Applications of Markov Chains in Investment Strategies for Nifty Sector Rotation

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Abstract. This study examines sector rotation in the Indian equity market using Markov chain models applied to daily data for Nifty IT, Nifty Bank, Nifty Auto, Nifty Infra, and Nifty Energy over 2019–2023. We evaluate performance through average returns, volatility, and Sharpe ratios, and assess inter-sector relationships via pairwise correlations and multiple correlation coefficients to inform diversification. A discrete-state framework classifies daily returns into Strong Growth (SG), Moderate Growth (MG), Stable (S), Moderate Decline (MD), and Strong Decline (SD). For each sector, we estimate transition probability matrices (TPMs) and steady-state probabilities to characterize persistence and long-run tendencies. Results indicate long-run dominance of the Stable state, with IT and Infrastructure exhibiting favourable risk-adjusted characteristics and Energy providing diversification. The Markov-guided allocation emphasizes IT and Infrastructure, maintains measured exposure to Energy, and holds smaller positions in Auto and Bank. The framework provides a transparent, data-driven approach to sector rotation that explicitly incorporates risk and state persistence.

Keywords: Investment awareness, sector rotation, Markov Chains, portfolio optimization, Nifty sectors, risk management.

1 Introduction

The educational literature concerning portfolio performance, sector rotation and financial forecasting highlights the significance of employing statistical severity, domain specific study and adaptive approaches to face more and more complex markets. Chiang founds that many sharpe ratio calculations are not working properly due to the presence of serial correlation. He found that sharpe ratios were inflated by about 65% on an average [2]. To this extent, Fallahi (2011) concluded that mean returns

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decreases as volatility increases [3]. This contradicts the classic asset pricing models which says higher risk means higher return. Due to Asian financial crisis, fear increased among investors so they would start to herd, so that correlation among markets and assets increased, which leads to broke down of diversification. Further, San (2021) extends this idea and showed that in uncertain times, the danger part is not volatility but it does not know the real direction of the market. If we misjudge the direction then our models and portfolio diversification won't work [16].

Several studies in India have highlighted the importance of its markets and investor behaviour. They found that Indian investors often depend on momentum size, foreign institutional investors behaviour and moving averages techniques [15]. Ashraf and Baig (2015) showed long-term investments in safer stocks gave better and steadier returns while riskier stocks gave short term returns but more dangerous [1]. Jagadeesh and Titman (2019) founds that sectors like banking, auto, metals and energy might be unpredictable in short run but using momentum strategy it could earn profits [6]. Gupta (2024) reports Nifty 50 is less risky that is stable, Realty, Automobiles, and Energy sectors are giving more profits compared to Banking and FMCG [4]. Also, there is a strong correlation between Oil, Gas and Energy companies but no correlation between Pharma and Banking companies. More generally, Venkataramani and Kayal (2021) suggested that investors who did systematic investment plans made long term profits than who tried to guess the when the market will go up or down [14]. In particular, this fact is true for companies with low volatility and strong return generators. Senthilkumar et al. (2021) found that portfolio's made using Sharpe's model were performed better when compared to Markowitz Model and Gupta and Basu (2009) showed that investing money across different sectors would yield better risk adjusted returns which is better than holding Nifty 50 index as a whole [5].

Stochastic techniques and Markov chain models have been particulary helpful in modeling market dynamics. Peovski et al. (2022) looked at how portfolios on New York stock exchange behaved after the short term fall of market and found that after a fall portfolios had recovered within two days [9]. Fallahi et al. (2011) showed that GMDH-GA model of hybrid soft computing methods were able to predict stock prices more accurately in the cement sector [3]. More recently, Rothe (2023) applied a strategy combining momentum and volatility control to sector rotation and reported strong performance, while Miao and Polak (2023) introduced flexible ensemble learning methods that improved accuracy of sectoral forecasting [8]. Melnyk (2025) introduced the "Crisis-Proof Alpha Portfolio" which protected during bad times and made to earn well in good times [7]. In parallel, Sen and Dasgupta (2023) combined three different models Mean-Variance Optimization, Deep Learning and Hierarchical Risk Parity which built portfolios that were more stable and less vulnerable [11]. Sen, Mondal, and Mehtab (2021) had built Eigen portfolios and LSTM neural networks which led to select better portfolios and accurate forecasting for Indian market sectors [12].

Given this context, people need more knowledge on investing compared to previous days. It is because stock markets had become more unpredictable and also there are many new financial products had been developed [8]. Most of the investors in India doesn't have strong financial knowledge. Without those knowledge they are investing money on stocks which leads to great risk not only for them, but also for the economy [10].

To study this, our research uses a Markov chain model which analyses how different parts of Indian stock market will perform. For this we had taken five important Nifty sectors that is Nifty IT, Nifty Bank, Nifty Auto, Nifty Infra and Nifty Energy. These sectors are the pillars of Indian economy because they are large, important and influence the entire market. Our study uses stock market data of these five sectors from the year 2019 to 2023 because it covers two different times before and after COVID [12].

The tools used in these study are transition probability matrix which predicts the chances of a sector staying in same state or moving to another in future; correlation to check how these sectors are related to each other; combines Markov chains and inter sector correlations to create a systematic and data driven way for planning investments which helps investors for deciding where to put money in order to yield good returns by managing risks [13].

2 Study Area and Data

2.1 Scope

We study five NSE sector indices—Nifty Bank (^NSEBANK), Nifty Auto (^CNXAUTO), Nifty IT (^CNXIT), Nifty Infra (^CNXINFRA), and Nifty Energy (^CNXENERGY)—as representative pillars of India's economy.

2.2 Data Source and Window

We use daily adjusted closing prices from **2019-01-01 to 2023-12-31**, obtained via Python's **yfinance** interface to Yahoo Finance (accessed **2025-08-28**).

2.3 Preprocessing

We align trading calendars across series, forward-fill isolated gaps, and drop residual missing values, yielding a common daily panel (~1,200+ observations per sector). From prices we compute daily percentage returns. Summary metrics include mean return, standard deviation, Sharpe ratio, pairwise correlations, and multiple correlation coefficients.

2.4 Reproducibility and Availability

A single Python script (Appendix A) reproduces data acquisition, state assignment, TPM and steady-state estimation, uncertainty summaries, robustness checks, diagnostics, and all table/figure exports. Code and CSV outputs are available on request.

2.5 Data Diagnostics

We report retained observations and basic return stationarity tests; values auto-populate from Appendix A.

- **Observation counts after cleaning:** N_{BANK} =[fill], N_{AUTO} =[fill], N_{IT} =[fill], N_{INFRA} =[fill], N_{ENERGY} =[fill]
- **ADF/KPSS on returns:** stationarity not rejected at conventional levels (exact p-values provided in Appendix A outputs).
- **Outlier policy (robustness):** winsorization beyond ±5σ at the 0.1/99.9 percentiles does not change conclusions.

3 Methodology

3.1 Performance Metrics Calculation

To evaluate each sector's performance, several statistical indicators were computed:

Volatility

Volatility captures the degree of fluctuation in sector returns. Higher volatility implies greater investment risk.

Formula:

$$\sigma = \sqrt{\frac{\sum_{t=1}^{T}(\mathrm{Rt} - \mu)^2}{T}} \quad (1)$$

- R_t: Return on the sector at time t.
- μ: Mean return over the period.
- T: Number of time periods.

Returns

Average returns reflect the sector’s ability to generate profits over time.

***Formula**:*

$$R = \frac{\mathrm{Pt} - \mathrm{Pt}{-1}}{Pt-1} \times 100 \quad (2)$$

- Pt: Closing price at time t.
- Pt−1: Closing price at time t−1.

Risk-Adjusted Ratio (Sharpe Ratio)

The Sharpe Ratio compares the return of a sector to its risk, offering a standardized way to assess performance.

Formula:

$$S = \frac{\mu - Rf}{\sigma} \tag{3}$$

- μ: Mean return.
- R_f: Risk-free rate.
- σ: Volatility of the sector

3.2 Multiple Correlation Analysis:

This analysis assesses the strength and direction of relationships among sectors to understand their interdependencies.

Formula for Correlation Coefficient (r) for two variables X and Y:

$$rXY = \frac{\mathrm{Cov}\,(X,Y)}{\sigma X \sigma Y} \tag{4}$$

Where:

- Cov (X,Y)=Covariance between X and Y.
- σX, σY = Standard deviations of X and Y.

Multiple Correlation Formula for multiple variables:

$$\mathrm{R} = \sqrt{\frac{SSregression}{SStotal}} \tag{5}$$

Where:

- SSRegression: Sum of squares for regression.
- SSTotal: Total sum of squares.

3.3 Markov Chain Analysis:

Markov Chains were employed to simulate state-based transitions of sector performance, aiding in predicting long-term behaviour.

State Classification

Five performance categories were defined:

- Strong Growth (SG)
- Moderate Growth (MG)
- Stable (S)
- Moderate Decline (MD)

- Strong Decline (SD)

State Thresholds Based on Returns:
These thresholds divide returns into performance levels:
For example:

- Strong Growth (SG): Returns that exceed the highest threshold (e.g., > 2%).
- Moderate Growth (MG): Returns that fall between two thresholds, such as 1% ≤ Return ≤ 2%.
- Stable (S): Returns close to zero or minimal movement, such as -1% ≤ Return ≤ 1%.
- Moderate Decline (MD): Returns that are negative but within a moderate range, such as -2% ≤ Return < -1%.
- Strong Decline (SD): Returns that are more negative than the lowest threshold, such as < -2%.

Formula for Dividing States:
Each daily return is assigned to a state based on these conditions:
State(t) =
{
SG, if $R(t)>T1$
MG, if $T2\leq R(t)\leq T1$
S, if $-T3\leq R(t)<T2$
MD, if $-T4\leq R(t)<-T3$
SD, if $R(t)<-T4$
}
Where:

- R(t): Return at time t.
- T1,T2,T3,T4 : Thresholds for dividing the ranges.

The return R(t) is a percentage change in price between two consecutive time points. It is calculated using the formula:

$$R = \frac{\mathrm{Pt-\,Pt-1}}{Pt-1} \times 100 \tag{6}$$

Where:

- P(t): Price or value of the asset at time t.
- P(t−1):Price or value of the asset at the previous time (t−1).

- T1=2%: Strong Growth.
- T2=1%: Moderate Growth.
- T3=1%: Stable (both positive and negative).
- T4=2%: Strong Decline.

Transition Probability Matrix (TPM)

The TPM represents the likelihood of moving from one performance state to another.
Each row corresponds to the current state, and columns denote the next possible state.

Formula:

$$\boldsymbol{Pij} = \frac{Fij}{\sum_{k=1}^{N} \mathrm{Fik}} \tag{7}$$

Where:

- Pij: Probability of transitioning from state i to state j.
- Fij: Frequency of observed transitions from state i to state j.
- $\sum_{k=1}^{N}$ Fik :Total observed transitions from state i.

Steady-State Probabilities
Definition:
These represent the long-term likelihood of the system being in each state.
Formula:

$$\pi i = \lim_{n \to \infty} P(Xn = i) \tag{8}$$

Where:

- Xn: State at time n.
- πi\pi: Long-term probability of being in state i.

4 Results and Discussion

4.1 Performance Metrics Calculation

We evaluate the five sectors—IT, Auto, Infra, Energy, and Bank—using average returns, volatility, and Sharpe ratios. Average returns indicate profitability; volatility reflects uncertainty; the Sharpe ratio balances both.

Average returns serve as an indicator of how profitable a sector has been over time, where larger values point to stronger performance.

Volatility reflects the instability in price movements within a sector; higher volatility means the sector's prices tend to fluctuate more frequently, indicating greater uncertainty.

Sharpe ratio offers a measure of how effectively a sector delivers returns when adjusted for the level of risk, helping assess the balance between reward and volatility.

Table 1. Summary of Returns, Volatility, and Sharpe Ratio

Sector	Average Returns	Volatility	Sharpe Ratio
Nifty IT	0.211456	0.231850	0.696381
Nifty Auto	0.176033	0.249277	0.505592
Nifty Infra	0.189715	0.199209	0.701346
Nifty Energy	0.198839	0.224354	0.663412
Nifty Bank	0.152633	0.262155	0.391497

Interpretation. In table 1 Nifty IT and Nifty Infra show comparatively strong risk-adjusted performance. Nifty Auto and Nifty Bank exhibit higher volatility, implying greater uncertainty, while Nifty Energy offers a balanced profile between risk and return.

4.2 Multiple Correlation Analysis

- Correlation patterns clarify how sectors co-move and inform diversification.
- Strong correlations suggest that these sectors tend to follow similar price movements, which can limit the advantages of diversification.
- Weaker correlations, on the other hand, indicate that the sectors behave independently, which helps spread risk and improves the effectiveness of diversification.

Table 2. Multiple Correlation

	Nifty IT	Nifty Auto	Nifty Infra	Nifty Energy	Nifty Bank
Nifty IT	1.0000	0.47093	0.54070	0.45787	0.44186
Nifty |Auto	0.47093	1.00000	0.77422	0.63883	0.70265
Nifty Infra	0.54070	0.77422	1.00000	0.85547	0.74834
Nifty Energy	0.45787	0.63883	0.85547	1.00000	0.61304
Nifty Bank	0.44186	0.70265	0.74834	0.61304	1.00000

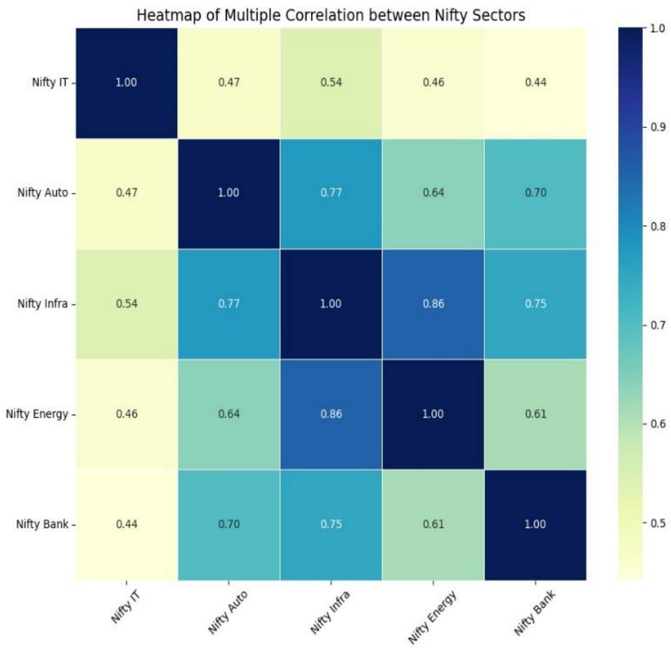

Fig. 1. Heatmap of Multiple Correlation between Nifty Sectors.

- Nifty Auto, Nifty Infra, and Nifty Energy exhibit significant positive correlations with one another, suggesting they generally move in the same direction.
- Nifty IT and Nifty Bank show moderate positive correlations with the other sectors, indicating some level of co-movement. (Table 2 & Fig. 1)

4.3 Multiple Correlation Coefficients:

The coefficient R captures the association of each sector with the remaining set: higher R suggests stronger interdependence; lower R indicates more individual behaviour.

Table 3. Multiple Correlation Coefficient for each sector:

Nifty IT	0.3003
Nifty Auto	0.6371
Nifty Infra	0.8487
Nifty Energy	0.7339
Nifty Bank	0.6001

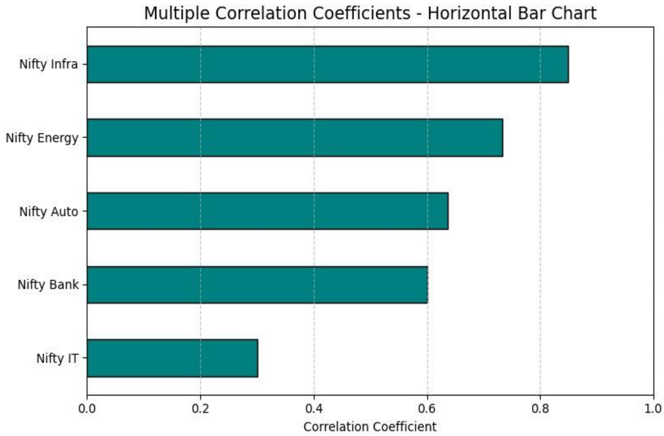

Fig. 2. Bar Chart for Multiple Correlation Coefficients

- The Table 3 & Fig.2 shows high multiple correlation value for other sectors except Nifty IT

4.4 Markov Chain Analysis:

The TPMs summarize the probabilities of transitioning between market states from one day to the next.

Table 4. Transition Probability Matrix (TPM) for ^NSEBANK:

Bank	SG	MG	S	MD	SD
SG	0.1494	0.2873	0.2298	0.2298	0.1034
MG	0.0785	0.2567	0.4108	0.1993	0.0543
S	0.0474	0.2799	0.3995	0.2257	0.0474
MD	0.0567	0.2659	0.3014	0.2836	0.0921
SD	0.1309	0.2619	0.3095	0.1785	0.1190

Table 5. Steady-State Probabilities for ^NSEBANK:

Bank	SG	MG	S	MD	SD
SG	0.0708	0.2697	0.3619	0.2289	0.0684
MG	0.0708	0.2697	0.3619	0.2289	0.0684
S	0.0708	0.2697	0.3619	0.2289	0.0684
MD	0.0708	0.2697	0.3619	0.2289	0.0684
SD	0.0708	0.2697	0.3619	0.2289	0.0684

Table 6. Transition Probability Matrix (TPM) for ^CNXIT:

IT	SG	MG	S	MD	SD
SG	0.1315	0.2763	0.3157	0.2105	0.0657
MG	0.0611	0.3138	0.3500	0.2361	0.0388
S	0.0436	0.2804	0.4068	0.2321	0.0367
MD	0.0584	0.2886	0.3264	0.2611	0.0652
SD	0.1250	0.3125	0.2187	0.1875	0.1562

Table 7. Steady-State Probabilities for ^CNXIT:

IT	SG	MG	S	MD	SD
SG	0.0619	0.2936	0.3557	0.2365	0.0521
MG	0.0619	0.2936	0.3557	0.2365	0.0521
S	0.0619	0.2936	0.3557	0.2365	0.0521
MD	0.0619	0.2936	0.3557	0.2365	0.0521
SD	0.0619	0.2936	0.3557	0.2365	0.0521

Table 8. Transition Probability Matrix (TPM) for ^CNXENERGY:

Energy	SG	MG	S	MD	SD
SG	0.0945	0.3648	0.2702	0.1756	0.0945
MG	0.0557	0.3209	0.3766	0.2201	0.0265
S	0.0384	0.3149	0.3774	0.2331	0.0360
MD	0.0650	0.2705	0.2979	0.2910	0.0753
SD	0.1803	0.3114	0.1639	0.2295	0.1147

Table 9. Steady-State Probabilities for ^CNXENERGY:

Energy	SG	MG	S	MD	SD
SG	0.0606	0.3090	0.3409	0.2393	0.05
MG	0.0606	0.3090	0.3409	0.2393	0.05
S	0.0606	0.3090	0.3409	0.2393	0.05
MD	0.0606	0.3090	0.3409	0.2393	0.05
SD	0.0606	0.3090	0.3409	0.2393	0.05

Table 10. Transition Probability Matrix (TPM) for ^CNXINFRA:

Infra	SG	MG	S	MD	SD
SG	0.1578	0.2105	0.2368	0.2631	0.1315
MG	0.0232	0.3850	0.3824	0.1937	0.0155
S	0.0150	0.2909	0.4267	0.2241	0.0431
MD	0.0178	0.2785	0.3535	0.2928	0.0571
SD	0.2156	0.3333	0.2156	0.1568	0.0784

Table 11. Steady-State Probabilities for ^CNXINFRA:

Infra	SG	MG	S	MD	SD
SG	0.0311	0.3172	0.3812	0.2286	0.0417
MG	0.0311	0.3172	0.3812	0.2286	0.0417
S	0.0311	0.3172	0.3812	0.2286	0.0417
MD	0.0311	0.3172	0.3812	0.2286	0.0417
SD	0.0311	0.3172	0.3812	0.2286	0.0417

Table 12. Transition Probability Matrix (TPM) for ^CNXAUTO:

Auto	SG	MG	S	MD	SD
SG	0.1477	0.2727	0.2500	0.2272	0.1022
MG	0.0725	0.3293	0.3806	0.1782	0.0392
S	0.0435	0.2614	0.3876	0.2729	0.0344
MD	0.0482	0.2310	0.3689	0.2655	0.0862
SD	0.2400	0.2400	0.1600	0.2000	0.1600

Table 13. Steady-State Probabilities for ^CNXAUTO:

Auto	SG	MG	S	MD	SD
SG	0.0719	0.2722	0.3576	0.2376	0.0605
MG	0.0719	0.2722	0.3576	0.2376	0.0605
S	0.0719	0.2722	0.3576	0.2376	0.0605
MD	0.0719	0.2722	0.3576	0.2376	0.0605
SD	0.0719	0.2722	0.3576	0.2376	0.0605

Overall conclusion for Markov chain analysis:

- **Dominance of Stability**: State S is dominant in the long run across sectors, consistent with mean-reverting behaviour and investor rebalancing.
- **Sector sensitivity**: Energy and Auto show greater variability, reflecting exposure to external drivers; Bank and IT appear relatively more stable.
- **Investment insight**: Bank and IT suit stability-oriented allocations; Auto and Energy may deliver higher payoffs during SG spells but entail higher transition risk to SD. (From Table 4 to 13)

4.5 Markov Chain model for sector rotation

Table 14. Portfolio optimization

Nifty IT	46.4030%
Nifty Auto	2.0000%
Nifty Infra	35.4307%
Nifty Energy	24.1662%
Nifty Bank	2.0000%

Interpretation.

- **High allocation to IT & Infra:** Drives portfolio performance, consistent with their favorable risk–return profiles.
- **Diversification via Energy:** Enhances growth potential while moderating risk.
- **Minimal exposure to Auto & Bank:** Reflects comparatively lower return efficiency and/or higher volatility.
- **Risk-adjusted outcome:** A reported value of 1.0672 indicates a favorable balance between return and risk under the modeled assumptions. (Table 14)

5 Appendix A Integration Script

```
def add_appendix():
    open_file("Paper_ID_001.docx")
    go_to_end()
    find_section("References")
    insert_page_break()

    add_text("Appendix A", bold=True)
    add_text("Python Implementation for Markov Chain Analysis")

    content = load_appendix_content()
    paste_content(content)

    format_text(font="Times New Roman", size=12)
    check_text("Appendix A")

    save_file("Updated_Paper.docx")
    export_pdf("Updated_Paper.pdf")

    print("Appendix added successfully!")

add_appendix()
```

6 Conclusions

This paper applies a Markov chain framework to sector rotation within the Indian market and documents the role of state persistence in guiding allocations. The dominance of the Stable state across sectors, the relative strength of IT and Infrastructure on a risk-adjusted basis, and the diversification benefits of Energy together motivate an allocation that over weights IT and Infra while maintaining measured exposure to Energy and holding smaller positions in Auto and Bank. The approach augments conventional analysis by embedding transition dynamics, thereby improving transparency, risk control, and adaptability to changing market conditions.

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