The Differential Market Valuation of Software and Hardware AI Assets in Generative AI Adoption

Siwei Zhang*
School of Economics and Management, Tongji University, Shanghai, China
**Corresponding Author*

Abstract: Generative AI (GenAI) can raise productivity, but adopting it imposes significant costs on firms. Prior research examines how capital markets react to AI adoption announcements, yet no study has investigated whether firms' existing software and hardware AI assets differentially shape those reactions. This gap is worth addressing because the two asset types follow diverging value logics under the emerging Model-as-a-Service paradigm. Using event study methodology and threshold regression on a hand-collected sample of 241 GenAI adoption announcements by Chinese A-share listed firms, we find that the market reacts positively overall (CAAR[0,1]= 1.07%, $p < 0.01$), but the effect is moderated by asset structure. Software assets exhibit a positive but diminishing marginal effect, becoming insignificant beyond 0.24% of total assets. Hardware assets exhibit a neutral marginal effect at low scale that turns significantly negative beyond 0.64% of total assets. These contrasting nonlinear patterns indicate that capital markets differentiate between software and hardware AI assets when pricing GenAI adoption.

Keywords: GenAI Adoption; Event Study; Threshold Regression; IT Asset Structure; Resource-Based View

1. Introduction

Generative Artificial Intelligence such as Large Language Models has extended automation from routine jobs to intellectual activities like writing, programming and data analysis [1,2]. The present Information Technology systems are incapable of converting implicit knowledge into explicit rules. Our model overcomes this problem by acquiring statistical patterns from a large quantity of data and performing cognitive tasks without the necessity of explicit programming [3]. Experimental results indicate an enhancement in productivity, both in the speed and precision of task completion, varying from 15% to 42.5% [4-6]. Nevertheless, the practical use involves significant expenses, for example, charges for API usage and problems related to personal information management, as well as organizational modifications and personnel recruitment [7,8]. Therefore, it is crucial to assess the anticipated benefits of employing GenAI in companies from a financial perspective.

The question is also complicated by the different resource conditions of various firms. During the process of digitalization, enterprises have built up some information related software assets (such as data governance platforms, API interfaces and business integration systems) and hardware assets (including servers, GPU clusters and computing facilities). According to the Resource-Based View (RBV), the information technology resources can serve as supplementary assets which help in the absorption of technology [9]. However, with the emerging "Model as a Service" (MaaS) concept, the computing power is rapidly moving to the cloud [3]. In this changing environment, are the present software and hardware assets real promoters for the adoption of General Artificial Intelligence (GenAI), or might the hardware assets become unutilized resources which are punished by the market?

Existing event studies on artificial intelligence give useful references, but do not solve this problem. In the United States, the cumulative abnormal returns (CARs) of artificial intelligence adoption announcements are from 0.2% to 0.5% [10,11]. In Europe, there is mainly a negative reaction [12]. As for genetic artificial intelligence (GenAI), some early Chinese research indicates a stronger market response over 1% [13,14]. However, these studies consider artificial intelligence investment as a homogeneous entity and do not differentiate between different types of assets. Choi et al.

have proposed a distinction between the quantity and configuration of IT investment, but no study has investigated whether software and hardware assets affect differently the market evaluation of GenAI adoption [15]. The two types of assets follow distinct value-transformation principles in the MaaS system, therefore this distinction has theoretical significance.

We investigate this issue with a hand-picked sample of 241 GenAI adoption announcements from Chinese A-share listed companies, which is suitable for our research: it causes obvious information-based price changes, and the financial disclosures of Chinese companies allow us to clearly distinguish between software and hardware assets. The sample covers from November 2022 (the release of ChatGPT) to mid -2024, including the initial stage of GenAI commercialization in manufacturing, finance, software and retail. We use the event study method to evaluate the short-term market responses and apply Hansen's threshold regression to detect nonlinear effects[16]. Two different trends are found. The software assets show a positive but decreasing impact which becomes insignificant when more than 0.24% of the total assets are involved. On the contrary, the hardware assets are neutral at small scale but turn out to be significantly negative when more than 0.64% of the total assets are used. Up to now, we have not known of any other results indicating that the capital market distinguishes between software and hardware AI assets in valuing GenAI adoption. Not all Information Technology resources have the same effect on the firm value in the MaaS model.

2. Theoretical Development

GenAI adoption announcements convey strategic signals about a firm's commitment to technological transformation [17]. Because the real financial returns from technology adoption take years to materialize [18], investors must assess expected performance improvements from the information available at the time of announcement. Prior research confirms that AI investment drives firm growth through product innovation rather than cost reduction, with effects taking two to three years to fully manifest [19]. Event study methodology captures investors' discounted expectations of future cash flows in announcement-window stock price movements, thereby providing a forward-looking proxy for the expected performance gains from GenAI adoption. The magnitude of this reaction, however, should depend on whether investors perceive the adopting firm as possessing the complementary assets needed to integrate the new technology.

2.1 Software Assets

Software resources such as data governance systems, API interfaces and business integration platforms connect the general-purpose GenAI models with the business situations. At a small scale of software expenditure, these resources decrease the difficulty in adopting technology by setting up the digital framework through which external models can obtain internal information and get useful results. According to the RBV theory, these integration functions are hard for the competitors to imitate since they contain specific knowledge about the business procedures and data organization [9].

The benefit of software assets is not necessarily in a linear form. Heimberg et al. have found that on the OpenAI platform, complementors are divided into an acquisition stage (establishing the basic interfaces necessary to use the platform for particular tasks) and a differentiation stage (supplying exclusive contextual data and refined output pipelines which result in unique and unreplaceable values) [20]. During the acquisition stage, companies invest in data middle-platforms, API connections and business information flow systems which connect the external model capabilities with the internal data silos. These investments yield high additional returns since they solve the basic problem of access: without these systems, the general model outputs cannot be transformed into practical business information. In the differentiation stage, the creation of value relies on the supply of exclusive data, verification of domain-specific outputs and customized model tuning, processes which need profound organizational knowledge instead of common IT facilities. When this access infrastructure is available, further investments in homogeneous software mainly perform the acquisition function and provide little contribution to differentiation. Therefore, investors should consider the marginal value of additional software investment after it reaches a certain level. We predict that the value of software assets exists, but is limited to the extent that access is obtained. We suppose:

H1: The existing software assets show a positive but decreasing impact on the market response to the implementation of GenAI, which becomes negligible after reaching a certain basic level.

2.2 Hardware Assets

The difference in the value of hardware assets is significant. In the MaaS model, the large-scale basic computing power is mainly controlled by the cloud providers and the foundation model developers [3]. The application-oriented enterprises are changing from possessing computing power to managing the cloud-based resources. It is necessary and neutral to make moderate hardware expenditures to ensure the basic network operation and light inference.

When companies use more hardware resources than necessary for their work, three risks arise. Large models require high-performance computers which are frequently updated, leading to a quick decline in the value of the local assets and the risk of being out of date [21]. A lot of assets will consume a great deal of fixed assets capital, thus decreasing the financial flexibility and competitiveness for future free cash flow. Heavy local hardware investment is contrary to the trend of cloud computing: investing in resources that can be efficiently replaced by cloud services indicates capital misallocation rather than strategic accumulation. Dong et al. give convincing proof: the cost of equity (CAR) for the firms using DeepSeek via API (asset-light) is 5.7 percentage points higher than that for the firms adopting local deployment (asset-heavy)[13]. Wade and Hulland point out that the internal information system resources such as infrastructure are easily imitated and only bring short-term benefits [9]. In the Model-as-a-Service (MaaS) model, excessive hardware investment may be worse than temporary; it may even destroy value. This opinion is also consistent with the general Information Technology (IT) productivity paradox. Brynjolfsson believes that IT investment without supportive organizational changes cannot improve productivity [18]. In the field of General Artificial Intelligence (GenAI), hardware investment without appropriate software and organizational capabilities to integrate AI into business processes shows a modern form of this old misalignment. The capital market, which can distinguish between productive and unproductive IT expenditures, should fairly evaluate the over-investment in hardware. We suggest that:

H2: The existing hardware assets have no significant impact at small scales, but show a negative impact when the hardware investment exceeds the necessary operational costs.

3. Data and Methodology

3.1 Sample Construction

We investigate Chinese A-share listed companies, which is an appropriate field for our research problem due to three aspects. Firstly, the A-share market is mainly composed of retail investors with considerable information imbalance, resulting in obvious price changes caused by information. Secondly, China has experienced a fast commercialization of General Artificial Intelligence (GenAI) after the release of ChatGPT, and various enterprises such as those in manufacturing, finance, software and retail have announced the integration of GenAI, providing a wide range of adoption events in different industries and asset structures. Additionally, the Chinese companies have disclosed their financial statements clearly regarding intangible and fixed assets, which helps to distinguish the investments in software and hardware of Artificial Intelligence in our empirical study.

Our data set includes companies which have announced substantial GenAI usage since November 30, 2022 (the release of ChatGPT) until mid-2024. An event is considered as the first public announcement that a company has incorporated GenAI technology into its business operations. By using a machine-matching dictionary containing keywords such as "GenAI", "AIGC", "LLM" and "GPT", we found 6,127 potential news articles from the CSMAR database. After carefully checking each article to delete the non-significant announcements and the ones released by the model suppliers, we kept 1,689 articles. Taking only the earliest article for each company resulted in 343 initial events. Furthermore, we eliminated the observations with incomplete stock transaction records, companies under Special Treatment or Stopped Trading status, and those having other confusing events during the event period (such as earnings announcements, seasoned equity issues and major asset reorganizations), leading to a final sample of 241 events.

3.2 Event Study

We calculate the abnormal returns by means of the market-adjusted model. The event day (t = 0) is defined as the first trading day when the genAI adoption is publicly announced. Non-trading-day announcements are regarded as the next trading day. The main event period is from -2 to 2, which aims at obtaining the whole information diffusion process while reducing the possibility of confusing events in wider periods [22]. The core period [0, 1]reflects the immediate reaction and includes the announcements made after the end of the event day market, which affect the following trading day's price. The estimation period covers from -250 to -31, providing 220 trading days for the stable parameter estimation with a 30-day interval between the event period to prevent contamination. For the purpose of testing the significance, we apply the standardized cross-sectional test [23], its adjusted version which controls for cross-sectional correlation [24], and the sign test [25]. Additionally, we estimate the abnormal returns using the Fama-French three-factor model for the sake of robustness [26].

3.3 Variables and Threshold Regression

The CAR[0,1]is the dependent variable representing the total abnormal return of the company during the key time period. The major independent variables are AISoftLevel (the ratio of the end-of-year balance of intangible assets involving artificial intelligence to the total assets) and AIHardLevel (the ratio of the end-of-year balance of fixed assets associated with artificial intelligence to the total assets), which are derived from the examination of the companies' financial statement appendices. All the asset data refer to the fiscal year prior to the disclosure. The controlling factors include the size of the company (the base-10 logarithm of total assets), the debt level, the return on assets, Tobin's Q, institutional holding and analyst attention, with industry and year taken as fixed effects. An exhaustive description of the variables is shown in Table 1.

Table 1. Variable Definitions

Variable	Name	Definition
Dependent variable		
CAR[0,1]	Cumulative abnormal return	Cumulative abnormal return over the event window [0,1]
Independent variables		
AISoftLevel	AI software asset level	(Year-end balance of AI-related intangible assets) / total assets, measured in the fiscal year prior to the announcement
AIHardLevel	AI hardware asset level	(Year-end balance of AI-related fixed assets) / total assets, measured in the fiscal year prior to the announcement
Control variables		
Size	Firm size	Natural logarithm of total assets
Lev	Leverage	Total liabilities / total assets
ROA	Profitability	Net income / total assets
TobinQ	Tobin's Q	Market value / replacement cost of assets
InsInvestorProp	Institutional ownership	Institutional investor holdings / shares outstanding
Analyst	Analyst coverage	ln(number of analysts or reports covering the firm + 1)
Year FE	Year fixed effects	Dummy variables for each year
Industry FE	Industry fixed effects	Dummy variables for CSRC two-digit industry classifications

To determine nonlinear threshold effects, we use Hansen's threshold regression. The single-threshold model is expressed as:

$$\begin{aligned} CAR_{[0,1],i} = \alpha &+ \beta_1 \cdot ThreshVar_i \cdot I(ThreshVar_i \le \gamma) \\ &+ \beta_2 \cdot ThreshVar_i \cdot I(ThreshVar_i > \gamma) \\ &+ \delta \cdot Controls_i + \varepsilon_i \end{aligned} \quad (1)$$

Where I(·) represents the indicator function and γ is the threshold parameter. For each possible threshold value γ, the model calculates different coefficients for the observations in the low regime (ThreshVar ≤ γ) and the high regime (ThreshVar > γ). The best threshold is the one which makes the total squared residuals smallest. The confidence intervals for the threshold parameter are determined by the likelihood-ratio inversion method proposed by Hansen.

4.Result

4.1 Baseline Market Reaction

Table 2 shows the daily and total average abnormal returns (AARs and CAARs) under different event periods. When t equals 0, the AAR is 0.89%, which is significantly different from zero according to all the tested parametric and non-parametric methods at the 1% significance level. The AAR on t = 1 is 0.18% (not significant) and becomes -0.21% on t = 2. The market responds quickly to the new information without any obvious post-announcement drift or reversal. Before the event, the AARs on t = -2 and t = -1 are 0.36% and 0.51% respectively, both being significant in many cases. This previous change in information is similar to the partial information leakage usually seen in voluntary corporate disclosures, where strategic intentions might be disclosed via supplier relationships or industry networks before the official announcement. The AAR on the event day (0.89%) is much higher than those before the event, indicating that the formal announcement gives rise to additional important information.

Table 2. Event Study Result

	Obs	Abnormal Return	BMP	Adjusted BMP	Rank Test	GRANKT
Panel A:		**AAR**				
t = -2	241	0.36%				-
t = -1	241	0.51%	**	*		-
t = 0	241	0.89%	***	***	***	-
t = 1	241	0.18%				-
t = 2	241	-0.21%				-
Panel B:		**CAAR**				
[-2 -1]	241	0.87	**	*	-	*
[0, 1]	241	1.07%	***	***	-	***
[-2, 2]	241	1.73	***	**	-	**

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The CAAR in the core window [0,1]is 1.07% ($p < 0.01$), while the CAAR over [-2,-1]is 0.87% ($p < 0.05$ under certain conditions). The CAAR for the whole event window [-2,2]is 1.73% ($p < 0.01$). This indicates a general positive market reaction which confirms the benefit of using GenAI by the applying companies. During two trading days, the reaction is higher than the usual values of AI adoption events in the U.S. (usually 0.2-0.5%) [10,11]; and more noticeable than the slight or negative responses to European AI announcements [12]. However, it is smaller than the 5-10% effects caused by the release of foundation models [13,14]. Such a moderate response is suitable for the situation where the application-using enterprises are the users of the technology rather than its developers, since their adoption influences the value but does not bring about a significant difference in comparison with the developers.

4.2 Threshold Analysis

Table 3 presents the threshold regression results. For software assets (Panel A), the optimal threshold is AISoftLevel = 0.24%. Below this threshold, the coefficient is 19.10 ($p < 0.05$); above it, the coefficient drops to -0.02 and is not statistically significant. The economic magnitude is large: for firms in the low-software regime, a one-percentage-point increase in software assets relative to total assets is associated with roughly 19.10 percentage points higher CAR[0,1]. This reflects the high marginal value of initial software investments that establish digital infrastructure (data middle-platforms, API connections, and business information flow systems) through which external GenAI models can reach internal data and produce actionable outputs. The sample splits into 99 low-software-investment and 124 high-software-investment observations; both regimes contain adequate observations for reliable inference. The likelihood-ratio function (Figure 1) shows a pronounced valley at the threshold with a narrow confidence interval, confirming the threshold is precisely identified. The sharp contrast between the coefficients below and above the threshold (from a large, significant positive effect to one that is economically and statistically negligible) matches the predicted diminishing-returns pattern. H1 is supported.

Table 3. Threshold Regression Result

Panel A: Software assets (AISoftLevel)		
	Below thresh	Above threshold (***$X > \gamma$***)
Threshold	γ=0.0024	
AISoftLevel	19.1005 **	-0.0188
	(7.6157)	(0.1786)
Control variables	Yes	Yes
Fixed effects	Yes	Yes

Obs	99	124
Panel B: Hardware assets (AIHardLevel)		
	Below thresh **($X \le \gamma$)**	Above threshold **($X > \gamma$)**
Threshold	γ=0.0064	
AIHardLevel	-1.6473	-2.5320 *
	(1.8433)	(1.4297)
Control variables	Yes	Yes
Fixed effects	Yes	Yes
Obs	188	35

Note: * p < 0.10, ** p < 0.05, *** p < 0.01.

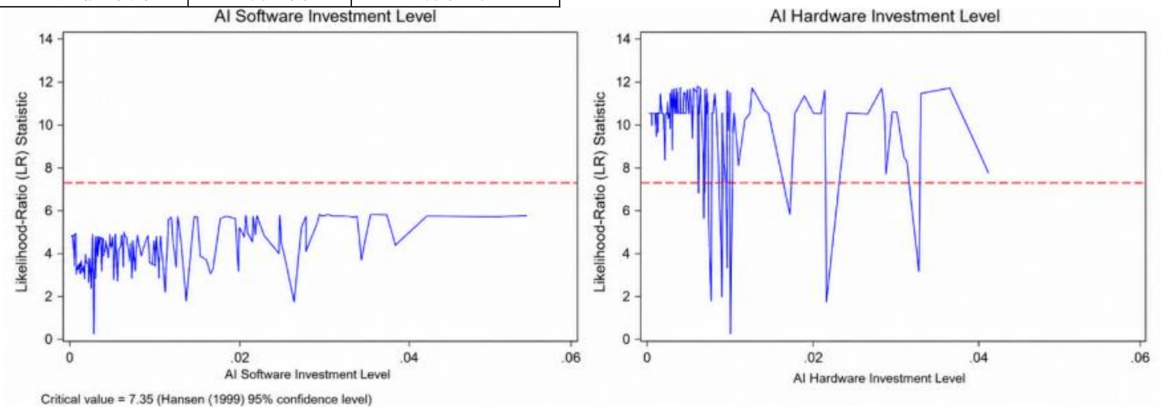

Figure 1. Likelihood-ratio Function

For hardware assets (Panel B), the optimal threshold is AIHardLevel = 0.64%. Below the threshold, the coefficient is -1.65 (not significant); above it, the coefficient drops to -2.53 (p < 0.10). The sample splits into 188 low-hardware-investment and 35 high-hardware-investment observations. The negative coefficient in the high regime, together with the statistically flat relationship in the low regime, supports the predicted neutral-then-negative pattern. For a firm in the high-hardware regime, a one-percentage-point increase in hardware assets relative to total assets is associated with roughly 2.53 percentage points lower CAR[0,1], enough to roughly offset the entire positive baseline reaction (1.07%). This reversal is notable: hardware overinvestment does not just dilute the positive signal of GenAI adoption; it can fully cancel it out. The small high-regime sample (35 observations) may contribute to the marginal significance level and calls for some caution. Still, several factors bolster confidence in the finding. The threshold location is precisely identified (the LR function valley is deep and concentrated, with a narrow confidence interval). The result holds across alternative event windows ([0,0], [-1,1], [-2,2]). And it converges with independent evidence from Dong et al. and Yang on the advantage of asset-light deployment models. The low-hardware-regime coefficient not being significantly different from zero is itself informative: at moderate levels, hardware investment is neither rewarded nor punished, consistent with its role as necessary but non-strategic infrastructure. H2 is supported.

4.3 Robustness

We run two sets of robustness checks. First, we re-estimate abnormal returns with the Fama-French three-factor model [26]and repeat all threshold regressions. The CAAR[0,1]under the three-factor model is 1.06% (p < 0.01), and the threshold patterns for both software and hardware assets remain unchanged in direction and significance. For total AI investment (treated as a benchmark), the three-factor-based threshold regression also identifies a significant structural break (coefficient = 1.37, p < 0.05 below the threshold vs. 0.10, n.s. above), consistent with the aggregate diminishing-returns pattern that the separate software and hardware analyses help disentangle. Second, we replace the dependent variable with CARs computed over alternative windows ([0,0], [-1,1], and [-2,2]). The software diminishing-returns effect and the hardware negative-returns effect remain stable across all windows, with the high-hardware-regime coefficient consistently negative and significant. Detailed results are available on request.

5. Discussion

The event study indicates that the market responds positively to the announcements of GenAI adoption (CAAR[0,1]= 1.07%), and the threshold regressions indicate that this response is influenced by the existing artificial intelligence asset structure of the adopting firm. The software assets have a positive effect but with decreasing returns, losing its significance when more than 0.24% of the total assets are software. On the other hand, the hardware assets are neutral at small amounts but become significantly negative when more than 0.64% of the total assets are hardware. These different non-linear patterns are the main results of our study.

Software assets usually show a decrease in return rather than a linear one. The main reason may be the change in the constraint which the software assets solve. When the investment is small, the main restriction is the access to technology: without basic data middle-platforms and API connections, external GenAI models cannot obtain the internal data, and the general model outputs cannot be transformed into business insights. The initial investment in software can eliminate this access barrier, thus explaining the significant marginal effect below the threshold. However, when the access infrastructure has been set up, the main constraint changes to the organizational integration: the capability of incorporating AI outputs into decision-making procedures, work-flows and products. To solve this new problem, extensive professional knowledge, managerial efforts and process re-design are required instead of further homogeneous software investment. From the market perspective, it seems that it appreciates software assets which can provide convenient conditions, but does not reward those which only increase the unnecessary capacity.

For hardware assets, the neutral-then-negative pattern shows a special calculation. It is necessary to invest in moderate hardware: companies require servers and computing resources for operation. The market does not give greater rewards for this than for office furniture. However, when the hardware investment exceeds the 0.64% level, it indicates something beyond the basic needs. According to the MaaS principle, the computing power is mainly provided by the cloud suppliers. A company which keeps a large amount of local hardware investment is against the trend of the industry. The market seems to consider this as an unreasonable allocation of capital (investing in fixed assets which can be supplied more flexibly by cloud services) and prices it correspondingly. The fact that the high hardware coefficient (-2.53) nearly balances the whole positive base reaction (1.07%) implies that the market does not only discount the hardware adopting enterprises, but also regards their strategy of using GenAI as inconsistent.

The IT business value literature usually treats IT investment as a whole [27,28], but recently Choi et al. have distinguished the investment quantity and configuration [15]. Our study finds an aspect which has been ignored by the previous models: the kind of IT resources affects the expected returns after introducing new technologies. If software and hardware are considered as one IT factor, their distinct effects on market value may be overlooked. The Resource-Based View (RBV) literature has traditionally classified IT infrastructure as an easily imitated internal resource with only short-term advantages [9]. Our investigation on hardware also supports this view: in the Model-as-a-Service (MaaS) system, if the computing power is transferred to the upstream, the local hardware assets of the downstream enterprises may lose their advantage or cause harm; it may reduce the value due to the improper allocation of resources. Therefore, the strategic importance of an IT resource is not only determined by its VRIN features, but is also related to the position of the enterprise in the changing industrial structure. Our findings are significant for the absorptive capacity theory [29]. The software assets possess the knowledge about data flow and business logic which is closely related to the integration of General Artificial Intelligence (GenAI) results; while the hardware assets supply basic computational power without any specific firm's knowledge. This difference in knowledge embedding and general prior investments may be applicable in other fields besides artificial intelligence.

These results have some practical significance. The downstream companies using GenAI should concentrate their resources on the proprietary data integration and business-oriented software system development, which can establish stable competitive advantages through the specific complementarity. The investment in general-purpose computing equipment should be adjusted according to the actual needs. Exceeding this requirement may be considered as a strategic inconsistency by the market. For the investors, an organized evaluation of the software and hardware asset configuration of the firm gives a more reliable indicator of the potential for GenAI adoption than the total IT investment intensity.

This research has some restrictions. The event study method only reflects short-term market anticipations; it is uncertain whether the recorded threshold effects will affect the longterm operational efficiency. Our asset evaluation depends on the financial reports and cannot consider the detailed aspects like the advanced features of software systems or the age of the equipment. The sample includes only Chinese A -share companies during the initial period of GenAI commercialization. The predominance of retail investors in the A-share market may intensify the price changes caused by information comparison with those in institutions-controlled markets, and the adoption behaviours may vary from the later stages of technology dissemination.

6. Conclusion

This study intends to solve one issue: what is the expected value of GenAI usage assessed by capital markets, and do the current AI resources of the companies influence these assessments in different manners? The outcome is that the markets usually show a positive response, but the reaction differs according to the resource structure. The software resources are advantageous, but only to a certain degree. Conversely, the hardware resources become disadvantageous when their quantity is greater than a small amount.

The main purpose of this research is to demonstrate that the profits of software and hardware AI resources lie on different curves when considering the application of General Artificial Intelligence. Previous studies do not focus on this distinction, and our results indicate that there is more than a small difference; the two kinds of resources have opposite influences beyond their respective limits. Another contribution is to expand the Resource-Based View (RBV) to incorporate the ecological position in the industrial structure. If an industry focuses on the upstream of a resource (for example, computing power in Model-as-a-Service, MaaS), the ownership of this resource may transform from an asset to a liability. This phenomenon cannot be explained by the conventional VRIN framework.

Two possible subjects for further research arise from the limitations of this study. Firstly, investigations with a longer time span should investigate whether the threshold patterns observed in market expectations affect the actual performance of firms during the two-to-three year period when the benefits of AI usually become effective. Secondly, a comparative study among markets with different investor structures and technological environments is necessary to determine whether these patterns hold true in other than the China's A-share market and the initial stage of GenAI commercialization.

References

[1] Autor DH, Levy F, Murnane RJ. The skill content of recent technological change: an empirical exploration. Quarterly Journal of Economics. 2003;118(4):1279–1333.

[2] Eloundou T, Manning S, Mishkin P, et al. GPTs are GPTs: Labor market impact potential of LLMs. Science. 2024;384(6702):1306–1308.

[3] Wessel M, Adam M, Benlian A, et al. Generative AI and its Transformative Value for Digital Platforms. Journal of Management Information Systems. 2025;42(2):346–369.

[4] Brynjolfsson E, Li D, Raymond L. Generative AI at Work. The Quarterly Journal of Economics. 2025;140(2):889–942.

[5] Dell'Acqua F, McFowland III E, Mollick ER, et al. Navigating the jagged technological frontier: field experimental evidence of the effects of AI on knowledge worker productivity and quality. Organization Science. 2026;37(2):online.

[6] Noy S, Zhang W. Experimental evidence on the productivity effects of generative artificial intelligence. Science. 2023;381(6654):187–192.

[7] Mikalef P, Gupta M. Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management. 2021;58(3):103434.

[8] Sharma AJ, Rathore B, Biswas B, et al. Generative AI implementation in enterprises: lessons from a case study of enhanced IT service management. Information Systems Journal. 2026;1–30.

[9] Wade M, Hulland J. Review: The Resource-Based View and Information Systems Research: Review, Extension, and Suggestions For Future Research. MIS Quarterly. 2004;28(1):107–142.

[10] Fotheringham D, Wiles MA. The effect of implementing chatbot customer service on stock returns: an event study analysis. J of the Acad Mark Sci. 2023;51(4):802–822.

[11] Huang CK, Lee YT. Market Valuation of Artificial Intelligence Implementation

Announcements. SIGMIS Database. 2023;54(2):9–28.

[12]Keil S, Martin P, Schiereck D. Do Investors Trust in AI Investments of European Companies? Proceedings of the 59th Hawaii International Conference on System Sciences. 2026. p. 5472–5481.

[13]Dong L, Liu J, Yang J, et al. The deployment of general large language models and corporate value: Evidence from the stock market. Finance Research Letters. 2025;86:108625.

[14]Wu Q, Zhuang Q, Liu Y, et al. Technology shock of ChatGPT, social attention and firm value: Evidence from China. Technology in Society. 2024;79:102756.

[15]Choi I, Pinsonneault A, Han K. IT investment differentiation, strategic distinctiveness, and firm performance. The Journal of Strategic Information Systems. 2026;35(1):101925.

[16]Hansen BE. Threshold effects in non-dynamic panels: Estimation, testing, and inference. Journal of Econometrics. 1999;93(2):345–368.

[17]Spence M. Job Market Signaling. The Quarterly Journal of Economics. 1973;87(3):355–374.

[18]Brynjolfsson E. The productivity paradox of information technology. Communications of the ACM. 1993;36(12):66–77.

[19]Babina T, Fedyk A, He A, et al. Artificial intelligence, firm growth, and product innovation. Journal of Financial Economics. 2024;151:103745.

[20]Heimburg V, Schreieck M, Wiesche M. Complementor Value Co-Creation in Generative AI Platform Ecosystems. Journal of Management Information Systems. 2025;42(2):491–528.

[21]Yang X. AI competition and firm value: Evidence from DeepSeek's disruption. Finance Research Letters. 2025;80:107447.

[22]Konchitchki Y, O'Leary DE. Event study methodologies in information systems research. International Journal of Accounting Information Systems. 2011;12(2):99–115.

[23]Boehmer E, Musumeci J, Poulsen AB. Event-study methodology under conditions of event-induced variance. Journal of Financial Economics. 1991;30(2):253–272.

[24]Kolari JW, Pynnönen S. Event Study Testing with Cross-sectional Correlation of Abnormal Returns. Rev Financ Stud. 2010;23(11):3996–4025.

[25]Corrado CJ, Zivney TL. The Specification and Power of the Sign Test in Event Study Hypothesis Tests Using Daily Stock Returns. Journal of Financial and Quantitative Analysis. 1992;27(3):465–478.

[26]Fama EF, French KR. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics. 1993;33(1):3–56.

[27]Brynjolfsson E, Hitt L. Paradox Lost? Firm-Level Evidence on the Returns to Information Systems Spending. Management Science. 1996;42(4):541–558.

[28]Dewan S, Min C. The Substitution of Information Technology for Other Factors of Production: A Firm Level Analysis. Management Science. 1997;43(12):1660–1675.

[29]Cohen WM, Levinthal DA. Absorptive Capacity: A New Perspective on Learning and Innovation. Administrative Science Quarterly. 1990;35(1):128–152.

