The Option Value of Waiting: Market Valuation of AI Investments Under Uncertainty

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Abstract

This study examines how capital markets value artificial intelligence investments through economic theory lenses. Using a novel firm-level AI exposure index derived from 2,083,371 job postings across Chinese firms (2019-2023), we document a significant negative relationship between AI exposure and market valuation, consistent with real options theory's 'option value of waiting'. However, industry analysis reveals positive valuation effects for financial firms but amplified negative impacts for high-technology enterprises, aligning with rational expectations theory. This highlights a concerning misalignment between strategic technology investments and market rewards requires urgent attention. Our industry analysis reveals that financial firms experience positive valuation effects while high-technology enterprises face amplified negative valuations. Our findings integrate investment under uncertainty and rational expectations theories, contributing to our understanding of technology valuation mechanisms in emerging markets.

Key Words: Firm Value; Real Options Theory; Rational Expectations; Investment Under Uncertainty; Technology Adoption; Chinese Market

1. Introduction

Despite substantial investor interest in AI-driven opportunities, quantifying the market valuation implications of AI adoption remains challenging, particularly in emerging economies with unique institutional dynamics (Babina et al., 2024). China's aggressive AI policy initiatives create an ideal context to examine how markets value technological investments under uncertainty. The identification of market inefficiencies in valuing AI investments is increasingly urgent as delayed recognition can lead to suboptimal resource allocation and competitive disadvantages.

While classic investment theory (Dixit and Pindyck, 1994) highlighted the rational basis for investment hesitancy under uncertainty, contemporary research by Bloom et al.(2007) ,Smit and Trigeorgis (2012) has demonstrated how these dynamics specifically impact technological investments. Recent studies by Furman,

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Seamans (2019) and Kelly et al.(2021) show that market signals penalizing forward-looking investments can trigger vicious cycles where firms delay critical technology adoption.

We contribute to the economics literature by: (1) developing a novel AI exposure metric from job postings; (2) applying complementary economic theories—investment under uncertainty and rational expectations—building on both foundational (Muth, 1961) and contemporary models (Evans and Honkapohja, 2001); and (3) revealing industry-contingent valuation effects that challenge conventional technology adoption economics (Hall and Khan, 2003).

2. Theoretical Framework and Hypotheses

2.1. Investment Under Uncertainty and Option Value

The theory of investment under uncertainty (Dixit and Pindyck, 1994) establishes that when investments entail irreversible costs, outcome uncertainty, and timing flexibility, there exists a positive option value for delaying commitment. This framework has been extended by Bloom et al.(2007), who demonstrated how uncertainty shocks amplify investment hesitancy, and further refined by Smit and Trigeorgis (2012) for strategic technology investments.

AI investments represent a quintessential case for real options theory, entailing significant irreversible expenses while facing uncertain returns (Brynjolfsson et al., 2019). Furman and Seamans (2019) extended this framework to AI-specific contexts, noting that high fixed costs create significant option value in adoption timing. This framework predicts that markets will assign a positive value to the waiting option, thereby potentially penalizing firms that exercise their options "prematurely." Therefore:

H1: Based on investment under uncertainty theory, AI exposure will be negatively associated with firm market valuation in the short term.

2.2. Rational Expectations and Industry-Specific Valuations

Rational expectations theory (Muth, 1961) posits that economic agents form forecasts using all available information. This theory has been enhanced by Evans and Honkapohja (2001), who introduced adaptive learning mechanisms, and by Sargent (2008), who incorporated bounded rationality into expectation models. Malerba and McKelvey (2020) have demonstrated how investors form heterogeneous expectations about emerging technologies based on industry-specific complementary assets.

Babina et al.(2024) empirically confirmed that AI investments yield differential returns across sectors based on data intensity and complementary capabilities. Raj and Seamans(2019) found that financial firms possess significant data advantages and clear AI use cases, while Agrawal et al.(2019) demonstrated that high-technology enterprises face talent competition and implementation complexity. Therefore:

H2a: The relationship between AI exposure and firm value will be positively moderated for financial firms.

H2b: The relationship between AI exposure and firm value will be negatively moderated for high-technology enterprises.

3. Data and Methods

3.1. Sample and Measure Construction

Our dataset comprises 2,083,371 job postings collected from China's major online recruitment platforms spanning 2019-2023, covering 5,152 Chinese firms. After standardizing job titles using the O*NET classification system, our final sample included 18,728 postings from 4,932 firms with complete financial data from WIND and CSMAR databases.

Our key independent variable, AI Exposure (AIE), is constructed in three steps following Felten et al.(2018). First, we calculate occupation-level AI exposure (AIOE) by mapping O*NET ability requirements to AI suitability using the formula:

$$AIOE_j = \sum_{k-1}^{K} w_{jk} \times AI_{Suitability_k} \tag{1}$$

where w_{jk} represents the importance weight of ability $k$in occupation j. Second, we compute each firm's occupational composition using job posting shares. Finally, we aggregate to firm level with

$$AIE_{it} = \sum_{j=1}^{J} \omega_{ijt} \times AIOE_j \tag{2}$$

where ω_{ijt} represents the proportion of job postings for occupation j in firm i during year t. The dependent variable is the natural logarithm of year-end market capitalization, with controls including Firm Age, ROA, Size, Cash Flow, and Leverage. Table 1 provides detailed definitions of all variables.

Table 1: Variable Definitions

Variables	Definition
Dependent Variable	
MV	Firm value, measured as the natural logarithm of firm market capitalization at fiscal year-end (in millions of RMB).
Independent Variable	
AIE	AI Exposure, constructed as described above, winsorized at the 1st and 99th percentiles and standardized.
Control Variables	
FirmAge	Number of years since firm incorporation
ROA	Return on assets, calculated as net income divided by total assets
Size	Natural logarithm of total assets (in millions of RMB)
Cflow	Cashflow is measured in billion RMB to facilitate interpretation.
Leverage	Total liabilities divided by total assets
Moderating Variables	
Finance	Dummy variable: 1 if the firm belongs to the financial industry, 0 otherwise (based on industry classification from WIND/CSMAR).
HTSE	Dummy variable: 1 if the firm is classified as a high-technology service enterprise, 0 otherwise (based on industry classification from WIND/CSMAR).

Table 2 Descriptive statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
MV	18,484	23.01	1.38	19.33	31.40
AIE	18,728	0.00	1.00	-2.83	2.40

FirmAge	17,960	10.64	8.66	0.00	33.00
ROA	18,727	0.02	0.35	-30.69	7.45
Size	18,504	22.37	1.56	16.65	31.31
Cashflow	18,323	-1.76	18.0	-4280	5120
Lev	15,069	1.39	3.86	-20.20	270.99

Table 2 summarizes the descriptive statistics for our final sample of 18,728 job postings. The average firm has a firm value (MV) of 23.01 in logarithmic terms, with considerable variation (Std. Dev. = 1.38). AI Exposure (AIE) is standardized with a mean of 0 and ranges from -2.83 to 2.40, reflecting diverse levels of AI adoption across firms.

3.2. Empirical Strategy

We employ panel regression with firm and year fixed effects:

$$MV_{it} = \beta_0 + \beta_1 AIE_{it-1} + \beta_2 Controls_{it-1} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{1}$$

For industry-specific effects, we include interaction terms:

$$MV_{it} = \beta_0 + \beta_1 AIE_{it-1} + \beta_2 MOD_{it} + \beta_3 (AIE_{it-1} \times MOD_{it}) + \beta_4 Controls_{it-1} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{2}$$

where MOD_{it} represents the industry moderator (Finance or HTSE). This approach follows established methods in technology adoption literature (Acemoglu and Restrepo, 2020)

4. Empirical Results

4.1. Baseline Analysis

In Columns 1 of table 3, our results reveal a negative and significant association between lagged AI exposure and firm value (β=-0.108, p<0.01), supporting H1. This aligns with real options theory, where markets impose a "waiting premium" on firms that aggressively pursue AI investments, consistent with the productivity paradox identified by Brynjolfsson and Hitt (2000).

4.2. Industry-Specific Effects

Columns 2 and 3 of Table 3 explore moderating effects of industry characteristics. For financial firms, the interaction term (AIE×Finance) is positive and significant (β=0.556, p<0.01), yielding a net positive effect (0.448), supporting H2a. For high-technology service enterprises, the interaction (AIE×HTSE) is negative and significant (β=-0.0499, p<0.01), supporting H2b. These findings validate rational expectations theory and align with research on industry-specific technology adoption patterns (Mishra et al., 2022).

Table 3 Regression result for baseline model and moderating effect

	(1)	(2)	(3)
VARIABLES	Baseline Model	Finance	HTSE
AIE	-0.108***	-0.108***	-0.0990***
	(0.0104)	(0.0104)	(0.0105)

FirmAge	-0.00918***	-0.00918***	-0.00922***
	(0.00104)	(0.00104)	(0.00104)
ROA	1.196	1.196	1.200
	(0.784)	(0.785)	(0.782)
Size	0.764***	0.764***	0.765***
	(0.00846)	(0.00847)	(0.00842)
Cashflow	-0***	-0***	-0***
	(0)	(0)	(0)
Lev	-0.00283	-0.00283	-0.00286
	(0.00260)	(0.00260)	(0.00261)
Finance		[omitted]	
Finance×AIE		0.556***	
		(0.155)	
HTSV			[omitted]
HTSV×AIE			-0.0499***
			(0.0175)
Constant	6.111***	6.104***	6.074***
	(0.210)	(0.210)	(0.209)
Observations	10,447	10,447	10,447
R-squared	0.832	0.832	0.832
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Notes: Robust standard errors in parentheses, clustered at the firm level. Significance levels: ***p<0.01, ** p<0.05, * p<0.1. Variables Finance and HTSE are omitted due to collinearity with firm fixed effects.

4.3. Robustness Checks

We conducted four robustness tests to validate the negative relationship between lagged AI exposure (AIE) and firm value (Table 4). First, a difference-in-differences (DID) approach defines Post as 1 for years ≥2020 and DID as AIE×Post, capturing potential shifts after 2020, which is a pivotal year marked by accelerated AI adoption in China, driven by the government's push for digital transformation during the COVID-19 pandemic and the release of the 14th Five-Year Plan emphasizing AI innovation. The DID coefficient is negative and significant (β=-0.184, p<0.01), suggesting that post-2020 AI exposure intensifies market penalties, possibly due to heightened investor scrutiny amid economic uncertainty. Second, following Acemoglu et al.(2022), using 2019 initial values of AIE (AIEI) produces a smaller but still negative effect (β=-0.065, p<0.01). Third, a placebo test with randomly generated AIE (uniform distribution) produces an insignificant coefficient (β=-0.010, p>0.1), confirming our results are not spurious. Finally, propensity score matching (PSM) defines treatment as above-median AIE, matching on lagged controls. The matched sample regression aligns with the baseline (β=-0.108, p<0.01), reinforcing robustness. These tests collectively strengthen confidence in our findings, with variations in effect sizes highlighting the temporal and contextual nuances of market responses to AI exposure.

Table 4 Robust Test

VARIABLES	(1) DID	(2) Initial AIE	(3) Placebo Test	(4) PSM Sample
DID（AIE×Post）	-0.184***			
	(0.011)			
AIEI		-0.065***		
		(0.011)		
Random AIE			-0.010	
			(0.017)	
AIE				-0.108***
				(0.010)
Constant	7.099***	5.570***	4.676***	6.111***
	(0.222)	(0.209)	(0.133)	(0.210)
Observations	10,447	8,709	10,447	10,447
R-squared	0.836	0.822	0.829	0.832
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses, clustered at the firm level. Significance levels: ****p*<0.01, ** *p*<0.05, * *p*<0.1. All models include lagged control variables (Firm Age, ROA, Size, Cash Flow, Leverage) as in the baseline regression.

5. Discussion and Conclusion

Our findings reveal the economic mechanisms governing market valuations of AI investments in China. The negative baseline effect affirms that markets rationally price the option value of waiting when facing irreversible investments with uncertain returns, aligning with the threshold principle established by Dixit and Pindyck (1994) and extended by contemporary researchers (Bloom et al., 2007; Smit and Trigeorgis, 2012). This dynamic has been specifically observed in emerging technology contexts by Kelly et al.(2021).

The industry-specific effects demonstrate that rational expectations are formed conditional on industry characteristics, consistent with modern adaptations of expectation theory (Evans and Honkapohja, 2001; Sargent, 2008). The differential effects across industries align with recent findings by Babina et al. (2024) , Malerba and McKelvey (2020) regarding heterogeneous technology returns based on complementary capabilities. Integrating these theories provides a nuanced framework for understanding technology valuation. The option value of waiting establishes a baseline market penalty, while industry-specific rational expectations modulate this penalty based on structural economic factors.

Our study challenges the assumption that advanced technologies universally enhance market valuation in the short term. Instead, we demonstrate the economic rationality of market skepticism under uncertainty and the critical role of industry context in determining optimal investment timing. For policymakers, our findings suggest that blanket technology promotion policies may face market resistance without addressing industry-specific economic frictions. For managers, communicating clear investment pathways with defined return horizons may mitigate negative market reactions.

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