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Corporate AI Adoption Announcements and Stock Market Reactions

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Abstract. Since the launch of ChatGPT in late 2022, generative AI has become a major focus for global capital markets. However, the market reactions to AI-related announcements of listed companies are very heterogeneous, and the underlying mechanisms are still underexplored. In this study, this paper analyze AI announcements by firms in a fixed list of S&P 100 constituents over the period 2023–2024. Researchers test, using event study methods and cross-sectional regressions, whether implementation intensity and technological capabilities are associated with short-term market reactions. The mean cumulative abnormal return (CAR) for the [-5, +5] window is 3.0%, which is statistically different from zero at the 5% level and is based on 26 announcements with complete return data. This paper find that implementation-oriented announcements are associated with CARs that are about 4.6 percentage points higher than intention-oriented announcements, although the effect is only marginally significant at the 10% level and becomes insignificant under alternative specifications. The implementation hypothesis is thus supported in a suggestive but not robust way. The interaction of implementation stage with R&D intensity is not significant. Hence, the technological-capability hypothesis is not supported. Overall, the observed implementation evidence seems to be associated with more positive market reactions within the short window, but the small sample and the sensitivity of the results to the specification urge caution in interpretation.

Keywords: Artificial intelligence announcements, Event study, Cumulative abnormal returns, Implementation intensity, Signal transmission

1. Introduction

Since the launch of the generative AI model, ChatGPT, in late 2022, the field has rapidly evolved from an emerging technology to a general-purpose technology that is reshaping corporate production, innovation, and competition. As such, AI has become an important driver of corporate strategy and capital market valuation. In this context, U.S.-listed companies are increasingly reporting AI-related investments, R&D, product development, and strategic alliances through SEC Form 8-K filings, investor-relations announcements, and corporate press releases. Disclosures related to AI have thus become increasingly important information events in capital markets [1]. But investors do not react in the same way to such announcements. Companies announcing specific AI deployment, large-scale adoption, or key technology partnerships may enjoy positive abnormal

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returns; ambiguous announcements about AI exploration or AI expansion may not be well received by the market or even cause negative stock price reactions. The difference largely stems from different perceptions of information credibility: implementation-oriented disclosures provide more verifiable signals of a company's ability to translate AI capabilities into commercial value, whereas conceptual statements provide little evidence [2]. Firm-specific resources, including data assets, R&D capabilities, and prior AI experience could further enhance market response to believable AI announcements.

But even if these disclosures have identifiable event dates, the observed returns might be affected by information leakage, investor anticipation, uncertainty about the event date and concurrent firm-specific news. Thus, it is important from an economic and practical perspective to study how markets react to different types of AI disclosures and whether firm capabilities shape these responses.

2. Literature review and problem formulation

2.1. Event study methodology and information content of corporate announcement

The standard way of measuring capital market response to informational events is the event-study methodology [3]. Abnormal returns are estimated as the difference between an actual return and an expected return if the event would not have occurred, as proposed by MacKinlay. Cumulative abnormal returns (CARs) consider the possible effects of after-hours announcements, information leakage, and delayed price adjustment [4]. Brown and Warner show that the event-study statistics are reliable in the short term using daily returns [5]. Kothari and Warner argue that short-window estimates are more reliable than long-window estimates because long-window estimates are subject to model interference [6]. Thus, this study employs short event windows to capture investors' immediate valuation responses to AI announcements.

2.2. Conditional features of IT investment announcements

Research on IT investment offers an important theoretical foundation. Dos Santos, Peffers and Mauer did not find significant abnormal returns following early announcements of IT investment, suggesting that spending on technology does not necessarily create value [7]. In contrast, positive market reactions were reported by Im, Dow and Grover. This shows that the effects of technology announcements are conditional on the type of investment, the firm, the industry and the context [8]. Together, these studies indicate that investors do not value technology spending uniformly; the nature of the investment and firm context matter [7, 8]. This conditional-value logic motivates examining whether observable implementation evidence differentiates AI announcements. Firm-level evidence also suggests that IT investment can complement R&D and other technological inputs in improving productivity [9]. This supports examining whether firm capabilities condition the value relevance of AI announcements.

2.3. Empirical evidence on AI announcements

Evidence on AI announcements is sparse and mixed. Kurter and Bhatti report an insignificant average announcement-date abnormal return of 0.114% in FTSE 100 firms with reactions differing by firm size, credit rating and stage of technology adoption [10]. Their study, however, has not yet been peer-reviewed. Laviola et al. find that there is no significant effect of AI innovation

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announcements on the stock return of S&P 500 firms, while the announcement of strategic alliances does generate more positive reactions [11]. The results reveal significant heterogeneity, but little effort has been made to systematically identify observable implementation evidence and examine the moderating role of prior technological capability.

2.4. Firm heterogeneity and AI's capabilities

Additionally, firm-level research accounts for these differences. Babina et al. found firms with more complementary resources including data, talent, and computing power are more likely to grow in AI-related revenue and valuation [12]. Eisfeldt et al. also demonstrate that firms with more data assets experienced larger valuation gains after the ChatGPT shock [13]. Therefore, R&D intensity and prior AI-related activities could be more informative measures of technological capability than a simple technology vs. nontechnology classification.

2.5. Research gap and hypothesis

To summarize, the prior literature finds that short-window CARs capture immediate market reactions, the value of technology investment depends on substantial implementation, and the value of AI creation depends on complementary firm resources. Building on this literature, researchers distinguish intention-oriented announcements from those which provide observable evidence of product launch or operational deployment, and test whether prior technological capability, proxied by R&D intensity, moderates their market impact. Its contribution is the application of a transparent two-stage implementation classification to a hand-collected post-ChatGPT sample of S&P 100 announcements. Based on this, this paper proposes two core hypotheses:

H1: Compared to AI announcements that merely articulate strategic intentions, AI announcements accompanied by evidence of implementation and deployment elicit a stronger positive market reaction;

H2: The positive association between implementation-oriented AI announcements and cumulative abnormal returns is stronger for firms with greater prior technological capabilities.

3. Research method

3.1. Sample selection and data sources

In this study, this paper consider the S&P 100 constituents on 31 December 2022 and analyze AI-related announcements from January 2023 to December 2024. The S&P 100 was selected because of the visibility of the firms in it and because of its manageable size. Announcements were identified through company investor-relations pages, newsrooms, press releases and partner releases, then manually verified for relevance and date of publication. The screening process yielded 44 announcements from 37 firms.

To reduce potential contamination, candidate announcements were screened for major observable firm-specific events within the [-5,+5] window, including earnings releases, M&A transactions, major personnel changes, equity issuance or repurchases, and major regulatory or litigation events. Two announcements with clear contemporaneous confounds were excluded, leaving 42 candidate events. Because this screening relied on publicly available news sources and the Nasdaq event calendar rather than an exhaustive case-by-case EDGAR audit, residual confounding cannot be ruled out.

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Of the 42 candidate events remaining after the preliminary confound screen, 16 did not have usable complete return histories in the public Nasdaq data extraction. The final analytical sample therefore comprises 26 announcements with complete data for both the estimation and event windows.

The data on announcements were obtained from company investor-relations pages, official newsrooms, press releases and announcements by partners. Event dates are based on the first confirmed release. Stock and SPY data are from NASDAQ. Financial variables such as firm size, current ratio, ROA and R&D intensity were gathered from public financial reports.

3.2. Event study design

This paper adopts the event study method as its core empirical approach. The basic logic is as follows: within the framework of the efficient market hypothesis, stock prices reflect all known public information, and investors' reactions to new information are quickly reflected in stock prices. Therefore, by examining changes in the returns of sample stocks before and after an event, this research can identify the event's impact on stock prices. Specifically, by subtracting the normal return that the stock would have earned had the hypothesized event not occurred from the actual return within the event window, researchers obtain the abnormal return, which quantifies the magnitude and direction of the market's reaction to the event information. This study strictly follows the standardized event study procedure proposed by MacKinlay [4].

The event date (τ=0) is defined as the date of the initial public AI announcement. Regarding the time window, this paper uses the period from the 120th trading day prior to the announcement to the 31st trading day prior to the announcement (i.e., [-120,-31]), totaling 90 trading days, to estimate the normal-return parameters of the market model. The main event window is set from the 5th trading day before the announcement date to the 5th trading day after it (i.e., [-5,+5]). This relatively wide window can accommodate after-hours announcements, possible early information diffusion, and brief lags in market price adjustment. In the sensitivity analysis, this paper also reports estimates for a shorter [-3,+3] window. A buffer of 25 trading days ([-30,-6]) is maintained between the estimation window and the main event window to prevent event-related price movements from contaminating the parameter estimates.

The market model is used to estimate normal returns. Specifically, for firm i, the following equation is estimated using ordinary least squares within the estimation window:

$$R_{it}=\alpha_i+\beta_i R_{mt}+\varepsilon_{it} \tag{1}$$

where R_it is the return of firm i on day t, and R_mt is the SPY return on day t. Based on the estimated parameters α̂_i and β̂_i, the abnormal return on day t within the event window is defined as the difference between the actual return and the expected normal return:

$$AR_{it}=R_{it}-(\hat{\alpha}_i+\hat{\beta}_i R_{mt}) \tag{2}$$

Based on this, the cumulative abnormal return for firm i within the event window [a, b] is:

$$CAR_i[a,b]=\sum_{t=a}^{b} AR_{it} \tag{3}$$

For descriptive interpretation, this paper also reports the event-level average daily abnormal return over the event window, defined as:

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$$AAR_i[a,b]=\frac{CAR_i[a,b]}{b-a+1} \tag{4}$$

Thus, AAR expresses the cumulative market reaction on an average daily basis. Because it is a linear rescaling of CAR within a fixed event window, it facilitates economic interpretation rather than serving as an independent robustness test; CAR remains the primary inferential outcome.

3.3. Variable definitions

The primary dependent variable is the cumulative abnormal return (CAR). For descriptive interpretation, the corresponding event-level average daily abnormal return (AAR) is also reported. The main analysis uses CAR[-5,+5] and its average-daily equivalent, AAR[-5,+5], while the shorter-window sensitivity analysis reports CAR[-3,+3] and AAR[-3,+3].

The key explanatory variable is a two-category implementation-stage variable. It is coded 1 for Stage 1 announcements and 2 for Stage 2 announcements. Stage 1 comprises announcements that express an intention for strategic cooperation, a pilot project, or an investment commitment but do not provide clear evidence of product launch or operational deployment. Stage 2 comprises announcements stating that an AI product has been officially launched or made fully available, or that AI has entered actual operational deployment.

The moderating variable is R&D intensity, measured as the ratio of R&D expenditures to operating revenue in the year prior to the announcement.

Control variables include firm size, current ratio, return on assets (ROA), sector fixed effects, and year fixed effects.

3.4. Research model

This study conducts empirical tests through three progressive steps. First, a one-sample t-test is performed on the full-sample CAR, with the null hypothesis that the mean CAR equals zero. The corresponding event-level AAR is also reported to express the same cumulative response on an average daily basis. Because AAR is a fixed scalar transformation of CAR within a given event window, the two measures produce the same t-statistic and p-value.

Second, to test H1 (that the market reaction to implementation-type announcements is higher than that to intention-type announcements), the following cross-sectional OLS model is employed:

$$CAR_i=\alpha+\beta_1 Implementation_i+\beta_2 Controls_i+\beta_3 SectorFE_i+\beta_4 YearFE_i+\varepsilon_i \tag{5}$$

If β_1 is significantly positive, it indicates that the market assigns a higher valuation to announcements providing verifiable evidence of implementation, supporting H1.

Finally, to test H2 (that a firm's ex ante technological capability positively moderates the relationship between implementation-oriented announcements and CAR), researcher extend the baseline cross-sectional specification in Equation (5) by adding R&D intensity and its interaction with Implementation Stage:

$$CAR_i=\alpha+\beta_1 Implementation_i+\beta_2 R\&D\ intensity_i+ \tag{6}$$

$$\beta 3(Implementation_i \times R\&D\ intensity_i)+\gamma' X_i+\varepsilon_i$$

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where gamma' X_i represents control variables and fixed effects. If β_3 is significantly positive, it indicates that firms with stronger technological capabilities receive greater market rewards for implementation-type announcements, supporting H2.

4. Results

4.1. Market reactions to AI announcements in the full sample

To test the first research question, this study conducts a one-sample t-test on the full-sample CAR. Table 1 reports that the mean CAR[-5,+5] is 3.0%, which is statistically different from zero at the 5% level ($t = 2.606$, $p = 0.015$). Table 2 expresses the same cumulative response on an average daily basis. The mean event-level AAR is approximately 0.3%, obtained by dividing each event's CAR by the 11 trading days in the [-5,+5] window. The identical t-statistics and p-values in Tables 1 and 2 arise from this scaling relationship and should not be interpreted as two independent tests. The result indicates a positive average short-window market reaction to the AI-related announcements in the sample. It differs from the positive but statistically insignificant average effect reported by Kurter and Bhatti [10] for FTSE 100 firms, although differences in market setting, sample construction, and measurement may contribute to the discrepancy. The preliminary exclusion of two events with clear observable confounds may have reduced some contamination, but residual confounding cannot be ruled out.

Table 1. Descriptive statistics and t-tests for cumulative abnormal returns (CAR[-5, +5]) across the full sample

Variable	Mean	SE	t	p
CAR[-5,5]	0.030	0.011	2.606	0.015

Table 2. Descriptive statistics and one-sample t-test for event-level average daily abnormal returns over the [-5,+5] window

Variable	Mean	SE	t	p
AAR[-5,5]	0.003	0.001	2.606	0.015

4.2. The differential effects of AI announcement implementation intensity

To test the second research question—whether AI announcements with evidence of implementation yield higher cumulative abnormal returns compared to those that merely express intentions regarding AI development—this study first divides the sample into two groups based on announcement implementation intensity: Stage 1 (intention-oriented) and Stage 2 (implementation-oriented). It then conducts comparisons of group means and cross-sectional regression analyses.

Table 3 reports the baseline cross-sectional OLS results. In the CAR specification, CAR[-5,+5] is the dependent variable, and a two-category implementation-stage variable is coded 1 for Stage 1 and 2 for Stage 2. Controlling for firm size, current ratio, ROA, sector fixed effects, and year fixed effects, the coefficient on Implementation Stage is 0.046 and is marginally significant at the 10% level ($t = 1.828$, $p < 0.1$). This implies that Stage 2 announcements are associated with CARs approximately 4.6 percentage points higher than Stage 1 announcements, holding the other variables constant. The AAR column reports the event-level average daily abnormal return over the [-5,+5]

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window. Because AAR[-5,+5] equals CAR[-5,+5]/11, the coefficient of 0.004 presents the same baseline result on an average daily scale rather than providing an independent specification.

The baseline results provide tentative support for H1. Implementation-oriented announcements are associated with higher CARs than intention-oriented announcements, but the coefficient is only marginally significant at the 10% level and becomes statistically insignificant in the alternative specifications reported below. Given the analytical sample of 26 events, the estimate should therefore be interpreted cautiously. The coefficient on firm size is negative but statistically insignificant, so the analysis does not provide sufficient evidence of a systematic size effect.

Table 3. Cross-sectional regression on the impact of announcement implementation intensity on cumulative abnormal returns

Variables	CAR[-5,5]	AAR[-5,5]
Implementation Stage	0.046*	0.004*
	(1.828)	(1.828)
Size	-0.023	-0.002
	(-1.445)	(-1.445)
Current Ratio	0.023	0.002
	(0.425)	(0.425)
ROA	0.002	0.000
	(0.320)	(0.320)
Sector Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Constant	0.552	0.050
	(1.008)	(1.008)
R^2	0.454	0.454
Adj. R^2	0.025	0.025
N	26	26

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The values in parentheses are t-statistics. For the [-5,+5] window, AAR is calculated as CAR/11; the AAR column therefore presents the corresponding CAR estimates on an average daily scale and is not an independent robustness specification.

4.3. Moderating effect of firms' ex-ante technological capabilities

To test the third research question—whether a firm's prior technological capability positively moderates the positive relationship between implementation-oriented AI announcements and CAR—this study introduces a measure of firm technological capability (R&D intensity) and its interaction term with Implementation Stage into the baseline regression model.

Table 4 reports the regression results after incorporating the interaction term. In the CAR specification, with CAR [-5, +5] as the dependent variable, the coefficient for Implementation Stage is 0.066, and the coefficient for R&D Intensity is 0.556; however, the coefficient for the interaction term Implementation Stage × R&D Intensity is -0.241, which is not statistically significant (t =

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-0.519). This result implies that, in the current sample, this study failed to find sufficient evidence to support the hypothesis that R&D intensity positively moderates the market premium of implementation-type announcements. In other words, H2 was not empirically supported.

Table 4. Cross-sectional regression on the moderating effect of firm R&D intensity

Variables	CAR[-5,5]	AAR[-5,5]
Implementation Stage	0.066	0.006
	(1.325)	(1.325)
R&D Intensity	0.556	0.051
	(0.604)	(0.604)
Implementation Stage* R&D Intensity	-0.241	-0.022
	(-0.519)	(-0.519)
Size	-0.026	-0.002
	(-1.472)	(-1.472)
Current Ratio	0.013	0.001
	(0.204)	(0.204)
ROA	0.003	0.000
	(0.538)	(0.538)
Sector Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Constant	0.592	0.054
	(1.008)	(1.008)
R^2	0.475	0.475
Adj. R^2	-0.093	-0.093
N	26	26

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The values in parentheses are t-statistics. For the [-5,+5] window, AAR is calculated as CAR/11; the AAR column therefore presents the corresponding CAR estimates on an average daily scale and is not an independent robustness specification.

4.4. Robustness tests

Tables 5 and 6 report two sensitivity tests. When the event window is shortened from [-5,+5] to [-3,+3], the coefficient on Implementation Stage remains positive but becomes statistically insignificant. One possible explanation is that the market response is distributed across several trading days because of after-hours disclosure, information leakage, event-date uncertainty, or gradual price adjustment, so the wider window may capture a larger share of the cumulative response. However, a wider window also increases exposure to unrelated market movements and potential confounding events. Table 6 replaces market-model abnormal returns with market-adjusted returns. The coefficient on Implementation Stage again remains positive but is statistically

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insignificant. Overall, the direction of the estimated association is consistent across specifications, but its statistical significance is sensitive to both the event-window definition and the normal-return model. H1 should therefore be interpreted as suggestive rather than conclusive evidence.

Table 5. Robustness tests: regression results with a shorter event window ([-3, +3])

Variables	CAR[-3,3]	AAR[-3,3]
Implementation Stage	0.025	0.004
	(1.527)	(1.527)
Size	-0.025**	-0.004**
	(-2.416)	(-2.416)
Current Ratio	0.015	0.002
	(0.422)	(0.422)
ROA	0.002	0.000
	(0.525)	(0.525)
Sector Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Constant	0.647*	0.092*
	(1.842)	(1.842)
R^2	0.601	0.601
Adj. R^2	0.287	0.287
N	26	26

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The values in parentheses are t-statistics. For the [-3,+3] window, AAR is calculated as CAR/7; the AAR column therefore presents the corresponding CAR estimates on an average daily scale and is not an independent robustness specification.

Table 6. Robustness tests: regression results for the market-adjusted return model

Variables	CAR (market-adjusted) [-5, 5]	AAR (market-adjusted) [-5, 5]
Implementation Stage	0.029	0.003
	(1.219)	(1.219)
Size	-0.011	-0.001
	(-0.742)	(-0.742)
Current Ratio	-0.061	-0.006
	(-1.178)	(-1.178)
ROA	0.006	0.001
	(1.221)	(1.221)
Sector Fixed Effects	YES	YES
Year Fixed Effects	YES	YES

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Table 6. (continued)

Constant	0.415	0.038
	(0.800)	(0.800)
R^2	0.466	0.466
Adj. R^2	0.047	0.047
N	26	26

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. The values in parentheses are t-statistics. For the [-5,+5] window, AAR is calculated as CAR/11; the AAR column therefore presents the corresponding CAR estimates on an average daily scale and is not an independent robustness specification.

5. Discussion

Building on prior research distinguishing substantive from rhetorical AI signals, this study operationalizes implementation evidence through a transparent two-stage classification and applies it to a post-ChatGPT sample of S&P 100 announcements [2]. It also investigates if R&D intensity moderates the relationship between implementation-oriented announcements and market reactions. Thus, the study expands the literature on IT investments and the conditional-value perspective to the context of AI announcements and offers a transparent and replicable framework for classifying announcements.

The findings have tentative implications for corporate AI communication and investor assessment. Verifiable information on product launches, investment commitments, partners or operational deployment could improve the credibility of AI-related disclosures by listed companies. When reviewing announcements with the AI label, investors may also look for implementation evidence. However, these implications should be interpreted cautiously because the baseline implementation-stage result is only marginally significant and is sensitive to alternative specifications.

The results should be interpreted in the light of several limitations. The analytical sample comprises 26 announcement events, which constrains statistical power and the precision of the cross-sectional estimates. Some firms make multiple announcements, so event-level observations may not be perfectly independent and the reported conventional standard errors should be interpreted with caution. Secondly, announcement classification is a judgment call; future work could use multiple independent coders and report inter-coder reliability, or use transparent text-analysis methods as a supplementary check. Third, R&D intensity is a noisy proxy for AI-specific technological capability. Future work could explore AI talent, patent stock, previous AI activity, or 10-K disclosures. Fourth, the study measures short-term market reactions, not realized long-term operating outcomes. Finally, the sample is limited to large U.S. firms in the S&P 100 universe, so the results may not be generalizable to smaller firms or other markets.

6. Conclusion

The study analyzes AI-related announcements of S&P 100 companies in the years 2023-2024. The study applies the event study methodology to analyze the short-term market reactions to the announcements with a focus on the degree of implementation of the announcements and the previous technological capabilities of the firms. This results in a final sample of 26 announcements with full estimation- and event window data.

First, the mean CAR around the [-5,+5] window is 3.0% and statistically significant at the 5% level, indicating a positive short-term market reaction. This contrasts with the positive but insignificant effect found by Kurter and Bhatti [10] for firms in the FTSE 100 and may be due to the difference in the market setting, sample, definition of event and the measure of return. Second, this paper find that implementation-oriented announcements are associated with CARs that are 4.6 percentage points higher than intention-oriented announcements (marginal significance at the 10% level). However, under the shorter-window and market-adjusted-return specifications, the effect becomes insignificant, providing only suggestive support for H1. This finding suggests that the market reacts more positively to visible evidence of implementation, rather than that investors discriminate between sincere and superficial AI announcements. Third, the results do not support H2. The interaction of implementation stage and R&D intensity is negative and insignificant. This may reflect the limited capacity of aggregate R&D intensity to capture AI-specific technological capabilities, investors' increased reliance on direct implementation signals, or lack of statistical power due to the small sample.

Overall, the results provide suggestive evidence that implementation-oriented announcements are associated with more positive market reactions. The moderating role of technological capability is not supported in the current sample and needs further study with larger samples and more precise measures.

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