 & 0.460 & 0.360 & 0.040 & 0.040 \\ 0.020 & 0.080 & 0.460 & 0.360 & 0.040 & 0.040 \\ 0.020 & 0.080 & 0.460 & 0.360 & 0.040 & 0.040 \\ 0.020 & 0.080 & 0.460 & 0.360 & 0.040 & 0.040 \\ 0.020 & 0.080 & 0.460 & 0.360 & 0.040 & 0.040 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 2)

ITC

POPULATION:

$$P = \begin{pmatrix} 0.403 & 0.597 \\ 0.712 & 0.288 \end{pmatrix}$$

STATE 1

$$P^9 = \begin{pmatrix} 0.544 & 0.456 \\ 0.544 & 0.456 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.000 & 0.000 & 0.500 & 0.250 & 0.000 & 0.250 \\ 0.083 & 0.166 & 0.166 & 0.292 & 0.125 & 0.166 \\ 0.010 & 0.090 & 0.450 & 0.310 & 0.110 & 0.030 \\ 0.000 & 0.083 & 0.452 & 0.369 & 0.083 & 0.012 \\ 0.000 & 0.044 & 0.478 & 0.434 & 0.434 & 0.000 \\ 0.000 & 0.300 & 0.100 & 0.400 & 0.100 & 0.100 \end{pmatrix}$$

STATE 2

$$P^9 = \begin{pmatrix} 0.013 & 0.098 & 0.412 & 0.343 & 0.094 & 0.040 \\ 0.013 & 0.098 & 0.412 & 0.343 & 0.094 & 0.040 \\ 0.013 & 0.098 & 0.412 & 0.343 & 0.094 & 0.040 \\ 0.013 & 0.098 & 0.412 & 0.343 & 0.094 & 0.040 \\ 0.013 & 0.098 & 0.412 & 0.343 & 0.094 & 0.040 \\ 0.013 & 0.098 & 0.412 & 0.343 & 0.094 & 0.040 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 2)

SAMPLE:

$$P = \begin{pmatrix} 0.417 & 0.583 \\ 0.653 & 0.347 \end{pmatrix}$$

STATE 1

$$P^8 = \begin{pmatrix} 0.528 & 0.472 \\ 0.528 & 0.472 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.000 & 0.000 & 1.000 & 0.000 & 0.000 & 0.000 \\ 0.143 & 0.286 & 0.000 & 0.571 & 0.000 & 0.000 \\ 0.000 & 0.143 & 0.214 & 0.428 & 0.143 & 0.072 \\ 0.000 & 0.105 & 0.422 & 0.368 & 0.105 & 0.000 \\ 0.000 & 0.000 & 0.333 & 0.333 & 0.333 & 0.000 \\ 0.000 & 0.000 & 0.000 & 1.000 & 0.000 & 0.000 \end{pmatrix}$$

STATE 2

$$P^7 = \begin{pmatrix} 0.017 & 0.121 & 0.299 & 0.413 & 0.129 & 0.021 \\ 0.017 & 0.121 & 0.299 & 0.413 & 0.129 & 0.021 \\ 0.017 & 0.121 & 0.299 & 0.413 & 0.129 & 0.021 \\ 0.017 & 0.121 & 0.299 & 0.413 & 0.129 & 0.021 \\ 0.017 & 0.121 & 0.299 & 0.413 & 0.129 & 0.021 \\ 0.017 & 0.121 & 0.299 & 0.413 & 0.129 & 0.021 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 2)

HDFC BANK

POPULATION:

$$P = \begin{pmatrix} 0.317 & 0.683 \\ 0.690 & 0.310 \end{pmatrix}$$

STATE 1

$$P^{16} = \begin{pmatrix} 0.502 & 0.497 \\ 0.502 & 0.497 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.000 & 0.167 & 0.500 & 0.000 & 0.167 & 0.167 \\ 0.000 & 0.056 & 0.361 & 0.417 & 0.139 & 0.028 \\ 0.029 & 0.107 & 0.350 & 0.408 & 0.087 & 0.019 \\ 0.009 & 0.165 & 0.358 & 0.385 & 0.064 & 0.183 \\ 0.038 & 0.153 & 0.231 & 0.346 & 0.115 & 0.115 \\ 0.111 & 0.000 & 0.667 & 0.111 & 0.111 & 0.000 \end{pmatrix}$$

STATE 2

$$P^7 = \begin{pmatrix} 0.021 & 0.125 & 0.356 & 0.377 & 0.090 & 0.031 \\ 0.021 & 0.125 & 0.356 & 0.377 & 0.090 & 0.031 \\ 0.021 & 0.125 & 0.356 & 0.377 & 0.090 & 0.031 \\ 0.021 & 0.125 & 0.356 & 0.377 & 0.090 & 0.031 \\ 0.021 & 0.125 & 0.356 & 0.377 & 0.090 & 0.031 \\ 0.021 & 0.125 & 0.356 & 0.377 & 0.090 & 0.031 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 2)

SAMPLE:

$$P = \begin{pmatrix} 0.407 & 0.593 \\ 0.714 & 0.286 \end{pmatrix}$$

STATE 1

$$P^6 = \begin{pmatrix} 0.546 & 0.453 \\ 0.546 & 0.453 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.000 & 0.500 & 0.500 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.800 & 0.200 & 0.000 & 0.000 \\ 0.000 & 0.056 & 0.278 & 0.500 & 0.111 & 0.056 \\ 0.105 & 0.105 & 0.316 & 0.368 & 0.105 & 0.000 \\ 0.000 & 0.200 & 0.400 & 0.400 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.000 & 1.000 & 0.000 \end{pmatrix}$$

STATE 2

$$P^{10} = \begin{pmatrix} 0.040 & 0.100 & 0.360 & 0.380 & 0.010 & 0.020 \\ 0.040 & 0.100 & 0.360 & 0.380 & 0.010 & 0.020 \\ 0.040 & 0.100 & 0.360 & 0.380 & 0.010 & 0.020 \\ 0.040 & 0.100 & 0.360 & 0.380 & 0.010 & 0.020 \\ 0.040 & 0.100 & 0.360 & 0.380 & 0.010 & 0.020 \\ 0.040 & 0.100 & 0.360 & 0.380 & 0.010 & 0.020 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 2)

MRTI

POPULATION:

$$P = \begin{pmatrix} 0.380 & 0.619 \\ 0.655 & 0.344 \end{pmatrix}$$

STATE 1

$$P^5 = \begin{pmatrix} 0.514 & 0.485 \\ 0.514 & 0.485 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.200 & 0.000 & 0.600 & 0.000 & 0.200 & 0.000 \\ 0.000 & 0.100 & 0.650 & 0.200 & 0.050 & 0.000 \\ 0.028 & 0.075 & 0.386 & 0.405 & 0.075 & 0.028 \\ 0.000 & 0.083 & 0.464 & 0.333 & 0.095 & 0.023 \\ 0.043 & 0.086 & 0.391 & 0.260 & 0.173 & 0.043 \\ 0.000 & 0.000 & 0.285 & 0.428 & 0.142 & 0.142 \end{pmatrix}$$

STATE 2

$$P^6 = \begin{pmatrix} 0.020 & 0.077 & 0.435 & 0.343 & 0.094 & 0.028 \\ 0.020 & 0.077 & 0.435 & 0.343 & 0.094 & 0.028 \\ 0.020 & 0.077 & 0.435 & 0.343 & 0.094 & 0.028 \\ 0.020 & 0.077 & 0.435 & 0.343 & 0.094 & 0.028 \\ 0.020 & 0.077 & 0.435 & 0.343 & 0.094 & 0.028 \\ 0.020 & 0.077 & 0.435 & 0.343 & 0.094 & 0.028 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 2)

SAMPLE:

$$P = \begin{pmatrix} 0.280 & 0.720 \\ 0.680 & 0.320 \end{pmatrix}$$

STATE 1

$$P^5 = \begin{pmatrix} 0.485 & 0.514 \\ 0.485 & 0.514 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.000 & 0.000 & 1.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.142 & 0.428 & 0.428 & 0.000 & 0.000 \\ 0.050 & 0.200 & 0.250 & 0.200 & 0.200 & 0.100 \\ 0.000 & 0.071 & 0.500 & 0.357 & 0.071 & 0.000 \\ 0.000 & 0.166 & 0.500 & 0.166 & 0.166 & 0.000 \\ 0.000 & 0.000 & 0.500 & 0.500 & 0.000 & 0.000 \end{pmatrix}$$

STATE 2

$$P^{31} = \begin{pmatrix} 0.018 & 0.114 & 0.398 & 0.335 & 0.085 & 0.047 \\ 0.018 & 0.114 & 0.398 & 0.335 & 0.085 & 0.047 \\ 0.018 & 0.114 & 0.398 & 0.335 & 0.085 & 0.047 \\ 0.018 & 0.114 & 0.398 & 0.335 & 0.085 & 0.047 \\ 0.018 & 0.114 & 0.398 & 0.335 & 0.085 & 0.047 \\ 0.018 & 0.114 & 0.398 & 0.335 & 0.085 & 0.047 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 2)

POPULATION:

$$P = \begin{pmatrix} 0.544 & 0.455 \\ 0.596 & 0.404 \end{pmatrix}$$

STATE 1

$$P^4 = \begin{pmatrix} 0.567 & 0.433 \\ 0.567 & 0.433 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.181 & 0.090 & 0.363 & 0.272 & 0.000 & 0.090 \\ 0.037 & 0.074 & 0.370 & 0.407 & 0.111 & 0.000 \\ 0.032 & 0.107 & 0.408 & 0.290 & 0.107 & 0.053 \\ 0.059 & 0.107 & 0.357 & 0.380 & 0.071 & 0.023 \\ 0.000 & 0.190 & 0.333 & 0.333 & 0.047 & 0.095 \\ 0.000 & 0.100 & 0.300 & 0.500 & 0.100 & 0.000 \end{pmatrix}$$

STATE 2

$$P^6 = \begin{pmatrix} 0.044 & 0.109 & 0.373 & 0.345 & 0.085 & 0.040 \\ 0.044 & 0.109 & 0.373 & 0.345 & 0.085 & 0.040 \\ 0.044 & 0.109 & 0.373 & 0.345 & 0.085 & 0.040 \\ 0.044 & 0.109 & 0.373 & 0.345 & 0.085 & 0.040 \\ 0.044 & 0.109 & 0.373 & 0.345 & 0.085 & 0.040 \\ 0.044 & 0.109 & 0.373 & 0.345 & 0.085 & 0.040 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 2)

SAMPLE:

$$P = \begin{pmatrix} 0.481 & 0.518 \\ 0.652 & 0.347 \end{pmatrix}$$

STATE 1

$$P^6 = \begin{pmatrix} 0.557 & 0.442 \\ 0.557 & 0.442 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.000 & 0.000 & 1.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.285 & 0.428 & 0.142 & 0.142 & 0.000 \\ 0.000 & 0.050 & 0.450 & 0.050 & 0.000 & 0.000 \\ 0.187 & 0.125 & 0.250 & 0.187 & 0.250 & 0.000 \\ 0.187 & 0.125 & 0.250 & 0.187 & 0.250 & 0.000 \\ 0.000 & 0.000 & 0.500 & 0.000 & 0.000 & 0.500 \end{pmatrix}$$

STATE 2

$$P^{10} = \begin{pmatrix} 0.077 & 0.100 & 0.408 & 0.295 & 0.117 & 0.000 \\ 0.077 & 0.100 & 0.408 & 0.295 & 0.117 & 0.000 \\ 0.077 & 0.100 & 0.408 & 0.295 & 0.117 & 0.000 \\ 0.077 & 0.100 & 0.408 & 0.295 & 0.117 & 0.000 \\ 0.077 & 0.100 & 0.408 & 0.295 & 0.117 & 0.000 \\ 0.077 & 0.100 & 0.408 & 0.295 & 0.117 & 0.000 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 2)

<u>**ABCapital**</u>

<u>POPULATION:</u>

$$P = \begin{pmatrix} 0.504 & 0.496 \\ 0.496 & 0.504 \end{pmatrix}$$

STATE 1

$$P^5 = \begin{pmatrix} 0.499 & 0.500 \\ 0.499 & 0.500 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.000 & 0.285 & 0.142 & 0.285 & 0.285 & 0.000 \\ 0.000 & 0.193 & 0.258 & 0.419 & 0.096 & 0.032 \\ 0.011 & 0.129 & 0.364 & 0.352 & 0.105 & 0.035 \\ 0.047 & 0.141 & 0.317 & 0.364 & 0.105 & 0.023 \\ 0.020 & 0.000 & 0.306 & 0.163 & 0.163 & 0.346 \\ 0.100 & 0.000 & 0.300 & 0.100 & 0.200 & 0.300 \end{pmatrix}$$

STATE 2

$$P^6 = \begin{pmatrix} 0.305 & 0.116 & 0.317 & 0.314 & 0.126 & 0.094 \\ 0.305 & 0.116 & 0.317 & 0.314 & 0.126 & 0.094 \\ 0.305 & 0.116 & 0.317 & 0.314 & 0.126 & 0.094 \\ 0.305 & 0.116 & 0.317 & 0.314 & 0.126 & 0.094 \\ 0.305 & 0.116 & 0.317 & 0.314 & 0.126 & 0.094 \\ 0.305 & 0.116 & 0.317 & 0.314 & 0.126 & 0.094 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 2)

<u>SAMPLE:</u>

$$P = \begin{pmatrix} 0.375 & 0.625 \\ 0.583 & 0.416 \end{pmatrix}$$

STATE 1

$$P^5 = \begin{pmatrix} 0.482 & 0.517 \\ 0.482 & 0.517 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.000 & 1.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.250 & 0.000 & 0.500 & 0.025 & 0.000 \\ 0.067 & 0.067 & 0.467 & 0.267 & 0.067 & 0.067 \\ 0.058 & 0.176 & 0.294 & 0.411 & 0.000 & 0.058 \\ 0.000 & 0.000 & 0.200 & 0.200 & 0.200 & 0.400 \\ 0.000 & 0.000 & 0.333 & 0.333 & 0.000 & 0.333 \end{pmatrix}$$

STATE 2

$$P^7 = \begin{pmatrix} 0.039 & 0.158 & 0.281 & 0.345 & 0.073 & 0.102 \\ 0.039 & 0.158 & 0.281 & 0.345 & 0.073 & 0.102 \\ 0.039 & 0.158 & 0.281 & 0.345 & 0.073 & 0.102 \\ 0.039 & 0.158 & 0.281 & 0.345 & 0.073 & 0.102 \\ 0.039 & 0.158 & 0.281 & 0.345 & 0.073 & 0.102 \\ 0.039 & 0.158 & 0.281 & 0.345 & 0.073 & 0.102 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 2)

<u>**INFOSYS**</u>

POPULATION:

$$P = \begin{pmatrix} 0.312 & 0.688 \\ 0.699 & 0.300 \end{pmatrix}$$

STATE 1

$$P^3 = \begin{pmatrix} 0.504 & 0.496 \\ 0.504 & 0.496 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.000 & 0.100 & 0.400 & 0.400 & 0.100 & 0.000 \\ 0.125 & 0.083 & 0.125 & 0.583 & 0.041 & 0.041 \\ 0.025 & 0.062 & 0.300 & 0.475 & 0.112 & 0.025 \\ 0.018 & 0.110 & 0.339 & 0.431 & 0.082 & 0.018 \\ 0.047 & 0.190 & 0.428 & 0.285 & 0.047 & 0.000 \\ 0.200 & 0.000 & 0.800 & 0.000 & 0.000 & 0.000 \end{pmatrix}$$

STATE 2

$$P^7 = \begin{pmatrix} 0.036 & 0.096 & 0.324 & 0.437 & 0.084 & 0.020 \\ 0.036 & 0.096 & 0.324 & 0.437 & 0.084 & 0.020 \\ 0.036 & 0.096 & 0.324 & 0.437 & 0.084 & 0.020 \\ 0.036 & 0.096 & 0.324 & 0.437 & 0.084 & 0.020 \\ 0.036 & 0.096 & 0.324 & 0.437 & 0.084 & 0.020 \\ 0.036 & 0.096 & 0.324 & 0.437 & 0.084 & 0.020 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 2)

SAMPLE:

$$P = \begin{pmatrix} 0.320 & 0.680 \\ 0.653 & 0.346 \end{pmatrix}$$

STATE 1

$$P^6 = \begin{pmatrix} 0.490 & 0.509 \\ 0.490 & 0.509 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 1)

$$
P = \begin{pmatrix}
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0.046 & 0.458 & 0.416 & 0.041 & 0.041 \\
0 & 0.047 & 0.428 & 0.476 & 0.047 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
$$

STATE 2

$$
P^{10} = \begin{pmatrix}
0.036 & 0.096 & 0.324 & 0.437 & 0.084 & 0.020 \\
0.036 & 0.096 & 0.324 & 0.437 & 0.084 & 0.020 \\
0.036 & 0.096 & 0.324 & 0.437 & 0.084 & 0.020 \\
0.036 & 0.096 & 0.324 & 0.437 & 0.084 & 0.020 \\
0.036 & 0.096 & 0.324 & 0.437 & 0.084 & 0.020 \\
0.036 & 0.096 & 0.324 & 0.437 & 0.084 & 0.020
\end{pmatrix}
$$

SAMPLE STEADY STATE (MODEL 2)

ICICI Bank

POPULATION:

$$P = \begin{pmatrix} 0.419 & 0.581 \\ 0.523 & 0.477 \end{pmatrix}$$

STATE 1

$$P^3 = \begin{pmatrix} 0.473 & 0.526 \\ 0.473 & 0.526 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 1)

$$P = \begin{pmatrix} 0.000 & 0.167 & 0.500 & 0.333 & 0.000 & 0.000 \\ 0.065 & 0.161 & 0.290 & 0.452 & 0.032 & 0.000 \\ 0.012 & 0.072 & 0.325 & 0.434 & 0.133 & 0.024 \\ 0.022 & 0.152 & 0.304 & 0.380 & 0.109 & 0.033 \\ 0.038 & 0.115 & 0.500 & 0.192 & 0.115 & 0.038 \\ 0.000 & 0.286 & 0.571 & 0.000 & 0.000 & 0.143 \end{pmatrix}$$

STATE 2

$$P^7 = \begin{pmatrix} 0.024 & 0.126 & 0.342 & 0.376 & 0.102 & 0.029 \\ 0.024 & 0.126 & 0.342 & 0.376 & 0.102 & 0.029 \\ 0.024 & 0.126 & 0.342 & 0.376 & 0.102 & 0.029 \\ 0.024 & 0.126 & 0.342 & 0.376 & 0.102 & 0.029 \\ 0.024 & 0.126 & 0.342 & 0.376 & 0.102 & 0.029 \\ 0.024 & 0.126 & 0.342 & 0.376 & 0.102 & 0.029 \end{pmatrix}$$

POPULATION STEADY STATE (MODEL 2)

SAMPLE:

$$P = \begin{pmatrix} 0.419 & 0.581 \\ 0.469 & 0.531 \end{pmatrix}$$

STATE 1

$$P^6 = \begin{pmatrix} 0.474 & 0.526 \\ 0.474 & 0.526 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 1)

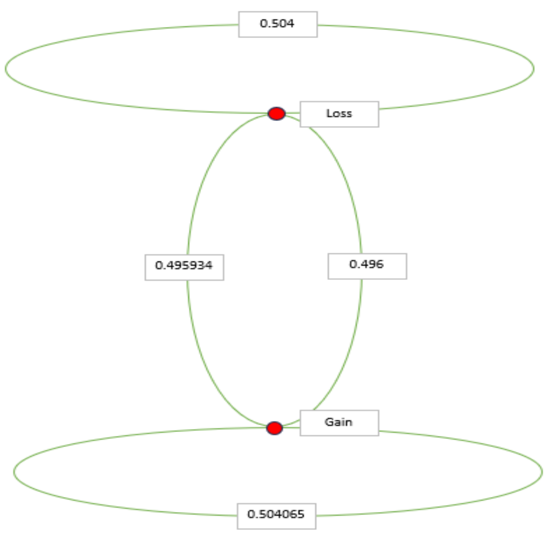
$$P = \begin{pmatrix} 0.000 & 0.000 & 1.000 & 0.000 & 0.000 \\ 0.143 & 0.286 & 0.286 & 0.143 & 0.143 \\ 0.000 & 0.050 & 0.400 & 0.450 & 0.100 \\ 0.063 & 0.125 & 0.250 & 0.375 & 0.188 \\ 0.000 & 0.333 & 0.500 & 0.167 & 0.000 \end{pmatrix}$$

STATE 2

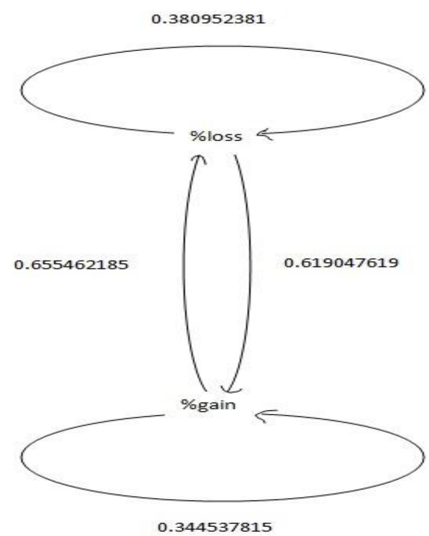
$$P^{10} = \begin{pmatrix} 0.041 & 0.139 & 0.280 & 0.330 & 0.119 \\ 0.041 & 0.139 & 0.280 & 0.330 & 0.119 \\ 0.041 & 0.139 & 0.280 & 0.330 & 0.119 \\ 0.041 & 0.139 & 0.280 & 0.330 & 0.119 \\ 0.041 & 0.139 & 0.280 & 0.330 & 0.119 \end{pmatrix}$$

SAMPLE STEADY STATE (MODEL 2)

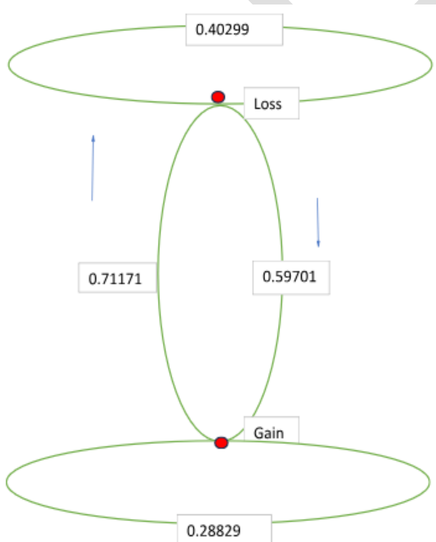
4. Transition diagram for individual stocks



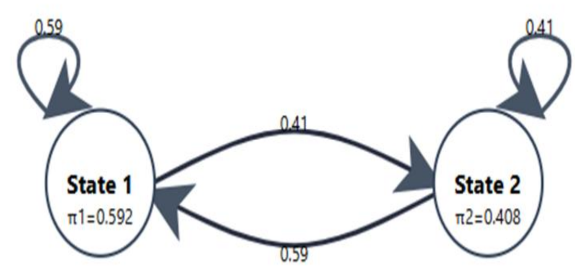
ABCapital Equity



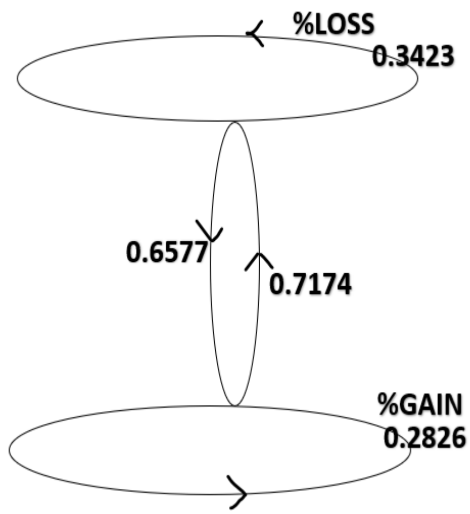
MRTI Equity



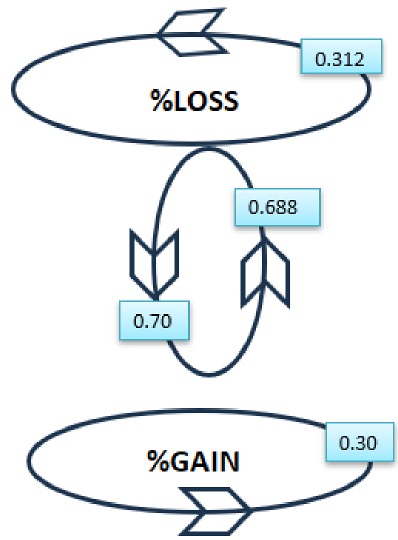
ITC Equity



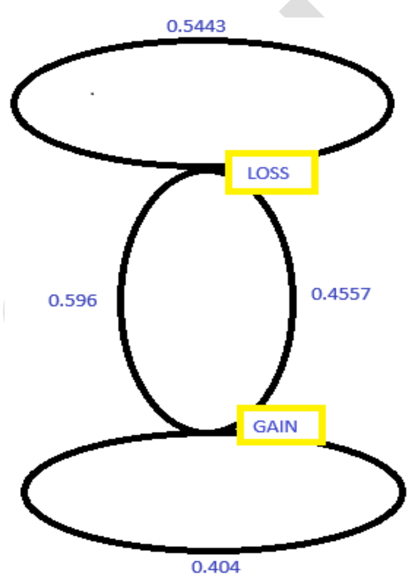
Nippon India ETF Gold BeES Equity



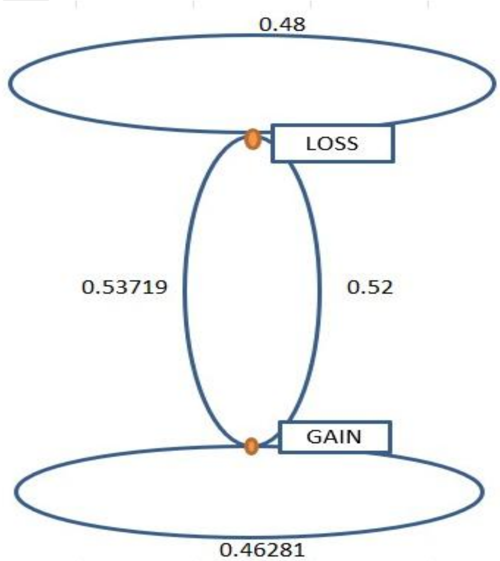
Tata motors Equity



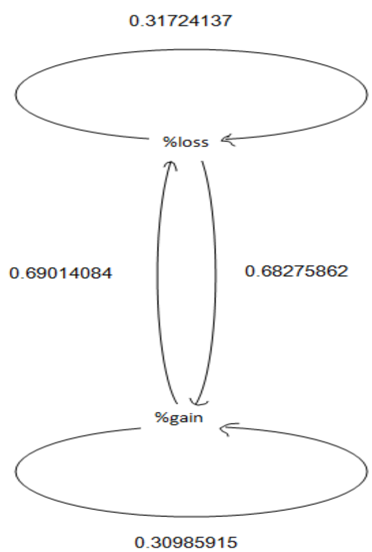
Infosys Equity



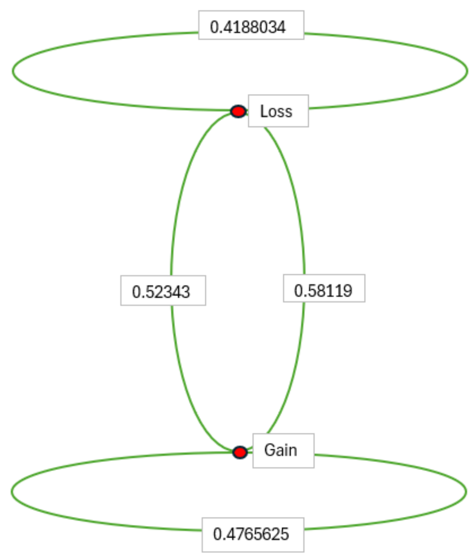
TCS Equity



HUL Equity



HDFC Bank Equity



ICICI Bank Equity

Summary Statistics for steady-state distributions and mean recurrent time for equities.

Equities	Steady state distribution: Loss	Gain	Mean recurrence time
NIP GOLD	0.4082	0.5918	2.0697
MARUTI SUZUKI	0.5142	0.4857	2.0016
TATA CONSULTANCY	0.5702	0.4299	1.7000
HINDUSTAN UNILEVER	0.5081	0.4919	2.1390
ITC	0.5438	0.4562	2.0062
TATA MOTORS	0.5245	0.4755	2.0038
INFOSYS	0.5043	0.5038	2.0172
ABCAPITAL	0.4374	0.5625	2.0000
HDFC BANK	0.5466	0.4534	2.2175
ICICI BANK	0.4739	0.5261	2.0055

Chi-Square Test for goodness of fit for the Markov Chain Model

Equity	Calculated	df	Tabulated
NIP GOLD	0.9297	1	6.635
MARUTI SUZUKI	8.0131	1	6.635
TATA CONSULTANCY	1.4680	1	6.635
HINDUSTAN UNILEVER	0.8050	1	6.635
ITC	2.1951	1	6.635
TATA MOTORS	3.2430	1	6.635
INFOSYS	5.6841	1	6.635
ABCAPITAL	2.0883	1	6.635
HDFC BANK	4.4933	1	6.635
ICICI BANK	1.9714	1	6.635

Stock Behaviour

ADITYA BIRLA CAPITAL

The transition matrix for ABC indicates a 43% chance of staying in a % loss state and a 49.6% chance of switching from % loss to % gain. Additionally, there is a 49.59% chance of transitioning from a gain state to a loss state, and a 56% chance of maintaining a gain state. The mean recurrent time to return to a gain state is 2.0000009 days.

HDFC

The transition matrix for HDFC BANK indicates a 50.27% chance of staying in a % loss state and a 49.73% chance of switching from % loss to % gain. Additionally, there is a 50.27% chance of transitioning from a gain state to a loss state, and a 49.73% chance of maintaining a gain state. The mean recurrent time to return to a gain state is 2.2 days. This symmetry implies that while HDFC Bank exhibits a balanced likelihood of sustaining gains or losses, recoveries take relatively longer, making it more suitable for medium-term strategies that prioritize stability rather than rapid, short-term tactical plays.

HUL

The transition matrix for HUL indicates a 48% chance of staying in a % loss state and a 53.72% chance of switching from % loss to % gain. Additionally, there is a 52% chance of transitioning from a gain state to a loss state, and a 46.28% chance of maintaining a gain state. The mean recurrent time to return to a gain state is 2.138979014 days.

ITC

The transition matrix for ITC indicates a 53% chance of staying in a % loss state and a 59.7% chance of switching from % loss to % gain. Additionally, there is a 71.17% chance of transitioning from a gain state to a loss state, and a 47% chance of maintaining a gain state. The mean recurrent time to return to a gain state is 2.006 days.

INFOSYS

The transition matrix for Infosys indicates a 50% chance of staying in a % loss state and a 50% chance of switching from % loss to % gain. Additionally, there is a 68% chance of transitioning from a gain state to a loss state, and a 32% chance of maintaining a gain state. The mean recurrent time to return to a gain state is 2.0172 days.

NIPPON GOLD

The transition matrix for Nippon Gold ETF indicates a 59% chance of staying in a gain state and a 41% chance of switching from a loss state to a gain state. Additionally, there is a 41% chance of transitioning from a gain state to a loss state, and a 59% chance of maintaining a gain state. The mean recurrent time to return to a gain state is 2.0697 days.

MARUTI SUZUKI

The transition matrix for MRTI indicates a 38% chance of staying in a % loss state and a 61.90% chance of switching from % loss to % gain. Additionally, there is a 65.54% chance of transitioning from a gain state to a loss state, and a 34.45% chance of maintaining a gain state.The mean recurrent time to return to a gain state is 2.05 days and that to return to a loss state is 1.944 days. This shows that both states recur quickly however down days recur slightly faster than up days and since both recurrence times are close to 2, it suggests the market has an oscillating behaviour rather than a long bullish or bearish streak.

TATA CONSULTANCY SERVICES

The transition matrix for TCS indicates a 54.4% chance of staying in a % loss state and a 45.5% chance of switching from % loss to % gain. Additionally, there is a 59.6% chance of transitioning from a gain state to a loss state, and a 40.4% chance of maintaining a gain state. The mean recurrent time to return to a gain state is 2.534days and that to return to a loss state is 1.652 days.

TATA MOTORS

The transition matrix for TATA Motors indicates a 34.23% chance of staying in a % loss state and a 65.77% chance of switching from % loss to % gain. Additionally, there is a 71.74% chance of transitioning from a gain state to a loss state, and a 28.26% chance of maintaining a gain state.This asymmetry implies that while Tata Motors tends to recover quickly from downturns, upward movements are often short-lived, pointing to its suitability for short-term tactical strategies rather than momentum-driven long-term positions. The mean recurrent time to return to a gain state is 2.00377 days.

ICICI BANK

The transition matrix for ICICI Bank indicates a 41.88% chance of staying in a % loss state and a 58.12% chance of switching from % loss to % gain. Additionally, there is a 52.34% chance of transitioning from a gain state to a loss state, and a 47.65% chance of maintaining a gain state. The mean recurrent time to return to a gain state is 1.9 days and that to return to a loss state is 2.11 days.

Conclusion

The Markov chain analysis of ABC Capital shows that the stock is moderately volatile, with daily returns mostly clustered around small gains or losses and only occasional extreme moves. Transition probabilities highlight a mean-reverting pattern, where the stock tends to cycle between short bursts of growth and subsequent corrections rather than sustaining bullish trends for long. Overall, this suggests that ABC Capital is better suited for short- to medium-term strategies where investors can capitalize on its frequent fluctuations, rather than for long-term stable growth. The six-state transition probability model (Model 1) for HDFC Bank reveals a whipsaw-like behavior, with transitions showing nearly equal probabilities of moving between gain and loss states. This indicates a volatile, mean-reverting market structure where price direction frequently alternates without establishing strong bullish or bearish trends. Such dynamics characterize a sideways market environment, offering opportunities for short-term tactical trading strategies but making the stock comparatively less attractive for long-term passive holding.

The Markov model analysis for HUL's stock reveals and strongly shows the stock gravitates toward the mid-range (States 3 and 4), with State 4 being the dominant State. States 1 and 6 are sharp ups and downs and are not persistent. The 2-state model reinforces this, showing a frequent, balanced switching between states without a strong long-term directional bias. Consequently, the stock is better suited for range-bound trading strategies rather than momentum breakout plays. ITC's stock price generally shows small daily ups and downs, while large jumps (either upward or downward) are relatively rare. This indicates that the stock has a stable pattern of fluctuations with limited extreme volatility. The behaviour of the stock in the long run will have the Probability of being in a loss state is ~52.8%, while the chance of being in a gain state is ~47.2%. Although the probability of loss is slightly higher, the transition probability from loss to gain is strong, showing that ITC often recovers after a decline. The stock demonstrates low volatility, with most movements falling in the category of small gains or small losses. This stability makes ITC suitable for risk-averse investors who prefer steady and predictable performance over sudden swings. The Infosys stock displays a stagnant behaviour. The profit and loss for the same are equal creating a null effect. Major Fluctuations are a rare cause. This indicates that the stock has a stable pattern of fluctuations with limited extreme volatility. The behaviour of the stock in the long run will have a Probability of being in a loss state is ~50.428%, while the chance of being in a gain state is ~50.37%. The result portrays stagnation with the price resulting in no profits or losses. The stock demonstrates low volatility, with most movements falling in the category of small gains or small losses. This stability makes Infosys suitable for risk-averse investors who prefer steady and predictable performance over sudden swings.

The Markov analysis shows that the Nippon Gold ETF has a higher chance of rising than falling, with gains being more consistent than losses. Small price changes occur frequently, while large movements are rare but are persistent once they occur. In the long run, the ETF tends to stay in a gain state about 59% of the time, compared to 41% for losses. It displays a mild upward trend momentum that suggests short-term gains are more likely to continue rather than reverse. The Nippon Gold ETF tends to stay in gains more often than losses, making it a steady option. It can be a good choice for investors as a safe hedge with some growth potential in their portfolio. The

TPM of MRTI reveals a notable trend: there is a greater likelihood of transitioning to a state of loss than a state of gain. This is not a positive indicator for investors as the steady state probabilities suggest that days of losses are more probable than days of gains in both MRTI stock and the sample selected of 50 observations. This indicates a market that is prone to large, sustained swings, which is discouraging for investors focusing on long term growth and stability.

The TPM of TCS reveals a trend of transitioning to a state of loss rather than a state of gain. This is not a positive indicator for investors as the steady state probabilities suggest that days of losses are more probable than days of gains in both TCS stock and the sample selected observations. This indicates a market that is prone to large, sustained swings, which is discouraging for investors focusing on long term growth and stability. The six-state transition probability model (Model 1) for Tata Motors indicates a pronounced tendency toward central states i.e., small gains (State 3) and small losses (State 4) which exhibit the highest transition probabilities. This pattern reflects a stable price behaviour characterized by modest daily fluctuations, with moderate gains and losses occurring at a reasonable frequency and large jumps remaining infrequent. Such dynamics suggest a balanced risk-return profile, favourable for long-term investors seeking predictability and low volatility. The Sample TPM of ICICI Bank reveals a trend that there is a higher likelihood of transitioning to a state of loss than a state of gain, However, this contradicts the Population TPM. This is not a positive indicator for investors as the steady state probabilities suggest different outcomes in the ICICI stock Population and the sample selected observations.

Statistical Validation

The Chi-square test results across Aditya Birla Capital, HDFC, ITC, Infosys, Nippon Gold, Tata Consultancy, Tata Motors, ICICI, and HUL confirm a strong fit for the Markov chain model, indicating that their stock price movements are systematic rather than random, often showing tendencies like mean-reversion, frequent state switching, and memoryless behavior. Hul also demonstrated statistical stability and low volatility, reinforcing its reliability for long-term investors. Overall, these findings validate the use of Markovian analysis for understanding price dynamics in these stocks.

Portfolio Selection

The findings reveal distinct behavioural patterns in terms of volatility, resilience, and trends, allowing for a balanced and diversified portfolio structure. The suggested composition integrates risk averse, cyclical and market-timing adjustments to ensure both stability and growth potential.

Among the risk averse assets, **ITC**, **Infosys**, and **HUL** exhibit low volatility and consistent mean-reverting behaviour. These stocks demonstrate steady recovery from minor losses and limited extreme fluctuations, making them ideal for forming the stable foundation of the portfolio. Their predictable movement patterns indicate long-term reliability and are well suited for investors who prefer stability over rapid gains.

Mean-reverting dynamics are suggested by **Aditya Birla Capital** and **ICICI Bank's** moderate volatility and frequent recoveries after brief declines. This kind of behavior suggests that these stocks do well during cyclical periods and present chances for modest short- to medium-term returns. Their addition improves the portfolio's capacity to adjust to changes in the market without taking on undue risk.

Tata Motors, Maruti Suzuki, and the Nippon Gold ETF all exhibit more active price changes and stronger short-term momentum, which contributes to the more dynamic component. For longer periods of time, Nippon Gold typically stays in gain states, offering an average upward trend appropriate for tactical positioning. Tata Motors and Maruti Suzuki, on the other hand, show rapid fluctuations between profit and loss states, which opens possibilities for short-term trading strategies and increases agility.

The transition probabilities of **HDFC Bank and Tata Consultancy Services** show little directional movement and are either balanced or slightly loss-prone. These stocks can play a supporting role by increasing diversification and promoting medium-term stability, even though they are not appropriate as main growth drivers.

All things considered, the suggested portfolio blends tactical flexibility, cyclical adaptability, and defensive stability. While moderately dynamic assets like ICICI Bank and Aditya Birla Capital improve recovery potential, stable stocks like ITC, Infosys, and HUL offer resilience against volatility. Opportunities for active gain optimization are introduced by the tactical component, which is represented by Tata Motors and Nippon Gold ETF. The goal of attaining stable yet responsive portfolio performance in a range of market conditions is in line with this integrated structure, which exhibits a balanced approach.

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