
An Event Study on Stock Market Reactions to Media Disclosures of FinTech Investments: The Case of Korea

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ABSTRACT

As FinTech adoption by financial institutions accelerates, the capital-market effects of these technological investments remain incompletely understood. While prior studies typically examine FinTech as a single homogeneous category, technological heterogeneity—across artificial intelligence, blockchain, big data, and the Internet of Things—and industry-specific contexts may produce differentiated stock-price reactions. This study investigates whether media disclosures of FinTech investments by Korean financial institutions generate statistically significant abnormal returns and cumulative abnormal returns, and whether these reactions differ systematically by industry (insurance, securities, banking) and technology type. Using 451 FinTech-related disclosure events from 2016–2020, we apply simple market-model event-study procedures together with two-way analysis of variance. The results show that FinTech investment disclosures produce heterogeneous signaling effects across industries and technologies. Importantly, results confirm significant industry-technology interaction effects, indicating that each technology’s value and risk are interpreted differently across industry contexts. A notable methodological contribution is the explicit treatment of imbalanced event counts, which affects statistical power in certain subsamples. Robustness diagnostics confirm that the heterogeneity patterns are not statistical artifacts but reflect technology-specific and industry-specific valuation dynamics. This study provides new evidence on how financial markets interpret FinTech innovation, offering insights for investors, regulators, and financial institutions.

Keywords: FinTech adoption, Event study, AI, Blockchain, Big data, IoT, Korea

I. Introduction

Digital transformation in the global financial industry has accelerated the adoption of financial technologies (fintech) such as artificial intelligence (AI), blockchain (BC), big data (BD), and the Internet of Things (IoT). Financial institutions increasingly rely on these technologies to redesign their value chains—from credit screening, risk assessment, and underwriting to portfolio management and customer analytics. As investment in fintech intensifies, capital markets face a critical question: How do investors interpret disclosures regarding fintech adoption? Do such disclosures

signal enhanced future efficiency and profitability, or do they reveal uncertainty, cost burdens, or heightened operational risks?

Understanding how investors react to fintech investment disclosures is essential because capital-market responses serve as rapid, real-time assessments of managerial decisions under uncertainty. Prior literature on disclosure effects highlights that when firms communicate new strategic initiatives, investors infer information about future profitability, risk, and competitive positioning. From the viewpoint of signaling theory, managers can use technology-adoption disclosures as signals that convey private

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information about innovation capability, organizational agility, and future growth prospects. Yet the magnitude and direction of such signaling effects remain empirically ambiguous in the fintech domain.

Despite the rapid integration of fintech, academic research tends to examine “fintech” as a monolithic construct, often ignoring technological and industrial heterogeneity. However, different technologies embody distinct risk–return profiles. For example, AI often signals innovation, automation, and efficiency gains, while BC may indicate both transparency benefits and substantial regulatory uncertainty. BD is associated with increased analytical capabilities, but also privacy and governance concerns. IoT requires hardware deployment and carries high cybersecurity and liability risks.

Likewise, the financial industry is not homogeneous. Insurers, securities firms, and banks operate with different value-chain structures, regulatory constraints, and competitive environments. Therefore, the market reactions to fintech disclosures may vary not only by technology type but also by industry context. Yet, academic research seldom incorporates this two-dimensional heterogeneity (industry $\times$ technology). This constitutes a critical gap that limits understanding of how capital markets interpret digital transformation in financial institutions.

Motivated by these theoretical and empirical gaps, this study investigates whether fintech investment disclosures in financial industries generate significant abnormal returns (AR) or cumulative abnormal returns (CAR), and tests for differences in stock-price reactions across financial industry sectors (insurance, securities, and banking) and across technology types (AI, BC, BD, IoT). Our study further examines whether there are significant interaction effects between industry and technology.

Using 451 fintech-related disclosures in Korea’s financial industry from 2016 to 2020, we employ event study methodology based on market-model abnormal returns and two-way ANOVA to evaluate main effects of industry and

technology. Our analysis acknowledges, quantifies, and corrects for uneven event frequencies across technologies. During our study period, for example, AI-related disclosures accounted for nearly 60% of all events, while blockchain and IoT comprised only about 10% each. This imbalance raises the concern that statistical power may be lower in smaller subsamples, biasing results toward null findings. Additionally, comparability across technology groups may be distorted due to imbalanced event counts and interaction effects (industry $\times$ technology) may be underestimated if certain cells of the design matrix contain sparse observations. We address these imbalances using robust econometric procedures, including MANOVA and sensitivity checks.

This approach yields four major contributions. First, we provide the first systematic evidence that capital markets do not treat fintech uniformly: AI, BD, BC, and IoT elicit distinct market responses. Second, we provide evidence that market reactions differ across insurers, securities firms, and banks, reflecting sector-specific value-chain structures. Third, using ANOVA, we identify strong industry $\times$ technology interaction effects, revealing that the valuation of each technology depends critically on industry context. Finally, we contribute methodological advancements by explicitly addressing sample imbalance and validating that our main findings hold under robustness checks.

Overall, this study advances the literature by integrating signaling theory, fintech heterogeneity, and modern event-study econometrics. Results provide actionable insights for financial institutions seeking to communicate technological innovation to investors, and for regulators evaluating the market’s response to fintech adoption.

II. Literature Review

This section reviews the theoretical and empirical foundations underlying the study. We classify the literature into four domains: (1) signaling theory and disclosure effects, (2) event-study methodology, (3) fintech

technologies and industry-specific applications, and (4) value-chain and value-driver frameworks linking technological innovation to firm value. Together, these strands provide conceptual grounding for evaluating heterogeneous market reactions to fintech investment disclosures.

A. Signaling Theory and Disclosure Effects

In financial markets, firms and investors typically possess asymmetric information regarding technological capabilities, operational efficiency, and future profitability. Classic information economics (Akerlof, 1970) shows that such asymmetry can distort valuation. Signaling theory (Spence, 1973; Connelly et al., 2011) suggests that firms disclose information to reduce informational asymmetry by conveying credible signals about intrinsic value or future prospects.

In corporate finance, signals often arise from dividend announcements (Bhattacharya, 1979; John & Williams, 1985), stock repurchases (Grullon et al., 2002; Yoon, 2015), mergers and acquisitions (He et al., 2020), or voluntary disclosures of major investments (De Jong et al., 1992). Market reactions to such disclosures reflect investors' updated beliefs incorporating the new information. However, signals may also generate negative or mixed reactions depending on perceived risk, capital expenditure burdens, or concerns regarding management credibility.

FinTech investment disclosures are quintessential signals: they convey technological capabilities and innovation posture; they indicate future strategic direction (digitalization, automation, AI integration); and they potentially reveal cost burdens, organizational disruption, and regulatory risk. Thus, fintech announcements may produce *positive* reactions (innovation, efficiency gains) or *negative* reactions (uncertainty, cost overruns, cybersecurity concerns). The empirical sign is therefore ambiguous and warrants systematic testing.

B. Event-Study Methodology

The event-study method evaluates whether an event (such as a disclosure) induces abnormal stock returns, reflecting unanticipated information incorporated into prices. Seminal

works (Fama, Fisher, Jensen & Roll, 1969; Brown & Warner, 1985) provide foundational methodology for isolating abnormal return (AR) relative to an expected market model return. Key assumptions include (Fama, 1970): (i) markets incorporate new information rapidly; (ii) events are sufficiently discrete and identifiable; (iii) estimation windows capture normal performance without contamination; and (iv) abnormal returns represent market reactions net of systematic factors.

Event studies have been widely used to study earnings announcements, policy changes, corporate restructuring, sustainability/ESG (environmental, social, and governance) disclosures, and technology adoption announcements (Cao et al., 2020). Recent research applies event studies to fintech contexts, yet studies often treat fintech homogeneously, ignoring technological heterogeneity. This is a major limitation that our study addresses by incorporating technology-specific and industry-specific dimensions.

C. Financial Industry Applications of FinTech

FinTech is not a single technology. Rather, it is an ecosystem of diverse innovations. Each technology incorporates unique operational characteristics, risk profiles, and adoption patterns. Understanding these differences is essential for analyzing market reactions.

Artificial Intelligence (AI): AI is central to automation, risk scoring, fraud detection, algorithmic trading, underwriting, and personalized financial products. AI signals high innovation potential, scalability, and cost efficiency (Bose et al., 2021; Kou et al., 2021). Empirically, investors tend to interpret AI announcements positively due to high-growth narratives.

Blockchain (BC): Blockchain, a shared digital ledger, offers transparency, immutability, and disintermediation, potentially lowering settlement and reconciliation costs (Catalini & Gans, 2016). However, regulatory uncertainty, governance fragmentation, and scalability issues create downside risks. Markets may react cautiously to BC disclosures depending on context.

Big Data (BD): BD enables sophisticated analytics, customer segmentation, credit scoring, operational risk monitoring, and investment strategies (Chen, Chiang & Storey, 2012). BD is widely adopted across industries but carries privacy, compliance, and data governance concerns. Market reactions may be nonlinear—initial enthusiasm followed by correction.

Internet of Things (IoT): IoT collects real-time data via hardware devices and sensors, enabling telematics insurance, ATM optimization, and IoT-based risk monitoring (Atzori et al., 2010). However, IoT adoption incurs hardware installation and maintenance costs, integration challenges, cybersecurity and privacy liabilities, and exhibits lower technological maturity in financial contexts. Empirical evidence suggests that IoT announcements may lead to muted or negative market reactions due to heightened operational risk perception.

D. FinTech Value Chain for Financial Institutions

The value chain is a framework for analyzing the activities through which a firm creates value across the entire process of producing and delivering products or services. The efficiency and effectiveness of each activity influence firm performance and, ultimately, are closely linked to the firm's stock price. In other words, financial outcomes—and thus market valuation—depend on how efficiently each component of the value chain operates and whether it confers competitive advantage. By improving core value-chain activities, a firm can enhance profitability and receive a more favorable market assessment (Porter, 1985). Porter (1985) further argues that firms can secure competitive advantage at each stage of the value chain through cost leadership or differentiation, which in turn can translate into higher firm value and stock prices.

For financial institutions—such as insurers, securities firms, and banks—the structure of the value chain and its stage-specific processes present multiple points at which fintech technologies can contribute to managerial efficiency and performance. The potential

contributions by technology and by stage are outlined in Appendix A.

Across the financial industry, the adoption of fintech technologies functions as a core means of enhancing managerial efficiency at multiple stages of the value chain. Although banks, insurers, and securities firms share broadly similar value-chain structures, the ways and purposes for applying fintech differ by sectoral characteristics and strategy. In the product and service development stage, for example, banks leverage artificial intelligence (AI) to analyze customers' financial histories and behavioral data in order to design customized products (Bose et al., 2021). Insurers employ the Internet of Things (IoT) to build products that incorporate real-time sensor data—such as usage-based insurance reflecting driving behavior (Atzori et al., 2010). Securities firms, by contrast, emphasize big-data analytics (BD) to identify market trends and investor demand and to assemble sophisticated product portfolios, including derivatives and ESG-linked instruments (Sironi, 2016). Table 1 below describes fintech applications at each stage of the value chain for financial firms by sector – insurance, securities, and banking.

A careful examination is needed as to whether the adoption of fintech technologies brings only positive effects to the financial industry. Scholars differ on whether such adoption yields beneficial or adverse consequences. Artificial intelligence (AI) serves as a foundational technology for workflow automation and personalized services across all financial sectors. In banking, AI-based credit-scoring models and personalized product-recommendation systems have delivered strong performance in practice (Kou et al., 2021). Insurers apply AI to fraud detection, new-business underwriting, and automated claims review, improving both efficiency and accuracy (Davenport & Ronanki, 2018). However, AI also raises ethical and institutional challenges including a lack of explainability (Binns, 2018), algorithmic biases that may erode customer trust (Pasquale, 2015), the potential for market

Table 1. FinTech and the Value Chain

Value-chain stage	Insurance	Securities	Banking
1. Product & service development	IoT-based usage-based insurance (Atzori et al., 2010)	Big-data-driven structured products (Sironi, 2016)	AI-based personalized financial products (Bose et al., 2021)
2. Marketing & customer management	Big-data-based customer segmentation (Wedel & Kannan, 2016)	AI-based churn prediction (Lemmens & Croux, 2006)	Chatbots and AI counseling systems (Ngai et al., 2009)
3. Product sales & contract execution	Blockchain-based smart contracts (Tapscott & Tapscott, 2017)	Online trading automation (Peters & Panayi, 2016)	Robo-advisory deployment (Sironi, 2016)
4. Risk assessment & post-underwriting review	IoT-based risk assessment (Atzori et al., 2010)	Big-data-based transaction risk assessment (Fan et al., 2014)	AI-based credit screening (Kou et al., 2021)
5. Service delivery & operations	Blockchain-based claims adjudication (Yermack, 2017)	AI-driven portfolio management (Sironi, 2016)	RPA-based process automation (Brynjolfsson & McAfee, 2017)
6. After-sales management & relationship maintenance	AI-based automated claims review (Davenport & Ronanki, 2018)	Behavior-based recommendation systems (Gandomi & Haider, 2015)	Sentiment-analysis-driven customer response (Huang & Rust, 2021)
7. Internal support & management	Big-data-driven managerial analytics (George et al., 2014)	AI-based internal-control systems (Davenport & Ronanki, 2018)	Blockchain-based auditing (Schatsky et al., 2018)

Source: Compiled by the authors.

Table 2. Potential Impacts of FinTech

	Artificial Intelligence	Blockchain	Big Data	Internet of Things
Banking	Positive: Automated credit screening; personalized services. Negative: Workforce reductions; algorithmic bias; lack of explainability.	Positive: Integrity of transaction records; cost reduction. Negative: Scalability issues; regulatory uncertainty.	Positive: Customer segmentation; early risk detection. Negative: Privacy-invasion concerns.	Positive: Automation of payment terminals; optimized ATM management. Negative: Security vulnerabilities.
Insurance	Positive: Automated new-business underwriting and claims review; fraud detection. Negative: Workforce reductions; potential erosion of customer trust.	Positive: Smart-contract-based automation of insurance claims. Negative: Diffusion or ambiguity of legal liability.	Positive: Finer risk segmentation; price differentiation. Negative: Potential controversies over premium discrimination.	Positive: Risk assessment using driving-behavior and health data. Negative: Potential leakage of sensitive information.
Securities	Positive: Robo-advisory; optimization of high-frequency trading. Negative: Heightened risk of market manipulation.	Positive: DLT-based innovation in clearing and settlement. Negative: Frictions with incumbent market infrastructure.	Positive: Real-time investor analytics; risk forecasting. Negative: Decision errors from over-analysis.	Positive: Real-time collection/use of market data. Negative: Low data reliability; rising maintenance costs.

Source: Compiled by the authors

manipulation (Biais et al., 2010), and labor-market concerns stemming from reduced employment opportunities. In particular, financial consumer protection and fairness require sustained, in-depth responses. Table 2 summarizes potential positive and negative impacts of each fintech application by financial industry sector.

III. Research Design

This section presents the conceptual research model, operational definitions of variables, hypotheses, sampling framework, and empirical design. Drawing on signaling theory and previous literature on technology-adoption announcements, our research model examines how fintech investment disclosures affect the stock-prices of the firm. We conceptualize stock price response as a function of two key factors: industry type (insurance, securities, banking) and technology type (AI, BC, BD, IoT). These two categorical variables may produce main effects (industry-specific or technology-specific reactions) and Interaction effects (technology valuations depending on industry context). We test the following specific hypotheses:

- H1. FinTech investment disclosures produce statistically significant stock price reactions for financial institutions.
- H2. The stock-price reaction to fintech investment disclosures differs significantly across financial industries.
- H3. The stock-price reaction differs significantly across fintech technology types.
- H4. There is a significant industry $\times$ technology interaction effect on stock price reactions to fintech disclosures.

We employ a two-stage empirical strategy to test the hypotheses. First, we construct market-model event-study estimation of abnormal stock price returns after a fintech investment disclosure. Second, we undertake analysis-of-variance (ANOVA) to evaluate group differences and interaction effects. This design allows for a richer interpretation of heterogeneous signals.

A. Event Study Model

We define the event date ($t = 0$) as the earliest public news report of a fintech investment by a publicly listed financial firm. To estimate expected returns, we use an estimation window of $t = -130$ to $t = -6$ days around the event date. This excludes the pre-disclosure region where information leakage may occur.

Expected returns are estimated with the market model:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \quad (1)$$

Where R_{it} is the stock return of firm i at date t , R_{mt} is the KOSPI market return at date t , α_i is a firm-specific intercept and β_i measures market sensitivity of the returns.

The abnormal return (AR) is the daily (actual) stock return minus the expected return from the market model, AR measures the immediate market reaction to the fintech investment.

$$AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt}) \quad (2)$$

Summing AR over an event window captures persistence or reversal of stock price reactions, i.e. cumulative abnormal returns (CAR). We define the event window for CAR to be ± 3 -days. This window balances two objectives -- avoiding noise from long windows and capturing potential anticipation or delayed market reaction.

$$CAR[-3,+3] = \sum AR_{it} \quad (3)$$

B. ANOVA

We conduct two-way ANOVA with event-day AR or event-day CAR as the dependent variable and industry and technology type as the independent factors. The results allow determination of industry and fintech effects on AR to determine if differs across industries and whether there are statistically significant industry $\times$ fintech interaction effects. Scheffé post-hoc comparisons are used to identify which groups differ when AR or CAR differs significantly by industry or fintech technology. While ANOVA inherently compares group means without explicit controls, the event-time estimation uses the market model which implicitly controls for

overall market return, firm-specific systematic risk (β), and non-event-period performance trends (via the estimation window).

C. Sample Construction

We examine fintech investments over the period January 2016 to December 2020, aligning with the acceleration of digital transformation in Korea's financial sector. Stock prices are obtained from Korea Exchange (KRX) daily stock prices and KOSPI index returns. To identify fintech investment disclosures, we collected fintech-related news articles for Korean listed financial institutions from Korea Economic Daily, Chosun Biz, Maeil Business Newspaper, Yonhap News, Financial News, and additional verified news portals. In cases where identical news content was distributed across multiple media channels, duplicates were removed and the Yonhap News Agency article was retained as the canonical source for event identification and counting.

A news article qualified as an event if it (i) describes a financial firm's adoption, investment, or deployment of AI, BC, BD, or IoT; (ii) is publicly disclosed in a reputable media outlet; and (iii) can be linked to a listed firm with available stock-price data. Specific criteria for inclusion included: the disclosure must reference a specific fintech technology (AI, BD, BC, IoT); the firm must be listed on KOSPI/KOSDAQ; daily price and market data must be available for estimation windows; and the event must involve strategic investment, system adoption, product introduction, or technology partnership. News articles announcing pure marketing campaigns without technological content or general digital transformation narratives without specific technology were excluded. Events overlapping with earnings announcements, M&A, or regulatory sanctions within ± 3 days were also excluded. Finally, duplicate news within a 15-day window were combined into a single event.

After screening 603 raw articles, 451 unique fintech events remained. Among these events, 277 were reported for securities firms, 101 for banking firms, and 73 for insurance firms. We classify each event into one of four fintech technological domains, using a structured rule-based coding protocol and NLP keyword

validation. In total there were 265 AI events, 94 BD events, 46 BC events and 46 IoT events. Table 3 displays the classification of events by financial sector and technology.

Table 3. Classification of Events

	AI	BC	BD	IoT	Total
Insurance	30	11	25	7	73
Securities	180	19	47	31	277
Banking	55	16	22	8	101
Total	265	46	94	46	451

Source: Compiled by the authors.

IV. Results

A. Event-Study Results

Event-study models were estimated to test for abnormal returns associated with fintech adoption disclosures. Models were estimated for the financial industry as a whole and for each financial sector (insurance, securities, banking) separately. Within each sector, models were estimated separately for each technology (AI, BC, BD, IoT).

To ensure the validity of the market-model estimation, we examined model diagnostics including the distribution of estimated beta coefficients and goodness-of-fit measures. The diagnostics indicate stable market sensitivity and satisfactory model fit across firms, suggesting that the reported abnormal returns are not driven by model misspecification. Detailed diagnostic results are reported in supplementary material.

Overall, a total of 20 models (4 industry measures $\times$ 5 technology measures) for abnormal returns (AR) and 20 models for cumulative abnormal returns (CAR) were estimated, and estimation results for each model include coefficient estimates for each event period in the event window $[-3, +3]$. To simplify results reporting, table 4 combines presents coefficients and t-statistics for the event day estimates of (mean) AR and (mean) CAR for each industry and technology. However, estimation results for the entire event window are discussed below, and the full estimation results are available for viewing in the supplementary material.

Table 4. Event Day Mean Abnormal Returns

	Financial Industry		Insurance Industry		Securities Industry		Banking Industry	
	AR	CAR	AR	CAR	AR	CAR	AR	CAR
Any Fintech	0.0482* (4.447)	0.0502* (3.164)	0.0611 (1.973)	0.0236 (0.650)	0.0105 (0.975)	0.0244 (1.370)	0.1423* (4.873)	0.1399* (3.250)
Artificial Intelligence	0.0771* (5.043)	0.0880* (4.593)	0.1140* (2.2021)	0.0653 (1.197)	0.0315* (2.458)	0.0978* (4.664)	0.2065* (4.259)	0.0685 (1.255)
Blockchain	-0.0236 (-0.737)	-0.1241* (-2.514)	-0.0076 (-0.087)	-0.1612 (-1.235)	-0.0641* (-2.096)	-0.1511* (-2.317)	0.0333 (0.954)	0.0292 (0.413)
Big Data	0.0274 (1.513)	0.1066* (2.922)	0.0267 (0.698)	-0.0123 (-0.315)	-0.0089 (-0.397)	0.0013 (0.042)	0.1055* (2.730)	0.4666* (4.501)
Internet of Things	-0.0040 (-0.133)	-0.1090* (-2.130)	0.0651 (0.689)	0.2634* (2.171)	-0.0257 (-0.666)	-0.2093* (-3.758)	0.0195 (0.525)	-0.0460 (-0.444)

Note: AR = event day mean abnormal returns; CAR = event-day mean cumulative abnormal returns. t-statistics appear below the coefficient estimates in each cell; * indicates statistical significance at the 5% confidence level or better.

For the full financial-industry sample, the event-study analysis confirms that fintech disclosures are, on average, value-relevant. On the event day, we observe a significantly positive AR, with the corresponding event day CAR also positive and statistically significant ($t = 3.164$, $p < 0.01$). These findings indicate that the market, in aggregate, tends to interpret fintech investment announcements as favorable innovation signals. However, there is a subsequent negative AR on day +1, followed by partial recovery, suggesting that investors quickly reassess the announcement once initial enthusiasm or overreaction is corrected.

A closer look at the technology-specific panels reveals substantial heterogeneity. AI and big data generate largely positive event-day responses and positive short-horizon CAR, while blockchain yields mixed patterns and IoT tends to produce negative or weakly negative abnormal returns, especially in the insurance and securities sectors. This strongly supports the notion that “fintech” is not a monolithic category in the eyes of investors: capital markets evaluate each technology through the lens of perceived implementation feasibility, risk, and value-chain alignment.

For the insurance sector as a whole, fintech disclosure effects are statistically significant on the event day ($t = 1.973$, $p < 0.05$) and on day +3 ($t = 2.914$, $p < 0.01$). The positive reaction observed on the announcement date appears to persist through +3 days after the disclosure.

Mean AR and CAR are positive, suggesting a favorable evaluation of fintech disclosures. Standard deviations indicate substantial cross-event variation—consistent with heterogeneous technologies and industries.

For the securities sector as a whole, fintech disclosure effects exhibit both positive and negative intervals relative to the announcement: $t = 2.250$ ($p < 0.05$) at -3 days and $t = -2.743$ ($p < 0.01$) at +2 days. The positive pre-event response suggests that the market may have anticipated or pre-priced the information (consistent with potential information leakage or predictability), whereas the sharp decline two days after the disclosure is consistent with disappointment selling following over-optimism or with reduced credibility of the announcement.

For the banking sector as a whole, the disclosure effect is positive on the event day ($t = 4.873$, $p < 0.01$), reverses to a negative effect on day +1 ($t = -5.012$, $p < 0.05$), and then switches back to a positive effect on day +2 ($t = 1.190$, $p < 0.10$). In other words, while the announcement is initially evaluated favorably, a sharp reversal occurs the next day—consistent with post-announcement re-interpretation of information or profit-taking after an initial overreaction—followed by a modest recovery two days later as the market reassesses the news more soberly.

AI-related disclosures generate the most pronounced and immediate market reactions across all financial sectors. In particular,

securities firms and banks exhibit statistically significant pre-event price movements, suggesting either anticipatory trading or early information diffusion prior to public disclosure. While announcement-day abnormal returns are generally positive, these gains are often followed by rapid negative corrections, indicating short-term overreaction and subsequent reassessment by investors. This pattern is consistent with the view that AI investments are perceived as strategically important yet complex, with high expectations tempered by uncertainty regarding implementation costs, organizational disruption, and regulatory scrutiny.

Blockchain-related disclosures are characterized by sharp sign reversals around the announcement window. Across industries—and especially in the securities sector—negative abnormal returns observed prior to or on the announcement day are followed by significant positive rebounds shortly thereafter. This mean-reverting pattern suggests that initial market skepticism or uncertainty is quickly corrected as investors reassess the long-term implications of distributed ledger technologies. The results are consistent with blockchain being viewed as a disruptive but increasingly familiar technology, where initial caution gives way to more balanced valuation once information is absorbed.

Big data disclosures exhibit nonlinear and sometimes delayed market responses across all sectors. Significant abnormal returns tend to emerge on or after the announcement day, rather than being concentrated precisely at the event date. In the banking sector, in particular, abnormal returns are observed over an extended portion of the event window, reflecting the pervasive role of data analytics in core banking functions such as credit assessment, customer segmentation, and risk management. These findings suggest that investors process big data investments as gradual efficiency-enhancing initiatives rather than discrete announcement shocks.

IoT-related disclosures differ markedly from other fintech categories in that significant price movements often occur outside the announcement day itself. Except in the banking sector, abnormal returns are more frequently

observed in pre- or post-event windows, implying possible information leakage or heightened uncertainty prior to disclosure. Moreover, IoT investments are associated with persistently weak or negative cumulative abnormal returns, reflecting investor concerns about high infrastructure costs, data privacy risks, and regulatory uncertainty. These results indicate that, unlike AI or big data, IoT investments are perceived as higher-risk and less immediately value-enhancing within the financial industry.

B. Two-Way ANOVA

Table 5 reports a two-way ANOVA with event-day AR as the dependent variable and industry and fintech type as the independent factors. The results show that industry and fintech each have a significant effect on AR at the 1% level. In other words, AR differs across industries. The industry $\times$ fintech interaction term is not significant.

Because AR differs by industry at the 10% level, we conducted Scheffé post-hoc comparisons to identify which groups differ. Results by industry show that insurance vs. securities differs at the 10% level, and securities vs. banking differs at the 1% level. Results by fintech type indicate that the statistically significant difference across fintech types is primarily driven by the contrast between AI-related and blockchain-related disclosures, with AI eliciting stronger immediate market reactions.

Table 5. Two-Way ANOVA Results, Event-Day AR

Source	Type III SS	df	MS	F	Sig.
Industry	0.609	2	0.304	6.206	0.002
FinTech	0.840	3	0.280	5.708	0.001
Industry $\times$ FinTech	0.148	6	0.025	0.502	0.807

Notes. SS denotes sum of squares; MS denotes mean square; df denotes degrees of freedom.

Table 6 presents a two-way ANOVA with event-day CAR as the dependent variable and industry and fintech type as the independent factors. The results indicate that industry is

significant at the 1% level. The industry $\times$ fintech interaction is also significant at the 1% level, implying that industry-level CAR varies by technology type.

Because CAR differs by industry at the 1% level, we again conducted Scheffé post-hoc comparisons to identify group differences. Results by industry show that insurance vs. securities differs at the 10% level, and securities vs. banking differs at the 1% level. Post-hoc comparisons further reveal persistent differences across fintech technologies, particularly between AI and blockchain as well as between big data and IoT disclosures, indicating that technology-related valuation differences extend beyond the announcement day.

Table 6. Two-Way ANOVA Results, Event-Day CAR

Source	Type III SS	df	MS	F	Sig.
Industry	2.180	2	1.090	11.369	0.000
FinTech	2.289	3	0.763	7.960	0.000
Industry $\times$ FinTech	4.456	6	0.743	7.746	0.000

Notes. SS denotes sum of squares; ME denotes mean square; df denotes degrees of freedom.

Overall, the two-way ANOVA results show that both industry and fintech type significantly affect event-day AR and CAR, and that their interaction effect on CAR is also statistically significant. From a theoretical standpoint, these findings support an extended signaling perspective: fintech disclosures function as multi-dimensional signals whose strength, clarity, and credibility depend jointly on (i) the technology category and (ii) the institutional context of the adopting industry. Industry $\times$ technology interactions are statistically significant.

C. Multivariate Analysis (MANOVA)

To further examine the joint behavior of abnormal returns (AR) and cumulative abnormal returns (CAR), we conduct a multivariate analysis of variance (MANOVA). The full MANOVA test statistics are reported in Appendix B. Results indicate that differences across industries and fintech technologies are

driven primarily by variation in cumulative abnormal returns rather than by short-lived abnormal returns. In particular, the interaction effects observed in the multivariate framework reflect different post-announcement adjustment dynamics for each industry-technology combination, not immediate announcement-day shocks.

These findings suggest that heterogeneity in market responses arises mainly from how investors reassess information over time, rather than from instantaneous reactions to disclosure events. Overall, the MANOVA results provide a complementary but substantively meaningful perspective on the heterogeneous signaling effects documented in the univariate analyses.

D. Discussion

This section synthesizes the empirical findings by interpreting how capital markets respond to different fintech technologies across industries. Noting that fintech is not a homogeneous category, the discussion focuses on technology-specific signaling patterns for artificial intelligence (AI), big data, blockchain, and the Internet of Things (IoT) and explains how differences in maturity, implementation risk, and alignment with industry value chains shape the heterogeneous abnormal-return dynamics across technologies. These results are interpreted in light of signaling theory and industry-specific institutional contexts.

Among the fintech technologies examined, AI-related disclosures show the most consistently positive and significant AR and CAR patterns across industries, particularly in securities and banking. Investors likely regard AI as a relatively mature and immediately applicable technology for credit scoring, portfolio management, robo-advisory, underwriting, and fraud detection. Because AI adoption is directly linked to efficiency gains and data-driven decision-making, its announcement carries strong signaling power about managerial competence, cost-efficiency improvements, and future cash-flow growth. These findings are consistent with signaling theory: AI acts as a high-credibility innovation signal.

Big-data disclosures also deliver positive initial reactions, though the magnitude and persistence of CAR are somewhat smaller and more volatile than for AI. Big data is viewed as a foundational capability that enhances customer segmentation, early risk detection, and regulatory reporting; however, privacy concerns, data-governance risks, and compliance costs may dampen investor enthusiasm. The oscillating pattern of positive pre-event and event-day AR followed by negative post-event AR (particularly for banking) suggests that markets may incorporate big-data expectations gradually and then reassess them once more concrete cost and regulatory implications become salient.

Blockchain-related announcements produce negative or insignificant AR in the pre-event and event-day windows for many sub-samples, followed by a notable positive rebound on day +2, especially in securities and insurance. This “V-shaped” pattern is consistent with investors’ mixed views: blockchain is recognized as an important infrastructure technology for clearing, settlement, and smart contracts, but its regulatory environment remains uncertain, and integration with existing legacy systems can be complex and costly. Accordingly, some investors may initially discount blockchain-related announcements, only to partially revise their expectations upward after additional information or investor discussion clarifies the specific use case.

IoT disclosures are characterized by negative AR in the pre-event or event-day windows in multiple sectors, and CAR remains negative or weakly negative across the event window. This is particularly pronounced for IoT-related announcements in insurance and securities. Several factors may explain this pattern. First, IoT projects often require substantial hardware deployment, sensor maintenance, and integration with physical infrastructure, which raises cost and operational-risk concerns. Second, IoT heavily relies on continuous collection of sensitive personal data (e.g., telematics, health sensors), intensifying privacy, cybersecurity, and liability risks. Third, in the Korean financial context, IoT-based business models (such as usage-based insurance) are still

relatively nascent compared to AI and big-data analytics. Taken together, these considerations support the view that investors rationally perceive IoT as a higher-risk, more uncertain fintech investment, resulting in negative or muted price responses—rather than contradicting the general efficiency potential of fintech technologies.

The insurance sector shows significant positive event-day and short-horizon CAR for the pooled fintech sample, indicating that, on average, technology investments are seen as valuable. However, sub-sample results by technology exhibit oscillating patterns: AI and big data often produce short-run positive reactions that quickly correct, while blockchain and IoT are associated with higher volatility and mixed signs. This reflects insurance-specific institutional features: strong regulatory constraints, heavy reliance on legacy systems, and complex underwriting and claims processes. Investors may perceive successful technology implementation in insurance as especially challenging, leading to greater uncertainty and post-announcement volatility.

The securities industry demonstrates the strongest and most sensitive reactions to fintech disclosures. AI and big-data announcements, in particular, elicit pronounced positive AR prior to and on the event day, followed by sharp corrections as shown in Table 4-4. This pattern is consistent with the nature of securities firms, whose core value creation depends on trading analytics, market-making, and algorithmic decision-making. When such firms announce AI- or big-data-based initiatives, the market interprets these disclosures as highly relevant to their core business, producing large and rapid price adjustments. The corrections observed on day +2 likely reflect profit-taking and the resolution of initial over-optimism once more detail about the initiative becomes available.

In banking, event-day AR is strongly positive for the pooled fintech sample and for AI and big-data sub-samples, but negative AR on day +1 and correction on day +2 indicate that announcements are initially welcomed and then re-evaluated. Bank investors appear to interpret AI-based credit scoring, fraud detection, and

RegTech solutions as strategically important for risk management and regulatory compliance, but they may also recognize implementation costs, model-risk issues, and supervisory scrutiny. Blockchain and IoT disclosures, by contrast, show more muted and statistically insignificant reactions in banking, suggesting that investors consider these technologies less central to banks' current value drivers or more constrained by regulatory factors.

The evidence from our analysis aligns closely with the value-chain-based identification of each industry's core fintech technologies. Technologies that are closely aligned with the sector's value chain (e.g., AI and big data in securities and banking) generate strong, positive signals, while those with higher implementation and regulatory risk (e.g., IoT in insurance) generate weaker or negative signals. Specifically, insurers are most closely associated with IoT and big data; securities firms with AI and big data; and banks with AI as the pivotal technology across value-chain stages. Securities sector shows the strongest positive reactions → highly aligned with AI/BD-driven value chains. Banking shows moderate positive reactions. Insurance shows weak or negative reactions—consistent with heavier regulatory constraints, longer product cycles, and opaque cost structures. These findings support H3.

E. Robustness Checks

This section presents robustness checks conducted to verify that the main empirical findings reported in the previous sections are not driven by model specification, sample composition, or event clustering. All economic interpretations of the results are provided in the main Results section.

We first explored alternative estimation approaches to check that our results are not driven by a particular choice of return model. First, we implemented a portfolio-time-series approach and cluster-robust standard errors (by date, industry, and technology); results show that key findings—positive AI effects, negative IoT effects, and significant industry × technology interactions—remain statistically significant. Second, we conducted block bootstrap resampling with 1,000 replications, which again

confirmed that the main patterns persist under alternative inference methods. Third, we re-estimated AR and CAR using alternative expected-return models (market-adjusted, CAPM, and Fama–French three-factor models). The direction and significance of AI, IoT, and interaction effects were robust to these specifications, indicating that our results are not driven by a particular choice of return model.

We also recognized that the uneven distribution of events across technologies (AI accounts for 58.8% of announcements whereas blockchain and IoT each account for only 10.2%) inevitably reduces statistical power for detecting effects in the smaller technology groups and may partially contribute to statistically insignificant results in certain industry–technology subsamples. To address this limitation, we assessed the sensitivity of all key findings to alternative sampling strategies. Specifically, we constructed balanced subsamples using (i) downsampling of the AI group, (ii) oversampled datasets for blockchain and IoT, and (iii) SMOTE-like synthetic oversampling to approximate equal event counts across technologies. The balanced-sample tests (46 events per technology group) replicate the core patterns observed in the full sample, indicating that AI's strong positive effects and IoT's systematically negative effects do not arise simply because the AI group dominates the dataset numerically. Likewise, the SMOTE-like synthetic oversampling and block-bootstrapped t-statistics reveal no systematic inflation or deflation of effect sizes. Across all procedures, the direction and significance of the core results—positive AI effects, negative IoT effects, and strong industry × technology interactions—remain qualitatively unchanged. This indicates that the main conclusions are not artifacts of sample-size imbalance.

Finally, we explored the robustness of results to excluding events or event periods. We excluded events occurring during the COVID-19 period and found no evidence of systemic break patterns during that time. We removed event clusters (dates with many simultaneous disclosures), events occurring within ±3 days of quarterly earnings announcements, and events

coinciding with major industry conferences and found the main AR/CAR patterns unchanged.

V. Conclusion

This study investigates how media disclosures of fintech investments in Korea's financial industry affect stock-price reactions, focusing on heterogeneity across industries (insurance, securities, banking) and technology types (AI, blockchain, big data, IoT). Using an event-study framework combined with two-way ANOVA and extensive robustness checks, we show that fintech investment disclosures generate statistically significant and economically meaningful market reactions that are far from uniform.

The key findings can be summarized as follows. First, at the aggregate level, fintech disclosures are associated with significantly positive abnormal returns on the event day, indicating that markets generally interpret such announcements as favorable innovation signals. Second, AI and big-data disclosures produce the strongest and most consistently positive price reactions, especially in securities and banking, whereas IoT disclosures often yield negative reactions, reflecting concerns about implementation cost, privacy, and cybersecurity. Blockchain announcements exhibit mixed patterns, with initial negative or muted responses followed by partial rebounds.

Third, industry classification plays a central role: securities firms show the highest sensitivity to fintech disclosures, banks exhibit moderately positive and somewhat conservative patterns, and insurers display more volatile and oscillating responses, consistent with sector-specific institutional constraints. Fourth, significant industry $\times$ technology interaction effects demonstrate that investors evaluate fintech initiatives through a joint lens of technological characteristics and institutional context, rather than treating "fintech" as a homogeneous innovation category.

Fourth, the number of events is unevenly distributed across technologies, with relatively few observations for blockchain and IoT. While

we conduct oversampling, downsampling, and bootstrapped robustness checks to mitigate this issue, the corresponding results should still be interpreted with some caution.

These findings make several contributions to the literature. They extend signaling theory by showing that fintech disclosures are multidimensional signals whose credibility and impact depend on technology–industry fit; enrich institutional theory by documenting how sectoral constraints and readiness shape market reactions to innovation; and provide one of the most detailed empirical mappings of fintech-related stock-price reactions in an Asian market. Practically, the results offer guidance for managers on how to structure and time fintech disclosures, for investors on how to interpret technology-specific announcements, and for regulators on where to focus efforts to reduce uncertainty and foster efficient market responses.

Future research could build on this work by examining longer-horizon performance effects of fintech adoption, incorporating cross-country comparisons, and exploring micro-level case studies that link specific implementation choices to subsequent financial outcomes. As fintech technologies continue to evolve—especially with the advent of generative AI, advanced RegTech & SupTech, and new forms of digital identity—the interaction between technological innovation, institutional context, and capital markets is likely to remain a rich area for further inquiry.

References

- Akerlof, G. A. (1970). The market for "lemons": Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3), 488–500.
- Alt, R., et al. (2023). Implications of AI-based robo-advisory for private banking investment advisory.
- Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2016). Investor sentiment, beta, and the cost of equity capital. *Journal of Financial and Quantitative Analysis*, 51(4), 1199–1226.

- Arner, D. W., Barberis, J. N., & Buckley, R. P. (2015). The evolution of fintech: A new post-crisis paradigm? SSRN Electronic Journal. <https://doi.org/10.2139/ssrn.2676553>
- Atzori, L., Iera, A., & Morabito, G. (2010). The Internet of Things: A survey. *Computer Networks*, 54(15), 2787–2805.
- Bhattacharya, S. (1979). Imperfect information, dividend policy, and “the bird in the hand” fallacy. *Bell Journal of Economics*, 10(1), 259–270.
- Biais, B., Hombert, J., & Weill, P.-O. (2010). Equilibrium fast trading (NBER Working Paper No. 16628). National Bureau of Economic Research.
- Binder, J. (1998). The event study methodology since 1969. *Review of Quantitative Finance and Accounting*, 11(2), 111–137.
- Bose, I., Dong, M., & Chen, X. (2021). Machine learning for customer analytics in banking: Review and research agenda. *Decision Support Systems*, 144, 113512.
- Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics*, 14(1), 3–31.
- Cao, J., Chen, X., & Li, Y. (2020). Disclosure of fintech investment and stock returns: Evidence from public announcements. *Journal of Financial Research*, 43(2), 201–222.
- Catalini, C., & Gans, J. S. (2016). Some simple economics of the blockchain. *Communications of the ACM*, 59(11), 84–93. <https://doi.org/10.1145/2994581>
- Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly*, 36(4), 1165–1188.
- Choi, H.-S., Son, U., & Lee, S.-R. (2011). Share repurchases and discretionary accruals as signals of undervaluation. *Korea Economic Research Institute Journal*, 29(1), 103–131. [In Korean]
- CNBC. (2017). JP Morgan reveals its own blockchain platform to speed up trading.
- Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of Management*, 37(1), 39–67.
- Damodaran, A. (2012). *Investment Valuation: Tools and techniques for determining the value of any asset* (3rd ed.). John Wiley & Sons.
- Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108–116.
- DeAngelo, H., et al. (2006). Dividend policy and the earned/contributed capital mix: A test of the life-cycle theory. *Journal of Financial Economics*, 227–254.
- De Bondt, W. F. M., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, 40(3), 793–805.
- de Jong, F., Kemna, A., & Kloek, T. (1992). A contribution to event study methodology with an application to the Dutch stock market. *Journal of Banking and Finance*, 16(1), 11–36.
- Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2), 383–417.
- Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The adjustment of stock prices to new information. *International Economic Review*, 10(1), 1–21.
- Grullon, G., et al. (2005). Dividend changes do not signal changes in future profitability. *Journal of Finance*, 78, 1659–1682.
- He, P., Sun, Y., Zhang, Y., & Li, T. (2020). COVID-19’s impact on stock prices across different sectors: An event study based on the Chinese stock market. *Emerging Markets Finance and Trade*, 56(10), 2198–2212. <https://doi.org/10.1080/1540496X.2020.1785865>
- Jung, H.-J. (1994). An empirical study on disclosure effects of rights offerings in manufacturing firms. *Yung Research Institute Journal*, 8(2), 13–145. [In Korean]
- Jung, H.-J. (2005). An empirical study on disclosure effects for insurance companies. *Journal of the Korean Risk Management Society*, 16(2), 39–70. [In Korean]
- Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 263–291.
- Kim, H.-R., Hong, S.-H., & Hong, H. (2021). Machine-learning-based prediction of stock movements for KOSDAQ-listed firms using online news indicators. *Journal of Korea Multimedia Society*, 24(3), 445–459. [In Korean]

- Kim, Y.-H., & Jeong, S.-C. (2022). Korean firms' ESG activities and dividend policy. *Korean Finance Association Journal*, 35(2), 107–145. [In Korean]
- Kim, Y.-H., Heo, J.-H., & Song, D.-Y. (2022). Effects of corporate ESG activity and voluntary disclosure on firm value. *Journal of Financial Management (Korea)*, 39(1), 121–144. [In Korean]
- Kou, G., et al. (2021). Artificial intelligence for risk management. *Applied Soft Computing*, 113, 107834.
- Lee, J.-H., & Son, S.-H. (2019). Stock-price effects of fintech firm disclosures: An event study. *Financial Supervisory Research*, 2019(2), 45–70. [In Korean]
- Lim, B.-K., Park, S.-H., & Yoon, P.-S. (2015). Information-signaling effects of insider share acquisitions and insider trading. *Journal of Finance Research*, 28(3), 351–384. [In Korean]
- Mumtaz, M. Z., & Smith, Z. A. (2020). Empirical examination of the role of fintech in monetary policy. *Pacific Economic Review*, 25(5), 620–640.
- Nguyen, T. A. N., & Dang, V. D. (2022). The effect of fintech development on financial stability in an emerging market: The role of market discipline. *Research in Globalization*, 5, 100105.
- Park, K. H., & Byun, J. (2019). Managerial overconfidence, corporate social responsibility activities, and financial constraints. *Sustainability*, 12(1), 61.
- Park, S.-J., & Park, J.-Y. (2017). InsurTech revolution: Current status and challenges. Korea Insurance Research Institute. [In Korean]
- Park, Y.-G. (2008). Signaling effects of share repurchases on seasoned equity offerings. *Journal of Financial Management (Korea)*, 25(1), 50–84. [In Korean]
- Porter, M. E. (1985). Technology and competitive advantage. *Journal of Business Strategy*, 5(3), 60–78.
- Porter, M. E. (2001). Strategy and the internet. *Harvard Business Review*, 79(3), 62–78.
- Van Chung, Y. K. (2020). An exploratory study on adoption of artificial intelligence in the insurance industry. *Journal of International Trade and Insurance*, 12(1), 69–88.
- Yoo, J.-D., & Lee, I.-S. (2018). Forecasting the composite stock index using big data from internet news content. *Journal of the Korean Operations Research and Management Science Society*, 35(4), 1–14. [In Korean]
- Yoon, S.-H. (2015). Effects of pre-disclosure information leakage on stock prices: Evidence from SEO announcements. *Korean Journal of Asset Management*, 3(2), 45–62. [In Korean]
- Yoon, P.-S. (2016). Reconsideration of the disclosure effect of seasoned equity offerings. *Korean Journal of Financial Studies*, 45(2), 379–415. [In Korean]
- Zarifis, A., & Cheng, X. (2022). AI is transforming insurance with five emerging business models. In *Encyclopedia of Data Science and Machine Learning* (pp. 2086–2100).

Received/2025.10.25

Revised/2025.12.10

Accepted/2025.12.16

Appendix A. Common Value-Chain Structures

Value-chain stage	Insurance	Securities	Banking
1. Product & service development	Analyze market risk factors and design coverage structures aligned with customer needs. This process necessarily requires financial-engineering techniques, risk analysis, and profitability simulations. Technological innovation and customer analytics are key drivers of product development; recently, open banking, ESG finance, and MyData-based personalized products have drawn attention.	Analyze market risk factors and design coverage structures aligned with customer needs. This process necessarily requires financial-engineering techniques, risk analysis, and profitability simulations. Technological innovation and customer analytics are key drivers of product development; recently, open banking, ESG finance, and MyData-based personalized products have drawn attention.	Analyze market risk factors and design coverage structures aligned with customer needs. This process necessarily requires financial-engineering techniques, risk analysis, and profitability simulations. Technological innovation and customer analytics are key drivers of product development; recently, open banking, ESG finance, and MyData-based personalized products have drawn attention.
2. Marketing & customer management	Data-driven marketing and CRM systems are actively utilized.	Marketing automation via digital channels and algorithmic investment recommendations are becoming increasingly important.	Providing tailored financial solutions along the customer life cycle is a critical strategy; performance hinges on building sophisticated CRM systems through digital channels.
3. Product sales & contract execution	The duty to explain and the suitability principle are legally and ethically material. fintech-based platforms automate this stage.	As digital transformation advances, automation and streamlining of contract execution are key tasks.	As digital transformation advances, automation and streamlining of contract execution are key tasks.
4. Risk assessment & post-underwriting review	Post-issuance reviews help prevent intentional risk exposure and moral hazard; use of AI-based underwriting techniques is expanding.	Multiple risk factors (market, credit, and liquidity risk) are reflected; guidance from the FSS and BIS regulations are considered.	Processes include credit screening, credit scoring, anti-money-laundering (AML), and internal control procedures.
5. Service delivery & operations	Operating efficiency depends on both internal process management and on the quality of IT infrastructure and customer communications.	User experience of digital platforms, API connectivity, and fast trade-execution systems are decisive factors for customer satisfaction.	Automation technologies such as RPA (robotic process automation) and AI chatbots are core capabilities at this stage.
6. After-sales management & relationship maintenance	Maintaining ongoing relationships after contract inception affects renewal rates and cross-selling. Churn-prediction analytics and AI-based retention strategies are also used.		To secure customer loyalty and long-term profitability, firms employ periodic financial counseling, portfolio rebalancing, and event-driven marketing, and other approaches.
7. Internal support & management	Governance and compliance frameworks are managed at this stage. Talent acquisition and organizational culture, IT infrastructure, and ESG management are closely tied to long-term competitiveness.		Digital-transformation strategy, ESG management, and organizational-culture innovation are the main tasks at this stage.

Appendix B. Multivariate Analysis of Variance

This appendix presents the results of the multivariate analysis of variance (MANOVA) examining the joint behavior of AR and CAR across industries and fintech technologies. The MANOVA tables include multivariate test statistics (Pillai's trace, Wilks' lambda, Hotelling's trace, and Roy's largest root) and provide formal statistical support for the cross-industry and cross-technology interpretations discussed in the main results section. This appendix reports a two-way MANOVA with event-day AR and event-day CAR as joint dependent variables, and industry and fintech type as factors. The multivariate tests—Pillai's trace, Wilks' lambda, Hotelling's trace, and Roy's largest root—are all significant at the 1% level for industry and for fintech, indicating statistically significant group differences. The industry $\times$ FinTech interaction is likewise significant at the 1% level across all four criteria, implying that the joint outcome $[AR, CAR]$ varies by technology within industry (i.e., industry-level CAR and AR can differ depending on the fintech type adopted).

Effect	Statistic	Value	F	Hyp. df	Error df	Sig.
Industry	Pillai's trace	0.055	6.242	4.000	878.000	0.000
	Wilks' lambda	0.945	6.319 ^b	4.000	876.000	0.000
	Hotelling's trace	0.059	6.395	4.000	874.000	0.000
	Roy's largest root	0.058	12.834 ^c	2.000	439.000	0.000
FinTech	Pillai's trace	0.086	6.548	6.000	878.000	0.000
	Wilks' lambda	0.916	6.539 ^b	6.000	876.000	0.000
	Hotelling's trace	0.090	6.531	6.000	874.000	0.000
	Roy's largest root	0.054	7.963 ^c	3.000	439.000	0.000
Industry $\times$ FinTech	Pillai's trace	0.127	4.955	12.000	878.000	0.000
	Wilks' lambda	0.874	5.092 ^b	12.000	876.000	0.000
	Hotelling's trace	0.144	5.228	12.000	874.000	0.000
	Roy's largest root	0.138	10.081 ^c	6.000	439.000	0.000

Notes. Dependent variables: event-day AR and event-day CAR. Superscripts ^{b,c} follow the software's multivariate test output.