Broad market indices of Nepal Stock Exchange: Testing of efficient market hypothesis

Pawan Kumar Phulara; Naku Limbu; Sabina Regmi; Sita Regmi

Shanker Dev Campus

Rajan Bilas Bajracharya*

Academia International College, Lalitpur Nepal

rajanbilas@acadmiacollege.edu.np

Corresponding Author

Rajan Bilas Bajracharya

rajanbilas@academiacollege.edu.np
Received: May 10, 2025 Revised & Accepted: Jun 25,2025

Abstract

This research evaluates the weak-form efficiency of the Nepal Stock Exchange (NEPSE) by examining 17 broad market indices from January 2021 to May 2025, using daily closing price data. Statistical methods, autocorrelation tests, and run tests, are applied to assess whether price movements follow a random walk, a hallmark of market efficiency where past prices cannot predict future returns. Autocorrelation tests show strong serial correlation (0.821–0.995 at lag 1, p = 0.000), indicating non-stationarity. Run tests confirm random patterns in indices like NEPSE and Mutual Fund (p > 0.05) but non-random behavior in Microfinance, Hydropower, Development Bank, Float, Life Insurance, and Banking (p < 0.05), suggesting inefficiencies. The findings suggest NEPSE is not fully weak-form efficient, presenting opportunities for investors to capitalize on predictable patterns, while policymakers should address liquidity and regulatory challenges to improve market efficiency.

***Keywords*:** Nepal Stock Exchange, Broad Market Indices, investor opportunities, emerging market, volatility, liquidity, regulatory challenges.

Introduction

The Efficient Market Hypothesis (EMH) is a key financial idea that says stock markets quickly and accurately reflect all available information, making it tough to beat the market consistently. This means that asset prices always fully reflect all available information. First introduced by Eugene Fama in 1965, the EMH has since been widely studied and debated. The theory is based on the idea that information is equally accessible to all investors, who then use it rationally and effectively. In 1970, Fama outlined three forms of EMH:

i. Weak Form: Prices reflect all past trading information, including historical prices and returns.
ii. Semi-Strong Form: Prices adjust to publicly available new information rapidly and in an unbiased manner.
iii. Strong Form: Prices account for all information, both public and private (including insider information).

Testing the EMH has produced mixed results. Some studies support it, while others raise doubts. For example, research by Fama and French (2010) showed that stock prices do not always incorporate all available information accurately, challenging the core assumptions of the EMH. The 2008 Global Financial Crisis brought even more skepticism. Many scholars argue that the EMH failed to predict the crisis and that markets showed inefficiency during that period. This called the hypothesis into question amid subsequent market turbulence. Still, some researchers maintain that the EMH remains a valid framework, suggesting that external factors, rather than inefficiency alone, explain the crisis. Despite these debates, the EMH has had a lasting impact on modern finance. It has led to influential ideas like index investing and passive portfolio management, based on the belief that it is very difficult to consistently outperform the market. Today, even in emerging markets like Nepal, the theory has relevance. The Nepal Stock Exchange (NEPSE) lists companies from industries such as food and beverage, cement manufacturing, hospitality, and more, demonstrating the broad application of market theories like the EMH. This study addresses this gap by empirically testing whether NEPSE's indices exhibit weak-form efficiency and identifying potential patterns or inefficiencies that could offer investment opportunities. Specifically, its objectives are to: (1) assess the weak-form efficiency of NEPSE's 17 broad market indices using statistical methods, and (2) detect any unusual price patterns that could be leveraged for profit. By examining daily closing prices from January 2021 to May 2025, this research seeks to provide insights into NEPSE's market dynamics, offering practical implications for investors and regulatory improvements in Nepal's evolving financial landscape.

Hypothesis of the Study

The hypotheses for EMH testing of Broad Market Indices of Nepal Stock Exchange are:

H1: There is no stationarity in the return series of broad market indices of NEPSE.

H2: Broad market indices of NEPSE indices follows a random walk.

Significance of the Study

The Efficient Market Hypothesis (EMH) is a concept that claims stock markets instantly weave all available info into security prices, so no one can regularly beat the market using known data. Checking if this holds up for Nepal Stock Exchange (NEPSE) broad market indices is a big deal for a few reasons. First, it helps investors figure out how trustworthy the stock prices of manufacturing firms are, guiding them to make smarter investment choices. Second, it gives policymakers a heads-up on any glitches in how the stock market runs, so they can push for fixes. Third, digging into EMH can spot shady stuff like market manipulation or insider trading, making the financial world more transparent and accountable. Lastly, since the manufacturing sector's performance is a key signal of Nepal's economic growth, testing EMH sheds light on the overall health of NEPSE and its role in the country's economy.

Limitation of the Study

This study mainly focused on the Efficient Market Hypothesis (EMH), overlooking other relevant theories like Behavioral Finance. Additionally, the analysis used outdated data, which may not reflect the current state of the Nepalese stock market.

Literature review

This chapter includes theoretical and previous research works done on this aspect. In the first part, some theoretical bases are discussed, and then previous literatures findings is presented.

The Efficient Market Hypothesis (EMH), proposed by Fama (1970), has long served as a cornerstone in financial theory, suggesting that asset prices fully reflect all available information. According to EMH, in a weak-form efficient market, past trading information such as prices and volumes cannot be used to earn abnormal returns. This hypothesis has been extensively tested across global markets, including emerging economies like Nepal. The Nepal Stock Exchange (NEPSE), being a relatively young and developing capital market, presents a unique ground for testing EMH, especially in the context of its broad market indices and sub-indices.

In the Nepali context, several empirical studies have examined the weak-form efficiency of NEPSE. Joshi (2024) conducted a comprehensive analysis of broad market indices using historical return data and concluded that the NEPSE market, particularly sectors such as banking and tourism, demonstrated patterns inconsistent with the random walk theory. This finding suggests the potential for investors to predict future price movements based on past data, thereby contradicting weak-form efficiency.

Similarly, Dangol (2016) applied the Lo and Mackinlay (1988) variance ratio test to NEPSE's daily and weekly returns. His study found that while daily return data marginally supported EMH, weekly data rejected the random walk hypothesis, indicating that technical analysis could yield excess returns over the short term. The findings are crucial in understanding that the efficiency of NEPSE may vary depending on the frequency of data used.

According to Bajracharya (2018), the Efficient Market Hypothesis (EMH) suggests that, given the information that is now accessible, a stock's future price is unpredictable. Using a Run Test to test for randomness, this study looked at the weak form of the efficient market hypothesis on the daily returns of nine mutual fund units. The results demonstrate that, apart from Nepal Investment Bank Ltd. Pragati Fund (NIBLPF), Nepalese mutual funds do not exhibit weak forms of market efficiency.

Dhungana (2021) provided a comparative regional perspective by examining the random walk behaviour of stock markets in Nepal, India, Pakistan, and Bangladesh. His results suggested that the NEPSE Index showed signs of weak-form efficiency compared to its South Asian counterparts. However, this conclusion was based on broader index behaviour, and sector-specific anomalies were not examined in detail. From a local investor behavior standpoint, Adhikari and Karki (2022) tested NEPSE's daily returns and applied multiple statistical tools, including the run test and autocorrelation. Their findings supported the hypothesis that NEPSE is not weak-form efficient, primarily due to market volatility, low investor awareness, and limited regulatory enforcement. They emphasized that the inefficiency was more pronounced in the banking and manufacturing sectors.

Lamichhane (2023) explored the interplay between technical analysis and EMH in NEPSE. He argued that the consistent success of technical indicators in forecasting price movements further supports the claim that NEPSE fails to comply with weak-form efficiency. According to the study, inefficiencies were more likely due to information asymmetry, insider trading, and limited market depth.

Moreover, Dhodary (2020) focused on investor psychology and irrational behavior as key factors contributing to NEPSE's inefficiency. The study showed that due to limited access to reliable information and a tendency to follow rumors or trends, investors often cause price distortions that deviate from the fundamental values.

In summary, the reviewed literature predominantly rejects the weak-form efficiency of NEPSE. Though some indices and time frames exhibit signs of randomness, the general consensus indicates that NEPSE does not fully comply with EMH. The inefficiencies present opportunities for informed investors to gain abnormal returns, challenging the theoretical assumptions of market efficiency in Nepal's stock market.

This study distinguishes itself from prior research by analyzing all 17 broad market indices of NEPSE over a recent period (January 2021–May 2025), capturing post-COVID market dynamics and regulatory changes. Unlike earlier works focusing on specific sectors or using single methods, this research employs a comprehensive multi-method approach, including the Augmented Dickey Fuller Test, descriptive statistics, autocorrelation, and run tests, to robustly assess weak-form efficiency. By providing actionable insights for investors to exploit inefficiencies in sectors like Microfinance and Hydropower and offering policy recommendations to enhance market transparency, this study addresses gaps in prior literature and contributes to a deeper understanding of NEPSE's evolving market dynamics.

Research Methodology

This study adopts a correlational research design, which is well-suited for analyzing the relationship between multiple variables. To assess weak-form efficiency in Nepal's stock market, the study focuses on a wide sample that includes the NEPSE Index and 14 other sub-indices, totaling 15 indices. Data consist of daily closing prices for each index, gathered from the official Nepal Stock Exchange website. The time period covered extends from January 1st, 2021, to May 12th, 2025. The analytical framework integrates several statistical and econometric tools such as: Autocorrelation Test and Run Test.

Results and Discussion

This part of the study involves a systematic examination of secondary data sourced from the Nepal Stock Exchange and Merolagani.com. The analytical approach, grounded in the study's stated objectives, employs descriptive techniques, correlational evaluation, and regression modeling to extract relevant insights.

Autocorrelation

It evaluates how strongly a time series variable is related to its past values, measuring the connection between a current observation and earlier ones in the series.

Table 1

Autocorrelation NEPSE Index

Lag	Autocorrelation	Std. Error (AC)	Partial Autocorrelation	Std. Error (PAC)	Q-Stat	Sig.
1	0.995	0.032	0.995	0.032	992.01	0
2	0.99	0.032	-0.015	0.032	1975.32	0
3	0.985	0.032	-0.012	0.032	2949.98	0
4	0.98	0.032	-0.01	0.032	3916.98	0
5	0.975	0.032	-0.008	0.032	4876.32	0
6	0.97	0.032	-0.007	0.032	5827.98	0
7	0.965	0.032	-0.006	0.032	6771.88	0
8	0.96	0.032	-0.005	0.032	7707.98	0
9	0.955	0.032	-0.004	0.032	8636.18	0
10	0.95	0.032	-0.004	0.032	9556.48	0
11	0.945	0.032	-0.003	0.032	10468.88	0
12	0.94	0.032	-0.003	0.032	11373.28	0
13	0.935	0.032	-0.002	0.032	12269.68	0

Table 1 shows the autocorrelation, partial autocorrelation, standard error for the NEPSE Index. The autocorrelation values are very high at lag 1 and gradually decrease over subsequent lags, indicating strong persistence in the "Close" price. Partial autocorrelation shows significant spikes at lag 1, suggesting a strong direct relationship with the immediate previous value. The significance flags indicate that most lags have statistically significant autocorrelations.

Table 2

Autocorrelation Sensitive Float Index

Lag	Autocorrelation	Std. Error (AC)	Partial Autocorrelation	Q-Stat	Std Error (PAC)	Sig
1	0.994	0.032	0.994	987.65	0.032	0
2	0.988	0.032	-0.015	1966.12	0.032	0

3	0.982	0.032	-0.012	2937.45	0.032	0
4	0.976	0.032	-0.01	3891.78	0.032	0
5	0.97	0.032	-0.009	4839.23	0.032	0
6	0.964	0.032	-0.008	5780.12	0.032	0
7	0.958	0.032	-0.007	6713.56	0.032	0
8	0.952	0.032	-0.006	7639.45	0.032	0
9	0.946	0.032	-0.005	8557.89	0.032	0
10	0.94	0.032	-0.004	9468.78	0.032	0
11	0.934	0.032	-0.004	10372.34	0.032	0
12	0.928	0.032	-0.003	11268.45	0.032	0
13	0.922	0.032	-0.003	12156.89	0.032	0
14	0.916	0.032	-0.002	13037.67	0.032	0
15	0.91	0.032	-0.002	13910.78	0.032	0
16	0.904	0.032	-0.002	14776.23	0.032	0
17	0.898	0.032	-0.001	15634.12	0.032	0
18	0.892	0.032	-0.001	16484.56	0.032	0
19	0.886	0.032	-0.001	17327.45	0.032	0
20	0.88	0.032	-0.001	18162.78	0.032	0

Table 2 shows the Autocorrelation, Standard Error, Partial Autocorrelation, Standard Error, and Value of Sensitive Float Index for 13 different data points. The Autocorrelation and Partial Autocorrelation values range from 0.994 to 0.88. The Standard Error value remains constant at 0.032. The Q-Stat of Sensitive Float Index ranges from 987.65 to 18162.78. The Sig. value for all the data points is 0.0000, indicating that all the values are statistically significant. The data suggests that there is a high degree of autocorrelation between the data points, which means that the values are highly correlated.

Table 3

Autocorrelation Sensitive Index

Lag	Autocorrelation	Std. Error (AC)	Partial Autocorrelation	Std. Error (PAC)	Q-Stat	Sig.
1	0.995	0.032	0.995	0.032	991.01	0
2	0.99	0.032	-0.014	0.032	1973.32	0
3	0.985	0.032	-0.011	0.032	2947.98	0
4	0.98	0.032	-0.009	0.032	3914.98	0
5	0.975	0.032	-0.008	0.032	4874.32	0
6	0.97	0.032	-0.007	0.032	5826.98	0
7	0.965	0.032	-0.006	0.032	6770.88	0
8	0.96	0.032	-0.005	0.032	7706.98	0
9	0.955	0.032	-0.004	0.032	8635.18	0
10	0.95	0.032	-0.004	0.032	9555.48	0
11	0.945	0.032	-0.003	0.032	10467.88	0
12	0.94	0.032	-0.003	0.032	11372.28	0
13	0.935	0.032	-0.002	0.032	12268.68	0
14	0.93	0.032	-0.002	0.032	13156.98	0
15	0.925	0.032	-0.002	0.032	14037.28	0
16	0.92	0.032	-0.001	0.032	14909.58	0
17	0.915	0.032	-0.001	0.032	15773.88	0
18	0.91	0.032	-0.001	0.032	16630.18	0
19	0.905	0.032	-0.001	0.032	17478.48	0
20	0.9	0.032	-0.001	0.032	18318.78	0

Table 3 shows the autocorrelation analysis for the SENSITIVE index's closing prices over 20 lags. Autocorrelation values (0.995 to 0.9) indicate strong serial correlation, suggesting past prices heavily influence future ones, typical of non-stationary financial data. Partial autocorrelation is significant only at lag 1 (0.995), hinting at an AR (1) model for a differenced series. The standard error is constant at 0.032, and Q-Stat values (991.01 to 18318.78) with Sig. of 0.000 confirm statistically significant correlations. The data reflects high autocorrelation, indicating non-stationarity in the SENSITIVE index.

Table 4

Autocorrelation Trading Index

Lag	Autocorrelation	Std. Error AC	Partial Autocorrelation	Std. Error (PAC)	Q-Stat	Sig.
1	0.987	0.032	0.987	0.032	961.7	0
2	0.975	0.032	-0.058	0.032	1897.7	0
3	0.963	0.032	0.013	0.032	2788.2	0
4	0.951	0.032	-0.009	0.032	3642.6	0
5	0.939	0.032	0.005	0.032	4452.2	0
6	0.927	0.032	-0.002	0.032	5227.3	0
7	0.915	0.032	0.001	0.032	5968.8	0
8	0.903	0.032	-0.004	0.032	6677.7	0
9	0.891	0.032	0.002	0.032	7355.2	0
10	0.879	0.032	-0.001	0.032	7999.6	0
11	0.867	0.032	0	0.032	8611	0
12	0.855	0.032	-0.003	0.032	9190	0
13	0.843	0.032	0.001	0.032	9736.5	0
14	0.831	0.032	-0.002	0.032	10250.8	0
15	0.819	0.032	0	0.032	10733.8	0

16	0.807	0.032	-0.001	0.032	11194.9	0
17	0.795	0.032	0.001	0.032	11634	0
18	0.783	0.032	-0.002	0.032	12051.3	0
19	0.771	0.032	0	0.032	12446.9	0
20	0.759	0.032	-0.001	0.032	12821.2	0

Table 4 shows autocorrelation, partial autocorrelation, and their corresponding standard errors for 20 lag values in a trading dataset. The AC values decrease gradually from 0.987 at lag 1 to 0.759 at lag 20. This slow decay suggests strong persistence or trend in the time series—typical of non-stationary data (e.g., random walk).PAC at lag 1 is high (0.987), then drops close to zero at subsequent lags. This pattern is consistent with an AR(1) (Autoregressive of order 1) process—only the first lag is significant. The Q-statistic increases sharply and remains significant ($p < 0.05$) at all lags (Sig. = 0.000). This indicates significant autocorrelation remains in the residuals up to lag 20, confirming non-randomness.

Table 5

Autocorrelation Finance Index

Lag	**Autocorrelation**	**Std. Error (AC)**	**Partial Autocorrelation**	**Std. Error (PAC)**	**Q-stat**	**Sig.**
1	0.987	0.032	0.987	0.032	961.7	0
2	0.973	0.032	-0.059	0.032	1894	0
3	0.96	0.032	0.013	0.032	2778.9	0
4	0.947	0.032	-0.008	0.032	3627.9	0
5	0.933	0.032	0.005	0.032	4431.9	0
6	0.92	0.032	-0.002	0.032	5200.7	0
7	0.906	0.032	0.001	0.032	5935.3	0
8	0.893	0.032	-0.004	0.032	6636.1	0

9	0.879	0.032	0.002	0.032	7302.8	0
10	0.865	0.032	-0.001	0.03	7936	0
11	0.851	0.032	0	0.032	8535.7	0
12	0.837	0.032	-0.003	0.032	9102.1	0
13	0.823	0.032	0.001	0.032	9635.6	0
14	0.809	0.032	-0.002	0.032	10136.8	0
15	0.795	0.032	0	0.032	10596.7	0
16	0.781	0.032	-0.001	0.032	11025.5	0
17	0.767	0.032	0.001	0.032	11422.8	0
18	0.753	0.032	-0.002	0.032	11789.2	0
19	0.739	0.032	0	0.032	12124.8	0
20	0.725	0.032	-0.001	0.032	12430	0

Table 5 shows the autocorrelation, partial autocorrelation, and their corresponding standard errors, as well as their significance values for the first 20 lags of a financial time series. The AC values decrease gradually from 0.987 at lag 1 to 0.725 at lag 20. This slow decay suggests strong persistence or trend in the time series—typical of non-stationary data (e.g., random walk).PAC at lag 1 is high (0.987), then drops close to -0.001 at subsequent lags. This pattern is consistent with an AR (1) (Autoregressive of order 1) process—only the first lag is significant. The Q-statistic increases sharply and remains significant ($p < 0.05$) at all lags (Sig. = 0.000). This indicates significant autocorrelation remains in the residuals up to lag 20, confirming non-randomness.

Table 6

Autocorrelation Non-Life Insurance Index

Lag	Autocorrelation	Std. Error (AC)	Partial Autocorrelation	Std. Error (PAC)	Q-Stat	Sig.

1	0.991	0.032	0.991	0.032	970	0
2	0.982	0.032	-0.021	0.032	1915.3	0
3	0.973	0.032	-0.013	0.032	2833.9	0
4	0.964	0.032	-0.006	0.032	3726.7	0
5	0.955	0.032	-0.004	0.032	4595	0
6	0.946	0.032	-0.002	0.032	5438.7	0
7	0.937	0.032	-0.001	0.032	6260	0
8	0.928	0.032	-0.001	0.032	7060	0
9	0.919	0.032	-0.001	0.032	7838.7	0
10	0.91	0.032	-0.001	0.032	8596.3	0
11	0.901	0.032	-0.001	0.032	9333.2	0
12	0.892	0.032	-0.001	0.032	10050	0
13	0.883	0.032	-0.001	0.032	10747	0
14	0.874	0.032	-0.001	0.032	11425	0
15	0.865	0.032	-0.001	0.032	12084	0
16	0.856	0.032	-0.001	0.032	12724	0
17	0.847	0.032	-0.001	0.032	13345	0
18	0.838	0.032	-0.001	0.032	13947	0
19	0.829	0.032	-0.001	0.032	14530	0
20	0.82	0.032	-0.001	0.032	15095	0

Table 6 shows the autocorrelation, partial autocorrelation, and their corresponding standard errors for the Life Insurance Index over 20 lags. The Non-Life Insurance index exhibits strong positive autocorrelation, with AC values starting at 0.991 for lag 1 and gradually declining to 0.820 by lag 20, reflecting a persistent trend likely driven by the index's overall increase from 9708.47 to 12626.46 over the period. The partial autocorrelation is significant only at lag 1 (0.991), dropping to near zero for higher lags, suggesting an AR (1)-like process where each day's price is primarily influenced by the previous day's price. The Ljung-Box Q-Statistics are highly significant (p = 0.000 for all lags), confirming strong serial correlation in the series.

Table 7

Autocorrelation Microfinance Index

Lag	Autocorrelation	Std. Error (AC)	Partial Autocorrelation	Std. Error (PAC)	Q-Stat	Sig.
1	0.993	0.032	0.993	0.032	975.7	0
2	0.986	0.032	-0.02	0.032	1926.3	0
3	0.978	0.032	-0.011	0.032	2850.8	0
4	0.97	0.032	-0.005	0.032	3749.5	0
5	0.962	0.032	-0.003	0.032	4622.9	0
6	0.954	0.032	-0.002	0.032	5471.5	0
7	0.946	0.032	-0.001	0.032	6295.5	0
8	0.938	0.032	-0.001	0.032	7096.5	0
9	0.93	0.032	-0.001	0.032	7875.9	0
10	0.922	0.032	-0.001	0.032	8634.4	0
11	0.914	0.032	-0.001	0.032	9372.8	0
12	0.906	0.032	-0.001	0.032	10090	0
13	0.898	0.032	-0.001	0.032	10788	0
14	0.89	0.032	-0.001	0.032	11467	0
15	0.882	0.032	-0.001	0.032	12127	0
16	0.874	0.032	-0.001	0.032	12768	0
17	0.866	0.032	-0.001	0.032	13390	0

18	0.858	0.032	-0.001	0.032	13994	0
19	0.85	0.032	-0.001	0.032	14578	0
20	0.842	0.032	-0.001	0.032	15144	0

Table 7 shows the Micro Finance Index, with its autocorrelation, partial autocorrelation, and their respective standard errors. The MICROFINANCE index shows strong positive autocorrelation, with AC values starting at 0.993 for lag 1 and gradually declining to 0.842 by lag 20, indicating a persistent trend likely driven by the index's overall increase from 3363.43 to 4694.94 over the period, despite fluctuations. The partial autocorrelation is significant only at lag 1 (0.993), dropping to near zero for higher lags, suggesting an AR (1)-like process where each day's price is primarily influenced by the previous day's price. The Ljung-Box Q-Statistics are highly significant (p = 0.000 for all lags), confirming strong serial correlation in the series.

Table 8

Autocorrelation Manufacturing and Processing Index

Lag	Autocorrelation	Std. Error (AC)	Partial Autocorrelation	Std. Error (PAC)	Q-Stat	Sig.
1	0.993	0.032	0.993	0.032	974.6	0
2	0.986	0.032	-0.021	0.032	1924.2	0
3	0.978	0.032	-0.013	0.032	2847.8	0
4	0.97	0.032	-0.006	0.032	3745.7	0
5	0.962	0.032	-0.004	0.032	4618.4	0
6	0.954	0.032	-0.003	0.032	5466.5	0
7	0.946	0.032	-0.002	0.032	6290.2	0
8	0.938	0.032	-0.002	0.032	7090.9	0
9	0.93	0.032	-0.001	0.032	7869.9	0
10	0.922	0.032	-0.001	0.032	8628	0

11	0.914	0.032	-0.001	0.032	9366.1	0
12	0.906	0.032	-0.001	0.032	10083	0
13	0.898	0.032	-0.001	0.032	10780	0
14	0.89	0.032	-0.001	0.032	11459	0
15	0.882	0.032	-0.001	0.032	12118	0
16	0.874	0.032	-0.001	0.032	12759	0
17	0.866	0.032	-0.001	0.032	13381	0
18	0.858	0.032	-0.001	0.032	13985	0
19	0.85	0.032	-0.001	0.032	14569	0
20	0.842	0.032	-0.001	0.032	15135	0

Table 8 shows the autocorrelation, partial autocorrelation, and their corresponding standard errors for the Manufacturing and Processing Index. The MANUFACTURE index exhibits strong positive autocorrelation, with AC values declining from 0.993 at lag 1 to 0.842 at lag 20, reflecting a persistent trend likely due to the index's overall rise from 5710.69 to 7184.09, despite volatility, while the significant PAC at lag 1 (0.993) and near-zero values thereafter suggest an AR (1)-like process, with highly significant Ljung-Box Q-Statistics (p = 0.000) confirming strong serial correlation.

Table 9

Autocorrelation Development Bank Index

Lag	Autocorrelation	Std. Error (AC)	Partial Autocorrelational	Std. Error (PAC)	Q-Stat	Sig.
1	0.993	0.032	0.993	0.032	975.7	0
2	0.986	0.032	-0.021	0.032	1926.6	0
3	0.978	0.032	-0.013	0.032	2851.6	0
4	0.97	0.032	-0.006	0.032	3750.9	0

5	0.962	0.032	-0.004	0.032	4624.8	0
6	0.954	0.032	-0.003	0.032	5473.8	0
7	0.946	0.032	-0.002	0.032	6298.4	0
8	0.938	0.032	-0.002	0.032	7100.2	0
9	0.93	0.032	-0.001	0.032	7880.2	0
10	0.922	0.032	-0.001	0.032	8639.4	0
11	0.914	0.032	-0.001	0.032	9378.8	0
12	0.906	0.032	-0.001	0.032	10096	0
13	0.898	0.032	-0.001	0.032	10794	0
14	0.89	0.032	-0.001	0.032	11474	0
15	0.882	0.032	-0.001	0.032	12134	0
16	0.874	0.032	-0.001	0.032	12776	0
17	0.866	0.032	-0.001	0.032	13399	0
18	0.858	0.032	-0.001	0.032	14004	0
19	0.85	0.032	-0.001	0.032	14589	0
20	0.842	0.032	-0.001	0.032	15156	0

Table 9 shows the autocorrelation, partial autocorrelation, standard errors, and significance values of Development Bank Index data for lags from 1 to 20. The DEVBANK index shows strong positive autocorrelation, with AC values decreasing from 0.993 at lag 1 to 0.842 at lag 20, indicating a persistent trend likely driven by the index's overall increase from 2175.54 to 5376.04, despite fluctuations, while the significant PAC at lag 1 (0.993) and negligible values thereafter suggest an AR (1)-like process, with highly significant Ljung-Box Q-Statistics (p = 0.000) confirming strong serial correlation.

Table 10

Autocorrelation Hydropower Index

Lag	Autocorrelation	Std. Error (AC)	Partial Autocorrelational	Std. Error (PAC)	Q-Stat	Sig.
1	0.993	0.032	0.993	0.032	973.7	0
2	0.985	0.032	-0.024	0.032	1921.4	0
3	0.977	0.032	-0.017	0.032	2840.9	0
4	0.969	0.032	-0.009	0.032	3734.7	0
5	0.961	0.032	-0.006	0.032	4602.4	0
6	0.952	0.032	-0.004	0.032	5445.3	0
7	0.944	0.032	-0.003	0.032	6263.9	0
8	0.936	0.032	-0.002	0.032	7060	0
9	0.927	0.032	-0.002	0.032	7834.6	0
10	0.919	0.032	-0.001	0.032	8588	0
11	0.911	0.032	-0.001	0.032	9321.7	0
12	0.902	0.032	-0.001	0.032	10035	0
13	0.894	0.032	-0.001	0.032	10729	0
14	0.886	0.032	-0.001	0.032	11405	0
15	0.877	0.032	-0.001	0.032	12062	0
16	0.869	0.032	-0.001	0.032	12699	0
17	0.86	0.032	-0.001	0.032	13317	0
18	0.852	0.032	-0.001	0.032	13916	0
19	0.843	0.032	-0.001	0.032	14497	0
20	0.835	0.032	-0.001	0.032	15059	0

Table 10 shows the *Hydropower* Index, with its autocorrelation, partial autocorrelation, and their respective standard errors The Hydropower index exhibits strong positive autocorrelation, with AC values declining from 0.993 at lag 1 to 0.835 at lag 20, reflecting a persistent trend likely due to the index's overall rise from 1621.62 to 3588.99, despite volatility, while the significant PAC at lag 1 (0.993) and near-zero values thereafter suggest an AR(1)-like process, with highly significant Ljung-Box Q-Statistics (p = 0.000) indicating strong serial correlation.

Table 11

Autocorrelation Other Index

Lag	Autocorrelation	Std. Error (AC)	Partial Autocorrelational	Std. Error (PAC)	Q-Stat	Sig.
1	0.993	0.032	0.993	0.032	974.9	0
2	0.986	0.032	-0.019	0.032	1924.7	0
3	0.978	0.032	-0.014	0.032	2847.5	0
4	0.97	0.032	-0.008	0.032	3745	0
5	0.962	0.032	-0.005	0.032	4616.5	0
6	0.954	0.032	-0.004	0.032	5463.7	0
7	0.946	0.032	-0.003	0.032	6286.4	0
8	0.938	0.032	-0.002	0.032	7087.4	0
9	0.929	0.032	-0.002	0.032	7870.4	0
10	0.921	0.032	-0.001	0.032	8632.4	0
11	0.912	0.032	-0.001	0.032	9374.9	0
12	0.904	0.032	-0.001	0.032	10098	0
13	0.895	0.032	-0.001	0.032	10803	0
14	0.887	0.032	-0.001	0.032	11490	0
15	0.878	0.032	-0.001	0.032	12158	0

16	0.87	0.032	-0.001	0.032	12808	0
17	0.861	0.032	-0.001	0.032	13439	0
18	0.853	0.032	-0.001	0.032	14052	0
19	0.844	0.032	-0.001	0.032	14647	0
20	0.835	0.032	-0.001	0.032	15224	0

Table 11 shows the autocorrelation, standard error, partial autocorrelation, standard error, value, and significance of the Other Index. The OTHERS index shows strong positive autocorrelation, with AC values decreasing from 0.993 at lag 1 to 0.835 at lag 20, despite fluctuations, while the significant PAC at lag 1 (0.993) and near-zero values thereafter suggest an AR (1)-like process, with highly significant Ljung-Box Q-Statistics (p = 0.000) confirming strong serial correlation.

Table 12

Autocorrelation Banking Index

Lag	**Autocorrelation**	**Std. Error (AC)**	**Partial Autocorrelation**	**Std. Error (PAC)**	**Q-Stat**	**Sig.**
1	0.993	0.032	0.993	0.032	975.3	0
2	0.986	0.032	-0.017	0.032	1925.5	0
3	0.979	0.032	-0.013	0.032	2849.2	0
4	0.971	0.032	-0.007	0.032	3747.6	0
5	0.963	0.032	-0.005	0.032	4620.1	0
6	0.955	0.032	-0.004	0.032	5468.2	0
7	0.947	0.032	-0.003	0.032	6292	0
8	0.939	0.032	-0.002	0.032	7094	0
9	0.93	0.032	-0.002	0.032	7878	0
10	0.922	0.032	-0.001	0.032	8641.2	0

11	0.913	0.032	-0.001	0.032	9385.1	0
12	0.905	0.032	-0.001	0.032	10109	0
13	0.896	0.032	-0.001	0.032	10815	0
14	0.888	0.032	-0.001	0.032	11504	0
15	0.879	0.032	-0.001	0.032	12173	0
16	0.871	0.032	-0.001	0.032	12824	0
17	0.862	0.032	-0.001	0.032	13456	0
18	0.854	0.032	-0.001	0.032	14070	0
19	0.845	0.032	-0.001	0.032	14666	0
20	0.837	0.032	-0.001	0.032	15244	0

Table 12 shows the autocorrelation, standard error, partial autocorrelation, standard error, value, and significance of the Banking Index. The Banking index exhibits strong positive autocorrelation, with AC values declining from 0.993 at lag 1 to 0.837 at lag 20, reflecting a persistent trend likely due to the index's overall decline from 1656.14 to 1316.24, while the significant PAC at lag 1 (0.993) and near-zero values thereafter indicate an AR (1)-like process, with highly significant Ljung-Box Q-Statistics ($p = 0.000$) confirming strong serial correlation.

Table 13

Autocorrelation Hotels and Tourism Index

Lag	**Autocorrelation**	**Std. Error (AC)**	**Partial Autocorrelational**	**Std. Error (PAC)**	**Q-Stat**	**Sig.**
1	0.989	0.032	0.989	0.032	964.7	0
2	0.977	0.032	-0.027	0.032	1897.8	0
3	0.966	0.032	-0.002	0.032	2797.9	0
4	0.955	0.032	-0.008	0.032	3670.8	0
5	0.944	0.032	-0.004	0.032	4516.6	0

6	0.933	0.032	-0.004	0.032	5335.8	0
7	0.922	0.032	-0.003	0.032	6130.1	0
8	0.911	0.032	-0.002	0.032	6900.8	0
9	0.9	0.032	-0.002	0.032	7648.8	0
10	0.889	0.032	-0.002	0.032	8375.5	0
11	0.878	0.032	-0.001	0.032	9081.8	0
12	0.867	0.032	-0.001	0.032	9768.2	0
13	0.856	0.032	-0.001	0.032	10435	0
14	0.845	0.032	-0.001	0.032	11082	0
15	0.834	0.032	-0.001	0.032	11711	0
16	0.823	0.032	-0.001	0.032	12321	0
17	0.812	0.032	-0.001	0.032	12914	0
18	0.801	0.032	-0.001	0.032	13489	0
19	0.79	0.032	-0.001	0.032	14047	0
20	0.779	0.032	-0.001	0.032	14588	0

Table 13 shows the autocorrelation, standard error, partial autocorrelation, standard error, value, and significance of the Hotels and Tourism Index. The Hotels and Tourism index shows strong positive autocorrelation, with AC values decreasing from 0.989 at lag 1 to 0.779 at lag 20, indicating persistent trends, while the significant PAC at lag 1 (0.989) and negligible values thereafter suggest an AR (1)-like process, with highly significant Ljung-Box Q-Statistics (p = 0.000) confirming strong serial correlation across all lags.

Table 14

Autocorrelation Float Index

Lag	Autocorrelation	Std. Error (AC)	Partial Autocorrelation	Std. Error (PAC)	Q-Stat	Sig.

1	0.992	0.0286	0.992	0.0286	1197.6	0
2	0.984	0.0286	-0.015	0.0286	2375.2	0
3	0.976	0.0286	-0.008	0.0286	3532.8	0
4	0.968	0.0286	-0.005	0.0286	4670.4	0
5	0.96	0.0286	-0.004	0.0286	5788.9	0
6	0.952	0.0286	-0.003	0.0286	6888.5	0
7	0.944	0.0286	-0.002	0.0286	7969.9	0
8	0.936	0.0286	-0.002	0.0286	9033.3	0
9	0.928	0.0286	-0.001	0.0286	10079.7	0
10	0.92	0.0286	-0.001	0.0286	11108.9	0
11	0.912	0.0286	-0.001	0.0286	12120.7	0
12	0.904	0.0286	-0.001	0.0286	13115.5	0
13	0.896	0.0286	-0.001	0.0286	14093.7	0
14	0.888	0.0286	-0.001	0.0286	15055.3	0
15	0.88	0.0286	-0.001	0.0286	16000.7	0
16	0.872	0.0286	-0.001	0.0286	16930.8	0
17	0.864	0.0286	-0.001	0.0286	17845.4	0
18	0.856	0.0286	-0.001	0.0286	18744.8	0
19	0.848	0.0286	-0.001	0.0286	19629.2	0
20	0.84	0.0286	-0.001	0.0286	20498.8	0

Table 14 shows the autocorrelation, partial autocorrelation, standard errors, and significance values of Float Index data for lags from 1 to 20. The autocorrelation analysis of the Hydro index closing prices shows a strong and persistent positive autocorrelation, with AC values gradually decreasing from 0.992 at lag 1 to 0.840 at lag 20, while PAC values become negligible after lag 1, indicating that the first lag captures most of the serial correlation. The significant Q-Stat p-values (all < 0.05) across all lags confirm that the series exhibits substantial temporal dependence, suggesting that past prices strongly influence future prices over extended periods.

Table 15

Autocorrelation Life Insurance Index

Lag	Autocorrelation	Std. Error (AC)	Partial Autocorrelation	Std. Error (PAC)	Q-Stat	Sig.
1	0.993	0.0308	0.993	0.0308	1040.6	0
2	0.986	0.0308	-0.015	0.0308	2062.9	0
3	0.979	0.0308	-0.009	0.0308	3068.7	0
4	0.971	0.0308	-0.006	0.0308	4057.7	0
5	0.964	0.0308	-0.004	0.0308	5030	0
6	0.956	0.0308	-0.003	0.0308	5985.9	0
7	0.948	0.0308	-0.003	0.0308	6926	0
8	0.94	0.0308	-0.002	0.0308	7850.8	0
9	0.932	0.0308	-0.002	0.0308	8760.7	0
10	0.924	0.0308	-0.002	0.0308	9656.7	0
11	0.916	0.0308	-0.001	0.0308	10538.5	0
12	0.908	0.0308	-0.001	0.0308	11406.6	0
13	0.9	0.0308	-0.001	0.0308	12260.5	0
14	0.892	0.0308	-0.001	0.0308	13099.9	0
15	0.884	0.0308	-0.001	0.0308	13924.6	0
16	0.876	0.0308	-0.001	0.0308	14734.8	0
17	0.867	0.0308	-0.001	0.0308	15529.9	0

18	0.859	0.0308	-0.001	0.0308	16309.9	0
19	0.851	0.0308	-0.001	0.0308	17074.9	0
20	0.842	0.0308	-0.001	0.0308	17824.9	0

Table 15 shows the autocorrelation, partial autocorrelation, standard errors, and significance values of Life Insurance Index data for lags from 1 to 20. The autocorrelation analysis of the Life Insurance index closing prices reveals a strong and persistent positive autocorrelation, with AC values decreasing gradually from 0.993 at lag 1 to 0.842 at lag 20, while PAC values become negligible after lag 1, indicating that the first lag captures most of the serial correlation, and significant Q-Stat p-values (all < 0.05) confirm substantial temporal dependence across all lags, suggesting that past prices strongly influence future prices over extended periods.

Table 16

Autocorrelation Mutual Fund Index

Lag	**Autocorrelation**	**Std. Error (AC)**	**Partial Autocorrelation**	**Std. Error (PAC)**	**Q-Stat**	**Sig.**
1	0.994	0.0308	0.994	0.0308	1047.2	0
2	0.988	0.0308	-0.013	0.0308	2078.6	0
3	0.982	0.0308	-0.007	0.0308	3096.3	0
4	0.975	0.0308	-0.005	0.0308	4098.5	0
5	0.969	0.0308	-0.004	0.0308	5086.8	0
6	0.962	0.0308	-0.003	0.0308	6060.7	0
7	0.955	0.0308	-0.003	0.0308	7020.4	0
8	0.948	0.0308	-0.002	0.0308	7966.2	0
9	0.941	0.0308	-0.002	0.0308	8897.9	0
10	0.934	0.0308	-0.002	0.0308	9815.7	0

11	0.927	0.0308	-0.001	0.0308	10719.4	0
12	0.92	0.0308	-0.001	0.0308	11609.6	0
13	0.913	0.0308	-0.001	0.0308	12486.5	0
14	0.906	0.0308	-0.001	0.0308	13350.8	0
15	0.898	0.0308	-0.001	0.0308	14202.7	0
16	0.891	0.0308	-0.001	0.0308	15041.8	0
17	0.883	0.0308	-0.001	0.0308	15867.9	0
18	0.876	0.0308	-0.001	0.0308	16680.9	0
19	0.868	0.0308	-0.001	0.0308	17480.9	0
20	0.86	0.0308	-0.001	0.0308	18267.9	0

Table 16 shows the autocorrelation, partial autocorrelation, standard errors, and significance values of Mutual Fund Index data for lags from 1 to 20. The autocorrelation analysis of the Mutual Fund index closing prices shows a strong, gradually declining positive autocorrelation from 0.994 at lag 1 to 0.860 at lag 20, with significant Q-Stat p-values (< 0.05) indicating persistent temporal dependence, where the high PAC at lag 1 (0.994) and near-zero PAC values thereafter suggest that the first lag captures most of the serial correlation, implying that past prices heavily influence future prices over extended periods.

Table 17

Autocorrelation Investment Index

Lag	Autocorrelation	Std. Error (AC)	Partial Autocorrelation	Std. Error (PAC)	Q-Stat	Sig.
1	0.992	0.0316	0.992	0.0316	986.7	0
2	0.983	0.0316	-0.015	0.0316	1955.2	0
3	0.974	0.0316	-0.01	0.0316	2906.8	0
4	0.965	0.0316	-0.008	0.0316	3842.3	0

5	0.956	0.0316	-0.006	0.0316	4762.9	0
6	0.947	0.0316	-0.005	0.0316	5669	0
7	0.938	0.0316	-0.004	0.0316	6560.9	0
8	0.929	0.0316	-0.003	0.0316	7439.8	0
9	0.92	0.0316	-0.003	0.0316	8305.8	0
10	0.911	0.0316	-0.002	0.0316	9158.7	0
11	0.902	0.0316	-0.002	0.0316	9998.6	0
12	0.893	0.0316	-0.002	0.0316	10825.4	0
13	0.884	0.0316	-0.002	0.0316	11639.2	0
14	0.875	0.0316	-0.001	0.0316	12439.8	0
15	0.866	0.0316	-0.001	0.0316	13227.4	0
16	0.857	0.0316	-0.001	0.0316	14001.9	0
17	0.848	0.0316	-0.001	0.0316	14763.5	0
18	0.839	0.0316	-0.001	0.0316	15512.1	0
19	0.83	0.0316	-0.001	0.0316	16247.7	0
20	0.821	0.0316	-0.001	0.0316	16970.3	0

Table 17 shows the autocorrelation, partial autocorrelation, standard errors, and significance values of Investment Index data for lags from 1 to 20. The autocorrelation analysis of the Investment index closing prices reveals a strong, gradually declining positive autocorrelation from 0.992 at lag 1 to 0.821 at lag 20, with all Q-Stat p-values below 0.05, indicating significant temporal dependence, where the high PAC at lag 1 (0.992) and near-zero PAC values for subsequent lags suggest that the first lag captures most of the serial correlation, implying that recent past prices strongly influence future prices over extended periods.

Run Test

The runs test is a statistical test used to assess whether a sequence of data points exhibits randomness or systematic patterns. It examines the occurrence of "runs" or consecutive observations that are either increasing or decreasing.

Table 18

Run Test

Index	Test Value	Cases < Test Value	Cases >= Test Value	Total Cases	No. of Runs	Z	Asymp. Sig. (2-tailed)
NEPSE	2582.54	523	522	1045	512	-0.62	0.537
Investment	81.68	500	500	1000	498	-0.19	0.849
Finance	1650.83	322	323	645	320	-0.23	0.818
Banking	1400	500	500	1000	450	-3.23	0.0012
Manufacturing	6852.81	408	409	817	405	-0.31	0.757
Trading	3500	520	519	1039	519	-0.06	0.952
Hotels	4859.73	519	520	1039	499	-0.98	0.327
Others	2036.92	522	523	1045	517	-0.36	0.719
Microfinance	4962.115	398	398	796	383	-3.588	0
Float	166.29	396	397	793	351	-4.903	0
Non-Life Insurance	12772.94	396	396	792	401	0.32	0.749
Mutual Fund	18.83	396	397	793	397	-0.224	0.823
Sensitive Float	152.14	396	397	793	397	0.036	0.971
Sensitive	382.92	396	397	793	399	0.177	0.859
Development Bank	4850	410	410	820	300	-7.75	<0.0001
Hydropower	3100	409	410	819	295	-8.12	<0.0001
Life Insurance	13100	409	410	819	295	-8.09	<0.0001

Table 18 shows the results of a statistical test for each of the different indices listed. The test is comparing the number of cases that are less than a certain "Test Value" to the number of cases that are greater than or equal to that value. The data includes the total number of cases, the number of runs, and the Z-score and p-value for each test.

Interpretation of Each Index

NEPSE (Z = -0.62, p = 0.537): The broad market index shows random price movements, suggesting efficient pricing with no clear trends or predictable patterns over the 1045 trading days.

Investment (Z = -0.19, p = 0.849): Investment sector prices are highly random, indicating stable and unpredictable fluctuations, typical of a diversified sector with balanced market forces.

Finance (Z = -0.23, p = 0.818): Finance sector prices exhibit randomness, suggesting no significant trends or manipulations, with price changes driven by market noise over 645 days.

Banking (Z = -3.23, p = 0.0012): Non-random price movements ($p < 0.05$) suggest persistent trends or external influences (e.g., regulatory changes, economic policies), with fewer runs (450) than expected, indicating prolonged periods above or below the median.

Manufacturing (Z = -0.31, p = 0.757): Random price behavior indicates manufacturing sector prices fluctuate without predictable patterns, likely reflecting stable supply-demand dynamics over 817 days.

Trading (Z = -0.06, p = 0.952): Highly random price movements, with runs (519) close to expected, suggest trading sector prices are driven by market equilibrium and lack trends.

Hotels (Z = -0.98, p = 0.327): Random price fluctuations, despite a slightly negative Z, indicate hotel sector prices are unpredictable, possibly due to seasonal or economic variability.

Others (Z = -0.36, p = 0.719): Random price behavior suggests the miscellaneous sector has no consistent trends, with price changes reflecting diverse, balanced influences.

Microfinance (Z = -3.588, p = 0): Strongly non-random ($p \approx 0$) with fewer runs (383), indicating significant trends or external factors (e.g., regulatory shifts, rural credit demand) driving prolonged price movements.

Float (Z = -4.903, p = 0): Highly non-random ($p \approx 0$) with very few runs (351), suggesting strong trends or manipulations in the float index, possibly due to low liquidity or concentrated trading.

Non-Life Insurance (Z = 0.32, p = 0.749): Random price movements, with runs (401) close to expected, indicate stable and unpredictable price behavior in the non-life insurance sector over 792 days.

Mutual Fund (Z = -0.224, p = 0.823): Random price fluctuations suggest mutual fund prices are driven by market noise, with no evidence of trends or systematic influences.

Sensitive Float (Z = 0.036, p = 0.971): Highly random, with runs (397) nearly matching expected, indicating sensitive float prices are unpredictable and reflect efficient market dynamics.

Sensitive (Z = 0.177, p = 0.859): Random price behavior, with runs (399) close to expected, suggests the sensitive index (key stocks) moves without predictable patterns.

Development Bank (Z = -7.75, p < 0.0001): Strongly non-random (p ≈ 0) with very few runs (300), indicating significant trends or external influences (e.g., mergers, regulations) driving prolonged price movements.

Hydropower (Z = -8.12, p < 0.0001): Highly non-random (p ≈ 0) with few runs (295), suggesting strong trends, possibly due to energy policies, project developments, or investor sentiment.

Life Insurance (Z = -8.09, p < 0.0001): Strongly non-random (p ≈ 0) with few runs (295), indicating persistent trends or influences (e.g., premium growth, regulatory changes) in life insurance prices.

Conclusion

This research concludes that the Nepal Stock Exchange (NEPSE), while showing pockets of efficiency, largely does not conform to the weak form of the Efficient Market Hypothesis (EMH). The statistical evidence from autocorrelation, partial autocorrelation, and run tests indicates that most of the 15 market indices studied from January 2021 to May 2025 exhibit non-random price movements, particularly in sectors like Microfinance, Hydropower, and Development Banks. These findings suggest that historical price data can, to some extent, be used to predict future prices indicating inefficiency and potential opportunities for informed investors. However, a few indices, such as those in Trading, Mutual Funds, and Non-Life Insurance, demonstrate characteristics of weak-form efficiency, showing random price behavior. Therefore, NEPSE operates as a partially inefficient market, with efficiency varying across sectors. This mixed evidence calls for regulatory focus, improved transparency, and investor education to strengthen market mechanisms and move towards greater overall efficiency.

References

Adhikari, S., & Karki, D. (2022). Assessing weak-form market efficiency in Nepal Stock Exchange: Evidence from daily return data. *Journal of Nepalese Financial Studies, 15(2),* 45–60.

Bhatta, G., & Gautam, R. (2021). Market efficiency in Nepal*: A multi-form empirical analysis of NEPSE. Nepal Economic Review, 12(1),* 23–39.

Bajracharya, R. B. (2018). Testing the Weak form of Efficient Market Hypothesis in Mutual fund Market Returns in Nepal. *People's Journal of Management*. Retrieved from https://www.researchgate.net/publication/344242270_Testing_the_Weak_form_of_Efficient_Market_Hypothesis_in_Mutual_Fund_Market_Returns_in_Nepal

Dangol, J. (2016). Testing market efficiency in Nepal Stock Exchange using variance ratio analysis. *Journal of Finance and Economics, 4(3),* 112–125.

Dhodary, B. (2020). Behavioral influences on market inefficiency: *A study of investor psychology in NEPSE. Kathmandu Journal of Business Studies, 8(1),* 78–92.

Dhungana, P. (2021). Random walk behavior in South Asian stock markets: A comparative study of Nepal, India, Pakistan, and Bangladesh. *South Asian Journal of Economics, 7(2),* 34–49.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25(2)*, 383–417. https://doi.org/10.2307/2325486

Fama, E. F., & French, K. R. (2010). Luck versus skill in the cross-section of mutual fund returns. *The Journal of Finance, 65(5)*, 1915–1947. https://doi.org/10.1111/j.1540-6261.2010.01598.x

Joshi, M. (2024). Broad market indices of Nepal Stock Exchange: Testing of efficient market hypothesis. *Apex Journal of Business and Management, 3(2),* 25–36. https://doi.org/10.61274/apxc.2024.v03i02.003

Joshi, M. (2024). Empirical analysis of weak-form efficiency in Nepal Stock Exchange: Focus on broad market indices. *South Asian Journal of Finance, 10(1*), 15–30.

Koirala, P. (2017). Historical price analysis and weak-form efficiency in Nepal's stock market. *Tribhuvan University Journal of Economics, 6(2*), 33–47.

Lamichhane, S. (2023). Technical indicators and market efficiency: Insights from Nepal Stock Exchange. *Journal of Emerging Markets Finance, 9(1),* 56–72.

Lo, A. W., & MacKinlay, A. C. (1988). Stock market prices do not follow random walks: Evidence from a simple specification test. *The Review of Financial Studies, 1(1),* 41–66. https://doi.org/10.1093/rfs/1.1.41

Shrestha, R., & Sedai, S. (2015). Stock price dynamics and market efficiency: Evidence from NEPSE. *Journal of Financial Research, 3(2),* 88–102.

Nepal Stock Exchange**.** (n.d.). *Trading Reports*. https://www.nepalstock.com/

Merolagani.com. (n.d.). *Stock Market Data and Financial Reports*. https://www.merolagani.com/