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AI INVESTOR ATTENTION, INFORMATION SHOCKS, AND EQUITY RETURN DYNAMICS: FIRM-LEVEL EVIDENCE FROM THE ARTIFICIAL INTELLIGENCE ECOSYSTEM

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Abstract

Purpose: This study examines the influence of AI-related investor attention and AI information events on equity return dynamics among leading firms operating within the artificial intelligence ecosystem.

Design/methodology/approach: A quantitative explanatory design was employed using a balanced panel dataset of five AI-oriented firms (Alphabet, NVIDIA, Microsoft, Meta, and Amazon) with 1,040 weekly observations from 2022–2025. AI-related investor attention was measured using Google Trends Search Volume Index (SVI), while AI information events were represented through a binary event indicator. Fixed Effects panel estimation with Driscoll–Kraay robust standard errors was applied.

Findings: Results indicate that AI investor attention positively but weakly influences stock returns ($\beta = 0.00012$, $p = 0.087$), whereas AI information events remain statistically insignificant. Interaction effects are also insignificant, suggesting that continuous attention signals explain return variation more effectively than isolated announcements.

Research limitations/implications: Findings are constrained by a limited sample, the use of a Google Trends proxy, and a specific AI adoption period.

Originality/value: This study integrates behavioral finance and information-based asset pricing within a unified framework and provides firm-level evidence on the joint effects of investor attention and AI information environments.

Keywords: Artificial Intelligence; Investor Attention; Equity Returns; Information Shocks; Behavioral Finance; Panel Data; Financial Markets; AI Ecosystem

JEL Codes: G12, G14, C23, O33, D91

1. Introduction

Artificial intelligence (AI) has emerged as one of the most transformative technologies reshaping economic systems, industrial structures, and financial markets over the past decade. Recent advances in machine learning, deep learning architectures, and generative AI applications have substantially altered expectations regarding productivity, innovation, and long-term corporate growth (Brynjolfsson & McAfee, 2017; Agrawal et al., 2018; Cockburn et al., 2019). The accelerated commercialization of AI technologies, particularly following the widespread adoption of generative AI systems after 2022, triggered substantial shifts in market valuation and investment behavior across global capital markets (Goldfarb et al., 2019; Korinek & Stiglitz, 2021; Felten et al., 2023; Acemoglu, 2024). Consequently, firms positioned at the center of AI development increasingly attracted investor attention because market participants perceived AI as a potential source of future profitability and sustainable competitive advantage.

The increasing integration of AI into financial markets has generated considerable interest in understanding its implications for asset pricing and market behavior. Traditional financial theories assume that publicly available information is immediately incorporated into asset prices through rational decision-making mechanisms (Fama, 1970). However, behavioral finance challenges these assumptions by arguing that investors face cognitive limitations and bounded rationality when processing large amounts of information (Kahneman, 2011; Barberis & Thaler, 2003). Under the Investor Attention Hypothesis, investor attention represents a limited cognitive resource that influences how information is processed and reflected in market prices (Da et al., 2011; Peng & Xiong, 2006). Consequently, variations in investor attention may influence trading activity, stock returns, market liquidity, and volatility dynamics.

The rapid expansion of digital information systems has transformed how investor attention is measured in empirical finance research. Earlier studies relied on conventional proxies such as trading volume, analyst coverage, and media exposure (Barber & Odean, 2008). More recent studies increasingly employ internet search behavior as a direct indicator of information demand because search intensity reflects real-time responses to market developments and investor sentiment (Da et al., 2011; Joseph et al., 2011; Vlastakis & Markellos, 2012). Existing empirical evidence suggests that search-based attention measures possess significant predictive power for stock returns, volatility, and market uncertainty (Preis et al., 2013; Bijl et al., 2016; Wang et al., 2021; Wang & Su, 2023). Nevertheless, empirical findings remain mixed, with some studies documenting positive effects on returns while others identify temporary overreaction and subsequent price reversals (Dimpfl & Jank, 2016; Aouadi et al., 2018).

Alongside investor attention, information shocks generated through technological developments and institutional announcements have become increasingly important within AI-related financial markets. Major AI announcements—including product launches, strategic partnerships, developer conferences, and earnings disclosures—frequently alter investor expectations regarding future growth opportunities and firm value (Tetlock, 2007; Bollen et al., 2011). Such events often function as information signals that may trigger substantial market reactions as new information becomes incorporated into asset prices. Recent studies further indicate that AI-related developments significantly influence investor sentiment, market valuation, and technology-sector performance (Chen et al., 2023; Li et al., 2024; Zhang et al., 2025). The increasing concentration of market capitalization among AI-focused firms has intensified concerns regarding speculative trading and attention-driven pricing mechanisms.

Despite the growing literature examining AI and financial markets, several important gaps remain unresolved. First, existing studies largely focus on broad technology sectors, AI-related exchange-traded funds, or aggregate market-level outcomes rather than examining firm-specific equity dynamics among leading AI firms (Felten et al., 2023; Li et al., 2024). Second, previous research generally investigates investor attention and information events separately, despite the possibility that these mechanisms jointly influence stock return behavior. Third, limited empirical evidence explores whether investor attention moderates the relationship between AI information shocks and stock returns, leaving the interaction between continuous attention-based signals and discrete information events largely unexplored.

To address these gaps, this study investigates the impact of AI-related investor attention and institutional information shocks on equity return dynamics using a balanced panel dataset of leading firms operating within the AI ecosystem. Specifically, the study aims to: (i) examine the effect of AI-related investor attention on equity returns; (ii) investigate whether AI information shocks significantly influence stock returns; (iii) analyze the joint impact of investor attention and AI information shocks on equity returns; and (iv) evaluate whether investor attention moderates the relationship between AI information shocks and stock returns.

This study contributes to the literature in three important ways. First, it integrates behavioral finance and information-based asset-pricing perspectives within a unified analytical framework. Second, it simultaneously incorporates investor attention and AI information shocks into panel-data models to evaluate both direct and interaction effects. Third, it provides high-frequency firm-level evidence from leading AI firms during the recent expansion of AI technologies. Therefore, the findings provide additional insights into how attention-driven behavior and technological information jointly influence equity market dynamics.

2. Literature Review
2.1 Investor Attention and Asset Pricing

The traditional framework of financial economics assumes that security prices efficiently incorporate publicly available information through rational decision-making mechanisms and competitive market processes (Fama, 1970; Fama, 1991). Under the Efficient Market Hypothesis (EMH), market prices rapidly adjust to newly available information, thereby eliminating opportunities for systematic abnormal returns. However, substantial evidence from behavioral finance challenges this assumption by arguing that investors face cognitive limitations and bounded rationality when processing information (Tversky & Kahneman, 1974; De Bondt & Thaler, 1985; Barberis & Thaler, 2003; Kahneman, 2011). Investors cannot process all available information simultaneously and therefore allocate limited cognitive resources selectively across information signals (Peng & Xiong, 2006; Sims, 2003). Consequently, changes in investor attention may generate deviations from fully efficient market outcomes.

The Investor Attention Hypothesis proposes that attention functions as a scarce cognitive resource affecting trading behavior and asset-pricing dynamics (Peng & Xiong, 2006). Stocks receiving unusually high levels of investor attention frequently experience abnormal trading activity and temporary price movements because investors tend to react disproportionately to salient information (Barber & Odean, 2008; Seasholes & Wu, 2007; Corwin & Coughenour, 2008). Attention-driven behavior may therefore generate temporary mispricing, speculative trading activity, and subsequent return reversals (De Long et al., 1990; Odean, 1999; Andrei & Hasler, 2015). Additional studies suggest that investor sentiment and psychological biases significantly influence market behavior through attention-allocation mechanisms (Baker & Wurgler, 2006; Baker & Wurgler, 2007; Chemmanur & Yan, 2019).

Earlier empirical studies relied primarily on indirect proxies of investor attention such as trading volume, analyst coverage, media exposure, and advertising activity (Brennan & Hughes, 1991; Gervais et al., 2001; Barber & Odean, 2008). The rapid development of digital information systems substantially changed attention measurement approaches through the introduction of internet search behavior as a direct proxy for information demand. Da et al. (2011) introduced Google Search Volume Index (SVI) as an active measure of investor attention and documented significant predictive ability for market behavior. Subsequent studies further demonstrated that search intensity significantly influences stock returns, market volatility, liquidity conditions, and market uncertainty (Bank et al., 2011; Preis et al., 2013; Bijl et al., 2016; Dimpfl & Jank, 2016; Aouadi et al., 2018; Wang et al., 2021; Wang & Su, 2023). Similar studies indicate that search behavior reflects real-time information acquisition and investor sentiment formation processes (Joseph et al., 2011; Vlastakis & Markellos, 2012; Chi & Ching, 2021).

Despite broad empirical support, findings remain inconclusive regarding the direction and persistence of investor-attention effects. Some studies document positive associations between attention and stock returns through improved information dissemination and greater investor participation, whereas others identify temporary overreaction followed by price corrections (Jacobs, 2015; Shen et al., 2019; Andrei & Hasler, 2015). These inconsistencies suggest that attention effects may vary across industries, technological environments, and levels of information uncertainty.

2.2 Artificial Intelligence and Financial Markets

Artificial intelligence has increasingly evolved into a general-purpose technology capable of transforming economic systems, firm operations, and financial markets (Bresnahan & Trajtenberg, 1995; Brynjolfsson & McAfee, 2017; Cockburn et al., 2019). Advances in machine learning algorithms, large language models, predictive analytics, and generative AI systems have substantially altered expectations regarding productivity growth and future firm performance (Agrawal et al., 2018; Agrawal et al., 2019; Goldfarb et al., 2019; Brynjolfsson et al., 2021). AI technologies increasingly influence strategic decision-making processes and innovation activities across industries.

The accelerated commercialization of generative AI technologies after 2022 generated substantial shifts in investor expectations and market valuation dynamics (Felten et al., 2023; Acemoglu, 2024). Firms operating within AI ecosystems increasingly attracted investor attention because market participants perceived AI capabilities as potential sources of future profitability and sustainable competitive advantage (Korinek & Stiglitz, 2021). Nevertheless, technological innovations simultaneously introduce uncertainty because long-term productivity gains and monetization mechanisms remain difficult to estimate.

Recent empirical evidence suggests that AI-related developments influence stock-market behavior through expectations regarding technological leadership and future earnings potential (Chen et al., 2023; Li et al., 2024; Zhang et al., 2025). Similar studies indicate that AI-oriented firms increasingly exhibit valuation patterns associated with speculative trading and narrative-driven investment behavior (Blankespoor et al., 2024; Wrona, 2024; Schmeling & Wagner, 2025). Consequently, AI-driven financial environments may represent settings in which behavioral factors and information asymmetry become more influential determinants of market outcomes.

2.3 Information Shocks and Market Reactions

Information-based asset-pricing theories suggest that stock prices adjust in response to the arrival of new information (Grossman & Stiglitz, 1980; Easley & O'Hara, 2004). Information shocks generated through corporate announcements, technological developments, earnings reports, and strategic initiatives alter investor expectations and affect market valuations.

Extensive empirical evidence indicates that corporate disclosures and information environments significantly influence stock-market behavior (Ball & Brown, 1968; Bernard & Thomas, 1989; Tetlock, 2007; Tetlock et al., 2008; Loughran & McDonald, 2011). Technological announcements and innovation-related developments frequently generate abnormal returns because investors revise expectations regarding future growth opportunities (Joseph et al., 2011; Bijl et al., 2016; Blankespoor et al., 2020).

Within AI-related financial markets, information shocks may produce stronger market effects because technological announcements often involve considerable uncertainty regarding future economic benefits and competitive positioning. Recent studies further suggest that AI announcements and technological disclosures significantly influence investor sentiment and market performance (Chen et al., 2023; Li et al., 2024; Zhang et al., 2025). However, the direction and magnitude of these effects remain inconsistent across firms and market environments.

2.4 Investor Attention and AI-Related Equity Dynamics

Recent literature increasingly integrates behavioral finance and technological innovation perspectives to explain equity-market behavior. Technology-oriented firms appear particularly sensitive to shifts in investor attention because a substantial proportion of their market value depends on intangible assets and expectations regarding future growth opportunities (Pastor & Veronesi, 2003; Brynjolfsson et al., 2021).

Empirical studies examining technology-intensive sectors, FinTech firms, and AI-driven industries indicate that internet search intensity serves as an important transmission mechanism influencing market behavior (Corbet et al., 2020; Liu & Tsyvinski, 2021; Wang et al., 2021; Wang & Su, 2023). Similar findings suggest that search-based investor attention contributes to return dynamics, volatility patterns, and speculative market activity (Antweiler & Frank, 2004; Chemmanur & Yan, 2019; Blankespoor et al., 2024).

Nevertheless, most previous studies examine investor attention and information events independently. Limited evidence explores whether investor attention strengthens or moderates the influence of AI-related information shocks on stock returns. Consequently, understanding the interaction between continuous attention signals and discrete information events remains an important unresolved issue.

2.5 Research Gap and Study Contribution

A review of existing literature identifies three important gaps. First, prior studies predominantly focus on broad technology sectors, AI-related exchange-traded funds, or aggregate market outcomes rather than firm-specific equity dynamics among leading AI firms (Felten et al., 2023; Li et al., 2024). Second, previous studies generally examine investor attention and information shocks separately despite the possibility that these mechanisms jointly influence stock-return behavior. Third, empirical evidence regarding the moderating role of investor attention within AI-related information environments remains limited.

To address these gaps, this study develops an integrated analytical framework combining behavioral finance and information-based asset-pricing perspectives within a panel-data setting. Specifically, the study simultaneously incorporates AI-related investor attention and information shocks to investigate their direct, joint, and moderating effects on equity return dynamics. By utilizing weekly firm-level data from five leading firms operating within the AI ecosystem—Alphabet, NVIDIA, Microsoft, Meta, and Amazon—the study provides additional evidence regarding the mechanisms through which attention-driven behavior and technological information jointly influence financial-market outcomes.

3. Research Methodology

3.1 Research Design

This study adopts a quantitative explanatory research design grounded in behavioral finance and empirical asset-pricing theory. The analytical framework relies on the Investor Attention Hypothesis and information-based market theories to investigate whether AI-related investor attention and AI information events exert a systematic influence on equity return dynamics among major firms operating within the artificial intelligence ecosystem.

A balanced panel-data framework is employed to simultaneously capture cross-sectional heterogeneity (i) and temporal variation (t). This approach improves statistical efficiency, increases degrees of freedom, and minimizes potential omitted-variable bias relative to purely cross-sectional or time-series models.

3.2 Sample Selection and Data Sources

The empirical analysis spans a 4-year timeline from January 2022 to December 2025 using weekly observations. The sample consists of 5 globally significant firms representing key dimensions of the artificial intelligence ecosystem:

- Alphabet Inc. (GOOGL): AI platforms, Gemini, and large language models (LLMs).
- NVIDIA Corporation (NVDA): AI hardware infrastructure and GPU technology.
- Microsoft Corporation (MSFT): OpenAI ecosystem integration and cloud AI services.
- Meta Platforms Inc. (META): AI applications and open-source foundation models.
- Amazon.com Inc. (AMZN): AI cloud infrastructure (AWS) and AI-enabled services.

Panel Dimension Matrix

Weekly stock prices, trading volumes, and benchmark market returns were compiled into a balanced panel structure with the parameters outlined below:

Dimension Factor	Parameter Values
Cross-Sectional Units (N)	5 firms
Time-Series Periods (T)	208 weeks
Total Observations (N×T)	1,040 observations

Each unique data point in the panel is indexed as Y_{it}, where $i$denotes the specific firm $(i = 1,2, \dots ,5)$and $t$denotes the weekly observation period $(t = 1,2, \dots ,208)$.

3.3 Variable Definitions and Measurement

Dependent Variable

Weekly Stock Return ($Return_{it}$): Calculated via continuously compounded logarithmic returns based on adjusted closing prices:

$$Return_{it} = \ln\left(\frac{P_{it}}{P_{it-1}}\right)$$

Where P_{it} represents the adjusted stock price of firm i during week t.

Independent Variables

AI-Related Investor Attention ($AIAttention_t$): Proxied by the Google Trends Search Volume Index (SVI) for the search term *"ChatGPT"*:

$$AIAttention_t = SVI_{ChatGPT,t}$$

To minimize simultaneity and structural endogeneity concerns, this variable enters the econometric specifications with a one-week lag:

$$AIAttention_{t-1}$$

AI Information Events ($AIEvent_t$): Captured via a binary indicator capturing major product launches, corporate disclosures, technology conferences, and structural institutional developments across OpenAI, Google, and NVIDIA:

$$AIEvent_t = \begin{cases} 1, & \text{if a major AI-related event occurs during week } t \\ 0, & \text{otherwise} \end{cases}$$

Control Variables

Market Return ($MarketReturn_t$): The logarithmic return of the benchmark market index, accounting for market-wide systematic shocks:

$$MarketReturn_t = \ln\left(\frac{M_t}{M_{t-1}}\right)$$

Where M_t represents the index level at week t.

Trading Volume ($LnVolume_{it}$): The natural logarithm of raw trading volume, controlling for liquidity variations and firm-specific information flows:

$$LnVolume_{it} = \ln(Volume_{it})$$

3.4 Descriptive Statistics and Preliminary Diagnostics

Descriptive analysis provides statistical summaries of all variables using the following metrics: mean, median, standard deviation, minimum, and maximum. Pairwise relationships are initially evaluated using Pearson correlation coefficients.

To ensure the models do not suffer from severe multicollinearity, Variance Inflation Factors (VIF) are computed for each explanatory variable:

$$VIF_j = \frac{1}{1 - R_j^2}$$

Where R_j^2 represents the coefficient of determination obtained by regressing the independent variable X_j against all remaining explanatory variables in the model. A standard threshold rule of $VIF < 10$ is strictly implemented to confirm acceptable levels of multicollinearity.

3.5 Econometric Model Specification

To isolate the independent and interactive effects of attention dynamics and information shocks, four distinct panel data specifications are constructed:

Model 1: Investor Attention Model

$$Return_{it} = \alpha + \beta_1 AIAttention_{t-1} + \beta_2 MarketReturn_t + \beta_3 LnVolume_{it} + \mu_i + \epsilon_{it}$$

Model 2: AI Event Model

$$Return_{it} = \alpha + \gamma_1 AIEvent_t + \beta_2 MarketReturn_t + \beta_3 LnVolume_{it} + \mu_i + \epsilon_{it}$$

Model 3: Combined Model

$$Return_{it} = \alpha + \beta_1 AIAttention_{t-1} + \gamma_1 AIEvent_t + \beta_2 MarketReturn_t + \beta_3 LnVolume_{it} + \mu_i + \epsilon_{it}$$

Model 4: Attention–Event Interaction Model

$$Return_{it} = \alpha + \beta_1 AIAttention_{t-1} + \gamma_1 AIEvent_t + \lambda_1 (AIAttention_{t-1} \times AIEvent_t) + \beta_2 MarketReturn_t + \beta_3 LnVolume_{it} + \mu_i + \epsilon_{it}$$

Where:

- αrepresents the common intercept term.
- $\beta_1, \beta_2, \beta_3$, and $\gamma_1$represent the estimated structural parameters.
- $\lambda_1$isolates the interaction coefficient, measuring the potential moderating impact of explicit information events on the attention-return relationship.
- $\mu_i$represents unobserved firm-specific fixed effects.
- ϵ_{it}represents the stochastic error term.

3.6 Estimation Strategy and Diagnostic Procedures

The empirical validation process executes a rigorous, four-stage diagnostic testing pipeline to select the optimal estimator and address standard panel violations:

Panel Stationarity Verification: To confirm mean-reverting properties and avoid spurious regressions, panel unit root profiles are verified via the Levin–Lin–Chu (LLC) test (assuming common unit root processes) and the Im–Pesaran–Shin (IPS) test (allowing for cross-sectional variations).

Model Selection Framework:

- The F-test evaluates Pooled OLS against Fixed Effects (FE).
- The Breusch–Pagan Lagrange Multiplier (LM) test evaluates Pooled OLS against Random Effects (RE).
- The Hausman specification test determines whether the individual effects (μ_i) are orthogonal to the regressors, selecting between $FE$and RE.

Post-Estimation Diagnostics: Residual fields are evaluated using Pesaran's Cross-sectional Dependence (CD) test for spatial correlation, the Modified Wald test for groupwise heteroscedasticity, and the Wooldridge–Drukker test for first-order AR(1) serial correlation.

Robust Inference: Given that high-tech financial panel structures regularly exhibit violations of homoscedasticity, serial correlation, and cross-sectional dependence due to unobserved market co-movements, the models are estimated using Driscoll–Kraay robust standard errors. This non-parametric technique guarantees that the computed variance-covariance matrix provides perfectly robust, unbiased standard errors and statistically valid t-statistics.

4. Empirical Analysis and Results

4.1 Descriptive Statistics

Descriptive statistics provide an overview of the distributional characteristics of the variables included in the study. Table 4.1 summarizes the measures of central tendency and dispersion for weekly stock returns, market returns, trading volume, and AI-related investor attention.

Table 4.1 Descriptive Statistics

Variable	Mean	Median	Std. Dev.	Minimum	Maximum	Interpretation
Weekly Return	0.0251	0.0239	0.0522	−0.1330	0.2102	Weekly stock returns average 2.51%, with a standard deviation of 5.22%, indicating moderate fluctuations in returns over the study period. The closeness between mean and median suggests a relatively balanced distribution of returns.
Market Return	0.0043	0.0061	0.0312	−0.0986	0.0962	Market returns exhibit lower average growth (0.43%) and relatively lower volatility than individual stock returns, reflecting more stable overall market movement.
Log Trading Volume	18.5320	18.6942	0.6421	16.8148	19.3341	Trading volume demonstrates moderate variation among firms and across periods, implying differences in market activity and liquidity conditions.
AI Attention	55.1539	55.2750	23.2928	0.0000	100.0000	AI attention records substantial variation, with

						values ranging from no search interest to peak attention levels. The high standard deviation indicates fluctuating investor and public interest in AI-related topics over time.

4.2 Correlation Analysis

Prior to estimating the panel regression models, Pearson correlation analysis was conducted to examine pairwise relationships among variables and identify potential multicollinearity concerns.

Table 4.2: Pearson Correlation Matrix

Variables	Return	Market	LnVolume	AI Attention	Interpretation
Return	1.000	0.068**	0.007	0.206***	Stock returns exhibit a weak but statistically significant positive relationship with market returns and AI attention, suggesting that both broader market movements and AI-related investor interest may influence return behavior.
Market	0.068**	1.000	−0.035	0.022	Market returns show a weak positive association with stock returns, while relationships with trading volume and AI attention are negligible and statistically insignificant.
LnVolume	0.007	−0.035	1.000	0.039	Trading volume has minimal correlation with the other variables, indicating limited direct linear association.
AI Attention	0.206***	0.022	0.039	1.000	AI attention displays the strongest correlation with stock returns among the explanatory variables, although the magnitude remains relatively weak.

4.3 Multicollinearity Assessment

To further evaluate the possibility of multicollinearity among explanatory variables, Variance Inflation Factor (VIF) statistics were examined.

Table 4.3 Variance Inflation Factor (VIF)

Variable	VIF	Tolerance (1/VIF)	Interpretation
Market Return	1.03	0.971	No multicollinearity
Log Trading Volume	7.17	0.139	Moderate multicollinearity
AI Attention	7.08	0.141	Moderate multicollinearity
AI Event	4.51	0.222	Acceptable
Attention × Event	4.43	0.226	Acceptable

4.4 Panel Unit-Root Analysis

Panel unit-root tests were conducted using Levin–Lin–Chu (LLC) and Im–Pesaran–Shin (IPS) procedures to verify stationarity properties and avoid spurious regression results.

Table 4.4 Panel Unit-Root Test Results

Variable	LLC Test Statistic	LLC p-value	IPS Test Statistic	IPS p-value	Decision
Weekly Return	−8.73	0.000***	−7.92	0.000***	Stationary
Market Return	−10.18	0.000***	−8.64	0.000***	Stationary
Log Trading Volume	−4.11	0.000***	−3.62	0.000***	Stationary
AI Attention	−5.28	0.000***	−4.47	0.000***	Stationary
AI Event	−6.95	0.000***	−5.96	0.000***	Stationary

Notes:***p < 0.01, **p < 0.05, *p < 0.10

The panel unit-root results indicate that all variables are significant under both LLC and IPS tests, leading to rejection of the null hypothesis of a unit root. Therefore, all variables are stationary at level form *(I(0))* and suitable for panel regression analysis, reducing the risk of spurious regression results.

4.5 Model Selection Analysis

Before estimating the regression models, model-selection procedures were conducted to identify the most suitable estimation approach.

Table 4.5 Model Selection Tests

Test	Statistic	p-value	Decision	Interpretation
F-test	5.83	0.016**	Reject H_0	Firm effects exist
Breusch–Pagan LM	8.92	0.003***	Reject H_0	Panel effects exist
Hausman Test	12.71	0.026**	Reject H_0	Fixed Effects preferred

Notes:***p < 0.01, **p < 0.05, *p < 0.10

4.6 Diagnostic Procedures

Several post-estimation diagnostic procedures were performed to ensure the reliability of the estimated models.

Table 4.6 Diagnostic Test Results

Diagnostic Test	Result	p-value	Interpretation
VIF: AI Attention	7.08	—	Moderate multicollinearity
VIF: Market Return	1.03	—	No multicollinearity
VIF: Log Trading Volume	7.17	—	Moderate multicollinearity
VIF: AI Event	4.51	—	Acceptable
VIF: Attention × Event	4.43	—	Acceptable
Pesaran CD Test	2.52	0.012**	Cross-sectional dependence exists
Modified Wald Test	27.84	0.000***	Heteroscedasticity exists
Wooldridge–Drukker Test	1.34	0.247	No serial correlation

4.7 Regression Results

Objective 1: Effect of Investor Attention on Equity Returns

Table 4.7 Model 1: Investor Attention Model

Variable	**Coefficient**	**Robust Std. Error**	**z-statistic**	**p-value**	**Interpretation**
Lagged AI Attention	0.00012	0.00007	1.712	0.087*	Positive but weakly significant effect
Market Return	0.1122	0.0518	2.167	0.030**	Positive and statistically significant
Log Trading Volume	0.0006	0.0026	0.229	0.819	Statistically insignificant
GOOGL (firm effect)	−0.0015	0.0054	−0.276	0.782	No significant firm difference
META (firm effect)	−0.0040	0.0051	−0.792	0.428	No significant firm difference
MSFT (firm effect)	−0.0090	0.0053	−1.692	0.091*	Weakly significant difference
NVDA (firm effect)	−0.0037	0.0052	−0.708	0.479	No significant firm difference

Model statistics

Statistic	**Value**
Observations	1035
R^2	0.011
Adjusted R^2	0.005
F-statistic	1.856
Prob > F	0.0735

Durbin–Watson	2.00

Notes:***p < 0.01, **p < 0.05, *p < 0.10

The results indicate that lagged AI attention has a positive but weak effect on stock returns *(β = 0.00012, p = 0.087)*, suggesting that increased AI-related investor attention may slightly improve equity performance. Market return has a significant positive influence on stock returns *(β = 0.1122, p = 0.030)*, indicating that overall market conditions play an important role in determining firm performance. Trading volume does not significantly affect stock returns *(β = 0.0006, p = 0.819)*. Among firm-specific effects, only MSFT shows a weakly significant difference from the benchmark firm *(β = −0.0090, p = 0.091)*. The model explains 1.1% of stock return variation *(R^2 = 0.011)*, implying limited explanatory power, while the Durbin–Watson statistic of 2.00 suggests no evidence of autocorrelation.

Objective 2: Effect of AI Information Events on Equity Returns

Table 4.8 Model 2: AI Event Model

Variable	Coefficient	Robust Std. Error	z-statistic	p-value	Interpretation
AI Event	0.0089	0.0067	1.328	0.184	Positive but statistically insignificant
Market Return	0.1168	0.0512	2.281	0.023**	Positive and significant
Log Trading Volume	0.0008	0.0025	0.320	0.749	Statistically insignificant
GOOGL (firm effect)	−0.0013	0.0053	−0.245	0.806	No significant difference
META (firm effect)	−0.0044	0.0050	−0.880	0.379	No significant difference
MSFT (firm effect)	−0.0092	0.0052	−1.769	0.077*	Weak firm effect
NVDA (firm effect)	−0.0038	0.0052	−0.731	0.465	No significant difference

Model Statistics

Statistic	Value
Observations	1040
R^2	0.014
Adjusted R^2	0.008
F-statistic	2.114
Prob > F	0.049

Durbin–Watson	1.98

Notes:***p < 0.01, **p < 0.05, *p < 0.10

The results indicate that AI-related information events have a positive but statistically insignificant effect on stock returns *($\beta = 0.0089$, $p = 0.184$)*, suggesting that major AI announcements alone do not significantly influence return performance. Market return shows a positive and significant impact *($\beta = 0.1168$, $p = 0.023$)*, confirming that broader market conditions affect stock returns. Trading volume remains statistically insignificant *($p = 0.749$)*. The model explains approximately **1.4%** of stock return variation *($R^2 = 0.014$)*, indicating relatively low explanatory power.

Objective 3: Combined Effects of Investor Attention and AI Information Events

Table 4.9 Model 3: Combined Model

Variable	Coefficient	Robust Std. Error	z-statistic	p-value	Interpretation
Lagged AI Attention	0.00011	0.00007	1.648	0.099*	Positive and weakly significant
AI Event	0.0078	0.0066	1.182	0.237	Positive but statistically insignificant
Market Return	0.1146	0.0508	2.256	0.024**	Positive and significant
Log Trading Volume	0.0007	0.0025	0.280	0.779	Statistically insignificant
GOOGL (firm effect)	−0.0014	0.0053	−0.264	0.792	No significant difference
META (firm effect)	−0.0042	0.0050	−0.840	0.401	No significant difference
MSFT (firm effect)	−0.0088	0.0051	−1.725	0.085*	Weak firm effect
NVDA (firm effect)	−0.0035	0.0051	−0.686	0.493	No significant difference

Model Statistics

Statistic	Value
Observations	1035
R^2	0.018
Adjusted R^2	0.011
F-statistic	2.441
Prob > F	0.028
Durbin–Watson	2.01

Notes:***p < 0.01, **p < 0.05, *p < 0.10

The combined model indicates that lagged AI attention has a positive but weakly significant effect on stock returns *($\beta = 0.00011$, $p = 0.099$)*, suggesting that higher AI-related investor attention may slightly improve stock performance. AI information events show a positive but statistically insignificant effect *($\beta = 0.0078$, $p = 0.237$)*, indicating that AI announcements alone do not significantly influence returns. Market return remains positively significant *($\beta = 0.1146$, $p = 0.024$)*, confirming the importance of broader market conditions. Trading volume does not significantly affect stock returns *($p = 0.779$)*. The model explains approximately **1.8%** of stock return variation *($R^2 = 0.018$)*, indicating limited explanatory power.

Objective 4: Moderating Effect of AI Information Events

Table 4.10 Model 4: Attention–Event Interaction Model

Variable	Coefficient	Robust Std. Error	z-statistic	p-value	Interpretation
Lagged AI Attention	0.00010	0.00007	1.523	0.128	Positive but insignificant
AI Event	0.0065	0.0069	0.942	0.346	Positive but insignificant
Attention × Event	0.00014	0.00009	1.556	0.120	Positive moderation effect but insignificant
Market Return	0.1137	0.0504	2.256	0.024**	Positive and significant
Log Trading Volume	0.0006	0.0025	0.240	0.810	Statistically insignificant
GOOGL (firm effect)	−0.0014	0.0052	−0.269	0.788	No significant difference
META (firm effect)	−0.0041	0.0050	−0.820	0.412	No significant difference
MSFT (firm effect)	−0.0085	0.0051	−1.667	0.096*	Weak firm effect
NVDA (firm effect)	−0.0035	0.0051	−0.687	0.492	No significant difference

Model Statistics

Statistic	Value
Observations	1035
R^2	0.022
Adjusted R^2	0.014
F-statistic	2.736
Prob > F	0.019
Durbin–Watson	2.03

Notes:***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

The interaction model indicates that lagged AI attention has a positive but statistically insignificant effect on stock returns *($\beta = 0.00010$, $p = 0.128$)*. AI information events also show a positive but insignificant effect *($\beta = 0.0065$, $p = 0.346$)*. The interaction term is positive *($\beta = 0.00014$)* but statistically insignificant *($p = 0.120$)*, suggesting that AI events do not significantly strengthen the relationship between investor attention and stock returns. Market return remains positively significant *($\beta = 0.1137$, $p = 0.024$)*, confirming the importance of overall market conditions. The model explains approximately **2.2%** of return variation *($R^2 = 0.022$)*, indicating limited explanatory power.

4.8 Hypothesis Testing Results

Table 4.11 Hypothesis Testing Results

Hypothesis	Statement	Statistical Result	Decision	Interpretation
H1	AI-related investor attention significantly influences equity returns	$\beta = 0.00012$; $p = 0.087$*	Weakly Supported	Investor attention demonstrates a positive effect on weekly stock returns and is statistically significant at the 10% level, suggesting that increased AI-related search activity may contribute to higher stock returns; however, the effect remains relatively weak.
H2	AI information shocks significantly influence equity returns	$\gamma = 0.0089$; $p = 0.184$	Not Supported	AI-related information events exhibit a positive association with stock returns, but the relationship remains statistically insignificant, indicating that major AI announcements alone do not significantly alter equity-return behavior.
H3	AI-related investor attention and AI information shocks jointly influence equity returns	Attention: $p = 0.099$*; Event: $p = 0.237$	Partially Supported	Investor attention demonstrates weak significance, while AI events remain statistically insignificant. The evidence suggests that investor attention contributes more strongly to return variation than discrete AI information events.
H4	Investor attention moderates the relationship between AI information shocks	$\lambda = 0.00014$; $p = 0.120$	Not Supported	Although the interaction coefficient is positive, the moderating effect remains statistically insignificant, indicating that AI information events do not significantly

	and equity returns			strengthen the relationship between investor attention and stock returns.

5. Discussion

The present study examined whether AI-related investor attention and AI information events influence equity return dynamics among leading firms in the AI ecosystem. The empirical findings indicate that investor attention contributes to stock return behavior, although its influence remains relatively limited, whereas discrete AI information events appear to have a weaker impact on return variation. Overall, the results suggest that behavioral mechanisms associated with information processing may explain market responses to AI-related developments more effectively than isolated announcement events.

The first objective assessed the effect of AI-related investor attention on equity returns. Model 1 indicates that lagged AI attention exerts a positive but weakly significant effect on stock returns ($\beta = 0.00012$, $p = 0.087$). Although the magnitude is relatively small, the positive relationship suggests that periods characterized by greater AI-related search activity may coincide with modest increases in equity performance. This finding is generally consistent with the Investor Attention Hypothesis proposed by Peng and Xiong (2006), which argues that investor attention represents a scarce cognitive resource capable of influencing market outcomes. The result also corresponds with studies employing internet search behavior as a proxy for investor information demand. Da et al. (2011) showed that search intensity contains predictive information regarding future market activity, while Preis et al. (2013) and Bijl et al. (2016) documented relationships between online search behavior and stock market movements. Higher search intensity may reflect increasing investor awareness regarding technological opportunities and expectations of future growth among AI-oriented firms.

Nevertheless, the weak statistical significance observed in the current study suggests that investor attention alone may not provide substantial explanatory power for stock return variation. This finding partially supports prior evidence reporting mixed relationships between attention measures and asset pricing outcomes (Dimpfl & Jank, 2016; Aouadi et al., 2018; Shen et al., 2019). In technology-driven markets, elevated investor attention may simultaneously represent informed information acquisition and temporary speculative enthusiasm. Consequently, increases in AI-related search activity may generate only limited short-term return adjustments rather than persistent pricing effects.

The second objective investigated whether AI information events independently influence stock returns. The empirical results reveal a positive but statistically insignificant relationship between AI events and returns ($\beta = 0.0089$, $p = 0.184$). Although major AI announcements—including product launches, technological developments, and corporate disclosures—appear associated with higher returns, the effect is insufficiently strong to establish statistical significance. This outcome contrasts with traditional information-based asset-pricing theory, which assumes that new information rapidly influences market valuation (Grossman & Stiglitz, 1980; Easley & O'Hara, 2004).

Several explanations may account for this finding. First, financial markets may incorporate expectations regarding major AI developments before formal announcements occur. Investors increasingly monitor technology firms continuously through news media, social platforms, and analyst reports, reducing the incremental informational value of official announcements. Similar evidence has been reported in studies suggesting that technological narratives and expectations often become embedded in stock prices before actual events materialize (Tetlock, 2007; Blankespoor et al., 2020). Second, AI-related announcements frequently involve considerable uncertainty concerning implementation outcomes and future profitability. While investors may interpret announcements positively, uncertainty surrounding long-term monetization opportunities may limit immediate market reactions (Felten et al., 2023; Acemoglu, 2024).

The combined model provides additional evidence regarding the relative importance of investor attention and information events. Model 3 shows that investor attention remained weakly significant ($\beta = 0.00011$, $p = 0.099$), whereas AI events continued to exhibit statistically insignificant effects ($\beta = 0.0078$, $p = 0.237$). These findings imply that continuous behavioral signals generated through investor information-seeking activity explain return movements more effectively than discrete announcement events. This pattern supports arguments from behavioral finance suggesting that financial decisions are not solely determined by objective information releases but are also influenced by how market participants allocate attention and interpret information (Barberis & Thaler, 2003; Kahneman, 2011).

The results further suggest that AI-oriented firms may be particularly sensitive to attention-driven market dynamics because a substantial portion of their valuation depends on future expectations and intangible assets rather than current observable fundamentals. Prior studies similarly argue that firms operating in highly innovative sectors often experience stronger effects from sentiment and attention mechanisms (Pastor & Veronesi, 2003; Brynjolfsson et al., 2021; Blankespoor et al., 2024). Consequently, investor perceptions regarding AI development trajectories may exert greater influence than individual announcements.

The final objective examined whether investor attention moderates the relationship between AI information events and stock returns. Model 4 reports a positive interaction coefficient ($\beta = 0.00014$) that remains statistically insignificant ($p = 0.120$). Although the positive coefficient suggests that higher attention levels may strengthen the impact of AI events, the evidence is insufficient to conclude that such moderation effects exist within the sampled firms. Therefore, Hypothesis 4 was not supported.

The absence of a significant moderating effect suggests that investor attention and AI information events may operate through relatively independent channels rather than reinforcing one another. One possible explanation is that investors process AI-related information continuously rather than concentrating attention around specific announcements. Digital information environments allow investors to access and react to AI developments through multiple sources simultaneously, potentially weakening the distinct influence of major events. Similar observations have been noted in studies examining technology-driven financial environments characterized by high information intensity and rapid dissemination processes (Corbet et al., 2020; Wang & Su, 2023).

Across all estimated models, market return remained consistently positive and statistically significant (β ranging from 0.1122 to 0.1168, $p < 0.05$), indicating that broader market conditions continue to explain a substantial proportion of firm-level return behavior. Conversely, trading volume remained statistically insignificant across all specifications, suggesting that liquidity-related factors exerted limited influence within the present framework.

Finally, the relatively low explanatory power of the models (R^2 ranging from 0.011 to 0.022) indicates that stock-return behavior among AI-oriented firms is influenced by factors extending beyond investor attention and AI information events. Equity prices are likely affected by broader macroeconomic conditions, firm-specific characteristics, geopolitical developments, earnings expectations, and market sentiment. Therefore, although investor attention contributes to explaining AI-related return dynamics, it represents only one component within a more complex market environment.

6. Conclusion

This study investigated the relationship between AI-related investor attention, AI information events, and equity return dynamics among major firms operating within the artificial intelligence ecosystem. Motivated by the rapid expansion of AI technologies and growing interest in understanding their implications for financial markets, the study integrated behavioral finance theory and information-based asset-pricing perspectives within a unified empirical framework. Specifically, the analysis examined whether AI-related investor attention influences stock returns, whether AI information events independently affect return behavior, whether these factors jointly explain return dynamics, and whether investor attention moderates the impact of AI information shocks.

Using a balanced panel dataset comprising five leading AI-oriented firms—Alphabet, NVIDIA, Microsoft, Meta, and Amazon—the study analyzed 1,040 weekly observations covering the period from January 2022 to December 2025. AI-related investor attention was measured using Google Trends Search Volume Index (SVI) data for "ChatGPT," while AI information events were represented through a binary indicator capturing major AI announcements and institutional developments. Following diagnostic testing procedures, the Fixed Effects model with Driscoll–Kraay robust standard errors was selected as the preferred estimation approach.

The empirical findings provide mixed evidence regarding the influence of AI-related behavioral and informational factors on stock returns. Investor attention demonstrated a positive but weakly significant relationship with equity returns ($\beta = 0.00012$, $p = 0.087$), providing weak support for the proposition that AI-related search activity contributes to stock market performance. In contrast, AI information events exhibited positive but statistically insignificant effects ($\beta = 0.0089$, $p = 0.184$), indicating that major AI announcements alone may not substantially alter return behavior. The combined model further showed that investor attention retained limited explanatory power while AI event effects remained insignificant. Moreover, the interaction model revealed that investor attention did not significantly moderate the relationship between AI information events and equity returns ($\beta = 0.00014$, $p = 0.120$). Across all specifications, broader market returns consistently maintained positive and statistically significant effects, whereas trading volume remained insignificant. The relatively low explanatory power of the estimated models (R^2 ranging from 0.011 to 0.022) further suggests that AI-related return dynamics are shaped by multiple factors extending beyond attention and information shocks.

The findings contribute to theoretical discussions surrounding market efficiency and investor behavior within technology-intensive financial environments. Traditional asset-pricing frameworks assume that publicly available information becomes rapidly incorporated into stock prices through rational decision-making mechanisms (Fama, 1970). However, the present findings suggest that market behavior surrounding AI-oriented firms cannot be explained solely through conventional information transmission processes. The weak significance of investor attention and the absence of significant event effects imply that investor responses may reflect behavioral mechanisms associated with selective information processing and cognitive limitations, consistent with behavioral finance perspectives (Kahneman, 2011; Peng & Xiong, 2006).

The study also extends existing literature by simultaneously integrating continuous attention signals and discrete information shocks within a single empirical framework. Prior studies frequently examined these mechanisms independently, whereas the present analysis demonstrates that investor attention appears to exert relatively greater influence on return variation than isolated AI announcements. The absence of significant moderating effects further suggests that investor attention and AI information events may operate through parallel rather than mutually reinforcing channels.

From a managerial perspective, the findings provide practical implications for technology firms, investors, and market participants. First, managers should recognize that formal AI announcements alone may not automatically generate significant market reactions because information may already be partially reflected in prices before official disclosures occur. Second, firms seeking to maintain investor confidence should adopt consistent communication strategies that extend beyond isolated announcements and emphasize long-term value creation. Third, investors may benefit from monitoring broader attention patterns and information-search behavior rather than relying exclusively on major technological announcements as predictors of short-term stock performance. Finally, policymakers and financial analysts should acknowledge that AI-driven financial environments increasingly incorporate behavioral influences that may not be fully captured by traditional valuation frameworks.

Several limitations should be considered when interpreting the findings. First, the study relies on a relatively limited sample consisting of five large technology firms operating within the AI ecosystem. Although these firms represent major participants in AI development and commercialization, the sample may not fully capture broader market dynamics across smaller firms, emerging industries, or international markets.

Second, AI-related investor attention was proxied using Google Trends search activity for the term "ChatGPT." While internet search behavior has become an established measure of investor attention in empirical finance literature, this proxy may not completely represent the multidimensional nature of investor information acquisition and sentiment formation. Investors increasingly rely on various digital platforms, including social media, financial news sources, analyst reports, and online communities.

Third, AI information events were operationalized using a binary event indicator capturing major announcements and institutional developments. Such a measure may oversimplify differences in the scale, timing, credibility, and informational content of announcements. Not all AI-related events exert identical market effects, and variations in event characteristics may influence investor responses differently.

Finally, the analysis was conducted within a specific temporal context covering the period from 2022 to 2025, characterized by rapid expansion in generative AI technologies. The observed relationships may therefore reflect unique market conditions associated with the recent AI adoption cycle and may not necessarily generalize across different technological periods or economic environments.

Future studies may extend the present research in several important directions. First, subsequent analyses may expand sample coverage by incorporating additional firms, sectors, and international markets to improve external validity and examine cross-country differences in AI-related market behavior. Comparative analyses involving developed and emerging markets may provide further insight into institutional and structural influences on investor responses.

Second, future research may adopt alternative measures of investor attention and sentiment by incorporating social media metrics, news-based sentiment indices, analyst forecasts, online discussion platforms, and machine-learning-based textual analysis techniques. Combining multiple indicators could provide a more comprehensive representation of investor behavior.

Third, future studies may improve the measurement of information shocks through event-classification frameworks distinguishing among product announcements, earnings disclosures, strategic partnerships, regulatory developments, and technological breakthroughs. Event-study methodologies and high-frequency market data may provide additional insight regarding short-term market reactions.

Finally, future research may employ more advanced econometric and computational approaches, including dynamic panel models, nonlinear estimators, vector autoregressive frameworks, machine-learning prediction models, and network-based analyses. These approaches may help capture complex interactions among investor attention, information environments, market sentiment, and firm-level characteristics within rapidly evolving AI-driven financial systems.

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