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Analysing The Impact Of COVID-19 On Indian Stock Market Trends Using Markov Models

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Abstract
This study investigates the impact of COVID-19 on the stock prices of three major Indian companies: State Bank of India (SBI), HDFC, and Tata Consultancy Services (TCS). Utilising a stochastic Markov model, the research analyses transition probability matrices (TPMs) and initial probability vectors (IPVs) to capture the dynamics of stock price movements before, during, and after the pandemic. The analysis segments the data into three distinct periods and computes statistical characteristics and stationary matrices to understand the long-term equilibrium states of these stocks. The findings reveal significant variations in stock price behaviours across the different periods, providing valuable insights for investors and portfolio managers to optimize their investment strategies amidst economic disruptions caused by the pandemic. This comprehensive study offers actionable recommendations to navigate market dynamics effectively and mitigate risks.

***Keywords**: Covid-19, NSE, BSE, Markov Model, Transition Probability Matrix, Initial Probability Vector.*

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I. Introduction

The financial market is a dynamic ecosystem where organisations, governments, and individuals transact various financial assets, such as derivatives, stocks, bonds, currencies, and commodities. This market is vital for risk management, efficient capital allocation, and driving economic growth. In India, it is divided into the primary market, where new securities are issued, and the secondary market, where existing securities are traded. Major exchanges like NASDAQ and NYSE exemplify secondary markets that facilitate liquidity and price discovery.

Stock markets play a pivotal role by providing platforms for trading shares, facilitating capital formation, and creating investment opportunities. Key components include regulated venues like the over-the-counter (OTC) market, NASDAQ, and NYSE. Participants such as market makers, specialists, traders, and investors collectively maintain liquidity and ensure smooth transactions. Stock market performance is influenced by government policies, global economic trends, supply and demand dynamics, and monetary policies set by regulatory bodies like the Reserve Bank of India (RBI) and the Securities and Exchange Board of India (SEBI). External factors such as natural calamities, currency exchange rates, technological advancements, geopolitical events, and economic indicators like GDP and oil prices also impact market dynamics. In India, the Bombay Stock Exchange (BSE) and the National Stock Exchange of India (NSE) are key players, contributing significantly to capital market development and economic stability. SEBI regulates market participants to ensure investor protection and market integrity, despite some criticisms regarding transparency.

Researchers have employed a variety of mathematical models and techniques to analyse and forecast stock market behaviour across different regions and markets. Deju Zhang (2009) utilized the Markov model to examine fluctuations in China's share market volatility, while Xiangyi Meng et al. (2015) applied diverse mathematical models for stock movement analysis. Rene D. Estember and Michael John R. Marana (2016) employed geometric Brownian motion (GBM) and Monte Carlo simulation to forecast share prices, asserting GBM's accuracy over techniques like Artificial Neural Network (ANN). Priti Mohite et al. (2018) utilized the Markov chain model to analyse optimal investment strategies in the financial market.

Additionally, Wajeeh Mustafa Sarsour and Shamsul Rijal Muhammad Sabri (2019) used the Markov chain approach to analyse the behaviour of the Malaysian stock market. Nopmanee Parungrojrat and Akaranant Kidsom (2019) employed Brownian motion process and Monte Carlo simulation to forecast selected stocks in SET50. Azubuike Samuel & Ephraim Okon (2020) utilized the Markov model to analyse share market trends, while Azubuike Samuel (2020) focused on the Nigerian Stock Market using the Markov chain model. Siti Raihana Hamzah et al. (2021) applied the Brownian motion model to assess Nestle stock prices.

Furthermore, Padi T. R. et al. (2022) employed Markov models to analyze the spread of COVID-19 in neighbouring Southern states. Tong Wang et al. (2022) utilized a hidden Markov model to assess the performance of companies like Apple and Google. Ranganath Kanakam et al. (2022) utilized machine learning tools for historical data analysis and future performance prediction of shares. Shuaiqi Zhou (2023) adopted the Brownian Motion process for an optimal investment policy, and David Umoru (2023) examined the link between exchange rate devaluation and stock prices in African stock markets.

Moreover, Zebin Guo (2024) employed various statistical techniques for share performance evaluation, while Riza Demirer et al. (2024) used forecasting techniques for predicting aggregate stock market prices in Borsa Istanbul. Lu Xu et al. (2024) explored the connection between investor sentiment and China's stock market, and Tran Phuoc et al. (2024) utilized statistical techniques like simple moving averages and convergence divergence moving average for share price prediction in the financial market.

Through extensive literature review, it is clear that most financial market research employs classical approaches or existing models, with a gap in studies focusing on parameter extraction, novel model development, and statistical characteristic computation. This gap motivates the present study.

Our study adopts a Markov model, focusing on constructing the Transition Probability Matrix (TPM) and the Initial Probability Vector (IPV) to establish probability distributions. We gather real-time data from public and private banking sectors and an IT company, conduct numerical illustrations, and perform comparative analyses.

The main objectives are: (i) Construct the parameters of the Markov model. (ii) Formulate probability distributions using TPM and IPV. (iii) Develop statistical characteristics based on these distributions. (iv) Collect real-time data from SBI, HDFC, and TCS, segregated into before, during, and after COVID-19. (v) Explore probability distributions for each data set. (vi) Compute statistical characteristics from different data sets. (vii) Illustrate comparative analysis results.

This study aims to fill the literature gap by providing a comprehensive understanding of market behaviour through the Markov model, contributing valuable insights to financial market analysis and statistical modeling.

II. Stochastic Model

Markov model is a kind of stochastic model. The basic essence of the Markov chains is that the future is not affected by the past but by the current happening only. This model consists of two parameters namely Transition Probability Matrix and Initial Probability Vector.

Transition Probability Matrix (TPM)

A transition probability matrix (TPM), also known as a stochastic matrix. The state transition probability matrix of a Markov chain gives the probabilities of transition from one state to another in a single time unit. The TPM assumptions while constructing the TPM are,

(i) The TPM must be a square matrix, (ii) The elements in TPM must be probabilities, and (iii) Each row sum should be equal to 1.

Whenever the row and column sum equal to 1; that kind of matrix in known as a doubly Stochastic matrix. The TPM's mathematical notation is given below

$$\mathrm{P} = [p_{ij}]_{3\times 3} \quad \forall i, j = 1,2,3$$

Where 'i' is the original state, 'j' is the destination state in the transition states.

Initial Probability Vector (IPV)

The IPV in Markov model represents the chance of likelihood of happening particular state in the process. The total of all likelihood in the IPV must be 1.

$$\pi = (\pi_1, \pi_2, \pi_3) \quad \Rightarrow \sum_{i=1}^{3} \pi_i = 1$$

The mathematical notation of Markov model is as follows:

$$P(X_{t+1} = S | X_0, X_1, \ldots, X_t) = P(X_{t+1} = S | X_t) \vee t \geq 0.$$

$$\text{i.e} \quad p_{ij} = P(X_{n+1} = j | X_n = i)$$

The focus of the study on the current research study is to understand the effect of COVID-19 on stock values. In this connection, we have considered three states namely, State- 1 as Increment, State-2 as Remain Same, and State-3 as Decrement state. Figure 2 represents the schematic diagram of the Markov model.

Schematic Diagram of the Model

The Markov model is illustrated in the schematic diagram shown in Figure 1.

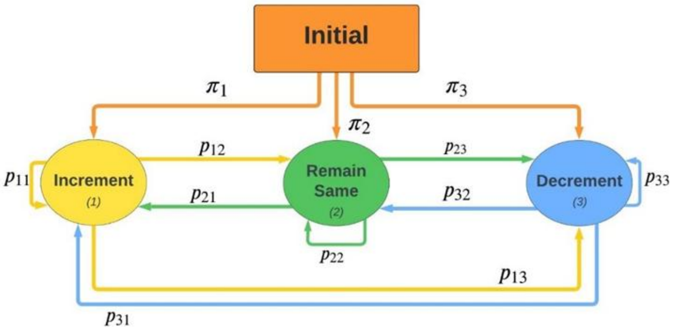

Figure 1: Schematic Diagram for Markov model

Here, π_1, π_2, and π_3 represents the Increment, Remain same and Decrement states respectively.

Probability Distribution for Increment State

Let $X(\omega)$ be a random variable denoting the occurrence of the Increment state. This variable can take on values of 0 or 1, where a value of '0' indicates the absence of the Increment state, and a value of '1' indicates its presence. The probability distribution of Increment state is

$$P[Y(\omega)] = \begin{cases} \sum_{j=1, j\neq 2}^{3} \sum_{i=1}^{3} \pi_i p_{ij} \quad \forall\, i, j = 1,3 & ; \text{for } Y(\omega) = 0 \\ \sum_{i=1}^{3} \pi_i p_{i2} & ; \text{for } Y(\omega) = 1 \\ 0 & ; \text{otherwise} \end{cases} \tag{2.8}$$

Statistical Characteristics of Probability Distributions of Increment State

This section describes the statistical measures or metrics of developed probability distribution placed in the equation 2.1.

2.4.1.1. Average number of times happening of Increment state

$$E[X(\omega)] = \alpha(\omega);\ \alpha(\omega) = \textstyle\sum_{i=1}^{3} \pi_i p_{ij} \ \ \forall\, j = 1,2,3 \tag{2.2}$$

2.4.1.2. Variance of Increment state

$$V[X(\omega)] = \alpha(\omega)[1 - \alpha(\omega)];\ \text{where } \alpha(\omega) = E[X(\omega)] \tag{2.3}$$

2.4.1.3. Third Central Moment for Increment state

$$\mu_3[X(\omega)] = \alpha(\omega)[1 - \alpha(\omega)][1 - 2\alpha(\omega)] \tag{2.4}$$

2.4.1.4. Pearson's Coefficient of Skewness for Increment state

$$\beta_1[X(\omega)] = [\alpha(\omega)[1 - \alpha(\omega)]][1 - 2\alpha(\omega)]]^2 [\alpha(\omega)[1 - \alpha(\omega)]]^{-3} \tag{2.5}$$

2.4.1.5. Pearson's coefficient of kurtosis for Increment state

$$\beta_2[X(\omega)] = [\alpha(\omega)[1 - \alpha(\omega)]^2[1 - 3\alpha(\omega)][1 - \alpha(\omega)]][\alpha(\omega)[1 - \alpha(\omega)]]^{-2} \tag{2.6}$$

2.4.1.6. Coefficient of variation for Increment state

$$CV[X(\omega)] = [\alpha(\omega)\ [1 - \alpha(\omega)]]^{1/2}[\alpha(\omega)]^{-1} \tag{2.7}$$

Probability Distribution for Remain Same State

Let $Y(\omega)$ be a random variable denoting the occurrence of the Remain same state. This variable can take on values of 0 or 1, where a value of '0' indicates the absence of the Remain same state, and a value of '1' indicates its presence. The probability distribution of Remain same state is

$$P[Y(\omega)] = \begin{cases} \sum_{j=1, j\neq 2}^{3} \sum_{i=1}^{3} \pi_i p_{ij} \quad \forall\, i, j = 1,3 & ; \text{for } Y(\omega) = 0 \\ \sum_{i=1}^{3} \pi_i p_{i2} & ; \text{for } Y(\omega) = 1 \\ 0 & ; \text{otherwise} \end{cases} \tag{2.8}$$

Statistical Characteristics of Probability Distributions of Remain Same State

This section describes the statistical measures or metrics of developed probability distribution placed in the equation 2.8.

2.5.1.1 Average number of times happening of Remain same state

$$E[Y(\omega)] = \beta(\omega); \quad \beta(\omega) = \sum_{i=1}^{3} \pi_i p_{ij} \quad \forall j = 1,2,3 \tag{2.9}$$

2.5.1.2 Variance of Remain same state

$$V[Y(\omega)] = \beta(\omega)[1 - \beta(\omega)] \tag{2.10}$$

2.5.1.3 Third Central Moment for Remain same state

$$\mu_3[Y(\omega)] = \beta(\omega)[1 - \beta(\omega)][1 - 2\beta(\omega)] \tag{2.11}$$

2.5.1.4 Pearson's Coefficient of Skewness for Remain same state

$$\beta_1[Y(\omega)] = [\beta(\omega)[1 - \beta(\omega)]][1 - 2\beta(\omega)]]^2 [\beta(\omega)[1 - \beta(\omega)]]^{-3} \tag{2.12}$$

2.7.2.5 Pearson's coefficient of kurtosis for Remain same state

$$\beta_2[Y(\omega)] = [r(\omega)[1 - r(\omega)]^2[1 - 3r(\omega)][1 - r(\omega)]][r(\omega)[1 - r(\omega)]]^{-2} \tag{2.13}$$

2.5.1.6 Coefficient of variation for Remain same state

$$CV[Y(\omega)] = [\beta(\omega)\,[1 - \beta(\omega)]]^{1/2}[\beta(\omega)]^{-1} \tag{2.14}$$

Probability Distribution for Decrement State

Let $Z(\omega)$ be a random variable denoting the occurrence of the Decrement state. This variable can take on values of 0 or 1, where a value of '0' indicates the absence of the Decrement state, and a value of '1' indicates its presence. The probability distribution of Decrement state is

$$P[Z(\omega)] = \begin{cases} \sum_{j=1}^{2}\sum_{i=1}^{3} \pi_i p_{ij} \quad \forall i,j = 1,2 & ; \text{for } Z(\omega) = 0 \\ \sum_{i=1}^{3} \pi_i p_{i3} & ; \text{for } Z(\omega) = 1 \\ 0 & ; \text{otherwise} \end{cases} \tag{2.15}$$

Statistical Characteristics of Probability Distributions of Decrement State

This section describes the statistical measures or metrics of developed probability distribution placed in the equation 2.15.

2.6.1.1 Average number of times happening of Decrement state

$$E[Z(\omega)] = \gamma(\omega); \quad \gamma(\omega) = \sum_{i=1}^{3} \pi_i p_{ij} \quad \forall j = 1,2,3 \tag{2.16}$$

2.6.1.2 Variance of Decrement state

$$V[Z(\omega)] = \gamma(\omega)[1 - \gamma(\omega)] \tag{2.17}$$

2.6.1.3 Third Central Moment for Decrement state

$$\mu_3[Z(\omega)] = \gamma(\omega)[1 - \gamma(\omega)][1 - 2\gamma(\omega)] \tag{2.18}$$

2.6.1.4 Pearson's Coefficient of Skewness for Decrement state

$$\beta_1[Z(\omega)] = [\gamma(\omega)[1 - \gamma(\omega)]][1 - 2\gamma(\omega)]]^2 [\gamma(\omega)[1 - \gamma(\omega)]]^{-3} \tag{2.19}$$

2.6.1.5 Pearson's coefficient of kurtosis for Decrement state

$$\beta_2[Z(\omega)] = [\gamma(\omega)[1 - \gamma(\omega)]^2[1 - 3\gamma(\omega)][1 - \gamma(\omega)]][\gamma(\omega)[1 - \gamma(\omega)]]^{-2} \tag{2.20}$$

2.6.1.6 Coefficient of variation for Decrement state

$$CV[Z(\omega)] = [r(\omega)\,[1 - r(\omega)]]^{1/2}[r(\omega)]^{-1} \tag{2.21}$$

Stationary Matrix

A higher-order transition probability matrix is used in the context of Markov chains and represents the probabilities of transitioning between states over multiple steps or periods. Here's a formal definition:

Let P be the one-step transition probability matrix of a Markov chain. The higher-order transition probability matrix, $P^{(n)}$, represents the probabilities of transitioning between states over n steps. It is defined as follows:

One-Step Transition Probability Matrix

$P = [p_{ij}]$ where p_{ij} is the probability of transitioning from state i to state j in one step.

Higher-Order (n-step) Transition Probability Matrix

$P^{(n)} = P^n$

where P^n is the matrix obtained by multiplying the one-step transition matrix P by itself n times. Mathematically:

$P^{(n)} = P.P.P\ldots\ldots P$ (n time)

Each element $P^{(n)}$of $P^{(n)}$ represents the probability of transitioning from state i to state j in n steps.

III. Data Collection And Methodology

This study investigates the impact of COVID-19 on the Indian stock market by analysing the historical opening and closing stock prices of three major companies: State Bank of India (SBI), Housing Development Finance Corporation Bank (HDFC), and Tata Consultancy Services (TCS). The stock price data were obtained from finance.yahoo.com and segmented into three periods: before COVID-19 (November 1, 2017, to October 31, 2019), during COVID-19 (November 1, 2019, to October 31, 2021), and after COVID-19 (November 1, 2021, to November 31, 2023). To assess the stock price movements, the study employs the method of first order finite differences, defined as i.e., d_t stock price (either opening or closing) on day t and y_{t-1} day.

The finite differences d_t where then classified into three states to determine the nature of stock price movements. State-1(Increment) is defined as $d_t \geq \mu + 3\frac{\sigma}{\sqrt{n}}$, indicating a significant positive change in stock prices, where is the mean and is the standard deviation of the differences over the period, and is the number of observations. State-2 (Remain Same) covers the range if $\mu - 3\frac{\sigma}{\sqrt{n}} < d_t < \mu + 3\frac{\sigma}{\sqrt{n}}$, representing typical fluctuations within three standard deviations of the mean, indicating stability or normal market volatility. State-3 (Decrement) is defined as $d_t \leq \mu - 3\frac{\sigma}{\sqrt{n}}$, indicating a significant negative change in stock prices.

By comparing the opening and closing prices, this classification framework allows for a detailed analysis of the stock price behaviour in different periods relative to the COVID-19 pandemic. It helps identify significant trends and anomalies in the stock market by comparing the frequency and magnitude of Increments, Decrements, and stable periods across the three defined time frames. This analysis provides valuable insights into how the pandemic has affected market behaviour and helps in understanding the broader economic impacts. Additionally, it aids in developing future market predictions and investment strategies by highlighting how major financial events influence stock prices.

In the below table 1 t, O_t, and do_t represents the date, opening price and finite difference in the opening price of SBI respectively.

In the below table 2 t, C_t, and dc_t represent the date, closing price and finite difference in the closing price of SBI respectively.

Specimen Data of SBI open price

S.No.	t	O_t	do_t	state
1	01-11-2017	309.4	-	-
2	02-11-2017	320	10.60001	Increment
3	03-11-2017	315.45	-4.54999	Decrement
. . .	. . .	. . .	. . .	. . .
489	29-10-2019	283.15	-1.80002	Decrement
490	30-10-2019	283	-0.14999	Remain Same
491	31-10-2019	293.35	10.35001	Increment

Table 1: Specimen data of SBI open price

Specimen Data of SBI close price

S.No.	t	C_t	dc_t	state
1	01-11-2017	319.85	-	-
2	02-11-2017	314.35	-5.5	Decrement
3	03-11-2017	325	10.64999	Increment
. . .	. . .	. . .	. . .	. . .
489	29-10-2019	280.65	-1.14999	Decrement
490	30-10-2019	289.9	9.25	Increment

491	31-10-2019	312.4	22.50001	Increment

Table 2: Specimen data of SBI close price

Data Collection and Description

The data collected includes the historical stock prices, specifically the opening and closing prices for SBI, HDFC, and TCS, across the specified periods. This data forms the basis for understanding the stock price movements and their response to the pandemic.

To analyse the stock price movements, the first order finite differences method is used. This involves calculating the difference between the stock prices of consecutive days:

$$d_t = y_t - y_{t-1}$$

The stock movements are classified into three states based on the first-order finite differences and their relation to the mean (μ) and standard deviation (σ) of the differences over a given period.

Explored TPM, and IPV all data sets. An extensive analysis was conducted on the opening and closing prices of stocks from SBI, HDFC, and TCS, spanning three distinct time periods: pre-COVID-19, during the COVID-19 pandemic, and post-COVID-19. Probability distributions were meticulously formulated to accurately model the data for each time period and stock individually. Essential statistical measures, such as mean, variance, third central moment, skewness, kurtosis, and coefficient of variation, were rigorously computed to comprehensively characterize the distribution properties across these states and datasets.

IV. Data Analysis And Discussion

TPMs Calculation and Analysis

Understanding transition trends in stock movements is crucial for investors and portfolio managers, especially during volatile times like the COVID-19 pandemic. Let's delve into the transition probabilities observed in prominent stocks such as SBI, HDFC, and TCS.

Transition Probability Matrix for opening and closing prices of SBI

		(1,1)	(1,2)	(1,3)	(2,1)	(2,2)	(2,3)	(3,1)	(3,2)	(3,3)
Open	Before	0.3493	**0.1005**	**0.5502**	0.4815	0.1667	0.3519	0.4889	0.1067	0.4044
	During	0.3861	**0.1238**	**0.4901**	0.4789	0.1549	0.3662	0.4009	0.1577	0.4414
	After	0.4147	0.1843	0.4009	0.4079	0.1842	0.4079	**0.4776**	**0.1095**	0.4129
Close	Before	0.4049	0.1366	0.4585	0.3788	0.1364	**0.4848**	0.4516	**0.1336**	0.4147
	During	0.4245	**0.1179**	0.4575	**0.5075**	0.1642	0.3284	0.4074	0.1435	0.4491
	After	0.4299	0.1403	0.4299	0.3939	**0.1212**	**0.4848**	0.4783	0.1353	0.3865

Table 3: TPM matrix of SBI open and close price

Interpreting the transition probabilities in the Table 3 involves analysing how values change across the three time points (Before, During, and After) for both stock prices (Open, Close). The higher and lower transition probabilities indicate a higher likelihood or greater magnitude a lower likelihood or smaller magnitude of the measured variable.

SBI Opening Share Price Before COVID-19:

Higher Values: Indicate stronger or more prevalent initial conditions for the variables.

A value of 0.5502 at previous day's Increment to the current day's Decrement state (1,3) suggests a relatively strong initial state for this variable.

Lower Values: Indicate weaker or less prevalent initial conditions. A value of 0.1005 at previous day's Increment to the current day's Remine same state (1,2) suggests a relatively weak initial state for this variable.

During COVID-19:

Higher Values: Suggest an increase or sustained high levels of the variable. The value of 0.4901 at previous day's Increment to the current day's Decrement state (1,3) shows a slight decrease from Before but still a relatively high value, indicating sustained presence.

Lower Values: Suggest a decrease or low levels of the variable. The value of 0.1238 at previous day's Increment to the current day's Remind same state (1,2) shows a slight increase from Before but still remains relatively low.

After COVID-19:

Higher Values: Suggest that the variable has either remained high or increased from the initial state. A value of 0.4776 at previous day's Decrement to the current day's Increment state (3,1) indicates a higher value compared to the initial state, suggesting an overall increase.

Lower Values: Suggest that the variable has either remained low or decreased from the initial state. A value of 0.1095 at previous day's Decrement to the current day's Remind same state (3,2)indicates a lower value compared to the initial state, suggesting an overall decrease.

By examining the higher and lower values of the opening price of SBI before, during, and after COVID-19, we can observe trends in how the variables were impacted, identifying areas of resilience, growth, decline, or recovery.

SBI Closing Share Price Before COVID-19:

Higher Values: Indicate stronger or more significant initial conditions for the variables. A value of 0.4848 at previous day's Remind same to the current day's Decrement state (2,3) suggests a strong initial state for this variable.

Lower Values: Indicate weaker or less significant initial conditions. A value of 0.1364 at previous day's Remind same to the current day's Remind same state (2,2) suggests a relatively weak initial state for this variable.

During COVID-19:

Higher Values: Suggest an increase or sustained high levels of the variable. The value of 0.5075 at previous day's Remind same to the current day's Increment state (2,1) indicates an increase from Before, showing an upward trend.

Lower Values: Suggest a decrease or low levels of the variable. The value of 0.1179 at previous day's Increment to the current day's Remind same state (1,2) indicates a slight decrease from Before, showing a downward trend.

After COVID-19:

Higher Values: Suggest that the variable has either remained high or increased from the initial state. A value of 0.4848 at previous day's Remind same to the current day's Decrement state (2,3) suggests a sustained high value or a return to a high state after a temporary change.

Lower Values: Suggest that the variable has either remained low or decreased from the initial state. A value of 0.1212 at previous day's Remind same to the current day's Remind same state (2,2) suggests a decrease or sustained low value after a temporary change.

By examining the higher and lower values of the closing price of SBI before, during, and after COVID-19, we can observe trends in how the variables were impacted, identifying areas of resilience, growth, decline, or recovery.

Transition Probability Matrix for opening and closing prices of HDFC

		(1,1)	(1,2)	(1,3)	(2,1)	(2,2)	(2,3)	(3,1)	(3,2)	(3,3)
Open	Before	0.4577	**0.1294**	0.4129	0.36	0.16	**0.48**	0.3803	0.1737	0.446
	During	0.3706	0.198	**0.4315**	0.4255	**0.1489**	0.4255	0.4069	0.201	0.3922
	After	0.448	**0.1131**	0.4389	**0.4923**	0.1385	0.3692	0.4258	0.1483	0.4258
Close	Before	0.4319	0.1174	0.4507	**0.4808**	0.1154	0.4038	0.433	**0.0893**	0.4777
	During	0.4575	**0.0943**	0.4481	0.3729	0.1864	0.4407	0.4152	0.125	**0.4598**
	After	**0.4888**	0.1659	0.3453	0.3944	0.1549	0.4507	0.4279	**0.1144**	0.4577

Table 4: TPM matrix of HDFC open and close price

Interpreting the transition probabilities in the Table 4 involves analysing how values change across the three time points (Before, During, and After) for both stock prices (Open, Close). The higher and lower transition probabilities indicate a higher likelihood or greater magnitude a lower likelihood or smaller magnitude of the measured variable.

HDFC Opening Share Price Before COVID-19:

Higher Values: Indicate stronger or more prevalent initial conditions for the variables.

A value of 0.48 at previous day's Remind same to the current day's Decrement state (2,3) suggests a relatively strong initial state for this variable.

Lower Values: Indicate weaker or less prevalent initial conditions. A value of0.1294 at previous day's Increment to the current day's Remind same state (1,2) suggests a relatively weak initial state for this variable.

During COVID-19:

Higher Values: Suggest an increase or sustained high levels of the variable. The value of 0.4315 at previous day's Increment to the current day's Decrement state (1,3) shows a slight decrease from Before but still a relatively high value, indicating sustained presence.

Lower Values: Suggest a decrease or low levels of the variable. The value of 0.1489 at previous day's Remind same to the current day's Remind same state (2,2) shows a slight increase from Before but still remains relatively low.

After COVID-19:

Higher Values: Suggest that the variable has either remained high or increased from the initial state. A value of 0.4923 at previous day's Remind same to the current day's Increment state (2,1) indicates a higher value compared to the initial state, suggesting an overall increase.

Lower Values: Suggest that the variable has either remained low or decreased from the initial state. A value of 0.1131 at previous day's Increment to the current day's Remind same state (1,2)indicates a lower value compared to the initial state, suggesting an overall decrease.

By examining the higher and lower values of the opening price of HDFC before, during, and after COVID-19, we can observe trends in how the variables were impacted, identifying areas of resilience, growth, decline, or recovery.

HDFC Closing Share Price Before COVID-19:

Higher Values: Indicate stronger or more significant initial conditions for the variables. A value of 0.4808 at previous day's Remind same to the current day's Increment state (2,1) suggests a strong initial state for this variable.

Lower Values: Indicate weaker or less significant initial conditions. A value of 0.0893 at previous day's Increment to the current day's Remind same state (3,2) suggests a relatively weak initial state for this variable.

During COVID-19:

Higher Values: Suggest an increase or sustained high levels of the variable. The value of 0.4598 at previous day's Remind same to the current day's Increment state (2,1) indicates an increase from Before, showing an upward trend.

Lower Values: Suggest a decrease or low levels of the variable. The value of 0.0943 at previous day's Remind same to the current day's Remind same state (2,2) indicates a slight decrease from Before, showing a downward trend.

After COVID-19:

Higher Values: Suggest that the variable has either remained high or increased from the initial state. A value of 0.4888 at previous day's Increment to the current day's Increment state (1,1) suggests a sustained high value or a return to a high state after a temporary change.

Lower Values: Suggest that the variable has either remained low or decreased from the initial state. A value of 0.1144 at previous day's Remind same to the current day's Decrement state (3,2) suggests a decrease or sustained low value after a temporary change.

By examining the higher and lower values of the closing price of HDFC before, during, and after COVID-19, we can observe trends in how the variables were impacted, identifying areas of resilience, growth, decline, or recovery.

Transition Probability Matrix for opening and closing prices of TCS

		(1,1)	(1,2)	(1,3)	(2,1)	(2,2)	(2,3)	(3,1)	(3,2)	(3,3)
Open	Before	0.4319	0.108	0.5502	0.4407	0.2203	0.339	0.4424	**0.106**	**0.4516**
	During	0.3952	**0.0905**	**0.5143**	0.4068	0.1695	0.4237	0.4582	0.1322	0.4097
	After	0.4227	0.1227	0.4545	**0.5161**	0.1452	0.3387	0.4413	**0.1221**	0.4366
Close	Before	**0.4493**	**0.1111**	0.4396	0.318	0.1831	0.4366	0.4076	0.1659	0.4265
	During	0.4058	0.1787	0.4155	0.4189	**0.1216**	**0.4595**	0.4326	0.1302	0.4372
	After	0.4521	0.1416	0.4064	0.3235	0.1765	**0.5**	0.4663	**0.1202**	0.4135

Table 5: TPM matrix of TCS open and close price

Interpreting the transition probabilities in the Table 5 involves analysing how values change across the three time points (Before, During, and After) for both stock prices (Open, Close). The higher and lower transition probabilities indicate a higher likelihood or greater magnitude a lower likelihood or smaller magnitude of the measured variable.

TCS Opening Share Price Before COVID-19:

Higher Values: Indicate stronger or more prevalent initial conditions for the variables.

A value of 0.4516 at previous day's Decrement to the current day's Decrement state (3,3) suggests a relatively strong initial state for this variable.

Lower Values: Indicate weaker or less prevalent initial conditions. A value of 0.106 at previous day's Decrement to the current day's Remind same state (3,2) suggests a relatively weak initial state for this variable.

During COVID-19:

Higher Values: Suggest an increase or sustained high levels of the variable. The value of 0. at previou5143s day's Increment to the current day's Decrement state (1,3) shows a slight decrease from Before but still a relatively high value, indicating sustained presence.

Lower Values: Suggest a decrease or low levels of the variable. The value of 0.0905 at previous day's Increment to the current day's Remind same state (1,2) shows a slight increase from Before but still remains relatively low.

After COVID-19:

Higher Values: Suggest that the variable has either remained high or increased from the initial state. A value of 0.5161 at previous day's Remind same to the current day's Increment state (2,1) indicates a higher value compared to the initial state, suggesting an overall increase.

Lower Values: Suggest that the variable has either remained low or decreased from the initial state. A value of 0.1221 at previous day's Decrement to the current day's Remind same state (3,2) indicates a lower value compared to the initial state, suggesting an overall decrease.

By examining the higher and lower values of the opening price of SBI before, during, and after COVID-19, we can observe trends in how the variables were impacted, identifying areas of resilience, growth, decline, or recovery.

TCS Closing Share Price Before COVID-19:

Higher Values: Indicate stronger or more significant initial conditions for the variables. A value of 0.4493 at previous day's Increment to the current day's Increment state (1,1) suggests a strong initial state for this variable.
Lower Values: Indicate weaker or less significant initial conditions. A value of 0.1111 at previous day's Increment to the current day's Remind same state (1,2) suggests a relatively weak initial state for this variable.

During COVID-19:

Higher Values: Suggest an increase or sustained high levels of the variable. The value of 0.4595 at previous day's Remind same to the current day's Decrement state (2,3) indicates an increase from Before, showing an upward trend.
Lower Values: Suggest a decrease or low levels of the variable. The value of 0.1216 at previous day's Remind same to the current day's Remind same state (2,2) indicates a slight decrease from Before, showing a downward trend.

After COVID-19:

Higher Values: Suggest that the variable has either remained high or increased from the initial state. A value of 0.5 at previous day's Remind same to the current day's Decrement state (2,3) suggests a sustained high value or a return to a high state after a temporary change.

Lower Values: Suggest that the variable has either remained low or decreased from the initial state. A value of 0.1202 at previous day's Increment to the current day's Remind same state (3,2) suggests a decrease or sustained low value after a temporary change.

By examining the higher and lower values of the closing price of TCS before, during, and after COVID-19, we can observe trends in how the variables were impacted, identifying areas of resilience, growth, decline, or recovery.

Implications for Investors and Portfolio Managers

Before-COVID, investors should monitor transitions from Increment to Decrement states in SBI and TCS for potential downturns. During-COVID, amid market uncertainties, the focus should be on shifts from Increment to Decrement states across all stocks. After-COVID, attention should be given to transitions from Remain same to Increment states, indicating potential growth opportunities in HDFC and TCS. By understanding these transition probabilities, investors and portfolio managers can make informed decisions to optimize their portfolios and navigate through various market conditions effectively.

Understanding transition probabilities can empower investors and portfolio managers in several crucial ways. Firstly, it facilitates risk assessment and management by providing insights into the likelihood of different stock price states before, during, and after the COVID- 19 pandemic. This knowledge enables stakeholders to gauge and mitigate risks associated with individual stocks. Secondly, it aids in portfolio allocation and strategy formulation, allowing managers to adjust allocations and formulate investment strategies based on expected transitions in stock price states. This optimization maximizes growth opportunities while minimizing risks. Lastly, continuous monitoring and adjustment based on observed market conditions and deviations from expected trends are vital. By staying vigilant and adapting investment strategies accordingly, investors can ensure that their portfolios remain aligned with market dynamics. Ultimately, by leveraging these insights, investors and portfolio managers can make informed decisions to optimize their portfolios and navigate through various market conditions effectively.

Initial Probabilities (IPs) for opening and closing prices of SBI, HDFC, and TCS
The IPs indicate the chance of occurrence of the particular state, which is placed in Table 6.

Table 6: Initial Probabilities (IPs) for opening and closing prices of SBI, HDFC, and TCS The results placed in Table 3 provides insights into the behavior of stock prices for two

		Opening price			Closing price		
		Increment	Remine same	Decrement	Increment	Remine same	Decrement
SBI	Before	0.4294	0.1104	0.4601	0.4213	0.1350	0.4438
	During	0.4073	0.1431	0.4496	0.4274	0.1371	0.4355
	After	0.4404	0.1535	0.4061	0.4465	0.1354	0.4182
HDFC	Before	0.4102	0.1531	0.4367	0.4367	0.1061	0.4571
	During	0.3964	0.1891	0.4145	0.4286	0.1187	0.4527
	After	0.4456	0.1311	0.4234	0.4496	0.1452	0.4052
TCS	Before	0.4367	0.1204	0.4429	0.4224	0.1449	0.4327
	During	0.4245	0.1187	0.4567	0.4185	0.1489	0.4326
	After	0.4435	0.125	0.4315	0.4415	0.1371	0.4214

major bank - SBI, HDFC, and one IT company – TCS: before, during, and after the COVID- 19 pandemic. The probabilities associated with the states of price changes (Increment, remain same, Decrement) offer valuable information for investors and portfolio managers.

Observation of Initial Probabilities of SBI

- Before COVID-19: There's a higher probability of price Decrement both at opening and closing, signaling caution for investors considering purchasing the stock.
- During COVID-19: Similar to pre-pandemic, the probabilities favor Decrement, suggesting continued caution.
- After COVID-19: The probabilities lean towards price Increment, indicating a potential opportunity for investors to consider selling the stock.

Observation of Initial Probabilities of HDFC

- Before COVID-19: Again, there's a higher likelihood of price Decrement, urging investors to exercise caution.
- During COVID-19: Similar to SBI, the probabilities still favor Decrement, emphasizing a conservative approach.
- After COVID-19: Interestingly, there's a shift towards Increment probabilities, suggesting a potential opportunity for investors to consider selling the stock.

Observation of Initial Probabilities of TCS

- Before COVID-19: The probabilities are relatively balanced between Increment and Decrement, but slightly favor Decrement, suggesting a cautious approach.
- During COVID-19: The probabilities indicate a higher likelihood of Decrement, reinforcing the need for vigilance.
- After COVID-19: Once again, there's a tilt towards Increment probabilities, indicating a potential opportunity for investors to consider selling the stock.

Implications for Investors and Portfolio Managers

- Before COVID-19: Caution is advised due to the higher likelihood of price Decrement across all companies.
- During COVID-19: The caution remains as the probabilities continue to favor price Decrement, indicating ongoing market volatility and uncertainty.
- After COVID-19: There's a notable shift towards Increment probabilities for most companies, signaling a

potential opportunity for investors to consider selling their holdings.

Overall, this detailed analysis of initial probabilities offers valuable insights for investors and portfolio managers to make informed decisions based on the probabilities associated with different states of stock price changes before, during, and after the COVID-19 pandemic.

Probability Distributions for SBI

The probability distributions of opening and closing prices of SBI are placed in Table 7.

		Opening Price			Closing Price		
		Increment	Remain same	Decrement	Increment	Remain same	Decrement
Before	P (0)	0.5719	0.8894	0.5388	0.5779	0.8648	0.5573
	P (1)	0.4281	0.1106	0.4612	0.4221	0.1352	0.4427
During	P (0)	0.5939	0.8565	0.5495	0.5716	0.8646	0.5639
	P (1)	0.4061	0.14345	0.4505	0.4284	0.1354	0.4361
After	P (0)	0.7868	0.6627	0.3303	0.8154	0.6232	0.3306
	P (1)	0.1031	0.2272	0.5796	0.0697	0.2609	0.5535

Table 7: Probabilities of Before, During, and After COVID of SBI

The analysis of SBI's stock prices before, during, and after the COVID-19 period reveals critical insights for investors. Before and during the pandemic, the opening prices show a higher likelihood of a decrease, suggesting that purchasing SBI stocks during these periods could be advantageous for daily traders and portfolio managers looking to capitalize on short-term price movements. Similarly, the closing prices indicate a higher probability of a decrease during the pandemic, reinforcing the strategy of buying stocks to benefit from expected downturns.

After COVID-19, the landscape shifts, with the probability of an increase in stock prices becoming more prominent in both opening and closing prices. This suggests that buying SBI stocks during this recovery phase could be advantageous as prices are expected to rise. Consequently, selling stocks during this period could yield favourable returns, aligning with the dominant Increment state.

Investors should consider purchasing SBI stocks before and during the pandemic to capitalize on anticipated price drops, as both the opening and closing prices during these periods indicate a higher likelihood of decreases. This strategy allows traders to buy at lower prices, potentially leading to significant gains when the market recovers. Post-pandemic, the analysis shows a shift towards a higher probability of price increases, suggesting that selling SBI stocks during this recovery phase could optimize returns. By aligning their strategies with these trends, investors can effectively navigate market fluctuations and maximize their investment outcomes.

Statistical Measures for SBI

The statistical measures for SBI are placed in below Table 8.

		Opening Price			Closing Price		
	Statistical Measure	Increment	Remain same	Decrement	Increment	Remain same	Decrement
Before	Mean	0.4281	0.1106	0.4612	0.4221	0.1352	0.4427
	Variance	0.2448	0.0984	0.2485	0.2439	0.117	0.2467
	μ_3	0.0352	0.0766	0.0193	0.038	0.0853	0.0283
	β_1	0.0844	6.1631	0.0242	0.0995	4.5502	0.0533
	β_2	1.0844	7.1631	1.0242	1.0995	5.5502	1.0533
	C.V	1.1558	2.8353	1.0808	1.1701	2.5286	1.1221
During COVID	Mean	0.4061	0.1435	0.4505	0.4284	0.1354	0.4361
	Variance	0.2412	0.1229	0.2475	0.2449	0.1171	0.2459
	μ_3	0.0453	0.0876	0.0245	0.035	0.0854	0.0314
	β_1	0.1464	4.1379	0.0396	0.0836	4.5415	0.0663
	β_2	1.1464	5.1379	1.0396	1.0836	5.5415	1.0663
	C.V	1.2094	2.4434	1.1045	1.155	2.5268	1.137
After COVID	Mean	0.1031	0.2272	0.5596	0.0697	0.2609	0.5553
	Variance	0.0925	0.1756	0.2464	0.0648	0.1928	0.2471
	μ_3	0.0734	0.0958	-0.029	0.0558	0.0922	-0.026
	β_1	6.8141	1.6861	0.0576	11.427	1.1854	0.0464
	β_2	7.8126	2.6861	0.8799	12.427	2.1709	0.8683
	C.V	2.9494	1.8444	0.8871	3.6541	1.683	0.8981

Table 8: Statistical measures of Before, During, and After COVID of SBI

The provided data offers statistical insights into the opening and closing prices of SBI bank shares before, during, and after the COVID period.

Before COVID, the mean of both opening and closing prices demonstrate a higher probability of the Decrement state compared to the remaining two states. Similarly, during COVID, also the mean of both opening and closing prices demonstrate a higher probability of the Decrement state compared to the remaining two states. Consistently higher probabilities of price decline states (Decrement) before and during COVID suggest a prevalent market trend. Investors should consider strategies that account for and mitigate against downside risks, such as diversification and active risk management, in their investment approach.

After the COVID period, a notable decrease in the mean of Increment state than remaining two states of both opening and closing prices is observed. The notable decrease in the mean of the Increment state post-COVID suggests a potential shift in market dynamics, urging investors to reassess strategies for capturing growth opportunities amidst evolving conditions and to remain vigilant for new trends emerging in the post-pandemic landscape.

Regarding Variance, both opening and closing prices, there less variance observed in the Remain same state of both before and during COVID. But coming to the coefficient of variance there is less coefficient of variation observed in the Decrement state than the remaining two state. Hence, the lower variance in the Remain same state and the lower coefficient of variation in the Decrement state imply relative stability and predictability in these respective market conditions. Investors may find opportunities in strategies that capitalize on stability during uncertain times and prioritize risk mitigation in volatile markets.

After COVID both opening and closing prices, there is less variance observed in Increment state and least coefficient of variation observed in Remain same state. Hence, the decrease in variance in the Increment state and the least coefficient of variation in the Remain same state post-COVID suggest a potential shift towards more stable market conditions. Investors may find value in strategies that capitalize on stability while remaining vigilant for emerging growth opportunities amidst a more predictable environment.

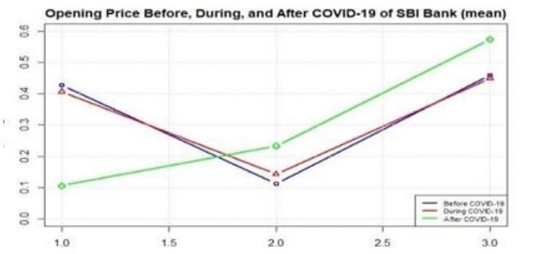

Figure 1: Opening price Before, During, and After COVID-19 of SBI (mean)

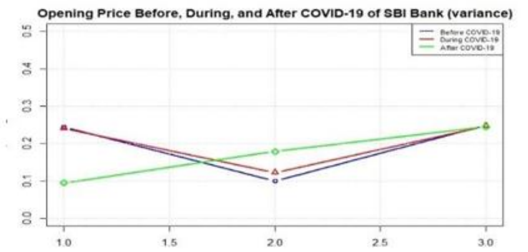

Figure 2: Opening price Before, During, and After COVID-19 of SBI (variance)

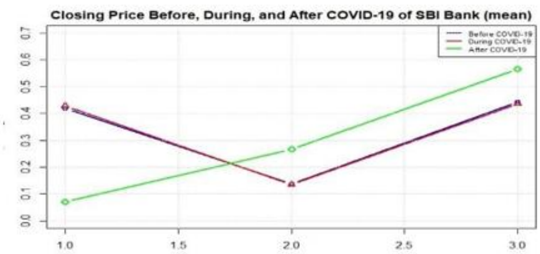

Figure 3: Closing price Before, During, and After COVID-19 of SBI (mean)

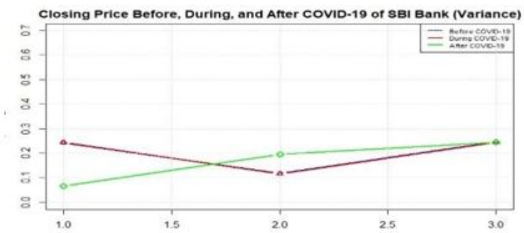

Figure 4: Closing price Before, During, and After COVID-19 of SBI (variance)

The non-negative third central moment (skewness) in all states before, during, and after COVID, except for the Decrement state, indicates a generally positively skewed distribution of prices or returns. However, the negative third central moment (skewness) in the Decrement state suggests a distribution skewed towards lower values, indicating a potential for more pronounced downside movements or asymmetry in returns during periods of price decrease. This implies that investors may face a greater risk of larger losses during declining market conditions compared to other states.

The kurtosis values exceeding 3 in the Remain same state before and during COVID imply occasional extreme price movements, signaling inherent market volatility. Post-COVID, a kurtosis value greater than 3 in the Increment state suggests an intensified frequency or magnitude of such extreme movements, prompting investors to exercise caution and consider robust risk management strategies to navigate heightened volatility.

Probability Distributions for HDFC
The probability distributions of opening and closing prices of HDFC placed in the Table 9.

		Opening price			Closing price		
		Increment	Remain same	Decrement	Increment	Remain same	Decrement
Before	P (0)	0.5911	0.8466	0.5624	0.5624	0.8957	0.5419
	P (1)	0.4089	0.1534	0.4376	0.4376	0.1043	0.4581
During	P (0)	0.604	0.8101	0.5859	0.5717	0.8808	0.5475
	P (1)	0.396	0.1899	0.4141	0.4283	0.1192	0.4525
After	P (0)	0.5072	0.8203	0.5758	0.5496	0.8565	0.5938
	P (1)	0.4444	0.1313	0.3759	0.4504	0.1434	0.4061

Table 9: probabilities of Before, During, and After COVID of HDFC

The analysis of opening and closing prices before, during, and after the COVID period provides valuable insights for investors considering HDFC stocks.

For the opening prices, both before and during COVID, there's a higher probability of a decrease in HDFC stock prices compared to an increase. This indicates that purchasing HDFC stocks during these periods could potentially lead to optimal returns.

However, after the COVID period, there's a notable shift. The probability of an Increment state becomes more prominent, suggesting that selling HDFC stocks might be advisable during this time.

Turning to the closing prices, similar patterns emerge. Before and during COVID, there's a higher likelihood of no significant change in HDFC stock prices or a decrease, with the chance of a decrease being more pronounced. This again points towards purchasing HDFC stocks during these periods for potentially favorable returns.

After COVID, the landscape changes once more. The probability of an Increment state becomes more dominant, indicating that selling HDFC stocks might be more advisable during this period.

In summary, the analysis of both opening and closing prices provides nuanced guidance for investors. Before and during COVID, purchasing HDFC stocks could be favourable, while after COVID, selling might be more advantageous. These insights can help investors make informed decisions to optimize their returns.

Statistical Measures for HDFC
The statistical measures for HDFC are placed in below Table 10.

		Opening Price			Closing Price		
	Statistical Measure	Increment	Remain same	Decrement	Increment	Remain same	Decrement
Before COVID	Mean	0.4089	0.1534	0.4376	0.4376	0.1043	0.4581
	Variance	0.2417	0.1299	0.2461	0.2461	0.0934	0.2482
	μ_3	0.044	0.09	0.0307	0.0307	0.0739	0.0208
	β_1	0.1372	3.6995	0.0632	0.0633	6.7023	0.0283
	β_2	1.1372	4.6995	1.0632	1.0633	7.7023	1.0283
	C.V	1.2022	2.3491	1.1336	1.1336	2.9302	1.0877
During COVID	Mean	0.396	0.1899	0.4141	0.4283	0.1192	0.4525
	Variance	0.2392	0.1539	0.2426	0.2449	0.105	0.2477
	μ_3	0.0497	0.0954	0.0417	0.0351	0.0799	0.0235
	β_1	0.1809	2.4992	0.1218	0.0839	5.5278	0.0364
	β_2	1.1809	3.4992	1.1218	1.0839	6.5278	1.0364
	C.V	1.235	2.0651	1.1896	1.1553	2.7189	1.0999
After COVID	Mean	0.4444	0.1313	0.3759	0.4504	0.1435	0.4062
	Variance	0.2469	0.1141	0.2346	0.2475	0.1229	0.2412
	μ_3	0.0275	0.0841	0.0582	0.0246	0.0876	0.0453
	β_1	0.0501	4.7646	0.2628	0.0398	4.1382	0.1461
	β_2	1.0191	5.7635	1.245	1.0398	5.1382	1.1461
	C.V	1.1181	2.5717	1.2886	1.1047	2.4435	1.2092

Table 10: Statistical measures of Before, During, and After COVID of HDFC

The provided data offers statistical insights into the opening and closing prices of HDFC bank shares before, during, and after the COVID period.

Before COVID, the mean of both the opening and closing prices demonstrate a higher probability of Decrement state compared to the remaining two states. Similarly, during COVID, the mean of both the opening and closing prices demonstrate a higher probability of Decrement state compared to the remaining two states. Consistently higher probabilities of price decline states (Decrement) before and during COVID suggest a prevalent market trend. Investors should consider strategies that account for and mitigate against downside risks, such as diversification and active risk management, in their investment approach.

After the COVID period, a notable decrease in the mean of Increment state than remaining two states of both opening and closing prices is observed. The notable decrease in the mean of the Increment state post-COVID suggests a potential shift in market dynamics, urging investors to reassess strategies for capturing growth opportunities amidst evolving conditions and to remain vigilant for new trends emerging in the post-pandemic landscape.

Regarding Variance, both opening and closing prices, there less variance observed in the Remain same state of both before and during COVID. But coming to the coefficient of variance there is less coefficient of variation observed in the Decrement state than the remaining two state. Hence, the lower variance in the Remain same state and the lower coefficient of variation in the Decrement state imply relative stability and predictability in these respective market conditions. Investors may find opportunities in strategies that capitalize on stability during uncertain times and prioritize risk mitigation in volatile markets.

After COVID both opening and closing prices, there is less variance observed in Increment state and least coefficient of variation observed in Remain same state. Hence, the decrease in variance in the Increment state and the least coefficient of variation in the Remain same state post-COVID suggest a potential shift towards more stable market conditions. Investors may find value in strategies that capitalize on stability while remaining vigilant for emerging growth opportunities amidst a more predictable environment.

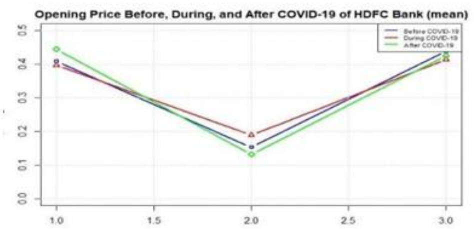

Figure 5: Opening price Before, During, and After COVID-19 of HDFC Bank (mean)

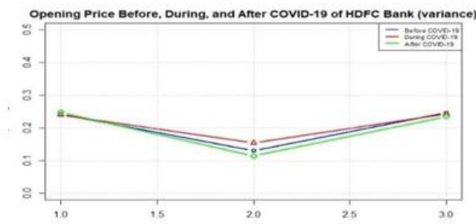

Figure 6: Opening price Before, During, and After COVID-19 of HDFC Bank (variance)

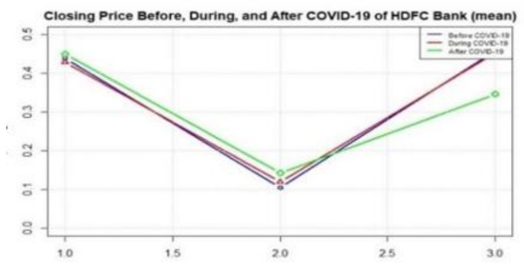

Figure 7: Closing price Before, During, and After COVID-19 of HDFC Bank (mean)

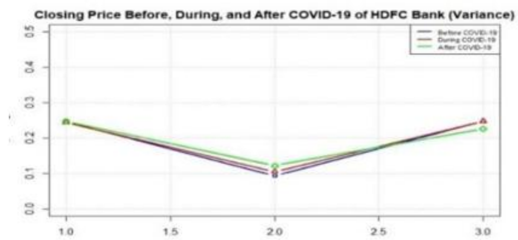

Figure 8: Closing price Before, During, and After COVID-19 of HDFC Bank (variance)

The non-negative third central moment (skewness) in all states before, during, and after COVID, except for the Decrement state, indicates a generally positively skewed distribution of prices or returns. However, the negative third central moment (skewness) in the Decrement state suggests a distribution skewed towards lower values, indicating a potential for more pronounced downside movements or asymmetry in returns during periods of price decrease. This implies that investors may face greater risk of larger losses during declining market conditions compared to other states.

The kurtosis values exceeding 3 in the Remain same state before and during COVID imply occasional extreme price movements, signaling inherent market volatility. Post-COVID, a kurtosis value greater than 3 in the Increment state suggests an intensified frequency or magnitude of such extreme movements, prompting investors to exercise caution and consider robust risk management strategies to navigate heightened volatility.

Probability Distributions for TCS

The probability distributions of opening and closing prices of TCS placed in the Table 11.

		Opening Price			Closing Price		
		Increment	Remain same	Decrement	Increment	Remain same	Decrement
Before	P (0)	0.5624	0.8794	0.5582	0.5788	0.8548	0.5665
	P (1)	0.4376	0.1206	0.4418	0.4212	0.1452	0.4335

	P (0)	0.5747	0.8811	0.5442	0.5807	0.8507	0.5686
During	P (1)	0.4253	0.11889	0.4558	0.4193	0.1493	0.4314
After	P (0)	0.5576	0.875	0.5677	0.5595	0.8627	0.5778
	P (1)	0.4424	0.125	0.4323	0.4405	0.1373	0.4222

Table 11: probabilities of Before, During, and After COVID of TCS

The analysis of opening and closing prices before, during, and after the COVID period offers key insights for investors, particularly in relation to TCS stocks.

In terms of opening prices, both before and during COVID, there's a higher probability of no significant change or decrease in TCS stock prices compared to an increase. This suggests that purchasing TCS stocks during these periods may not yield optimal returns.

Similarly, during the COVID period, the probability of no significant change remains higher, indicating that neither selling nor buying TCS stocks is advisable.

Looking at the closing prices, the trends remain consistent. Before and during COVID, there's a greater likelihood of no significant change or decrease in TCS stock prices. Again, this implies that purchasing TCS stocks during these periods may not lead to optimal returns.

Likewise, during the COVID period, the probability of no significant change remains higher, suggesting that neither selling nor buying TCS stocks is advisable.

In summary, the analysis of both opening and closing prices suggests that before, during, and after COVID, holding TCS stocks might be more prudent than actively buying or selling. These insights provide valuable guidance for investors in making informed decisions to optimize their returns.

Statistical Measures for TCS

The statistical measures for TCS placed in below Table 12.

		Opening Price			Closing Price		
	Statistical Measure	Increment	Remain same	Decrement	Increment	Remain same	Decrement
B	Mean	0.437	0.1206	0.4418	0.4212	0.1452	0.4335
	Variance	0.2461	0.1061	0.2466	0.2438	0.1241	0.2456
	μ_3	0.0307	0.0805	0.0287	0.0384	0.0881	0.0327
	β_1	0.0633	5.4271	0.055	0.1018	4.0552	0.072
	β_2	0.0633	6.4271	1.055	1.1018	5.0552	1.072
	C.V	1.1336	2.7	1.1241	1.1722	2.426	1.1431
During COVID	Mean	0.4253	0.1189	0.4558	0.4193	0.1493	0.4314
	Variance	0.2444	0.1048	0.248	0.2435	0.127	0.2453
	μ_3	0.0365	0.0798	0.0219	0.0393	0.0891	0.0336
	β_1	0.0912	5.5458	0.0316	0.1069	3.8755	0.0767
	β_2	1.0912	6.5458	1.0928	1.1069	4.8755	1.0767
	C.V	1.1623	2.7223	1.0928	1.1768	2.3875	1.148
After COVID	Mean	0.4424	0.125	0.4323	0.4405	0.1373	0.4222
	Variance	0.2467	0.11	0.2454	0.2465	0.1185	0.2439
	μ_3	0.0284	0.082	0.0332	0.0293	0.0859	0.038
	β_1	0.0538	5.127	0.0746	0.0575	4.4405	0.0992
	β_2	1.0538	6.127	1.0746	1.0575	5.4405	1.0992
	C.V	1.1226	2.643	1.1459	1.1271	2.5062	1.1698

Table 12: Statistical measures of Before, During, and After COVID of TCS

The provided data offers statistical insights into the opening and closing prices of TCS bank shares before during and after the COVID period

Before COVID, the mean of both the opening and closing prices demonstrate a higher probability of Decrement state compared to the remaining two states. Similarly during COVID, the mean of both the opening and closing prices demonstrate a higher probability of Decrement state compared to the remaining two states. Consistently higher probabilities of price decline states (Decrement) before and during COVID suggest a prevalent market trend. Investors should consider strategies that account for and mitigate against downside risks, such as diversification and active risk management, in their investment approach.

After the COVID period, a notable decrease in the mean of Increment state than remaining two states of both opening and closing prices is observed. The notable decrease in the mean of the Increment state post-COVID suggests a potential shift in market dynamics, urging investors to reassess strategies for capturing growth opportunities amidst evolving conditions and to remain vigilant for new trends emerging in the post-pandemic landscape.

Regarding Variance, both opening and closing prices, there less variance observed in the Remain same state of both before and during COVID. But coming to the coefficient of variance there is less coefficient of variation observed in the Decrement state than the remaining two state. Hence, the lower variance in the Remain same state and the lower coefficient of variation in the Decrement state imply relative stability and predictability in these respective market conditions. Investors may find opportunities in strategies that capitalize on stability during uncertain times and prioritize risk mitigation in volatile markets.

After COVID both opening and closing prices, there is less variance observed in Increment state and least coefficient of variation observed in Remain same state. Hence, the decrease in variance in the Increment state and the least coefficient of variation in the Remain same state post-COVID suggest a potential shift towards more stable market conditions. Investors may find value in strategies that capitalize on stability while remaining vigilant for emerging growth opportunities amidst a more predictable environment.

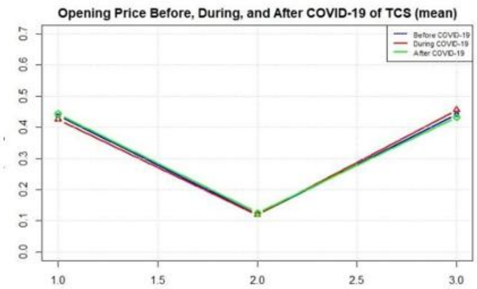

Figure 9: Opening price Before, During, and After COVID-19 of TCS (mean)

Figure 10: Opening price Before, During, and After COVID-19 of TCS (variance)

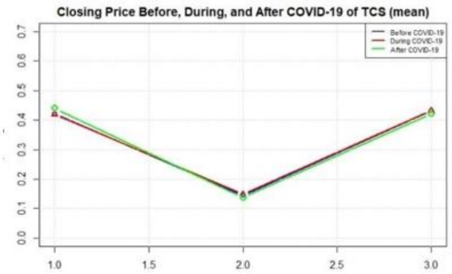

Figure 11: Closing price Before, During, and After COVID-19 of TCS (mean)

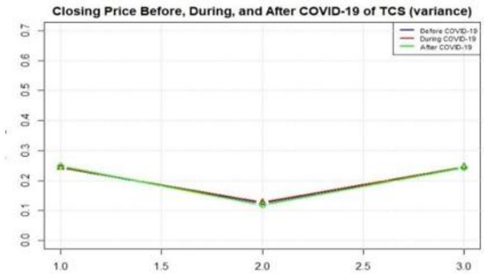

Figure 12: Closing price Before, During, and After COVID-19 of TCS (variance)

The non-negative third central moment (skewness) in all states before, during, and after COVID, except for the Decrement state, indicates a generally positively skewed distribution of prices or returns. However, the negative third central moment (skewness) in the Decrement state suggests a distribution skewed towards lower values, indicating a potential for more pronounced downside movements or asymmetry in returns during periods of price decrease. This implies that investors may face greater risk of larger losses during declining market conditions compared to other states.

The kurtosis values exceeding 3 in the Remain same state before and during COVID imply occasional extreme price movements, signaling inherent market volatility. Post-COVID, a kurtosis value greater than 3 in the Increment state suggests an intensified frequency or magnitude of such extreme movements, prompting investors to exercise caution and consider robust risk management strategies to navigate heightened volatility.

V. Summary

The paper explores the impact of the COVID-19 pandemic on the Indian stock market by analyzing the historical stock prices of three major companies: SBI, HDFC, and TCS. Utilizing a Markov model framework, the study constructs Transition Probability Matrices (TPMs) and Initial Probability Vectors (IPVs) to model the state transitions of stock prices before, during, and after the COVID-19 period. The research calculates the probability distributions and statistical characteristics for different states (Increment, Remain Same, and Decrement) to provide insights into market dynamics under varying conditions.

The findings reveal distinct patterns in stock price behaviours across the three time periods. Before and during COVID-19, SBI and HDFC showed higher probabilities of price decrements, suggesting caution for investors. Conversely, TCS displayed a more balanced probability distribution. After the pandemic, all three companies exhibited a shift towards increment probabilities, indicating potential growth opportunities. The study provides tailored recommendations for investors and portfolio managers, emphasizing risk assessment, portfolio allocation, and continuous monitoring to navigate the changing market landscape effectively.

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