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Stock Price Fluctuations: Understanding The Forces At Play

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Abstract: This paper serves as a primer on the mechanics of stock price movements, examining the factors behind price fluctuations. It highlights how autoregressive models can help explain these changes and distinguishes between stationary and non-stationary processes in stock prices. The paper also explores how market shocks influence prices. In efficient markets, new information is quickly reflected in stock prices, making them difficult to predict due to the presence of a unit root. However, investor emotions such as fear, greed, and overconfidence can lead to irrational behavior, causing mispricing and the formation of price bubbles. These psychological factors can create patterns of herd behavior that, while seemingly random, can be analyzed using technical tools like Moving Averages and the Relative Strength Index (RSI). Ultimately, the paper shows that while stock prices may appear unpredictable, human emotions and collective behavior generate recurring patterns that can be studied and used for forecasting.

Keywords: Stock Prices, Autoregression, Random Walk, Efficient Market Hypothesis, Behavioural Finance, Leading Indicators, Lagging Indicators, Volatility

JEL Classification: C22, C53, G12, G14, G17

I. Introduction

A stock represents ownership in a company, giving the holder a share in its assets and profits, while the stock price reflects the value at which a share is bought or sold in the market. The most distinctive feature of the stock market, as perceived by the common man, is the rapid and continuous fluctuation of prices, with curves constantly rising, falling, and shifting direction, often within microseconds (Black & Scholes, 1973; Shiller, 2000; Fama, 1991). One may wonder what may be the reasons behind this unique phenomenon. The fact is that the perpetual movement is not the result of any single factor, but rather the consequences of many factors. It is the complex interaction between these factors that constantly shapes and drives price fluctuations at every moment. The aim of this paper is to look into the mechanics of these price fluctuations by exploring the data generating process, analyzing it and linking it to underlying economic theory. Given the dynamic nature of stock prices, the question arises: is it possible to predict their future trajectory? Since stock prices change over time, they form a time series dataset, thus making time series forecasting—a method using historical data to predict future price movements—a key focus of this paper.

A commonly employed method in time series forecasting is Autoregression (AR), where the present value of a variable is predicted on the basis of its previous values, known as "lags." The term "autoregression" is derived from the fact that the model essentially uses the variable's own past values to forecast its future behavior. Applying an autoregressive model to stock price data involves examining how the future value of a stock can be predicted by regressing the current value on its past (historical) values. In essence, it measures the overall influence of past price movements in making meaningful insights into the future price behavior (Box, Jenkins, Reinsel, 2015). As regards past price movements, the next question, of course, is: how many past values (lags) should we rely on to predict the future? After all, how far back in history do we need to look to have a glimpse of the future?

Using too few lags will fail to properly capture the underlying structure. Using too many (lags) on the other, unnecessarily introduces complexity, making the model more prone to over-fitting resulting in a reduction of reliability. Thus, what is needed is a balance. Typically, the *Akaike Information Criterion* (AIC) (Akaike, 1974) and *Bayesian Information Criterion* (BIC) are used for selecting the optimal number of lags. Now, while AIC is better suited to slightly more complex models, BIC treats complexity as a drawback and penalizes it accordingly (Burnham & Anderson, 2004). The procedure to select the optimal lag length involves choosing the lag length that minimizes either the AIC or BIC values, thus maintaining a balance between accuracy and simplicity[1].

After specifying a time series in an *AR (p)* format, the goal is to understand how to predict the future value based on these *p* lagged values. However, is it always possible to determine the future based on the past? In other words, does the autoregressive process have forecasting power? The answer is that predictability depends on the values of the autoregressive coefficients attached to the lagged values, which determine whether the time series is classified as stationary or non-stationary—a distinction that will be explored further in the next section. The fact is, a stationary time series is predictable, while a non-stationary one is not (Hamilton, 1994).

As the current price is dependent on past prices, the former is also affected by the inflows of new information into the market. As the latter comes into the market, the same is absorbed into it resulting in changes in prices. Now how prices do change is determined by the speed at which news is disseminated and the degree market is capable of, i.e., efficiency of the market in processing this information. Investor sentiment varies in response to quickness with which market reacts to new information. The rapid spread of news triggers immediate reaction on part of the investors resulting in sharp price movements making large groups of investors behave similarly causing substantial price movements within a short span of time. The speed at which news spreads coupled with emotional reactions of the investors exaggerate price changes leading to increased market instability and price volatility (Shiller, 2000; Fama, 1970).

An important factor causing movements in stock prices is the *psychological behavior* of investors ─ investors are driven more by emotion rather than by reason. Impulsive reactions by them lead to price fluctuations that do not go at par with the company's true value. The theoretical foundation of *behavioral finance* is rooted in the irrational behaviors of individual investors which affects their financial decision-making. To the extent that investors fail to make rational financial decisions, there are repercussions in the movements of stock prices. The latter can thus be thought of as manifestations of investors' sentimental biases. While there are definite patterns in investors' emotional behaviors—such as reacting similarly to situations of fear, greed, and joy, though with varying levels of intensity—statistical tools can be used to factor out sentiment-driven fluctuations in stock prices. The specific statistical tools, known as technical indicators, are designed to uncover hidden patterns and identify underlying trends, if any, to enable informed decisions for optimal market entry and exit (Malkiel, 2003; Lo & MacKinlay, 1999).

Ultimately, this study has sought to integrate the principles of market efficiency with behavioral finance and technical analysis, providing a comprehensive understanding of the factors influencing stock price fluctuations. By examining the interplay between data patterns, investor psychology, and market efficiency, the paper has provided a deeper understanding of the intricate factors influencing stock price movements.

The structure of the paper is outlined as follows: Section II presents an overview of time series data representation through an autoregressive model. Section III explores the concept of Market Efficiency and related theories. Section IV examines Behavioral Finance within the framework of the Efficient Market Hypothesis. Finally, Section V provides the conclusions.

II. Modeling Stock Prices as Time Series Data: An Autoregressive Approach

Stock prices being recorded at regular time intervals—such as every minute, hour, or day─ form a time series $\{P_t\}$ dataset[2] that exhibits time-dependent characteristics, such as a trend (T_t) which represents the long term movement or direction in the data, a seasonal pattern (S_t) which is the regular and predictable pattern that repeats over time and random fluctuations (I_t). Thus P_t may be expressed as:

$$P_t = T_t + S_t + I_t \tag{1}$$

[1] See Hamilton (1994) for a detailed discussion on this.

[2] In high frequency trading or in advanced financial systems, stock prices can be recorded at every second or even in milliseconds.

Alternatively, P_t may be expressed in an autoregressive (AR) form which does not decompose the data into components as above but rather uses the past value to predict its future value. Following an AR (p) representation, P_t may expressed as a weighted (φ_i) combination of its k lagged (P_{t-i}) values:

$$P_t = c + \sum_{i=1}^{k} \varphi_i P_{t-i} + \varepsilon_t. \quad (2)$$

Here P_{t-i} is the i^{th} lagged value of P_t, φ_i being the weight associated with the same, c being a constant, ε_t embodying unpredictable fluctuations and random shocks to the system (Hamilton, 1994). Here the constant term, c accounts for *time-invariant* baseline characteristics, viz. long-term average price level or other factors controlling stock prices that are not captured by stock prices alone. While on the one hand the constant term ensures the un-biasedness of the AR specification as such, it also contains the effect of overall market conditions ensuring any significant trend or baseline shift that must be accounted for. The coefficients $\varphi_i's$ represent the nature and intensity of association between past prices and current price. The forecasting of future prices based on past prices is contingent upon the values of $\varphi_i's$.[3] The error term ε_t is assumed to follow a white noise (WN) distribution meaning that it has zero mean, constant variance and zero correlation between two error terms at different points in time[4]. The property of zero mean implies that on an average the errors do not overestimate or underestimate the true value of the variable of interest, i.e., the dependent variable (P_t, in this case). The property of constant variance implying that the spread of error does not depend on the time frame, i.e., the random ups and downs are not getting bigger or smaller over time-a property ensuring reliability of standard errors and model predictions. The property of zero correlation ensures that past errors do not impact future errors, an exception to which would indicate that the model has not fully captured the dynamics of the process. In essence white noise error term represents ideal randomness in the sense that it has no pattern, no trend and is entirely unpredictable in nature.

The strength of the AR structure lies in the fact that future can be predicted based on regression of the present on the past values of the same (variable) in a simple linear regression based exploratory structure. To the extent that the model is built upon the assumption of time-invariant structural characteristics, the assumption of linearity, and the absence of any external factors, it fails to account for sudden shifts or long-term trends. The model is thus more appropriate for tackling short-term movements in prices only.

To delve a bit deeper into the structure of an autoregressive (AR) process, it can be recognized that the autoregressive parameters, $\varphi_i's$ are instrumental in controlling the properties of the underlying time series. The characteristic equation of an AR model, expressed as: 1- $\varphi_1 z - \varphi_2 z^2 \quad - \varphi_p z^p = 0$, serves as the foundational framework for analyzing the relationship between current values and their past influences, where z represents the roots of the equation. Now, the stability condition of the time series is structurally dependent on the values of these roots: for the series to be *stationary*—indicating that its statistical properties, such as mean and variance, remain constant over time—the absolute values of all roots must lie outside the unit circle (greater than one). This condition ensures that any shocks or disturbances which may come to the system gradually go down rather than escalate. In a first-order AR process, the condition $|\varphi_1|$<1is of particular importance as it ensures that the effect of past values on current values diminishes over time, facilitating a process of what is known as *mean reversion*- a concept which is fundamentally related to the notion of predictability of a time series. This is because for any deviation from its (long-term) mean, a *mean-reverting* time series is likely to come back to its mean sooner or later. Thus the future path of a mean-reverting time series can be guessed based on its past trajectory, i.e., given the fact that there is no change in the underlying data structure, future can be modeled with confidence using the past (if the series is stationary). As against this if any root of the characteristic equation lies inside or on the unit circle, or if $|\varphi_1|$≥1, the series becomes *non-stationary* which is characterized by *divergence*. A non-stationary time series does not mean-revert – any deviation from its (long-term) mean creates further deviations away from the mean. This is because, any shocks that may come to the system do not fade out; rather, it stays in, making the series drift away from the mean indefinitely. Standing at any point in time, one cannot thus have an idea of the future path of a *non-mean-reverting non-stationary* time series based on its past trajectory. The root cause behind this is the presence of a unit-root in the system. The predictability of an AR process

[3] Lower values of $\varphi_i's$ indicate bad predicting power of the model as the stock prices do possess little memory in this case. Large coefficients, especially for distant lags, on the other hand, signify over-fitting or the requirement for a more complex model like ARMA or ARIMA. This is however not addressed in this study.

[4] In symbols ε_t~WN⟹ $E(\varepsilon_t) = 0$; $V(\varepsilon_t) = \sigma^2$; $cov(\varepsilon_t, \varepsilon_{t-k}) = 0$ ∀ k≠ 0

thus hinges on the intricate interdependence among the autoregressive parameters, the characteristic equation, and the nature of the roots[5]. One may take note of the shock transmission process in this context.

The shock transmission phenomenon in time series analysis describes how disturbances (or shocks) to a system affect future values over time. There is a significant divide in the process of shock transmission between stationary and non-stationary processes. In a stationary autoregressive (AR) process, where the characteristic equation roots lie outside the unit circle (i.e., $|\varphi_i|<1$), shocks tend to go down over time. Mathematically, if we consider a first-order AR process defined as:

$$P_t = \varphi_1 P_{t-1} + \varepsilon_t \quad (3)$$

where ε_t is a white noise error term with a mean of zero, we can analyze how a shock at time $t-1$ influences future values. If a shock ε_{t-1} occurs, the effect on future values diminishes geometrically:

$$P_t = \varphi_1 \varepsilon_{t-1} + {\varphi_1}^2 \varepsilon_{t-2} + \ldots\ldots\ldots. \quad (4)$$

Now since the absolute magnitudes of the autoregressive coefficients are less than unity, powers of φ_i will eventually go down to zero. This means that any initial shock will gradually fade out leading the series back to its long-term mean — equation (4) will mean-revert in the long-run. i.e., its expected value, $E[P_t]$ in the long run approaches the long-term mean, μ.

In contrast, if the absolute magnitudes of the autoregressive coefficients are greater than or equal to unity, powers of φ_i will escalate, as in the case of a non-stationary AR process, characterized by roots that lie inside or on the unit circle (e.g., $|\varphi_i| \geq 1$), resulting in a situation that shocks remain within the system indefinitely and have a lasting impact. As the same does not decay in course of time, price series does not mean-revert in the long run.

For instance, in the presence of a *unit root*, the process (4) can be represented as:

$$P_t = (1-B)^{-1}\varepsilon_t \quad (5)$$

Here B is the backshift operator.

Here, the effect of a shock does not diminish over time as it is shown that

$$P_t = (1 + B + B^2 + B^3 + \ldots\ldots\ldots\ldots\ldots.)\varepsilon_t$$

$$\Rightarrow P_t = \varepsilon_t + B\varepsilon_t + B^2\varepsilon_t + B^3\varepsilon_t + \ldots\ldots\ldots.$$

which simplifies to

$$P_t = \varepsilon_t + \varepsilon_{t-1} + \varepsilon_{t-2} + \ldots\ldots\ldots\ldots \quad (6)$$

Thus once a shock enters the system, it remains forever having a permanent impact on the value of P_t. Consequently, $E[P_t] \neq \mu$, if equation (5) holds. Now, equation (5) is equivalent to:

$$P_t = P_{t-1} + \varepsilon_t \quad (7)$$

Equation (7) represents a *random walk* process characterized by the presence of unit root in it. As explained any shock ε_t that occurs will have a permanent effect on the level of the series, leading to unpredictable future values that drift away from their previous mean ($E[P_t] \neq \mu$)

To summarize, while the gradual decay of shocks in stationary processes leads to mean reversion and predictability, shocks do not diminish over time in a non-stationary process, resulting in divergence and unpredictability. This implies that it is essential to understand how a stationary process is structurally different from a non-stationary process before attempting a forecasting exercise.

The process of price formation in financial markets can be viewed in the context of the influx of new information. This relationship can be mathematically represented through a price adjustment equation that connects the current price P_t, previous price P_{t-1} and the new information I_t:

$$P_t = P_{t-1} + \alpha(I_t - P_{t-1}) + \varepsilon_t \quad (8)$$

Here α is the sensitivity coefficient quantifying responsiveness of price to new information, while ε_t is a stochastic error term capturing random shocks or noise. Prices are thus adjusted based on the difference between the prior value (previous price) and new data (new information).The higher the value of α, the more rapid the process of adjustment to new information, i.e., the higher the market's ability to respond to significant events.

When new information, such as earnings announcements or economic data, comes in, investors try to evaluate its impact on a company's future performance. The significance of this information can alter expectations, changing the supply and demand for stocks. As the market processes this data, prices keep fluctuating as they keep adjusting to the new information. In efficient markets, this adjustment happens quickly, and prices instantly reflect the most up-to-date information.

[5] See (Brockwell & Davis, 2016; Dickey & Fuller, 1979; Poterba & Summers, 1988) for detailed discussion on this.

III. Market Efficiency: How the Arrival and Absorption of Information Shape Stock Prices

What matters is the ability of the market to absorb and integrate information into stock prices, i.e., in other words the capacity (efficiency) of the market to do the same. Depending on how external information is getting absorbed into prices, market efficiency is characterized as either weak efficiency with past price movements getting reflected in current prices or as semi-strong efficiency incorporating all publicly available information and as strong efficiency accounting for any insider information. In an efficient market, as the Efficient Market Hypothesis (EMH) suggests, stocks are fairly valued as they reflect all available information at any point in time. As a consequence of this neither undervalued nor overvalued stocks can be there in an efficient market[6]. Whenever new information comes in, whatever it may be, it gets readily absorbed into the market. Since prices already reflect the most up-to-date information, any attempt to forecast price movements is based on factors that are constantly changing. This makes it highly unlikely that investors can consistently outperform the market by predicting these movements, as the market is constantly adapting and adjusting to new, unforeseen information. The central idea here is that prices are always fair based on the information at hand. But the way individual investors act on this information can vary. Some investors may be risk-averse, seeking safer investments, while others might be risk-seeking, looking for high returns with higher risk. Regardless of these differences, all investors contribute to the process of buying and selling stocks based on new data. If a stock is undervalued, investors will buy it; if it is overvalued, they will sell it. This collective behavior helps to ensure that prices adjust to reflect the stock's true value. Now, understanding how investors weigh risk brings us to the *Capital Asset Pricing Model* (CAPM). CAPM helps explain how investors make decisions about risk and return[7]. The model is built on the premise that, before undertaking an investment project, investors weigh the potential return that might accrue in the future against the risk involved. To put it in the context of EMH, while acknowledging the differences in individual risk preferences—some being more cautious and others more aggressive—these differences do not interfere with the overall efficiency of the market, which continues to adjust to a variety of investor actions, whether risk-averse or risk-seeking. In summary, the collective responses of the investors as per their risk preferences which vary markedly do not lead to inefficiencies rather help keep the market efficient.

The idea of market efficiency holds major implications as far as predictability of stock prices is concerned. This becomes particularly so when random walk process as a specific realization is considered. In an efficient market, stock prices quickly incorporate all available information, meaning that any new data or news is reflected in the price almost instantaneously. This creates a framework where prices exhibit random walk characteristics: just like a random walk, with each step being independent of the last, stock prices move in a way that follows no definite pattern, making it impossible to predict the future value of a stock based on its past movements. The randomness in movements makes a Random Walk series inherently unpredictable. In this context, the expected price at time t, conditioned on all past information, is given by the equation:

$$E\left[P_t \mid P_{t-1}, P_{t-2,} \dots \dots .\right] = P_{t-1} \qquad (9)$$

As the movements of prices do follow a random pattern, past prices fail to have any impact on the present implying that the best predictor of tomorrow's price is simply today's price. Under the assumption that the markets are efficient, prices already reflect all available information meaning that future price movements are determined by new, unforeseen information alone, reiterating the notion of unpredictability that is unique to stock prices. The root of this unpredictability lies in the essential randomness in the effect of any new information which may come into the system, be it economic or otherwise, implying that past will have little or no effect on the present. As prices reflect new information almost instantaneously in an efficient market, there is no room for investors to exploit historical data for future gains. This invalidates strategies

[6] Key valuation metrics to spot under-valued, over-valued or fairly valued stocks include: P/E Ratio: Compares price to earnings, with lower values suggesting undervaluation; P/B Ratio: Compares price to book value, helping identify undervaluation when low; P/S Ratio: Assesses price relative to revenue, useful for non-profitable companies; DCF: Calculates the present value of future cash flows, identifying discrepancies with market price; Dividend Yield: A higher yield can indicate undervaluation, while lower yields may signal overvaluation.

[7] According to CAPM, Expected Return = Risk-Free Rate + Beta × (Market Return - Risk-Free Rate);
Where Risk-Free Rate: The return from a risk-free investment (like a government bond); Beta: A measure of how much the asset's price moves in relation to the overall market; Market Return: The expected return of the entire market. For a detailed discussion on CAPM refer to Sharpe (1964) and Linter (1965).

based on technical analysis or historical price patterns highlighting the challenges investors face when attempting to forecast future price movements[8]

IV. Challenging the Efficient Market Hypothesis: Investor Irrationality, Behavioral Finance, and the Role of Technical Analysis

Irrational behavior on part of the investors is a key obstacle to the practical validation of the Efficient Market Hypothesis (EMH). This happens as emotional biases while reacting to situations of fear, greed, and joy, often lead to irrational decision-making. This coupled with herd behavior; contribute to the generation of systematic mispricing in the market. Following the works of Shleifer (2000), Lux (1995), Black (1986), we proceed to the formal presentation of the above phenomenon within a price adjustment framework as:

$$P_t = P_{t-1} + \alpha + + \varepsilon_t \qquad (10)$$

Here P_t is the market price at time t, α being the systematic drift influenced by collective sentiment, and ε_t, the stochastic noise arising out of individual irrational behaviors. As investors suffer from herd psychology, i.e., act emotionally on the basis of actions of others rather than acting logically on their own, price adjustment equation transforms to:

$$P_t = V + k(x - 0.5)\mathrm{N} + \alpha + + \delta_t \qquad (11)$$

Here V is the intrinsic value[9], k is a sensitivity factor capturing the responsiveness of price to changes in sentiment, N is the total number of investors, x is the proportion of investors who are buying, and δ_t accounts for additional idiosyncratic factors affecting price. Now the value of x may be treated as a proxy for the market sentiment.

When $x > 0.5$, the majority of market participants are buying which leads to a buying spree. The optimistic environment causes the price to move away from its intrinsic value V, making the asset overvalued. This can create a *price bubble*, meaning the price becomes artificially inflated due to excessive buying.

In contrast, when $x < 0.5$, the majority of market participants are selling. As panic sets in, people begin selling even more, leading to an increase in the supply of the asset. As a result, prices start to fall. Prices may eventually drop below their true value V, causing mispricing, where the asset becomes undervalued.

Herd behavior can also be modeled using a feedback mechanism that incorporates the interactions among investors, expressed as: $x_t = \frac{1}{N}\sum_{i=1}^{N}\sigma_i$ (12)

Here σ_i is a binary variable that equals 1 if investor i is buying and 0 otherwise. As sentiment builds, we can relate it to price changes through:

$$\Delta P_t = \gamma(P_t - V) + \theta(x_t - 0.5)P_t + \eta_t \qquad (13)$$

where ΔP_t represents the change in price, γ quantifies the degree of feedback from prior mispricing, θ measures the influence of herd sentiment on price changes, and η_t captures additional noise.

The first term of the R.H.S of equation (11) denotes the *feedback effect* of mispricing of the asset. As P_t deviates from V, this term causes the price to adjust back towards V. The higher is the value of γ, the faster is the adjustment in prices to bring P_t back to V. On the contrary, a smaller value of γ signifies misalignment of prices for a longer time leading to larger deviations and potential formation of price bubbles or crashes.

The second term $\theta(x_t - 0.5)P_t$ reflects the *herd sentiment*. Investor sentiment, when skewed towards buying($x_t > 0.5$), amplifies price increases, while a predominance of selling ($x_t < 0.5$) exacerbates declines. These dynamics illustrate that collective behaviors driven by emotional processing contribute to systematic patterns and mispricing, revealing the complexities that can disrupt market efficiency[10]. The key idea is that herd behavior amplifies price movements.

The discussion so far has led to the understanding that if unit root is present in the price data, the same is following a random walk process which implies that future price movements are inherently unpredictable and the underlying market is efficient in nature and all stock prices are fairly valued as the EMH suggests. However market efficiency is disrupted due to emotional processing of price data (karmakar, 2024) which give rise to systematic patterns. Investors often react similarly to market stimuli,

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[8] This is where stochastic modeling is developed accepting the inherent uncertainty of the financial process. Geometrical Brownian Motion for example assumes that stock price follows a stochastic differential equation: $dS_t = \mu S_t dt + \sigma S_t dW_t$; S_t being the price of the stock at time t, μ is the drift term representing deterministic trend, σ is the volatility term representing random fluctuations, $dW_t$is a random process typically modeled as Weiner Process or Brownian Motion. This model is the foundation of Black-Scholes Option Pricing (Black & Scholes, 1973) and has become a standard tool in financial theory for modeling asset prices under uncertainty.

[9] See Appendix for the methodology to find the intrinsic value of a stock.

[10] These types of models fall under market microstructure models in general (Kyle (1985), Glosten and Milgrom (1985))

such as panic during downturns prompting rapid selling, or exuberance during rallies leading to excessive buying.

Trading and Investor's Sentiment:

To understand investor sentiment, we start with the core goal of any investor: trading stocks to make a profit. Investors aim to enter the market when prices are on the rise and exit when the same starts falling. The real challenge, here lies in deciding the right time to exit. Should they quit early avoiding potential losses but risk missing further gains? Or should they hold on, hoping for the uptrend to continue, even at the cost of facing bigger losses if the market turns the other way?

The situation becomes even more complex with sudden market shifts. For example, a stock that has shown steady growth might abruptly drop, wiping out gains and forcing tough decisions. Should the investor exit and accept the loss or stay in, hoping for a rebound while risking further erosion? These decisions are clouded by the uncertainties and probabilities tied to potential gains and losses, making the process both confusing and emotionally taxing.

Investors, being human, rely on both judgment and emotions. Their responses depend on two factors: their understanding of market trends and their emotional approach to gains and losses. While most investors react similarly to profit and loss, the intensity of their reactions varies—from strong optimism to deep pessimism. Moreover, these emotional reactions can fluctuate over time, influenced by personal moods and changing market conditions.

These emotional swings create opportunities in the market, which can be analyzed using tools like technical indicators. A key concept in understanding market direction is net sentiment, which measures the balance between optimistic investors (bulls) and pessimistic ones (bears). Bulls expect prices to rise, while bears anticipate a decline. The dynamic interplay between these opposing views drives the overall movement of the market. To speak of a nearly inevitable phenomenon regarding the price movement, there happens correction in stock prices—a temporary decline following a rise. Corrections occur because, regardless of whether the market trend is bullish or bearish, investors must *book profits* at some point. The timing of this profit booking depends on individual expectations on gains, risk tolerance, and investment time-frames. *Profit booking* involves selling shares, which increases the supply relative to its demand and causes prices to fall. After booking profits, investors may re-enter the market by buying shares, driving prices back up if buying activity outweighs selling. Ultimately, whether prices rise or fall after a correction depends on the balance between new buyers and those still selling to secure gains. This cycle of profit booking and re-entry makes correction a continuous and fundamental part of market dynamics. Now, how much a stock on the rise will retrace before continuing its previous trend is something that cannot be theoretically modeled. While correction is almost inevitable, the extent of correction remains unpredictable. Interestingly, it has been observed that price retracement often aligns with the celebrated *Fibonacci ratios*, derived from the Fibonacci sequence—a series of numbers where each number is the sum of the two preceding ones. Key ratios are calculated systematically. First, the golden ratio (61.8%) is derived by dividing a number by the next one (e.g., 34÷55≈0.61834)[11]. Then, 38.2% is calculated by dividing a number by the one two places to its right (e.g., 34÷89≈0.38234). Similarly, 23.6% comes from dividing a number by the one three places to its right (e.g., 21÷89≈0.23621). Additionally, 78.6% is found as the square root of the golden ratio (√0.618≈0.786), and 50%, though not directly derived from Fibonacci, is widely recognized due to its psychological importance (Prechter, 1999). Viewed this way, the Fibonacci Ratios can be used for identification of potential correction limits (retracement levels) and thus as a *forward looking* technical indicator; forward looking in the sense that it can be used for predictive purpose.

Going by this way, technical indicators can be categorized as *leading indicator* or *lagging indicator*. While the former is predictive in nature, that is, designed in such a way so as to anticipate future price movements, the latter refers to a type of indicators which are *confirmatory* in nature. The former provides *early signals* prior to the commencement of the trend while the latter *confirms* the same after its commencement. Before delving into the nomenclature and description of indicators in each category, it is essential to first understand their categorization based on *analytical* functions. These functions include: *trend indicators*, which identify and confirm the direction of market trends; *momentum indicators*, which measure the speed of price changes; *volatility indicators*, which assess the degree of price variability and identify potential breakout levels where a stock is likely to move significantly beyond its current range; *volume indicators*, which analyze trading volume to evaluate the strength of price movements; and *support or resistance* indicators, which pinpoint key price levels where trends may pause or reverse. The

[11] See Fibonacci (2002) for a discussion on Fibonacci series.

categorization of indicators by their analytical functions and their classification as leading or lagging enhances trading decisions by providing a balanced combination of predictive insights and confirmatory signals, thereby improving the accuracy of market predictions.

To begin with the description of technical indicator, one may start with *candlestick pattern* which is in fact the corner stone of technical analysis. The battle between bulls (buyers) and bears (sellers) in the market is vividly depicted through candlestick patterns, which provide a detailed snapshot of price action during a specific time interval (Nison, 1991). A single candlestick encapsulates the market's behavior within that period, with the opening and closing prices forming the two opposite sides of a rectangular "box," called the body. If the closing price is higher than the opening price, the candlestick is green (or white), signaling bullish dominance as buyers pushed the price higher. Conversely, if the closing price is lower than the opening price, the candlestick is red (or black), indicating bearish control, where sellers overpowered buyers. Each candlestick features two whiskers (also called wicks or shadows), which extend above and below the body: The upper wick represents the highest price reached, showcasing the maximum bullish strength during the interval. The lower wick marks the lowest price, highlighting the extent of bearish strength. The shape and size of the candlestick, along with its wicks, provide crucial insights into the intensity and outcome of the bull-bear struggle: A long upper wick indicates that bulls attempted to push prices higher but were met with strong resistance from bears, signaling potential weakness. A long lower wick reflects that bears drove prices lower, but bulls regained control, suggesting possible strength. A short body with long wicks reveals indecision or a tug-of-war, where neither side could maintain dominance, while a full body with short or no wicks indicates decisive control by either bulls or bears. Understanding these dynamics allows traders to anticipate potential price movements. For example, patterns with long wicks might signal price rejection and potential reversals at key levels, while successive bullish or bearish candles with large bodies might indicate strong momentum. Candlestick patterns are versatile tools that don't fit exclusively into one category. Their primary purpose is to provide a visual representation of market sentiment and signal potential price action. While they can serve as leading indicators in certain cases, their reliance on historical price data gives them a lagging aspect. They complement both trend and momentum analysis depending on the context in which they are applied.

As a trending indicator, simple moving averages (SMAs), calculated as

$$\bar{P}_n = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i} \quad (14)$$

n being the number of periods and P_{t-i} being the price at each preceding period, serve to smooth out price fluctuations over time, providing a clearer picture of the prevailing trend but as all observations are given equal weights, *SMA* may not instantaneously respond to sudden market changes, leading to delays during rapidly evolving market conditions. Exponential Moving Average (*EMA*) is designed in a way so as to make it more responsive to recent changes. *EMA* at period $t, \bar{P}_t^E$ is computed by applying a weighting factor, α to more recent prices:

$$\bar{P}_t^E = \alpha P_t + (1-\alpha)\bar{P}_{t-1}^E \quad (15)$$

$\alpha = \frac{2}{n+1}$ is the value smoothing parameter. This is a recurrence relation initialized as $\bar{P}_n = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i}$

A crossover between short-term and long-term *EMAs*, known as a "golden cross" or "death cross," can signal significant shifts in market sentiment, acting as reliable indicators for potential buy or sell opportunities (Murphy, 1999).

The Relative Strength Index (RSI), defined as

$$RSI = 100 - \frac{100}{1+RS}; \; RS = Average\ Gain/Average\ Loss \quad (16)$$

is a *momentum* indicator. It can be used to get early indication of impending market reversals (where the price is likely to change direction) or corrections. *Moving Average Convergence Divergence* (MACD), defined as the difference between the *12-day* and *26-day* exponential moving averages, is a *trend-following momentum indicator* that combines lagging trend confirmation with leading momentum signals (Appel, 1979). Due to its dual nature, it can be used to improve timing and accuracy in trading strategies[12].

The construction of Bollinger Bands is made with the help of three curves, a *central line* surrounded by two *outer lines*. While the *central line* is calculated by computing the simple *20-period* moving average (SMA) of the price data, the upper and lower bands are formed by taking *k* standard deviations (commonly two) above and below the central value, respectively (Bollinger, 2001). During periods of increased volatility, the bands expand, while they contract during calm periods. Adapting to changing market dynamics is the key feature. Designed as a *volatility* indicator, Bollinger Bands can also be used to identify

[12] The mathematical formula for the indices is given in the appendix.

trends, *potential reversals* (where the price is likely to change direction), and *breakout levels* (where the price moves beyond key support or resistance, often signaling the start of a new trend). They have a lagging component (based on historical data), but when coupled with momentum or trend indicators, they are used to generate leading signals about future market moves. The most distinctive feature of this index is observed when market volatility is exceptionally low, resulting in what is popularly known as the *squeezing* of the outer bands. The band contraction (*band squeeze*) is a signal of an impending surge in price movement, meaning a potential *breakout* (price moving upward) or *breakdown* (price moving downward) is likely to occur. The best way to utilize this situation for successful trading is by keeping a close eye on this phase, staying alert in anticipation of the change, and being prepared to act when the market will shift. While defining the markets boundaries, the bands act as an evolving indicator to point out where the market's energy is about to be released- whether a sudden increase in volatility is about to happen or a sharp reversal in direction that is in the offing.

The usefulness of Bollinger Bands is further enhanced when paired with *Average True Range (ATR)*. ATR is a volatility indicator constructed as the *14-period* moving average of the maximum of the three values of TR (True Range)[13] viz., *difference between the current high and the current low*; *difference between the current high and the previous close* and *difference between the current low and the previous close. i.e.,*

$$TR = max\ (High - Low, |\ High - Previous\ Close\ |, |\ Low - Previous\ Close\ |) \quad (17)$$

Synergy between Analytical and Temporal Frameworks in Technical Analysis

The essence of the above discussion is that the integration of analytical functions (trend, momentum, volatility, etc.) with the temporal classification of indicators (leading and lagging) forms the foundation of a well-rounded and academically grounded trading strategy. This dual framework provides a comprehensive view of market dynamics by addressing both the nature of price behavior and the timing of trading signals.

An optimal trading decision can be made using a hybrid strategy that employs various indicators in a sequential manner. For example, one might start by using a leading indicator like the **RSI** to anticipate market turning points.

Identification of oversold conditions: Oversold conditions mean that the price of the stock has fallen too far and too fast relative to its fundamentals, given the current market conditions. As the selling pressure continually gets weakened with the gradual building up of buying pressure, it becomes all the more likely that price trajectory will get reversed sooner or later , i.e., in other words a correction in the form of a bullish reversal is in the offing. However, identifying oversold conditions does not guarantee a reversal; it only increases the likelihood that prices will rise as buyers step in, perceiving the stock as undervalued.

Next, **anticipation of a reversal** can be validated with a *lagging indicator* like the **MACD**. When anticipating a *bullish reversal*, traders watch for specific MACD signals that confirm a shift in market sentiment from *bearish* to *bullish*: the emergence of a *bullish crossover*, where the MACD line (the faster moving average) crosses above the Signal line (the slower moving average), indicating that short-term momentum is getting strengthened over the long-term momentum. This suggests an increasing likelihood of a reversal from a downtrend to an uptrend, confirming that momentum is turning upward and supporting the anticipation of a bullish reversal. The confirmation is further bolstered as the MACD Histogram, which represents the difference between the MACD Line and the Signal Line, turns positive, indicating that bullish momentum is gaining traction. Additionally, the formation of a *bullish divergence*, where asset prices form lower lows but the MACD forms higher lows, signals that despite the asset price's decline, momentum is weakening, foreshadowing a potential reversal.

Once the emerging trend is validated, the market’s volatility can be assessed through the application of ATR. By understanding the uncertainty and risk involved, it is possible to set an appropriate stop-loss level that seeks to accommodate potential price fluctuations while preventing premature exits from the market.

This sequential approach increases the likelihood of success, as decisions are *predictive*, *confirmatory*, and well-aligned with market dynamics.

Thus, even within the efficient market framework, psychological factors and behavioral tendencies create predictable patterns that can be rigorously analyzed through technical analysis. The indices formed from these patterns often oscillate within defined ranges, providing insights into potential future movements. This oscillation allows a degree of predictability to emerge from the otherwise random fluctuations associated with a unit root. Ultimately, while prices may follow a random walk, the collective

[13] See Wilder, (1978) for a detailed discussion.

emotional responses of investors generate systematic patterns that savvy traders can extract from the apparent randomness of market price movements.

V. Conclusion

The paper provides a clear and vivid primer on the mechanisms of stock price movements. It offers a step-by-step, detailed discussion, breaking down the complex dynamics in an easily understandable and sequential manner. Each step is logically built upon the previous one, making the progression seem like an inevitable follow-up. The essence of the present study lies in its logical, sequential, and coherent structure, woven seamlessly as if in a single thread.

The study begins by explaining how stock prices are initially formed, and then explores how they evolve over time as part of a time series. The use of past data to understand future price trajectories, particularly through the application of *autoregressive models*, makes the concept of stock price forecasting more tangible. The paper discusses the significance of autoregressive coefficients, especially their magnitude, in determining the nature of predictability. For example, the value of unity in the simplest autoregressive structure ($AR(1)$) serves as a threshold for predictability. A value equal to unity makes the price series *non-stationary* and structurally unpredictable, while a value less than unity makes the series stationary and predictable. This dichotomy between *stationary* and *non-stationary* series forms the foundation for any subsequent analysis. In a stationary series, sudden shocks fade out gradually, whereas in a non-stationary series, shocks remain and have a lasting impact. The distinctive feature of this study is its ability to relate structural characteristics to underlying economic principles. For instance, when discussing predictability, the study links market efficiency to the value of the autoregressive coefficient of an AR (1) process being equal to unity—essentially, the presence of unit roots in the price structure. In an ideally efficient market, prices adjust almost instantaneously to new information, ensuring no divergence between the actual and intrinsic value of a stock. However, the ideal of market efficiency is disrupted by the emotional processing of price data. In reality, investors often make decisions based on emotions—fear, greed, and joy—driven more by herd mentality than logic. This emotional response causes stock prices to deviate from their fundamental values. Investors, reacting to emotional situations, often behave similarly, though with varying intensities, which gives rise to certain patterns in price movements. This is the theoretical foundation of behavioral finance, which examines how psychological factors and emotions influence investors' decisions. As a result, irrational behavior driven by emotional biases manifests in patterns those are otherwise hidden in the seemingly random price data. Herein lies the role of technical analysis, which seeks to identify these systematic patterns within the visible randomness of price movements. Technical analysts use various indicators to understand these patterns so as to actively participate in trading of stocks. The categorization of technical indicators based on their analytical functions—whether they are trending or lagging—helps traders understand when to enter or exit the market.

What makes this paper unique is its successful integration of idealized models with empirical reality, all from a theoretical perspective. The trading of stocks has been placed under the umbrella of behavioral finance, which has emerged as a logical evolution following the limitations of traditional finance theory. The statistical behavior of price data has been analyzed within the framework of core finance theory, ultimately leading to the integration of technical analysis as a statistical tool. Once considered outside the mainstream economic sphere, technical analysis is now discussed within the domain of behavioral finance. This study builds upon previous work by Karmakar (2024), reconciling technical analysis with the Efficient Market Hypothesis (EMH) and offering a broader perspective on the topic. Beginning with the availability of stock price data online, this study examines the data-generating process (DGP) behind price movements, exploring their potential for predictability. It links this predictability to the presence of a unit root and ties it to the EMH, which suggests that prices should be inherently unpredictable. However, this view is challenged by the emergence of inefficiencies, driven by emotional factors, which give rise to predictable patterns—patterns that can be effectively leveraged through technical analysis. In exploring the forces behind the constant fluctuations of stock prices, the study introduces technical analysis as a predictive tool to optimize decisions regarding market entry and exit. Ultimately, this paper serves as a valuable resource for those seeking a clearer, more structured understanding of the forces that shape stock price movements.

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Appendix: A1

Derivation of Formulae of Selected Technical Indicators

1. Moving Average Convergence Divergence (MACD)

The MACD is constructed through the interplay of three key components: the MACD line, Z; the signal line, S and the MACD histogram, H each serving specific analytical functions.

MACD Line Calculation: The MACD line, Z is computed as: $Z_t = \bar{P}^E_{12,t} - \bar{P}^E_{26,t}$;
$\bar{P}^E_{n,t}$ being the n-period EMA at time t and is computed as $\bar{P}^E_{n,t} = P_t \frac{2}{n+1} + \bar{P}^E_{n,t-1}\left(1 - \frac{2}{n+1}\right)$
This recursive calculation assigns exponentially decreasing weights to past prices, allowing the EMA to adjust more swiftly to recent price changes than a Simple Moving Average (SMA).

Signal Line Calculation:

The signal line is calculated as $S_t = \bar{Z}^E_{9,t}$

MACD Histogram Calculation:

The MACD histogram quantifies the difference between the MACD line and the signal line:
$H_t = Z_t - S_t$ provides a graphical representation of the distance between the MACD line and the signal line,

2. Bollinger Bands

Bollinger Bands are an advanced technical analysis tool that utilizes statistical principles to gauge market volatility and identify price extremes. The core of Bollinger Bands is computed as:

$$\bar{P}_{20,t} = \frac{1}{20}\sum_{i=0}^{19} P_{t-i}$$

This SMA serves as the central line around which the bands are constructed. To measure market volatility, the standard deviation of the closing prices over the same period is calculated: $\sigma_{20,t} = \sqrt{\frac{1}{20}\sum_{i=0}^{19}\left(P_{t-i} - \bar{P}_{20,t}\right)}$
The upper and lower Bollinger Bands are then defined as:
$U_t = \bar{P}_{20,t} + k\sigma_{20,t}$; $L_t = \bar{P}_{20,t} - k\sigma_{20,t}$

Here, k is a multiplier (typically set to 2), which, under the assumption of normal distribution, captures approximately 95% of the price data within these bands. The band width, given by:
$U_t - L_t = 2\,k\sigma_{20,t}$

3. Relative Strength Index (RSI)

The Relative Strength Index (RSI) is a momentum oscillator that seeks to make a quantitative assessment of price momentum and identifies overbought or oversold conditions.
The procedure to build the index is as follows: First measure average gains ($\bar{\Pi}_t$) and losses ($\bar{\Pi}^-{}_t$) over a specified period, n (typically 14 days), where gains and losses are defined as:

$\Pi_t = max(P_t - P_{t-1}, 0)$; $\Pi^-{}_t = max(P_{t-1} - P_t, 0)$
Π_t & $\Pi^-{}_t$ are smoothed using exponential moving averages as:

$\bar{\Pi}_t = \frac{\bar{\Pi}_{-t}\times(n-1)+\Pi_t}{n}$;$\bar{\Pi}_{-t}$ denoting previous average gain.
$\bar{\Pi}^-{}_t = \frac{\bar{\Pi}^-{}_{-t}\times(n-1)+\Pi^-{}_t}{n}$.
The Relative Strength (RS) at time t is then computed as: $RS_t = \frac{\bar{\Pi}_t}{\bar{\Pi}^-{}_t}$

To make RS bounded between zero and one, RS is converted to RSI as:
$RSI_t = 100 - \frac{100}{1+RS_t}$; an RSI above 70 indicates *overbought* conditions, indicating chances of price corrections, while an RSI below 30 denotes oversold conditions, signaling chances of rebounds.

Appendix: A2:

Finding the Intrinsic Value of a Stock

To calculate the intrinsic value of a stock mathematically, we rely on the Discounted Cash Flow (DCF) model. The intrinsic value is the present value of all expected future cash flows from the business, adjusted for risk and time.

1. Project Future Free Cash Flows to Firm (FCFF)

Free Cash Flow to Firm (FCFF) represents the cash available to all investors (equity and debt holders) after accounting for operating expenses, taxes, depreciation, changes in working capital, and capital expenditures.

$FCFF_t = EBIT_t \times (1 - Tax\ Rate) + Depreciation_t - \Delta NWC_t$-$CapEx_t$; $EBIT_t =$ Earnings Before Interest and Taxes in year *t*

Tax Rate = Corporate tax rate

$Depreciation_t$ =Depreciation expense in year *t*

ΔNWC_t =Change in Net Working Capital in year *t*

$CapEx_t$ =Capital Expenditures in year *t*

2. Discounting FCFF to Present Value

To account for the time value of money, we discount the future FCFFs to the present using the **Discount Rate** (usually the **Weighted Average Cost of Capital (WACC)**).

The present value of FCFF in year t is:

PV of $FCFF_t = \frac{FCFF_t}{(1+r)^t}$;

r is the discount rate.

3. Calculating the Terminal Value (TV)

After projecting FCFF for the explicit forecast period, we calculate the **Terminal Value (TV)**, which represents the value of the business beyond the forecast period. The terminal value is typically calculated using the **Perpetuity Growth Model**:

$$TV = \frac{FCFF_n \times (1+g)}{r-g}$$

4. Discounting Terminal Value to Present

PV of TV=$\frac{TV}{(1+r)^n}$

5. Intrinsic Value of a Firm:

Intrinsic Value of a Firm= $\sum_{t=1}^{n} \frac{FCFF_t}{(1+r)^t} + \frac{TV}{(1+r)^n}$

6. **Intrinsic Value per Share:**

Intrinsic Value per Share = $\frac{\text{Intrinsic Value of Firm}}{Shares\ Outstanding}$