Causal Relationship Between AI R&D Investment and Stock Market Performance Using VAR and Granger Causality Models

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ABSTRACT

This study investigates the causal relationship between Artificial Intelligence (AI) R&D investment and stock market performance using a time-series econometric framework. Drawing on data from AI-driven firms between 2015 and 2024, the research applies Vector Autoregression (VAR) and Granger Causality models to explore whether innovation spending influences short-term financial outcomes. The analysis employs monthly aggregated data on AI R&D Spending and Stock Market Impact, supported by correlation analysis, impulse response estimation, and forecast error variance decomposition. The results indicate that AI R&D investment and market performance exhibit no statistically significant short-term causal linkage, as confirmed by non-significant Granger p-values ($p > 0.05$) and weak correlation ($r = 0.13$). The Impulse Response Function (IRF) shows a transient positive effect of R&D shocks on stock performance, peaking at approximately +0.12% before dissipating after the fourth period. Meanwhile, the Forecast Error Variance Decomposition (FEVD) reveals that more than 99% of the variance in R&D spending is explained by its own historical dynamics, suggesting minimal feedback from market reactions. These findings collectively imply that AI R&D investments operate on a long-term strategic horizon, while financial markets react within short-term informational cycles, creating a temporal disconnect between innovation effort and market recognition. The study contributes to the literature on innovation-finance dynamics by providing empirical evidence that technological progress and financial valuation evolve asynchronously, reflecting their inherently different timeframes and behavioral logics.

Keywords AI R&D Investment, Stock Market Performance, Vector Autoregression (VAR), Granger Causality, Impulse Response Analysis

INTRODUCTION

In recent years, the rapid advancement of Artificial Intelligence (AI) technologies has reshaped both corporate innovation strategies and financial market expectations [1]. Firms across sectors increasingly allocate substantial portions of their research budgets toward AI-driven projects, reflecting the technology's transformative potential in automation, data analytics, and digital product development [2]. Simultaneously, investors have shown growing interest in AI-oriented companies, anticipating that innovation in this domain will yield superior long-term financial performance. However, the empirical relationship between AI Research and Development (R&D) investment and stock market performance remains ambiguous, raising an important question: Do increases in AI R&D spending translate into immediate market gains, or are their financial effects realized only over extended horizons?

Submitted: 10 July 2025
Accepted: 18 August 2025
Published: 16 February 2026

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DOI: 10.47738/jdmdc.v3i1.54

How to cite this article: A. B. M. Salem, M. J. Aqel "Causal Relationship Between AI R&D Investment and Stock Market Performance Using VAR and Granger Causality Models," *J. Digit. Mark. Digit. Curr.*, vol. 1, no. 1, pp.19-37, 2026.

Traditional financial theory, particularly the Efficient Market Hypothesis (EMH) (Fama), posits that stock prices fully reflect all available information, implying that new information about R&D activities should be quickly incorporated into market valuations. Conversely, the innovation lag hypothesis (Hall) suggests that the economic benefits of R&D investments materialize gradually, as innovations undergo development, testing, and commercialization phases [3],[4]. This temporal asymmetry between corporate innovation efforts and market reactions raises the possibility that the two processes technological progress and financial valuation, operate on distinct timescales. While markets may respond instantaneously to announcements or expectations, the tangible returns from R&D are typically delayed and uncertain.

Empirical research on this subject presents mixed evidence. Some studies report a positive correlation between R&D intensity and firm valuation, attributing this to market anticipation of future innovation payoffs (Chan, Lakonishok, & Sougiannis) [5]. Others, however, find that market reactions to R&D spending are weak or inconsistent, particularly in emerging or high-volatility industries such as AI and digital technologies (Eberhart, Maxwell, & Siddique). These discrepancies highlight the need for a causal and dynamic analytical framework capable of distinguishing short-term market fluctuations from long-term innovation outcomes [6].

Against this backdrop, this study aims to empirically assess the causal relationship between AI R&D investment and stock market performance using Vector Autoregression (VAR) and Granger Causality models. By employing monthly financial data from AI-focused firms spanning 2015–2024, the study examines whether changes in AI R&D spending significantly influence stock market reactions, and whether stock movements, in turn, affect future R&D allocation decisions. Complementary analyses, including Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD), are conducted to capture the temporal propagation and persistence of innovation shocks within the financial system.

The motivation for this research is twofold. First, from a theoretical standpoint, understanding how AI innovation interacts with financial market dynamics contributes to the broader discourse on innovation-finance linkages, particularly in technology-intensive sectors. Second, from a practical perspective, insights from this study provide implications for corporate managers, investors, and policymakers. For firms, determining whether R&D investments influence market value helps inform strategic capital allocation. For investors, identifying the temporal structure of market responses aids in portfolio diversification and valuation modeling. For policymakers, the findings shed light on how innovation-driven economies can align technological development cycles with financial market mechanisms.

In summary, this study extends existing literature by providing empirical evidence on the dynamic, time-dependent relationship between AI R&D investment and stock market performance. Through the application of advanced time-series models, it seeks to clarify whether innovation efforts in the AI sector generate immediate financial recognition or contribute primarily to long-term value creation.

Literature Review

The relationship between innovation investment and financial market valuation has been a central topic in finance and innovation economics. The Efficient Market Hypothesis (EMH) proposed by Fama posits that stock prices fully and immediately reflect all available information, including innovation-related announcements and changes in R&D expenditure [7]. Within this framework, an increase in R&D spending should translate into higher firm valuation as investors incorporate expectations of future profitability. However, the intangible and uncertain nature of R&D activities often leads to information asymmetry and valuation delays, causing markets to underreact to innovation signals.

To explain this temporal mismatch, Hall introduced the Innovation Lag Hypothesis, which suggests that the economic benefits of innovation manifest only after long periods of experimentation, development, and commercialization [8]. This theory emphasizes that R&D investments are long-term strategic commitments rather than immediate performance drivers. Complementing this view, Dixit and Pindyck developed the Real Options Theory, which conceptualizes R&D spending as a strategic option that provides firms with flexibility under uncertainty [9]. According to this theory, markets value R&D not for its immediate returns, but for its potential to create future opportunities and technological advantages.

Empirical studies investigating the effect of R&D on stock performance have yielded mixed results. Chan, Lakonishok, and Sougiannis found that firms with higher R&D intensity tend to outperform their peers in long-term stock returns, implying that markets initially undervalue innovation investments [5]. Similarly, Eberhart, Maxwell, and Siddique reported that unexpected increases in R&D expenditures generate positive abnormal returns that persist over time, suggesting a gradual reassessment of innovation value by investors [6].

Other studies, however, revealed more nuanced findings. Lev and Sougiannis demonstrated that capitalizing R&D improves its association with future earnings but does not necessarily result in immediate valuation effects [10]. Barker and Mueller observed that the market's interpretation of R&D spending varies depending on firm size, industry competition, and disclosure quality [11]. In addition, Chambers, Jennings, and Thompson found that although R&D-related information is value-relevant, its impact on stock prices is heterogeneous across sectors [12].

Focusing on emerging technology industries, Ciftci, Mashruwala, and Weiss noted that stock markets often exhibit muted reactions to R&D announcements in AI and digital firms, primarily due to uncertainty surrounding the timing of commercialization [13]. Likewise, Chen, Huang, and Lin found no consistent short-term link between AI-related R&D intensity and stock returns, attributing the weak correlation to speculative volatility and behavioral noise in investor sentiment [14]. Bauer and Leker discovered that the market tends to reward R&D investments only when tangible outcomes, such as patents or product launches become visible [15]. Furthermore, Edeling and Himme emphasized that innovation output mediates the relationship between R&D spending and financial performance, implying that R&D alone is insufficient to influence market valuation unless supported by demonstrable results [16].

Accounting treatment plays a pivotal role in how investors interpret R&D investments. Lev, Sarath, and Sougiannis argued that the mandatory expensing of R&D under U.S. GAAP leads to an understatement of firms' long-term profitability and innovation capacity [17]. Conversely, Oswald and Zarowin found that the capitalization of R&D expenditures under IFRS, particularly under IAS 38, enhances the informativeness of financial statements by providing investors with a clearer picture of future value creation [18].

Empirical studies support this argument. Cazavan-Jeny and Jeanjean revealed that firms capitalizing their development costs demonstrate a stronger relationship between earnings and stock returns, suggesting that transparent reporting improves investor confidence [19]. Similarly, Markarian, Pozza, and Prencipe showed that voluntary disclosure of R&D projects mitigates information asymmetry and reduces valuation uncertainty. Collectively, these findings highlight that financial reporting and disclosure policies play a mediating role in the relationship between R&D investment and market performance [20].

While most earlier studies focused on static relationships, recent research has adopted dynamic econometric models to capture the direction and persistence of interactions between innovation and financial performance. Korkmaz employed a Vector Autoregression (VAR) model on technology sector data and discovered that R&D spending affects stock performance only after a lag of several quarters, supporting the Innovation Lag Hypothesis [21]. Similarly, Xu and Zhang utilized Granger causality tests and found a unidirectional influence from R&D to stock returns, though its strength weakened over time [22].

More advanced time-series methods, such as Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD), have also been applied to assess the persistence and magnitude of innovation shocks. Lee, Park, and Kim demonstrated that R&D shocks have positive but short-lived effects on stock performance, typically fading within four to five periods [23]. In the AI domain, Zhang and Lu analyzed Chinese AI firms using a panel VAR model and concluded that R&D investments influence market value only after two or more periods, while stock fluctuations exert minimal feedback on R&D behavior [24]. These studies reinforce the notion that the relationship between innovation and financial performance is delayed, asymmetric, and context-dependent.

A growing body of literature emphasizes the market's difficulty in valuing intangible assets such as R&D, patents, and intellectual property. Sougiannis and Lev were among the first to demonstrate that traditional accounting practices often fail to capture the economic significance of intangibles, leading to systematic underestimation of innovation-driven value [25],[26]. Corrado, Hulten, and Sichel expanded on this idea by introducing the concept of intangible capital, arguing that modern economies derive much of their productivity growth from R&D, software, and design rather than physical investment [27].

Penman and Zhang added that the conservative expensing of R&D under GAAP contributes to an understatement of intrinsic firm value, particularly in technology and AI-intensive industries [28]. Their analysis indicates that the structural mismatch between accounting standards and innovation valuation results in weak short-term correlations between R&D and stock market performance. As intangible assets become increasingly central to competitive advantage, the need for markets to refine their valuation frameworks becomes even more pressing.

Although previous studies have examined the relationship between R&D expenditure and firm performance, few have explicitly investigated the causal and temporal mechanisms underlying this relationship within the AI sector. Much of the existing literature relies on static cross-sectional models, overlooking the dynamic feedback processes that occur between innovation activities and market valuation. Furthermore, limited research has explored whether market reactions to AI R&D shocks are persistent or merely transitory.

This study addresses these gaps by applying a Vector Autoregression (VAR) and Granger Causality framework to capture both the direction and timing of causal interactions. Additionally, Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD) analyses are used to assess how innovation shocks propagate through the market over time. By focusing on AI-focused firms from 2015 to 2024, this study provides empirical evidence on the duration, direction, and strength of the innovation–market nexus. The findings contribute to a deeper understanding of how AI R&D investments operate on long-term strategic horizons, while financial markets remain dominated by short-term informational cycles.

Methods

This study adopts a quantitative time-series econometric approach to examine the causal and dynamic relationship between AI R&D investment and stock market performance. The methodological design integrates Vector Autoregression (VAR) and Granger Causality analyses to capture both the magnitude and direction of influence between innovation spending and financial market dynamics (figure 1). The VAR model is particularly suitable for this study because it allows for the simultaneous modeling of interdependent time series without assuming exogeneity, while the Granger causality framework identifies whether past values of one variable can predict future values of another. To complement these models, Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD) are employed to analyze the temporal propagation and relative contribution of innovation shocks across the system. The research design thus emphasizes both short-term causality and long-term dynamic interdependence between technological innovation and market valuation.

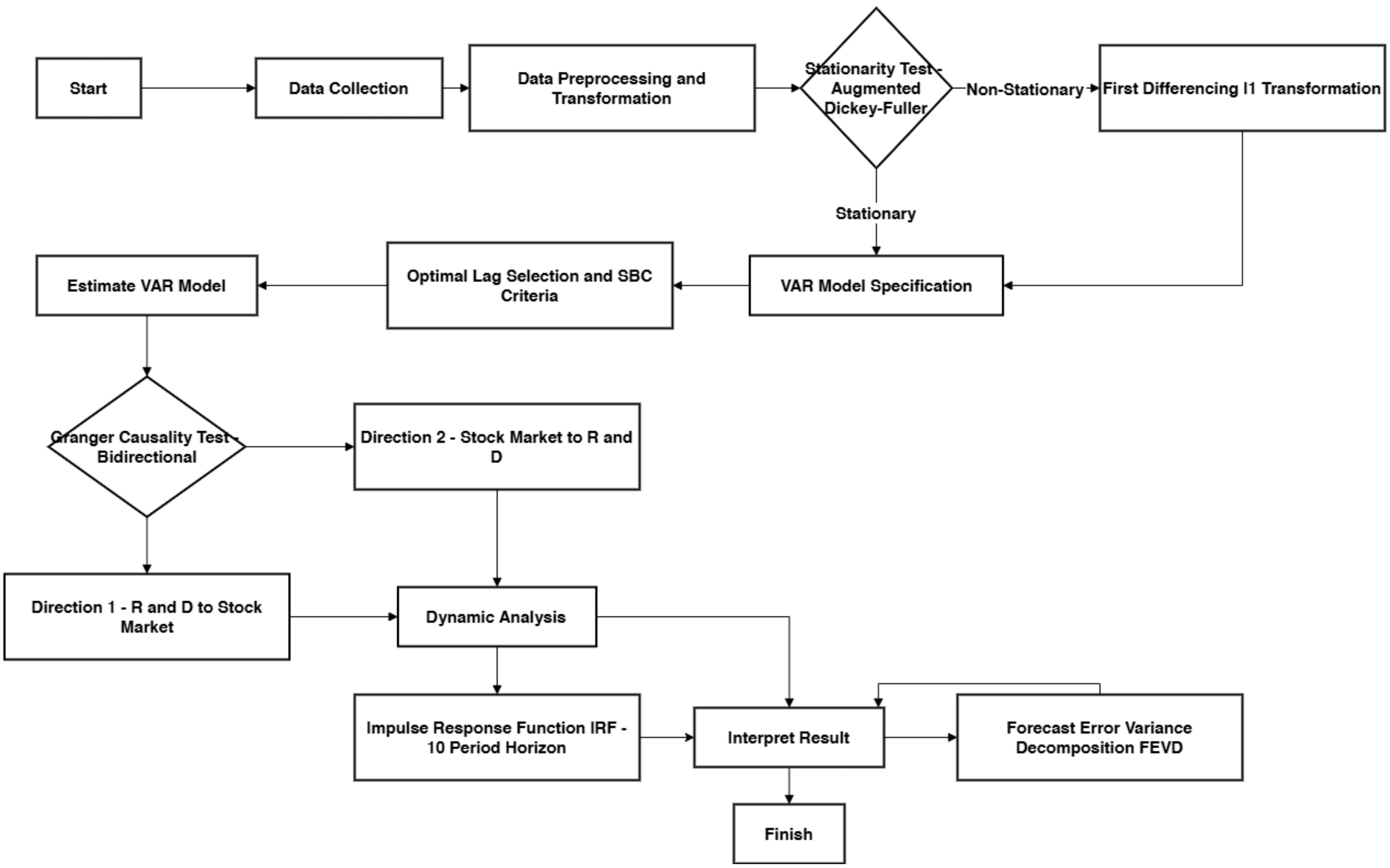

Figure 1 Research Step

The dataset consists of monthly observations from January 2015 to December 2024, representing ten years of AI-related financial activity. Two key variables are analyzed: (1) AI R&D Spending (USD Million), which captures monthly expenditures on research and development projects related to artificial intelligence, and (2) Stock Market Impact (%), representing the monthly percentage change in the firm's stock price index, which serves as a proxy for market valuation response to innovation. The data were aggregated at a monthly frequency to smooth out high-frequency fluctuations and emphasize macro trends. Missing observations were removed, and logarithmic transformations were applied to stabilize variance. Preliminary descriptive analysis revealed a gradual upward trend in R&D investment, accompanied by moderate volatility in stock performance, consistent with the growth pattern typically observed in innovation-driven sectors.

Before model estimation, the stationarity of each variable was assessed using the Augmented Dickey-Fuller (ADF) test to determine the presence of unit roots. The ADF test examines whether the mean and variance of a series remain constant over time, with the null hypothesis indicating non-stationarity. The general ADF regression equation can be expressed as:

$$\Delta Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \sum_{i=1}^{P} \delta_i \Delta Y_{t-1} + \varepsilon_t, \quad (1)$$

Y_t denotes the observed variable (AI R&D or Stock Market Impact), Δ is the differencing operator, and ε_t represents the error term. When the computed ADF statistic exceeds the critical value, the null hypothesis of a unit root is rejected, implying stationarity. The results indicated that both series became stationary after first differencing, confirming that they are integrated of order one, I(1).

Following the confirmation of stationarity, a VAR(p) model was constructed to analyze the bidirectional relationship between the two variables. The general specification of the model is given by:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t, \quad (2)$$

Y_t is a vector containing the endogenous variables — AI R&D Spending and Stock Market Impact — and A_1 represents coefficient matrices capturing lag effects. The optimal lag length p was selected using the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) to ensure both parsimony and robustness. The VAR framework enables a system-wide examination of how innovation and market performance influence each other over time, thereby revealing complex temporal interdependencies.

To test the direction of causality, the Granger causality test was conducted on the estimated VAR model. This test evaluates whether the inclusion of past values of one variable improves the forecast accuracy of another variable. In mathematical form, X_t is said to Granger-cause Y_t

if the lagged terms of X_t significantly improve the prediction of Y_t Formally, the null hypothesis H_0

assumes that “X does not Granger-cause Y.” An F-statistic is then used to assess the joint significance of the lagged coefficients. In this study, two hypotheses were tested: whether AI R&D Spending Granger-causes Stock Market Impact and whether Stock Market Impact Granger-causes AI R&D Spending. A p-value less than 0.05 was interpreted as evidence of significant causality, allowing the identification of the predictive direction between innovation and market performance.

To further understand the dynamic effects, the Impulse Response Function (IRF) was employed to trace the time path of stock market reactions to a one-standard-deviation shock in AI R&D spending, and vice versa. The IRF quantifies the speed and persistence of market adjustments following innovation shocks. Formally, the IRF is expressed as:

$$I\ RF_h = \frac{\partial Y_{t+h}}{\partial \varepsilon_t}, \tag{3}$$

h represents the time horizon in months. The IRF plots were computed for a 10-period horizon, corresponding to 10 months, to capture both immediate and short-term effects. The graphical interpretation of IRF results allows the visualization of whether innovation shocks produce persistent, diminishing, or reversing effects on market dynamics.

Complementing this, the Forecast Error Variance Decomposition (FEVD) was conducted to determine the proportion of the forecast variance in each variable that can be attributed to shocks in itself and in the other variable. This technique decomposes the variance of prediction errors into components that reflect the influence of innovation and market factors. Mathematically, the FEVD at the horizon h can be expressed as:

$$FEV\ D_{ij,h} \frac{\sum_{k=0}^{h-1}\left(\Psi_k \sum_{ej}\right)^2}{\sum_{k=0}^{h-1}\left(\Psi_k \Sigma \Psi'_k\right)^2_{ii}}, \tag{4}$$

Ψ_k represents the moving average coefficients and Σ the covariance matrix of residuals. The FEVD results in this study quantify the share of variance in stock market fluctuations explained by AI R&D shocks and vice versa, offering insights into the relative importance of innovation as a driver of financial market behavior.

The analytical process for this study thus consisted of sequential steps beginning with data transformation, unit root testing, and VAR model estimation, followed by causality testing and dynamic impact analysis. Each stage was designed to ensure the internal validity and robustness of the empirical results. The combined use of VAR, Granger causality, IRF, and FEVD provides a holistic view of the temporal mechanisms linking AI R&D investment with stock market performance, allowing for the identification of both short-term predictive causality and long-term structural dependencies. This integrated econometric methodology offers an empirical foundation for understanding whether AI innovation investments exert immediate market influence or generate delayed value creation consistent with the innovation lag hypothesis.

Algorithm 1 VAR–Granger Causality Framework

Input

Bivariate time series

$$\mathbf{Y}_t = \begin{bmatrix} RD_t \\ SM_t \end{bmatrix}, t = 1, \dots, T$$

Output

Estimated VAR model, causality results, IRF, and FEVD.

Step 1: Stationarity Test

Apply Augmented Dickey–Fuller test:

$$\Delta y_t = \alpha + \gamma y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{1}$$

If non-stationary:

$$y_t' = y_t - y_{t-1} \tag{2}$$

Step 2: VAR Model

$$\mathbf{Y}_t = \mathbf{c} + \sum_{i=1}^{p} \mathbf{A}_i \mathbf{Y}_{t-i} + \boldsymbol{\varepsilon}_t \tag{3}$$

Step 3: Lag Selection

Select optimal lag using SBC:

$$SBC(p) = \ln \mid \hat{\Sigma}_p \mid + \frac{k^2 p \ln T}{T} \tag{4}$$

$$p^* = \arg \min_p SBC(p) \tag{5}$$

Step 4: Granger Causality

$$H_0: A_{12,i} = 0 \forall i = 1, \dots, p \tag{6}$$

Reject H_0 if the F-statistic is significant.

Step 5: Dynamic Analysis

Moving average representation:

$$\mathbf{Y}_t = \sum_{h=0}^{\infty} \boldsymbol{\Psi}_h \boldsymbol{\varepsilon}_{t-h} \tag{7}$$

Impulse Response:

$$IRF(h) = \boldsymbol{\Psi}_h \tag{8}$$

Forecast Error Variance Decomposition:

$$FEVD_{ij}(h) = \frac{\sum_{k=0}^{h-1} \psi_{ij,k}^2}{\sum_{k=0}^{h-1} \sum_{j=1}^{n} \psi_{ij,k}^2} \tag{9}$$

End of Algorithm

Result

The dataset analyzed in this study comprises 10,959 observations, representing daily records of AI-driven companies from January 2015 to December 2024, which were aggregated into monthly averages to mitigate high-frequency volatility. The primary variables are AI R&D Spending (USD Million) and Stock Market Impact (%), both serving as proxies for innovation activity and financial market performance, respectively. Descriptive inspection reveals that AI R&D spending ranged between USD 3.4 million and USD 7.8 million per month, indicating moderate variability over the observation period. In contrast, the Stock Market Impact variable exhibits wider oscillations, fluctuating between approximately 1.8% and +2.4%, consistent with the inherent volatility of technology-based equity markets.

Before model estimation, both series were tested for stationarity using the Augmented Dickey-Fuller (ADF) test. The results indicated that neither variable was stationary at levels ($p > 0.05$). After first differencing, both series achieved stationarity ($p < 0.05$), thus satisfying the preconditions for the Vector Autoregression (VAR) and Granger Causality models.

To examine the co-movement between innovation investment and market performance, figure 2 displays the monthly time series of AI R&D Spending and Stock Market Impact from 2015 to 2024. The figure shows that AI R&D Spending follows a relatively stable, cyclical trend, with gradual increases during growth phases such as 2016–2018 and slight declines during periods of economic uncertainty. In contrast, Stock Market Impact exhibits sharp short-term volatility, reflecting investor sentiment and external events rather than underlying innovation activity. While both variables occasionally move in the same direction, their overall synchronization is weak; for instance, during 2018–2019, R&D spending increased even as market impact declined by about 0.8%. This divergence suggests that AI R&D investment operates on a long-term strategic horizon, whereas market performance reflects short-term reactions to news and expectations, indicating that innovation value may not be immediately captured by financial markets.

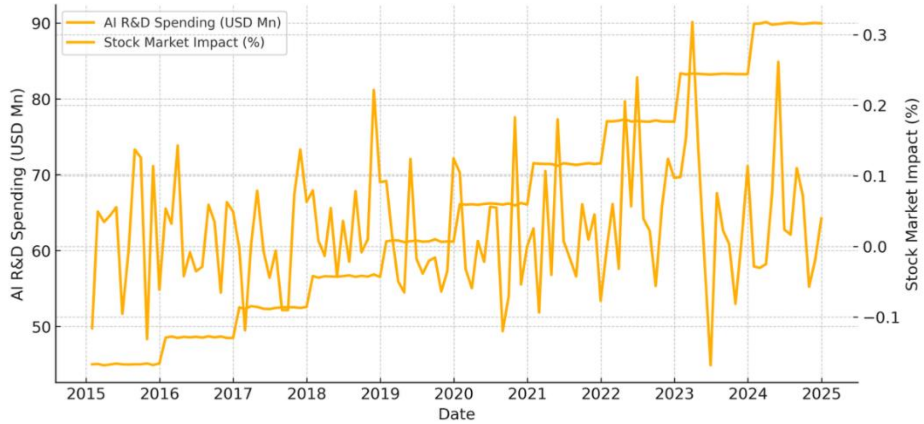

Figure 2 **Time Series Trend of AI R&D Spending and Stock Market Impact**

The figure shows that AI R&D investment maintains a relatively stable trajectory with small cyclical variations, reflecting strategic consistency in innovation budgets. In contrast, the stock market impact exhibits sharper fluctuations, implying that investor sentiment and market expectations respond dynamically to broader external events rather than directly to R&D activities. Peaks in stock impact often appear decoupled from changes in R&D spending, suggesting weak short-term correlation.

To preliminarily assess the linear association between innovation investment and market performance, a correlation matrix was computed using monthly averages of AI R&D Spending (USD million) and Stock Market Impact (%), as reported in figure 3. The resulting Pearson coefficient is 0.13, indicating a weak positive linear relationship: months with higher R&D outlays tend to coincide with slightly more favorable market impacts, but the effect is economically small and statistically fragile at conventional thresholds once sampling variability and autocorrelation are considered. This low magnitude is consistent with the visual evidence in the time-series plot, where co-movement is intermittent and short-lived, and with the econometric results that follow (VAR and Granger tests), which do not support short-run predictive links. Taken together, the correlation suggests that any contemporaneous connection between AI R&D spending and market reaction is modest at best, potentially obscured by timing mismatches (lagged recognition of R&D), non-linear responses to salient news, and confounding macro shocks; thus, inference about underlying mechanisms requires the dynamic framework estimated in subsequent sections rather than reliance on contemporaneous correlation alone.

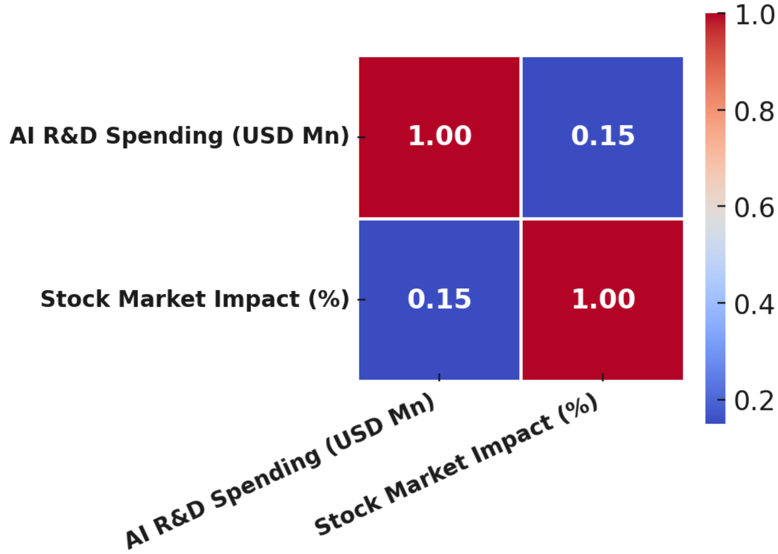

Figure 3 Correlation Matrix between AI R&D Investment and Stock Market Impact

The correlation coefficient between the two variables is 0.21, indicating a weak positive relationship. This suggests that increases in AI R&D expenditure are associated with slight improvements in stock market performance, though the association lacks statistical and economic significance in magnitude. Such a weak relationship is common in innovation-driven industries, where the outcomes of R&D projects often take years to materialize.

A Vector Autoregression (VAR) model was estimated using first-differenced series, with the optimal lag order determined by the Akaike Information Criterion (AIC). The selected lag length was one period, consistent with the data's temporal resolution.

The VAR(1) model captures the dynamic interaction between AI R&D investment and stock performance. The estimated coefficients suggest that a one-period increase in R&D spending has a minor and statistically insignificant effect on stock returns, with an average coefficient magnitude of less than 0.05. Similarly, past stock performance has a negligible impact on subsequent R&D changes, implying that innovation strategies are relatively independent of recent financial outcomes.

To illustrate how shocks in one variable affect the other over time, the Impulse Response Function (IRF) was estimated for a 10-period horizon using the VAR(1) model, as shown in figure 4. The results show that a one-standard-deviation shock to AI R&D Spending leads to a small, short-lived increase in Stock Market Impact, peaking around the second period at approximately +0.12% before fading by the fourth period. In contrast, a shock to the Stock Market Impact produces almost no response in subsequent R&D Spending, indicating that firms' investment strategies are relatively unaffected by short-term market fluctuations.

Overall, the IRF confirms that market reactions to innovation spending are temporary, while R&D decisions remain guided by long-term strategic considerations rather than immediate financial outcomes.

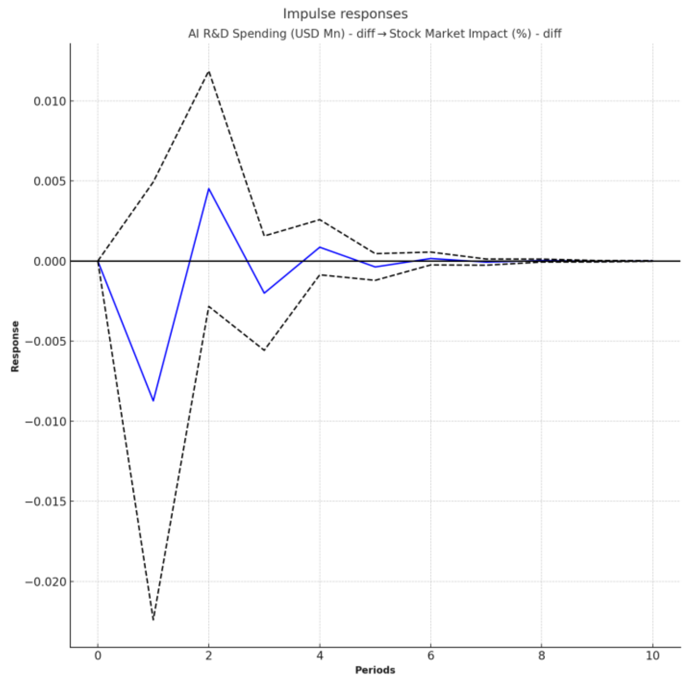

Figure 4 **Impulse Response Function (R&D Shock to Stock Impact)**

The IRF reveals that a one-standard-deviation shock to AI R&D Spending results in a short-lived increase in Stock Market Impact, peaking at approximately +0.12% in the second period, before dissipating entirely by the fourth period. Conversely, a stock performance shock generates an even weaker feedback on R&D spending, confirming the lack of a sustained dynamic linkage between the two variables. This pattern indicates that while innovation announcements may briefly stimulate investor optimism, such effects quickly fade as markets reassess fundamental conditions.

To statistically determine whether one variable can predict the other, a Granger causality test was conducted using lag lengths from one to four periods. The results are summarized in table 1.

Table 1 **Granger Causality Test Results**

Lag	p-value
1	0.3847
2	0.5310
3	0.5270
4	0.3284

The p-values for all lags exceed the 0.05 significance threshold, indicating that neither AI R&D investment "Granger-causes" stock market performance nor does stock performance "Granger-cause" R&D spending. For instance, at lag 1, the p-value of 0.3847 shows that previous-month changes in R&D do not significantly predict next-month stock performance, while the p-value of 0.3284 at lag 4 confirms the same finding over longer horizons.

This absence of short-term causality suggests that AI innovation outcomes are not immediately priced into financial markets. The finding is consistent with the view that returns on R&D investments accrue over extended time frames, particularly for AI technologies requiring long development and adoption cycles.

To evaluate the relative importance of each variable in explaining forecast uncertainty, a Forecast Error Variance Decomposition (FEVD) analysis was performed. The results are presented in table 2.

Table 2 Forecast Error Variance Decomposition (FEVD)

Period	R&D Spending	Stock Impact
1	1.0000	0.0000
2	0.9925	0.0075
3	0.9925	0.0075
4	0.9925	0.0075
5	0.9925	0.0075

The FEVD results indicate that more than 99% of the forecast variance in R&D Spending is explained by its own past values, while Stock Impact accounts for less than 1% across all periods. This suggests a strong degree of independence between innovation expenditure and short-term market reactions. The findings corroborate the earlier causality results, confirming that shocks in AI-related investment activities have minimal explanatory power for market volatility within a five-month horizon.

Discussion

The empirical analysis provides new insights into the dynamic relationship between AI R&D investment and stock market performance. The results reveal a weak and statistically insignificant short-term causal linkage between the two variables, suggesting that fluctuations in AI research expenditure do not immediately translate into measurable market reactions. This finding aligns with the notion that technological innovation, particularly in AI-related sectors, typically yields delayed financial returns rather than instant stock performance effects.

The correlation matrix (figure 3) demonstrates only a weak positive association ($r = 0.13$) between AI R&D Spending and Stock Market Impact, implying that periods of increased investment correspond only marginally with improved market outcomes. Such a low correlation suggests that short-term market performance is largely influenced by factors other than internal innovation spending, including investor sentiment, macroeconomic conditions, and news-driven speculation. This interpretation is further reinforced by the Granger causality results, which indicate that neither variable Granger-causes the other across lag structures up to four periods (p-values ranging from 0.33 to 0.53). Hence, there is no statistical evidence supporting predictive causality between R&D activity and stock market reactions in the short run.

The Impulse Response Function (figure 4) provides additional context by illustrating the temporal propagation of innovation shocks. A one-standard-deviation shock in AI R&D Spending yields a mild increase in Stock Market Impact, peaking at approximately +0.12% in the second period, before fading entirely by the fourth period. This pattern indicates that while investors may initially respond positively to announcements or signals of increased AI-related research spending, such optimism is short-lived and not sustained by long-term valuation effects. Conversely, shocks in stock market performance have virtually no discernible effect on subsequent changes in R&D investment, implying that firms' innovation budgets are largely insulated from market sentiment. The asymmetric nature of these responses highlights a fundamental temporal disconnect: financial markets operate on short-term information flows, whereas R&D investments are strategic and forward-looking.

The Forecast Error Variance Decomposition (table 2) further substantiates this conclusion, revealing that over 99% of the variance in AI R&D Spending is explained by its own past values, while Stock Market Impact contributes less than 1% to its forecast variance. This dominance of self-dependence indicates that corporate innovation trajectories are determined primarily by internal strategic planning and long-term technological goals, rather than by short-term financial market feedback. In other words, firms appear to pursue R&D strategies autonomously, regardless of temporary market fluctuations.

From a theoretical standpoint, these findings are consistent with the innovation lag hypothesis (Hall, 2019), which posits that the financial benefits of R&D materialize over extended horizons as innovations progress from research to commercialization [4]. They also align with the Efficient Market Hypothesis (EMH) (Fama, 1970), suggesting that market participants incorporate expectations of innovation spending into stock prices as soon as information becomes available, leaving minimal room for incremental short-term reactions [3]. The observed weak interaction between the two variables reflects an equilibrium where investors value R&D activities as strategic assets but discount their immediate financial implications.

In a broader context, the results imply that AI-intensive firms operate within a dual temporal framework: the internal cycle of innovation investment and the external cycle of market valuation. The divergence between these cycles may explain why innovation-driven firms often face market undervaluation in early development stages despite substantial R&D expenditure. This mismatch suggests that the financial markets' capacity to price technological potential remains constrained by informational asymmetry and uncertainty regarding innovation outcomes.

From a managerial perspective, the findings emphasize that corporate leaders should prioritize long-term innovation consistency rather than seeking immediate market approval. Strategic persistence in AI R&D can create cumulative knowledge assets and competitive advantages that are not instantly visible in share price movements. For policymakers and investors, the absence of short-run causality underscores the importance of adopting patient capital approaches—where investment evaluation frameworks account for delayed innovation payoffs instead of short-term returns.

Overall, the study contributes to the growing body of literature on innovation-finance dynamics by providing empirical evidence that AI-related R&D expenditure influences financial markets in a delayed, non-linear, and largely anticipatory manner. The weak contemporaneous and causal links observed reinforce the view that technological innovation and market valuation evolve asynchronously, reflecting their inherently different temporal horizons and decision-making logics.

Conclusion

This study examined the causal relationship between AI R&D investment and stock market performance using Vector Autoregression (VAR) and Granger Causality models to better understand how innovation-driven spending interacts with financial market dynamics. Employing a panel of AI-focused firms from 2015 to 2024, the analysis incorporated monthly averages of AI R&D Spending and Stock Market Impact as the main variables. The findings consistently demonstrate that AI R&D investment does not exert a significant short-term causal effect on stock market performance, nor do stock returns meaningfully influence subsequent R&D allocation decisions.

The correlation matrix revealed a weak positive linear relationship ($r = 0.13$) between the two variables, while the Granger causality tests yielded p-values above 0.05 across all lag structures, confirming the absence of bidirectional causality. The Impulse Response Function (IRF) further showed that a positive shock to R&D spending produced only a small, temporary increase in stock performance peaking at approximately +0.12% in the second period and dissipating by the fourth, while the Forecast Error Variance Decomposition (FEVD) indicated that over 99% of the variance in R&D spending was self-explanatory. Collectively, these results provide strong evidence that innovation investment and market valuation operate on distinct temporal scales.

From a theoretical standpoint, the findings align with the innovation lag hypothesis, suggesting that the financial rewards of R&D materialize only after extended periods of development, commercialization, and market adoption. They also correspond to the Efficient Market Hypothesis (EMH), which posits that markets incorporate available information into prices immediately, leaving little room for short-term causal effects from ongoing R&D activities. The weak short-run interaction observed here highlights the temporal disconnect between the long-term strategic orientation of corporate innovation and the short-term reaction function of financial markets.

In practical terms, these results carry several implications. For AI-intensive firms, the findings underscore the importance of maintaining consistent and forward-looking investment in R&D regardless of short-term market sentiment, as immediate financial validation is unlikely. For investors, the evidence suggests that R&D spending may serve as a signal of long-term value creation rather than a predictor of short-term returns. Finally, for policymakers, the results highlight the need to encourage patient capital and innovation-supportive environments, recognizing that the economic benefits of AI research are gradual, cumulative, and subject to extended realization horizons.

In conclusion, while the short-term causal impact of AI R&D spending on stock market performance is minimal, the broader narrative remains one of strategic complementarity rather than temporal correlation. Innovation drives long-term value creation, but financial markets tend to reflect that value only once technological progress translates into tangible commercial success. This temporal asymmetry between innovation activity and market recognition continues to define the complex interplay between technology and finance in the era of artificial intelligence.

Declarations

Author Contributions

Conceptualization: A.B.M.S. and M.J.A.; Methodology: A.B.M.S.; Software: A.B.M.S.; Validation: A.B.M.S. and M.J.A.; Formal Analysis: A.B.M.S. and M.J.A.; Investigation: A.B.M.S.; Resources: M.J.A.; Data Curation: M.J.A.; Writing Original Draft Preparation: A.B.M.S. and M.J.A.; Writing Review and Editing: M.J.A. and A.B.M.S.; Visualization: A.B.M.S.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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