Proceedings of CONF-APMM 2026 Symposium: Applied Mathematics and Quantitative Modeling
DOI: 10.54254/2753-8818/2026.PU37580

Research on the State Transition of US Stock Prices Based on Markov Chains: A Case Study of Eight Representative US Stocks and the Nasdaq Composite Index

Tianqi Yan

Faculty of Science, The University of Hong Kong, Hong Kong, China
u3644559@connect.hku.hk

Abstract. The U.S. stock market exhibits substantial volatility and regime-dependent behavior, yet the transition patterns among discrete price states are not well understood. This study investigates how price state transition dynamics vary across individual stocks and industries and whether they align with the broader market index. Eight representative U.S. stocks (AAPL, MSFT, AMZN, COST, AMGN, XOM, JPM, and NEE) and the Nasdaq Composite Index (IXIC) are examined using monthly closing prices from 2018 to 2025. Monthly price movements are classified as rising, fluctuating, or falling, and a discrete time homogeneous Markov chain is used to estimate one-step and multi-step transition probabilities, steady state distributions, and persistence and reversal patterns. The results reveal clear heterogeneity across individual stocks and industry groups. Technology stocks show stronger upward state persistence, weaker flat state persistence, and stronger rebounds after declines, defensive stocks display greater flat state persistence and more moderate rebounds, while cyclical stocks generally exhibit intermediate patterns. The Nasdaq Composite evolves more smoothly than individual stocks, with more frequent transitions between rising and fluctuating states and fewer direct reversals between rising and falling states, indicating that the index cannot fully represent firm-specific dynamics. These findings extend Markov chain analysis from single assets to systematic cross-stock comparison and provide useful evidence for understanding market state evolution and supporting industry sensitive portfolio decisions.

Keywords: Markov chain, US stocks, Nasdaq Composite Index, price state transition, state transition matrix

1. Introduction

Stock prices exhibit substantial volatility, uncertainty, and regime-dependent behavior, making it important to understand not only changes in returns and volatility but also how prices move between distinct market states. Markov chains offer a transparent framework for this purpose because transition probabilities describe short-run state changes, while multi-step probabilities and stationary distributions characterize longer-run dynamics [1, 2].

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2753-8818/2026.PU37580

Existing studies have applied Markov models to classify markets or individual stocks into rising, stable, and falling states and to examine transition probabilities, persistence, and long-run equilibrium behavior in markets such as Nepal, Kenya, and Nigeria [1-4]. Research on the U.S. market and hidden Markov models further suggests that financial variables often display regime-switching patterns [5, 6]. Dar et al. used finite-state Markov chains to analyze stock-price transitions and steady-state behavior, while Dar et al. and Padi et al. employed hidden Markov models to identify latent market regimes [7-9]. During the pandemic, stock returns and dependence structures also exhibited significant regime changes [10]. At the industry level, Ersen et al. documented heterogeneous transition structures across firms within the same sector, and Kijkarncharoensin identified distinct bullish, sideways, and bearish regimes in sector-specific indices [11, 12]. However, most existing studies focus on individual stocks or single market indices, with limited attention to cross-stock industry differences and the relationship between firm-level transitions and broader market benchmarks.

To address these gaps, this study compares three state transition matrices for eight U.S. stocks from six industries and the Nasdaq Composite Index using monthly closing prices from 2018 to 2025. It asks whether transition and persistence patterns differ across stocks and industries and whether individual stock dynamics align with the market index. The study contributes by extending Markov chain analysis from single asset applications to a unified multi-asset comparison, identifying industry-related differences in persistence, reversal, and long-run state distributions, and evaluating the extent to which an aggregate index represents firm-specific price dynamics. These findings provide a state-based perspective for understanding market heterogeneity and may support industry-sensitive portfolio analysis.

2. Research design: sample, variables and hypotheses

2.1. Sample selection and data sources

This study examines eight representative U.S. listed companies: Apple (AAPL), Microsoft (MSFT), Amazon (AMZN), Costco (COST), Amgen (AMGN), ExxonMobil (XOM), JPMorgan Chase (JPM), and NextEra Energy (NEE). At the formal sector level, these companies cover information technology, consumer discretionary, consumer staples, health care, energy, financials, and utilities. For the group level analysis in Section 4, the stocks are classified into three broader analytical categories: technology oriented stocks (AAPL, MSFT, and AMZN), defensive stocks (COST, AMGN, and NEE), and cyclical stocks (XOM and JPM). The Nasdaq Composite Index (IXIC) is included as the market benchmark. Evidence from seven firms in the paper and paper-products industry further shows that transition probabilities and long-run state distributions can vary across companies, supporting the use of a multi-firm comparison [11].

onthly closing price data from January 2018 to December 2025 are collected from the corresponding Nasdaq Market Activity pages for each stock and the Nasdaq Composite Index. Each price series contains 96 monthly observations, yielding 95 monthly returns and 94 state to state transitions. Monthly data are used because they reduce short term market noise and are more suitable than daily data for examining medium term state evolution. Previous studies have also shown that Markov chain models can be applied to lower-frequency financial data to investigate long-run dynamics and steady-state characteristics [1, 5].

DOI: 10.54254/2753-8818/2026.PU37580

2.2. Variable definition and state classification

Let Pt denote the closing price of a stock or an index in month t. The monthly price change rate is calculated as follows:

$$r_t=\frac{P_t-P_{t-1}}{P_{t-1}} \tag{1}$$

In this formula, rt measures the relative change in stock prices between two consecutive months. Since this paper focuses on state transitions rather than continuous price movements, monthly returns are converted into three discrete market states following previous studies [1-4]: (1) Down (D): $r_t<-2\%$, (2) Fluctuations (F): $2\%\geq r_t\geq-2\%$, (3) Up (U): $r_t>2\%$. Recent applications have likewise represented stock movements using five finite gain/loss states, three observable decrease/constant/increase states, and three latent bullish/sideways/bearish regimes [7, 10, 12]. The threshold, a=2%, distinguishes relatively stable periods from meaningful upward or downward movements. Defining the flat state solely by a zero return would yield few flat-state observations, whereas the selected interval provides a more balanced and interpretable three-state classification.

2.3. Research hypotheses

Based on the research objectives and existing literature, four hypotheses are proposed:

H1: The price state transitions of the selected U.S. stocks exhibit persistence. A stock is expected to have a relatively high probability of remaining in its current state. This persistence is represented by the diagonal elements of its transition matrix [1, 2].

H2: State transition characteristics differ across the selected U.S. stocks. Differences in business models, risk exposure, and firm-specific conditions may lead to different transition, persistence, and reversal probabilities [3, 4].

H3: The three analytical stock groups exhibit systematic differences in the persistence and transition probabilities of price states. Stocks belonging to different analytical groups differ in their exposure to economic cycles, growth expectations, and market risks, therefore, their persistence and reversal patterns are likely to differ [5, 6].

H4: The state transition patterns of individual stocks are not fully consistent with those of the Nasdaq Composite Index. Although the Nasdaq Composite Index reflects the general market trend, individual stock transitions are also affected by industry-level and firm-specific factors. Consequently, stock-level transition patterns may diverge from the market benchmark [5].

3. Research methodology: construction and analysis of the state transition matrix

3.1. Model specification

This study employs a discrete time homogeneous Markov chain to analyze stock price state transitions. Let $\{X_t\}$ denote the sequence of price states, where $X_t\in S$. And S is defined as state space, $S=\{U,F,D\}$. The model assumes the first-order Markov property, meaning that the state in the next month depends only on the current state and not on the complete history of previous states. This property can be expressed:

$$P(X_{t+1}=j|X_t=i,X_{t-1},X_{t-2},\cdots)=P(X_{t+1}=j|X_t=i) \tag{2}$$

DOI: 10.54254/2753-8818/2026.PU37580

The model also assumes time homogeneity, so the transition probabilities remain constant throughout the sample period. These assumptions allow the monthly state sequence to be represented by a fixed transition probability matrix.

3.2. Construction of the one step and n step transition probability matrix

After the monthly observations have been classified into the three states, transitions between consecutive months are counted. For any two states i and j in S, the one-step transition probability is defined as:

$$p_{ij}=P(X_{t+1}=j|X_t=i) \tag{3}$$

Let n_{ij} denote the number of observed transitions from state i to state j. The estimated one-step transition probability would be given as follows.

$$p1_{ij}=\frac{n_{ij}}{\sum_j n_{ij}} \tag{4}$$

This yields the 3×3 transition probability matrix for each stock:

$$P=(p_{ij})=\begin{matrix} p_{UU} & p_{UF} & p_{UD} \\ p_{FU} & p_{FF} & p_{FD} \\ p_{DU} & p_{DF} & p_{DD} \end{matrix} \tag{5}$$

In this matrix, the sum of entries in each row is 1. And the entries on the diagonal, p_{UU},p_{FF},p_{DD}, would represent the persistence of the three states, respectively. The off-diagonal elements reflect the transition and inversion probabilities between different states. Based on the one-step transition matrix P, the n-step transition matrix could be obtained by the matrix power operation.

$$P^{(n)}=P^n \tag{6}$$

Each pij(n) represents the probability that a stock currently in state i will be in state j after n months. These probabilities are used to examine whether differences in short-term transition patterns persist or diminish over long-run horizons.

3.3. Stationary distribution and long term state characteristics

To investigate long-term stable structure of stock price, this paper further derives the stationary distribution π. Since the state space of the Markov chain constructed in this paper is finite and the transition probability matrix is irreducible, according to the theory of Markov chains, there exists a unique stationary distribution π for this chain, which would satisfy the following.

$$\pi P=\pi,\ \sum_i \pi_i=1 \tag{7}$$

Where $\pi=(\pi_U,\pi_F,\pi_D)$ represents the proportion of time that stock prices are in an upward, volatile or downward state in the long term.

DOI: 10.54254/2753-8818/2026.PU37580

3.4. Evaluation criteria

The estimated results are evaluated from two perspectives. First, state persistence and reversal are examined. Persistence is measured by the diagonal probabilities pUU, pFF, pDD, larger values indicate stronger state inertia. Reversal is assessed primarily through pUD and pDU, which respectively represent an up to down reversal and a down to up recovery.

Second, comparisons are conducted at three levels. At the individual stock level, the one step matrices, n step probabilities, and stationary distributions of the eight stocks are compared. At the group level, equally weighted average transition probabilities and stationary distributions are calculated for the technology oriented, defensive, and cyclical groups. At the market level, the stock level estimates are compared with those of the Nasdaq Composite Index to determine whether the index adequately represents individual stock dynamics.

4. Empirical results and analysis

This section reports the main empirical results without repeating the formulas introduced in Section 3. To improve clarity and reduce length, the analysis focuses on key transition indicators, stationary distributions, group level differences, and comparisons with the Nasdaq Composite Index.

4.1. One step transition characteristics

Table 1 summarizes the principal one step transition indicators. The diagonal probabilities pUU, pFF, and pDD measure persistence in the up, flat, and down states, respectively. Pud captures a direct reversal from an up state to a down state, while Pdu measures recovery from a down state to an up state.

Table 1. Probability matrix

Stock	Puu	Puf	Pud	Pfu	Pff	Pfd	Pdu	Pdf	Pdd
AAPL	0.5882	0.1569	0.2549	0.4615	0.0000	0.5385	0.4667	0.1667	0.3667
AMGN	0.4390	0.1951	0.3659	0.3684	0.1053	0.5263	0.4706	0.2353	0.2941
NEE	0.4146	0.2927	0.2927	0.4333	0.3667	0.2000	0.4783	0.3043	0.2174
JPM	0.4545	0.2500	0.2955	0.3810	0.1429	0.4762	0.5862	0.2069	0.2069
XOM	0.4500	0.2500	0.3000	0.4231	0.3846	0.1923	0.4286	0.2143	0.3571
COST	0.4486	0.2553	0.2979	0.5000	0.3333	0.1667	0.6087	0.1739	0.2174
AMZN	0.5098	0.1176	0.3725	0.6250	0.0000	0.3750	0.5429	0.0857	0.3714
MSFT	0.4894	0.2766	0.2340	0.4286	0.2381	0.3333	0.5769	0.1154	0.3077
Nasdaq	0.4545	0.3636	0.1818	0.5000	0.2308	0.2692	0.4583	0.1667	0.3750

Up state persistence is the clearest common feature, as pUU exceeds one third for every sample and is the largest diagonal element in each transition matrix. AAPL records the strongest up state persistence at 0.5882, followed by AMZN at 0.5098 and MSFT at 0.4894. These values indicate that technology oriented stocks are relatively likely to remain in an upward state after a monthly increase.

DOI: 10.54254/2753-8818/2026.PU37580

Persistence is less uniform in the flat and down states. AAPL and AMZN have pFF = 0, indicating that their flat states are temporary rather than persistent. By contrast, XOM and NEE have relatively high flat state persistence probabilities of 0.3846 and 0.3667. Down state persistence ranges from 0.2069 for JPM to 0.3714 for AMZN among the individual stocks. Therefore, the evidence supports H1 primarily through the strong persistence of the up state, although persistence varies across states and stocks.

The results also reveal substantial cross stock heterogeneity. Among the individual stocks, pUU ranges from 0.4146 for NEE to 0.5882 for AAPL, while pFF ranges from 0 for AAPL and AMZN to 0.3846 for XOM. Recovery probabilities also differ: COST has the highest pDU at 0.6087, whereas XOM has the lowest at 0.4286. Similarly, the up to down reversal probability ranges from 0.2340 for MSFT to 0.3725 for AMZN. These differences support H2 by showing that each stock has a distinct combination of persistence, reversal, and recovery characteristics.

4.2. Multi step transitions and stationary distributions

To examine the medium term evolution of price states, the one step transition matrices are raised to the third and sixth powers. Rather than reporting every element of the resulting matrices, Table 2 presents the evolution of the up state persistence probability, $Puu^{(n)}$, which is the most prominent persistence indicator in the sample. The flat and down state probabilities display similar convergence patterns and are omitted to conserve space.

Table 2. Six step diagonal probabilities versus stationary distribution

Sample	Puu(1)	$Puu^{(3)}$	$Puu^{(6)}$	πU
AAPL	0.5882	0.5313	0.5305	0.5304
MSFT	0.4894	0.4985	0.5063	0.5062
AMZN	0.5098	0.5327	0.5330	0.5331
COST	0.4486	0.4823	0.4809	0.4808
AMGN	0.4390	0.4516	0.4510	0.4509
NEE	0.4146	0.4274	0.4299	0.4298
XOM	0.4500	0.4387	0.4386	0.4385
JPM	0.4545	0.4794	0.4922	0.4921
Nasdaq	0.4545	0.4686	0.4682	0.4681

The results show that the influence of the initial state declines rapidly. By the sixth step, $Puu^{(6)}$ differs from the corresponding stationary probability πU by no more than approximately 0.0001 for every sample. This indicates that the estimated Markov chains converge to their long run distributions within approximately six monthly transitions. AAPL adjusts downward from its relatively high one step persistence, whereas most other samples approach their stationary up state probabilities from below. The Nasdaq also converges rapidly, with $Puu^{(6)} = 0.4682$ compared with $\pi U = 0.4681$.

DOI: 10.54254/2753-8818/2026.PU37580

4.3. Group level differences

To evaluate H3, the eight stocks are divided into three analytical groups: technology oriented stocks (AAPL, MSFT, and AMZN), defensive stocks (COST, AMGN, and NEE), and cyclical stocks (XOM and JPM). Table 3 combines the most relevant group average transition indicators and stationary probabilities.

Table 3. Group average transition indicators and stationary distributions

Group	Puu	Pff	Pdu	πU	πF	πD
Technology oriented	0.5291	0.0794	0.5622	0.5232	0.1361	0.3407
Defensive	0.4341	0.2684	0.5192	0.4538	0.2669	0.2793
Cyclical	0.4523	0.2638	0.5074	0.4653	0.2517	0.2830

The group level indicators are calculated as simple unweighted arithmetic averages of the estimated probabilities for the stocks within each analytical group. A clear gradient appears in up state persistence. The technology oriented group has the highest average Puu at 0.5291, compared with 0.4523 for cyclical stocks and 0.4341 for defensive stocks. Technology oriented stocks also have the strongest average recovery probability, with Pdu = 0.5622.

Flat state persistence follows the opposite pattern. The technology oriented group has a very low average Pff of 0.0794, whereas the defensive and cyclical groups record 0.2684 and 0.2638, respectively. The stationary distributions reinforce this result: technology oriented stocks spend approximately 52.3% of the long run in the up state but only 13.6% in the flat state. Defensive stocks spend 45.4% in the up state and 26.7% in the flat state, while cyclical stocks occupy an intermediate position.

These patterns indicate that technology oriented stocks are characterized by stronger directional persistence and recovery, whereas defensive and cyclical stocks display more stable and range bound behavior. The systematic group differences provide descriptive support for H3.

4.4. Comparison with the Nasdaq Composite Index

The Nasdaq Composite Index exhibits a smoother transition structure than most individual stocks. Its probability of moving from an up state to a flat state is 0.3636, which is higher than the corresponding probabilities for AAPL, MSFT, and AMZN. Conversely, its direct up to down reversal probability is only 0.1818, lower than that of every individual stock in the sample. This combination suggests that changes in the index are more likely to pass through an intermediate flat state rather than reverse direction immediately.

The Nasdaq stationary distribution is $\pi = (0.4681, 0.2766, 0.2553)$. Its long run flat state probability is substantially higher than those of AAPL, MSFT, and AMZN, but closer to the values recorded for COST and XOM. No individual stock has the same stationary distribution as the index. Individual stocks therefore retain firm specific and group specific transition characteristics that are not fully captured by the aggregate benchmark. This evidence supports H4.

Overall, the descriptive evidence supports all four hypotheses. Price states exhibit persistence, particularly in the up state, transition structures differ materially across individual stocks, the three analytical groups display systematic differences in persistence and long run distributions, and individual stock dynamics do not fully coincide with those of the Nasdaq Composite Index.

DOI: 10.54254/2753-8818/2026.PU37580

5. Conclusion

This study investigates whether discrete price state dynamics differ across major U.S. stocks and analytical industry groups and whether individual stock transitions are consistent with those of the Nasdaq Composite Index. Monthly closing prices from January 2018 to December 2025 for eight representative stocks and the index were classified into up, flat, and down states using a ±2% threshold. A first order homogeneous Markov chain was then used to estimate one step transition probabilities, multi step probabilities, and stationary distributions.

The results reveal both persistence and substantial heterogeneity. The up state is the most persistent state for most samples, but the degree of persistence varies across stocks. Technology oriented stocks show the highest average up state persistence and long run up state probability, together with stronger rebounds from the down state and very low flat state persistence. Defensive and cyclical stocks display higher flat state persistence and more range bound behavior. The multi step analysis further shows that the influence of the initial state declines rapidly: by the sixth monthly transition, the estimated probabilities are effectively equal to their stationary values. The Nasdaq Composite has a smoother transition structure than the individual stocks, with a higher probability of moving from an up state to a flat state and a lower probability of reversing directly from up to down. No individual stock shares the same stationary distribution as the index. Overall, the descriptive evidence supports the four hypotheses and shows that an aggregate market index cannot fully represent firm specific or group specific dynamics. The study contributes to the literature by extending a conventional three state Markov chain framework from single asset applications to a unified comparison across several stocks, broad analytical groups, and a market benchmark. Nevertheless, the findings should be interpreted with caution. The sample is small and purposively selected, the ±2% threshold is fixed, and the homogeneous first order assumption does not allow transition probabilities to change across events such as the COVID 19 shock or shifts in monetary policy. In addition, the group differences are descriptive rather than based on formal significance tests. Future research could use a larger sample, test alternative thresholds, apply formal cross group tests, and compare time varying, higher order, or hidden Markov models.

References

[1] Bac, H. T., Thu, V. T. T., Tien, V. D. X., Thien, H. N., & Binh, L. T. (2024). Application of Markov chains in stock price trend forecasting. *VNU Journal of Science: Mathematics–Physics, 40*(4), 47–63. https://doi.org/10.25073/2588-1124/vnumap.4941

[2] Bhusal, M. K. (2017). Application of Markov chain model in the stock market trend analysis of Nepal. *International Journal of Scientific & Engineering Research, 8*(10), 1733–1745. DOI: 10.14299/ijser.2017.10.008

[3] Otieno, S., Otumba, E. O., & Nyabwanga, R. N. (2015). Application of Markov chain to model and forecast stock market trend: A study of Safaricom shares in Nairobi Securities Exchange, Kenya. *International Journal of Current Research, 7*(4), 14712–14721. https://www.researchgate.net/publication/281974470_APPLICATION_OF_MARKOV_CHAIN_TO_MODEL_AND_FORECAST_STOCK_MARKET_TREND_A_STUDY_OF_SAFARICOM_SHARES_IN_NAIROBI_SECURITIES_EXCHANGE_KENYA

[4] Choji, D. N., Eduno, S. N., & Kassem, G. T. (2013). Markov chain model application on share price movement in stock market. *Computer Engineering and Intelligent Systems, 4*(10), 84–95. https://www.iiste.org/Journals/index.php/CEIS/article/view/7972

[5] Chauvet, M., & Jiang, C. (2023). Nonlinear relationship between monetary policy and stock returns: Evidence from the U.S. *Global Finance Journal, 55*, article 100796. https://doi.org/10.1016/j.gfj.2022.100796

[6] Li, S. (2025). Momentum, volume and investor sentiment study for U.S. technology sector stocks—A hidden Markov model based principal component analysis. *PLOS ONE, 20*(9), article e0331658. https://doi.org/10.1371/journal.pone.0331658

DOI: 10.54254/2753-8818/2026.PU37580

[7] Dar, G. F., Padi, T. R., & Rekha, S. (2022). Stock price prediction using a Markov chain model: A study for TCS share values. *Advances and Applications in Statistics, 80*, 83–101. https://doi.org/10.17654/0972361722068
[8] Dar, G. F., Padi, T. R., Rekha, S., & Dar, Q. F. (2022). Stochastic modeling for the analysis and forecasting of stock market trend using hidden Markov model. *Asian Journal of Probability and Statistics, 18*(1), 43–56. https://doi.org/10.9734/ajpas/2022/v18i130436
[9] Padi, T. R., Rekha, S., & Dar, G. F. (2024). Predictive modeling for share closing prices through hidden Markov models with a special reference to the National Stock Exchange. *Advances and Applications in Statistics, 91*(6), 673–697. https://doi.org/10.17654/0972361724036
[10] Bouteska, A., Sharif, T., & Abedin, M. Z. (2023). COVID-19 and stock returns: Evidence from the Markov switching dependence approach. *Research in International Business and Finance, 64*, article 101882. https://doi.org/10.1016/j.ribaf.2023.101882
[11] Ersen, N., Akyüz, İ., & Akyüz, K. C. (2023). Markov chain model for predicting the stock price of paper and paper products industry. *Turkish Journal of Forest Science, 7*(2), 178–188. https://doi.org/10.32328/turkjforsci.1314333
[12] Kijkarncharoensin, A. (2025). Identifying risk regimes in a sectoral stock index through a multivariate hidden Markov framework. *Risks, 13*(7), article 135. https://doi.org/10.3390/risks13070135