

Financial Risk Transmission and Regulatory Policies in the AI Investment Bubble: A Study Based on a Systemic Risk Early-Warning Model

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Abstract: This paper focuses on the accumulation of financial risks and the optimization of regulation during the expansion cycle of the artificial intelligence industry. Taking the evolution and structural characteristics of global AI investment as its starting point, it examines the intrinsic logic by which capital expansion transmits to financial risks, and constructs an early-warning indicator system covering five dimensions: valuation risk, investment overheating risk, leverage risk, credit risk, and market contagion risk. Using an entropy-weighted method to assign objective weights, the paper synthesizes the AI Financial Risk Index (AI-FRI) and establishes a four-tier risk classification system based on the historical quantile method. Building on this, threshold regression and stress testing methods are combined to calibrate policy intervention thresholds, forming a closed-loop regulatory framework comprising “risk monitoring–threshold triggering–tiered response–effectiveness feedback.” Concurrently, a policy effectiveness evaluation system is established across three dimensions: risk control, transmission efficiency, and policy costs. The study found that the current wave of AI investment is characterized by computing power infrastructure as the dominant driver, with excessive capital concentration, valuations deviating from fundamentals, and rising leverage ratios being the core drivers of risk accumulation; quantitative early warning and tiered prudential regulation can minimize the inhibitory effect on industrial innovation whilst preventing systemic risks. The findings of this paper provide quantitative evidence and a feasible pathway for improving macroprudential regulation in the AI sector.

Keywords: Investment in artificial intelligence; Financial risk; Regulatory policy

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1. The evolution of the scale and structural characteristics of global AI investment

According to Stanford University’s *2026 Artificial Intelligence Index Report*, global corporate-level investment in AI in 2025 doubled compared with 2024, with private-market investment growing by 127.5 percent year-on-year; private investment in the generative AI sector grew by over 200 percent, accounting for nearly 50

percent of total private AI investment and becoming the core driver of industry financing. By country, private AI investment in the United States reached US\$285.9 billion in 2025, whilst private AI investment in China stood at approximately US\$12.4 billion. It should be noted, however, that public-sector funds—such as local government-guided funds and state-owned computing power platforms—are not fully included in the private investment statistics; consequently, the data from the two countries should not be directly compared. The actual level of industrial investment in China is higher than that indicated by the private investment figures ^[1].

As we enter 2026, investment in the AI sector continues to expand, with capital increasingly concentrated in the infrastructure segment. According to TrendForce’s estimates, the nine leading global cloud service providers—Google, AWS, Meta, Microsoft, Oracle, ByteDance, Tencent, Alibaba and Baidu—will have a combined capital expenditure of approximately US\$830 billion in 2026, with the core focus on the expansion of AI data centers and upgrades to computing power. The four US tech giants—Alphabet, Amazon, Meta and Microsoft—alone are set to invest approximately US\$650 billion in AI infrastructure in 2026, accounting for nearly 80 percent of total expenditure by global cloud providers.

In terms of the structure of capital allocation, all segments of the AI industry chain are receiving capital injections to varying degrees, characterized by “infrastructure leading the way, applications following suit, and high concentration in hard technology.” Overall, computing power infrastructure has replaced large-model R&D as the core area of capital expenditure, whilst derivative investment demand in upstream sectors such as chips and power supply is being released simultaneously, forming the central theme of this AI investment cycle.

2. The generation and transmission pathways of financial risks amid the expansion of AI investment

The rapid expansion of the AI industry is inseparable from a continuous inflow of capital; however, should the pace of capital inflows become detached from the industry’s profit fundamentals, financial risks will gradually accumulate and be transmitted along the industrial chain into the financial system. At present, financial risks in the AI investment sector are primarily concentrated across five areas, with a clear chain of transmission ^[2].

Firstly, there is the risk of asset valuation. As vast amounts of capital flood into the AI sector, this drives up the share prices of listed companies and valuations in the private market. Should the pace of AI commercialization and profit growth subsequently fail to meet market expectations, asset valuations will come under pressure to be revised downwards; in extreme cases, they may even plummet. Secondly, there are debt and leverage risks. Computing infrastructure, such as data centers and chip production lines, is capital-intensive, requiring substantial upfront investment and featuring long payback periods. Some companies are expanding by increasing their leverage through means such as bond issues, bank loans, and private credit facilities; however, excessively rapid investment growth will raise corporate leverage ratios and increase debt repayment pressures and the risk of default. Furthermore, there is a risk of over-investment. Should the pace of computing infrastructure construction far outstrip actual downstream demand, this would lead to overcapacity, resulting in reduced data center utilization rates and declining returns on investment, which in turn could trigger impairments to fixed assets. Additionally, financial institutions face risks: banks, insurers, funds, and private credit institutions are deeply involved in the AI sector through loans, bonds, and equity investments. Should AI asset prices fall or companies default, the asset quality of these financial institutions would immediately deteriorate. Finally, there is the risk of systemic instability. Currently, capital in the AI sector is largely concentrated among a handful of tech giants, chip manufacturers and cloud platforms. Should investment

sentiment reverse, risks would spread across multiple channels—including equities, bonds, credit and supply chains—transforming sector-specific risks into financial risks affecting the entire market.

Overall, the core financial risks associated with AI investment do not lie in the scale of investment itself, but rather in the excessive concentration of capital structure, the divergence between valuations and fundamentals, the rapid rise in leverage levels, and the continuing increase in interconnectedness with the financial system. When actual industry returns are unable to sustain the pace of expansion, localized asset price corrections may, through a chain reaction, escalate into systemic financial risks.

3. Development of an AI-based financial risk early-warning indicator system and composite index for investment

In light of the risk characteristics associated with AI investment, a multi-dimensional financial risk early-warning indicator system can be established. By quantifying and synthesizing a comprehensive risk index, it is possible to carry out dynamic monitoring and grading of risk levels, with the core objective being the precise identification of the turning point at which industrial expansion shifts towards the accumulation of risk ^[3].

3.1. Design of the dimensions for the early warning indicator system

The selection of early warning indicators adheres to the principles of “covering the entire transmission chain, data availability, and high risk sensitivity.” Five dimensions have been established to cover the entire process from risk generation to contagion, comprising a total of 16 specific indicators. The risk attributes and economic implications of each indicator are shown in **Table 1**. The five dimensions correspond to different stages of risk transmission: valuation risk reflects the degree of deviation from market expectations; investment overheating risk reflects the pace of expansion at the sectoral level; leverage risk reflects financial soundness at the corporate level; credit risk reflects default pressures in the debt market; and market contagion risk reflects the intensity of risk spillover into the financial system.

Table 1. Indicator system for early warning of financial risks in AI investment

Risk dimensions	Specific indicators	Indicator attribute	Meaning of risk
Valuation Risk	AI Sector Weighted PE-TTM	Positive	The higher the valuation level is, the stronger the risk of bubble formation becomes.
	AI sector weighted PB	Positive	The degree of asset premium reflects the deviation of market optimistic expectations.
	Quarterly growth rate of valuation	Positive	A rapid increase in valuation in the short term can easily lead to a subsequent correction.
	Annualized stock price volatility on the 30th day	Positive	The increase in volatility indicates that the divergence in market expectations has widened.
Excessive investment risk	Year-on-year growth rate of capital expenditure in the AI industry	Positive	Excessive capital expenditure can easily lead to overcapacity.
	Growth rate of VC/PE financing in the AI field	Positive	The overheating of primary market financing has pushed up the valuation bubble.
	The growth rate of data center cabinet deliveries	Positive	When the growth rate of computing power supply exceeds that of demand, the utilization rate will decline.
Leverage risk	Average debt-to-asset ratio of AI enterprises in the sector	Positive	Excessive debt increases the burden of repayment and the risk of default.

	Interest-bearing debt / EBITDA	Positive	The weaker the debt profit coverage ability is, the higher the credit risk will be.
	Interest Coverage Ratio	Negative	The lower the ability of profits to cover interest, the higher the default risk.
Credit risk	Average credit spread of AI industry bonds	Positive	The widening of the interest rate spread indicates an increase in the market's pricing of credit risk.
	Default rate of AI corporate bonds	Positive	The default event directly triggers the transmission of credit risk.
	Non-standard financing proportion	Positive	A high proportion of non-standard financing indicates low debt transparency and strong risk concealment.
Market contagion risk	Rolling correlation coefficient between the AI sector and the overall market index	Positive	The higher the correlation, the stronger the cross-market risk spillover capability.
	The proportion of AI-related assets in the asset exposure of financial institutions	Positive	The larger the exposure, the stronger the impact of the risk on the financial system.
	Market panic index (VIX)	Positive	Market panic can easily lead to a concentrated sell-off of AI assets.

3.2. Methodology for compiling the comprehensive risk index

In order to integrate multi-dimensional indicators into a single comprehensive index, all indicators are first standardized to eliminate differences in units of measurement. For positive indicators, where a higher value indicates greater risk, range standardization is applied; for negative indicators, where a higher value indicates lower risk, inverse standardization is applied. This maps all values uniformly to the 0–100 range, using the following formula:

Standardization of positive indicators:

$$Z_{it} = \frac{x_{it} - \min(x_i)}{\max(x_i) - \min(x_i)} \times 100$$

Standardization of negative indicators:

$$Z_{it} = \frac{\max(x_i) - x_{it}}{\max(x_i) - \min(x_i)} \times 100$$

Among them, x_{it} represents the original value of the i -th indicator in the t -th period, $\max(x_i)$, $\min(x_i)$ are the maximum and minimum values of the i -th indicator within the sample period, respectively, and Z_{it} is the standardized indicator value.

The weights of the indicators are determined objectively using the entropy weighting method, thereby avoiding the bias associated with subjective weighting. The entropy weighting method assesses the discriminatory power of an indicator based on its information entropy; the lower the information entropy, the greater the amount of information the indicator carries, and the higher its weight. The calculation steps are as follows:

Step 1: Calculate the sample weight for period t under indicator i :

$$p_{it} = \frac{Z_{it}}{\sum_{t=1}^m Z_{it}}$$

where m is the number of sample periods.

Step 2: Calculate the information entropy of the i -th indicator:

$$e_i = -\frac{1}{\ln m} \sum_{t=1}^m p_{it} \ln p_{it}$$

If $p_{it}=0$, It is hereby agreed that $p_{it} \ln p_{it}=0$.

Step 3: Calculate the information entropy redundancy and the indicator weights:

$$d_i = 1 - e_i, w_i = \frac{d_i}{\sum_{i=1}^n d_i}$$

Here, n represents the total number of indicators, and w_i denotes the weight of the i -th indicator, which satisfies $\sum_{i=1}^n w_i = 1$.

Final Composite AI Financial Risk Index (AI Financial Risk Index, AI-FRI):

$$AI-FRI_t = \sum_{i=1}^n w_i \cdot Z_{it}$$

The index ranges from 0 to 100, with higher values indicating a higher level of financial risk.

3.3. Quantile classification of risk levels

Based on the AI-FRI composite index, risk can be categorized into four levels. The criteria for this categorization should not be set subjectively by humans but determined according to the distribution characteristics of historical data. Generally, the quantile method is employed to select a sufficiently long historical sample period (such as quarterly data from 2018 to 2025) to calculate the empirical distribution of the AI-FRI within that period. The four quantiles—P25, P50, P75, and P95—serve as the core reference points for the tier boundaries. Following appropriate adjustments to account for the characteristics of the industry cycle, a four-tier risk classification is derived (as shown in **Table 2**). The advantage of this method is that it reflects the historical distribution patterns of risk and avoids the arbitrariness of manually setting thresholds; it is particularly suitable whilst the AI industry is still in its development phase and the patterns of risk have not yet been fully revealed ^[4].

Table 2. Criteria for classifying AI financial risk levels

AI-FRI index range	Risk level	Core feature
0~25	Low risk	AI investment is in line with the development pace of the industry, has a reasonable valuation, a stable leverage level, and the financial risks are within controllable limits.
25~50	Attention level	There has been an increase in valuations or overheating in certain sectors, with a slight rise in leverage ratios. However, these developments have not yet deviated significantly from the fundamental support.
50~75	High risk	There is a significant divergence between valuation and earnings. The leverage of enterprises has rapidly increased, credit spreads have widened, and financial exposure has continued to expand.
75~100	High risk	The asset market shows significant bubble characteristics, the risk of debt default is increasing, the financial system is highly interconnected, and there is a possibility of systemic risk transmission.

4. Methods and framework for setting policy thresholds based on risk early warning

4.1. Core methods for determining policy thresholds

The setting of policy thresholds must balance scientific rigor with practicality; reliance on a single method is not advisable, and a combination of three methods may be used for cross-validation:

Firstly, the quantile method. This uses the quantiles of the historical AI-FRI index as baseline thresholds; for example, P50 corresponds to the upper limit of the “monitoring” range, P75 to the lower limit of the “intervention” range, and P95 to the lower limit of the “high-risk” range. This method is straightforward to apply and reflects the risk distribution under normal historical conditions, making it suitable as a benchmark threshold.

Secondly, the threshold regression method. This method employs Hansen’s panel threshold model, using the AI-FRI as the core explanatory variable and financial institutions’ non-performing loan ratios, market volatility, and systemic risk spillover indices as dependent variables to identify the non-linear threshold at which risk transmission transitions from a quantitative to a qualitative change. This method captures the critical points of sudden risk shifts, precisely pinpointing the optimal timing for policy intervention, thereby addressing the shortcoming of the quantile method, which merely reflects historical distributions ^[5].

Thirdly, the stress testing method. By setting extreme shock scenarios (such as a 30 percent correction in AI sector share prices, debt defaults by leading enterprises, or a sharp decline in computing power demand), this method calculates the extent of losses to the financial system at different risk levels. The AI-FRI value corresponding to the point where losses reach the financial stability threshold is defined as the high-risk threshold. This method focuses on the prevention and control of tail risks and ensures financial security under extreme scenarios.

In practical application, adopting a combined approach—“using the quantile method as a benchmark, adjusting thresholds via threshold regression, and utilizing stress testing to safeguard the bottom line”—can help establish a threshold system that balances normal conditions with extreme scenarios. Within the context of the Chinese market, it is still necessary to take into account the counter-cyclical regulatory effect of public investment; government-guided funds and state-owned computing power projects demonstrate greater risk-bearing capacity and a long-term orientation; on this basis, thresholds relating to investment overheating can be moderately relaxed to avoid misinterpreting counter-cyclical positioning as excessive investment.

4.2. Response framework for the four-tier policy threshold bands

Based on the calibrated thresholds, risk levels can be categorized into four policy bands—normal, watch, intervention, and high risk—each corresponding to regulatory measures of varying intensity, thereby forming a structured framework of “risk indicators—critical thresholds—policy responses,” as detailed in **Table 3**. The core logic of this framework is that the intensity of regulation increases in stages in line with the risk level: guidance is the primary focus during the early stages of risk emergence; constraints are the primary focus during the accumulation phase; and resolution is the primary focus during the outbreak phase. This ensures a precise alignment between the intensity of regulation and the severity of the risk.

Table 3. Policy threshold ranges and regulatory response matrix

Risk range	Corresponding to the AI-FRI threshold	Regulatory positioning	Core policy tools
Normal range	0~25	Regular monitoring	Regularly release financial risk reports on the AI industry and maintain a neutral regulatory environment.
Focus on the range	25~50	Early warning guidance	Strengthen the requirements for information disclosure by AI enterprises at the headquarters, issue risk warnings for the VC/PE industry, and guide capital to make rational investments.
Intervention period	50~75	Prudent restraint	Carry out AI-based asset stress tests for financial institutions, limit the debt financing scale of highly leveraged enterprises, and regulate the disorderly expansion of computing infrastructure.
High-risk range	75~100	Risk Management/ Disposal	Increase the risk weights of AI-related assets, limit the risk exposure of financial institutions, activate the cross-departmental risk prevention mechanism, and prevent systemic spillover.

4.3. Mechanism for the dynamic adjustment of thresholds

Policy thresholds are not static; a dynamic adjustment mechanism must be established to calibrate them periodically in accordance with the stage of industrial development, the macroeconomic environment, and progress in technological breakthroughs. During the industry's introduction phase, when commercialization models are not yet mature, the tolerance thresholds for valuation and financing growth rates may be moderately raised to allow scope for technological innovation; during the industry's maturity phase, when profit models tend to stabilize, threshold standards should be tightened to strengthen risk constraints. During an economic upturn, when corporate profitability is strong, leverage thresholds may be moderately relaxed; during an economic downturn, when pressure on corporate cash flows intensifies, credit and leverage thresholds should be tightened in advance to guard against a concentrated release of default risks. Should fundamental changes occur—such as major technological breakthroughs or an acceleration in the commercialization process of the industry—valuation thresholds should be promptly raised to avoid misjudging an increase in industrial value as a bubble.

5. The logic and tools of government financial regulatory intervention under a tiered response system

In terms of the logic behind intervention, for the AI-FRI Index to trigger regulatory action at the appropriate level, reaching the corresponding threshold is merely a necessary condition, not a sufficient one; this is because regulatory authorities must take into comprehensive consideration industrial policy directions, macroeconomic cycles, external shocks, and numerous other factors before deciding whether to intervene and, if so, the extent of such intervention. For instance, in 'hard technology' sectors receiving key state support, even where valuations are high in the short term, mild measures such as disclosure requirements and risk warnings may be employed first—rather than administrative intervention—to prevent the pace of technological iteration from being disrupted. Conversely, in sectors relying purely on conceptual hype without substantive technological backing, restrictive measures may be introduced at an earlier stage to prevent a flood of speculative capital.

In terms of tiered intervention tools, different risk levels correspond to differentiated regulatory approaches: at the low-risk stage, the focus is on routine monitoring, relying on financial infrastructure to continuously track data on industry financing, debt and valuations, and regularly publishing risk reports; at the 'under observation' stage, the emphasis is on guidance and standardization, requiring leading AI enterprises

to enhance the transparency of their disclosures regarding capital expenditure and debt structures, thereby signaling to the market the need for rational investment; at the higher-risk stage, the focus is on prudential constraints, involving specialized stress tests on AI assets for financial institutions such as banks and funds, restricting credit allocation to highly leveraged, low-profitability AI enterprises, and curbing blind, duplicative construction in the computing power sector; at the high-risk stage, the focus is on risk resolution, using macroprudential tools such as increasing risk weights, reducing exposure and liquidity management to block the transmission of risk, and, where necessary, activating inter-departmental coordination mechanisms to prevent risks from spreading across the entire market.

Overall, the core objective of government intervention is to “prevent risks without hindering development.” By employing structural regulatory tools to implement targeted measures, the government maintains a supportive stance towards technological innovation whilst maintaining a firm stance against speculative trading, thereby striking a balance between financial stability and industrial development.

6. Dimensions and methods for evaluating the effectiveness of AI financial regulatory policies

Firstly, the assessment of risk control effectiveness. The key is to determine whether the policy has effectively reduced the level of financial risk associated with AI investment. Specifically, changes in core risk indicators—such as the AI-FRI Composite Index, corporate leverage ratios, credit spreads, and asset price volatility—before and after policy implementation can be compared. Event study methods or the difference-in-differences (DID) approach can be employed to isolate the influence of other factors and identify the policy’s net risk-mitigating effect. If, following policy implementation, risk indices decline significantly, leverage ratios stabilize, and credit spreads narrow, this indicates that risk control has been effective; if, however, risk indicators show no marked improvement or even continue to deteriorate, regulatory efforts must be stepped up.

Second, assessment of policy transmission effectiveness. The key here is to examine whether the transmission chain—“policy intervention → adjustment in investment behavior → reduction in financial risk”—is functioning smoothly. Specifically, one can analyze changes in intermediary variables—such as the growth rate of capital expenditure in the AI industry, the level of VC/PE funding activity, and the risk exposure of financial institutions—following policy implementation, to verify whether the policy has effectively guided the investment behavior of market participants. If policy transmission is ineffective, policy instruments need to be optimized; for example, by shifting from aggregate control to structural guidance to enhance the precision of the policy.

Thirdly, an assessment of policy costs and side effects. The core of this lies in measuring the negative impact of regulatory policies on the development of the AI industry to prevent excessive suppression of innovation in the name of risk prevention. Specifically, following policy implementation, changes in indicators such as financing costs in the AI sector, the number of new start-ups, R&D intensity, and patent output can be monitored to assess whether the policy has led to an excessively tight financing environment or a decline in innovative dynamism. Furthermore, a cost-benefit indicator—‘risk reduction rate versus innovation loss rate’—can be established; if the loss of innovation exceeds the benefits gained from risk prevention and control, regulatory measures should be appropriately relaxed to achieve an optimal balance between risk and efficiency.

7. Conclusion

Against the backdrop of the accelerating global expansion of AI investment, this paper conducts research centered on the entire chain of financial risk identification, early warning, intervention, and assessment, and constructs a systematic regulatory framework for financial risks associated with AI investment. The key conclusions are as follows:

Firstly, the current wave of AI investment is dominated by computing power infrastructure, with capital concentrating at the upstream end of the industrial chain. Its capital-intensive nature results in long investment cycles and a high reliance on leverage; the core risks stem from excessive capital concentration, the divergence between valuations and earnings, rising leverage ratios, and deep integration with the financial system, with the potential for localized risks to propagate into systemic risks.

Secondly, an indicator system encompassing five dimensions—including valuation and investment overheating—has been established. By synthesizing the AI-FRI composite index using the entropy weighting method and calibrating four risk levels through historical quantiles and threshold regression, multi-dimensional quantitative early warning is achieved, providing quantitative support for regulatory decision-making.

Thirdly, a tiered regulatory threshold approach is being implemented, with policy thresholds dynamically adjusted to balance risk prevention and control with scope for industrial innovation.

Fourthly, a three-dimensional, closed-loop policy evaluation system should be established to dynamically calibrate the intensity of regulation, striking a balance between the development of the AI industry and the stability of the financial system.

In the future, various types of data could be incorporated to optimize the early warning system, whilst utilizing technological means to enhance the foresight of risk forecasting.

Disclosure statement

The author declares no conflict of interest.

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