Tohoku University Research Center for Policy Design Discussion Paper

TUPD-2023-013

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November 2023

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Financial Systemic Risk behind Artificial Intelligence: Evidence from China*

Jingyi TIAN† Jun NAGAYASU‡

November 28, 2023

Abstract

As an important domain of information technology development, artificial intelligence (AI) has garnered significant popularity in the financial sector. While AI offers numerous advantages, investigating potential risks associated with the widespread use of AI has become a critical point for researchers. We examine the impact of AI technologies on systemic risk within China's financial industry. Our findings suggest that AI helps mitigate the increase of systemic risk. However, the impact of AI differs across different financial sectors and is more pronounced during crisis periods. Our study also suggests that AI can decrease systemic risk by enhancing the human capital of financial firms. Moreover, the theoretical framework presented in this paper provides insights into the notion that imprudent allocation of AI-related investment could potentially contribute to an increase in systemic risk.

JEL classification: O16; O33; G20; G32
Keywords: Artificial intelligence; Financial systemic risk; Copula-CoVaR approach; Two-sector model; China

*The first author gratefully acknowledges the financial support from the Advanced Graduate School Pioneering Research Support Project for Ph.D. Students at Tohoku University (J210002138).

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1 Introduction

Unconsciously, we are already approaching an era filled with advanced technology and machine learning, which we call the "Artificial Intelligence (AI)[1] revolution". By the mid-1980s, numerous enterprises began embarking on AI projects within their respective business domains. Since then, the application of AI has emerged as one of the most extensively researched subjects in economics. As AI technologies enable labor productivity to achieve a significant leap, its influence has been explored across various economic topics, such as labor productivity, wage inequality, unemployment, innovation, energy consumption, business risks, and economic growth (Qian et al., 2022).

Over the past few decades, the Chinese government has demonstrated a keen awareness of the significance of AI technologies, building a strong base to sustain its AI economy and contributing significantly to the global development landscape. According to Zhang et al. (2022), China's AI sector received nearly 20% of the global private investment in 2021, securing substantial funding for AI start-ups. In this context, the financial sector has emerged as a prominent domain for AI adoption. This shift towards AI in finance is evidenced by the increased online search interest indicated by Google Trends data, with a noticeable spike around 2004 and 2005 (Cao, 2020). To facilitate the AI advancement in the financial industry over the past decade, both the Chinese government and financial enterprises have significantly increased their investments in research and development (R&D) and AI-specific R&D funds (see Figure 1). However, the introduction of AI in China's financial industry occurred nearly three decades later than in developed countries, with the official introduction of the concept of financial technology by the Central Bank of China in 2017. As such, the application of AI in China's financial market is at an initial phase, warranting further research and exploration.

[Figure 1]

With the proliferation of AI applications in the financial industry, it is imperative to

[1] AI is defined as the capacity of a machine to replicate and display behaviors after thinking like humans (Philippe et al., 2019). It covers the application of machine learning, deep learning, decision-making, and other programming, thereby releasing humans from rudimentary jobs or routine physical labor. In the 1940s and 1950s, AI was first discussed by John McCarthy and other academics at the Dartmouth Conference. It experienced a boom in the 1970s, a shortage of funding between the mid-1970s and 1980s, and finally thrived again in the 1980s.

recognize the advantages bestowed by AI and acknowledge potential risks and crises that may arise from its widespread utilization. Previous research has extensively examined the risks inherent in integrating AI into the financial industry, encompassing credit, political, and security risks (Ellul and Yerramilli, 2013; Gu et al., 2019). Nevertheless, past empirical literature has rarely investigated the correlation between AI and systemic risk in the financial sector. Therefore, we explore the impact of AI technologies on financial systemic risk (FSR)—which emerges from the interconnectedness of financial institutions and forms the foundation of risk contagion (Acemoglu et al., 2012)—and its heterogeneity across various financial sectors and economic environments.[2]

The rest of this paper is organized as follows. Section 2 outlines the literature examining the relationship between AI and FSR in the financial industry. Drawing upon relevant theories between AI application and FSR, Section 3 illustrates the theoretical foundation for this study. Section 4 presents the measurement methodology and data description. Section 5 reports the empirical model, benchmark regression, endogenous test, and robustness analysis. Finally, Section 6 summarizes the key findings and offers policy recommendations based on the study's outcomes.

2 Literature Review

The literature on AI in finance can be broadly categorized into the following areas: financial system mechanisms modeling, agency-based finance, wise investment, financial market analysis and forecast, smart credit loan and risk management, and customer services (Mizuta, 2022; Noonpakdee, 2020). AI streamlines financial services procedures by implementing smart chatbots, financial intelligent terminal machines, Internet banking systems, and credit rating technologies. These AI technologies facilitate customer retention, enhance operational efficiency, and improve risk management for financial institutions (Qi and Xiao, 2018). Furthermore, AI has assumed an increasingly critical role in financial systems, reshaping the regulatory landscape and unveiling a range of possibilities to

[2] FSR is defined as a potential crisis that can bring about the total failure of the entire financial system in regional, national, or even global markets. It is characterized by its contagious and non-diversifiable nature, meaning that it cannot be eliminated or mitigated through individual actions or risk diversification strategies (Kou et al., 2019).

enhance the accessibility of financial services beyond our present capabilities (Giudici, 2018). The benefits of AI technologies include streamlining document review processes, shortening data mining and processing times, optimizing department structures to reduce operational costs and capital expenditures, and fostering collaboration among financial institutions (Temelkov, 2018). Regarding risk management, Chaudhry et al. (2022) argue that financial institutions integrating AI into their operations tend better to meet risk management requirements and control related costs. This is supported by Giudici (2018), who argues that AI can mitigate reputation and market violation risks, enhance fraud detection performance, and contribute to asset protection and financial market stability.

The Chinese government has continuously placed special focus on FSR since the outbreak of the 2008 financial crisis. FSR is not solely attributed to external factors such as war, natural disasters, and political or legal factors but is also significantly influenced and amplified by the interconnectedness among financial institutions (Billio et al., 2012; Zhang et al., 2021). Wang et al. (2014) conducted a comprehensive analysis utilizing the Conditional Value at Risk (CoVaR) approach to examine key determinants of FSR and the risk spillover of individual enterprises contributing to FSR in China. Their findings reveal that banks—compared to other financial institutions—play a more significant role in contributing to FSR. Furthermore, these institutions' size and leverage ratio determine the extent of buffer they can provide during crisis periods. Lan et al. (2020) assess the dynamics of FSR in China during the COVID-19 pandemic using a dynamic CoVaR model. They found a significant increase in FSR during this period, with the securities industry experiencing higher volatility in FSR than other sectors.

AI technologies have been effectively integrated into the financial system, aiding governments and financial institutions in monitoring and preventing systemic crises. In China, AI adoption in the financial industry has permeated into various sectors, such as online payment services (e.g., Yu'e Bao and WeChat Pay), and has expanded microloan accessibility to a broader population. Kou et al. (2019) utilize AI to analyze the outbreak and transmission mechanisms of FSR, simulate the effects of regulations on FSR by creating visualized financial systems based on actual bank transaction data, and identify the key factors contributing to the formation of FSR. Petrone et al. (2022) propose a dynamic financial network incorporating AI technologies. Their framework facilitates learning optimal bailout actions and clarifying the potential contagion effects of systemic crises. Chaudhry et al. (2022) examine the connection between financial technology and the volatility of FSR. They indicate that financial firms with technological characteristics possess a strong buffer to FSR volatility and decrease the probability of experiencing adverse events.

In contrast, several scholars have expressed concerns regarding the potential risks associated with the widespread application of AI (Erik Brynjolfsson, 2019; Philippe et al., 2019). For instance, establishing digital monopolies by financial giants could potentially exclude newly established firms. Consequently, this could increase complexity within the global financial system and serve as an emerging causation for systemic risk (Fernández, 2019). Likewise, AI can lead to increased interconnections among companies, resulting in a more intertwined and potentially unstable structure, thus contributing to the rise of FSR. Implementing AI systems can give rise to risks such as data disclosure, system instability, security breaches, and other emerging risks, which jeopardize economic stability and amplify systemic risks within the financial industry (Azarenkova et al., 2018).

These studies remind us that introducing AI technologies transforms the overall industrial ecosystem, distinguishing it from other machine technologies that merely enhance productivity. Consequently, the application of AI in the financial system is a subject of controversy. On the one hand, by integrating with financial operations, AI surpasses human capabilities and assists in simplifying processes, reducing costs, and enhancing risk control. On the other hand, it also poses vulnerabilities to the existing financial structure and potential information leakage. To the best of our knowledge, AI technologies' impact on the financial system's robustness remains uncertain because of the lack of research, and discussions in the existing literature regarding the relationship between AI and FSR primarily revolve around theoretical and literature analysis. Therefore, it is crucial to commence the investigation of AI's impact on FSR.

3 Theoretical Framework

Our analytical framework is based on the two-sector model (Wagner, 2010), which has three basic assumptions. First, the financial system comprises only two banks, initially holding the same type of traditional financial assets.[3] With the emergence of financial innovation assets (e.g., AI products and financial AI systems), these institutions allocate funds from traditional financial assets towards acquiring financial innovation assets or maintaining the initial status without making any changes. The second assumption is related to the default or bankruptcy behavior of institutions. The extreme tail event that both financial institutions default or go bankrupt is the result of the joint action of individual and systemic risk in pursuing profit maximization. Third, investors are rational and risk-averse. Investors withdraw their funds immediately once the value of assets drops below their invested capital.

Consider the status of two financial institutions before acquiring financial innovation assets. They hold one unit of funds and invest all into identical traditional financial assets with the value of x. x changes with the business conditions according to a distribution function $\phi(\cdot)$ and is subject to $[0, p]$, where p refers to the total scale of funds. For this unit of funds, a portion (d) is collected from depositors as debts, and the remaining $(1 - d)$ from shareholders as capital. When x is less than d, financial institutions cannot borrow funds from the depositors and announce bankruptcy or insolvency. Then, the financial institution would be required to liquidate the asset. If two financial institutions are insolvent together, FSR occurs. However, when only one financial company is insolvent, the bankrupt financial institution's asset could be sold to the solvent one, and a systemic crisis is averted.

Now, we consider that each financial institution diversifies and invests in the activity not previously engaged in. For instance, financial institutions invest in financial innovation assets (y) with a proportion of w_i ($w_i \in [0, 1]$). $w_i = 0$ means the bank's asset is not diversified, and $w_i = 1/2$ refers to the asset equally distributed between traditional and

[3] The term "traditional financial assets" in this context is specifically used to distinguish it from financial innovation assets. It encompasses equity, bonds, and other conventional financial instruments unrelated to digital or AI technology-based assets.

innovation assets (fully diversified). Specifically, w_1 and w_2 represent w_i of financial institutions 1 and 2, respectively, and they are mutually independent and determined solely by each financial firm. Then, the total asset values (v_i) of financial institutions 1 and 2 are expressed as follows:

$$
\begin{aligned}
v_1(x, y) &= (1 - w_1)\, x + w_1 y \\
v_2(x, y) &= (1 - w_2)\, x + w_2 y
\end{aligned}
\tag{1}
$$

Based on Equation (1), we can calculate the boundary conditions required for each financial institution to avoid bankruptcy. Recall that a financial institution encounters bankruptcy once the value v_i is lower than d.

$$
\begin{aligned}
v_1(x, y)\, (1 - w_1)\, x + w_1 y &\geq d \\
v_2(x, y) = (1 - w_2)\, x + w_2 y &\geq d
\end{aligned}
\tag{2}
$$

The minimum asset values y_i that avoid insolvency are:

$$
\begin{aligned}
y_1(x) &= \frac{d}{w_1} - \frac{1 - w_1}{w_1} x_1 \\
y_2(x) &= \frac{d}{w_2} - \frac{1 - w_2}{w_2} x_2
\end{aligned}
\tag{3}
$$

Therefore, financial institution 1 will announce bankruptcy once $y < y_1(x)$. Financial institution 2 faces insolvency if $y < y_2(x)$. Figure 2 portrays the threshold values of assets for two partially hedged financial institutions ($0 \leq w_i \leq 1$).[4]

[Figure 2]

Taking financial institution 1 as an example, it fails when $y < y_1(x)$, as stated. The individual risk of financial institution 1 (R_1) can be expressed as:

$$
R_1 = \int_0^{x_1(0)} \left(\int_0^{y_1(x)} \phi(x)\phi(y) dy \right) dx \tag{4}
$$

Similarly, the individual risk of financial institution 2 (R_2) will be:

[4] This figure is plotted under the condition that $w_2 \geq w_1$.

$$R_2 = \int_0^{x_2(0)} \left(\int_0^{y_2(x)} \phi(x)\phi(y)dy \right) dx \tag{5}$$

The insolvency of both financial institutions leads to systemic risk, and the expressions for systemic risk (R^S) are as follows:

$$\begin{aligned} R^S &= \int_0^d \left(\int_0^{y_2(x)} \phi(x)\phi(y)dy \right) dx + \int_d^{x_1(0)} \left(\int_0^{y_1(x)} \phi(x)\phi(y)dy \right) dx \quad (w_2 \geq w_1) \\ R^S &= \int_0^d \left(\int_0^{y_1(x)} \phi(x)\phi(y)dy \right) dx + \int_d^{x_2(0)} \left(\int_0^{y_2(x)} \phi(x)\phi(y)dy \right) dx \quad (w_2 \leq w_1) \end{aligned} \tag{6}$$

Considering the minimum asset value, $y_1(x)$ is negative when $x_1(0) = \frac{d}{1-w_1}$, and $\phi(x)$ and $\phi(y)$ follow the uniform distribution, that is, $\phi(x) = \phi(y) = 1/p$. Using Equation (6), we obtain:

$$\begin{aligned} R_1 &= \frac{d^4}{24p^2 w_1^2 (1-w_1)^2} \\ R_2 &= \frac{d^4}{24p^2 w_2^2 (1-w_2)^2} \end{aligned} \tag{7}$$

$$\begin{aligned} R^S &= \frac{d^4}{24p^2} \left[\frac{1}{w_1^2 (1-w_1)^2} - \frac{1+3w_1^2-2w_1}{w_1^2} + \frac{1+3w_2^2-2w_2}{w_2^2} \right] \quad (w_2 \geq w_1) \\ R^S &= \frac{d^4}{24p^2} \left[\frac{1}{w_2^2 (1-w_2)^2} - \frac{1+3w_2^2-2w_2}{w_2^2} + \frac{1+3w_1^2-2w_1}{w_1^2} \right] \quad (w_2 \leq w_1) \end{aligned} \tag{8}$$

Equation (8) suggests that R^S strongly correlates with the proportion of financial innovation assets and is positively related to the scale of funds from depositors and investors. The impact of financial innovation, such as AI and machine learning, on systemic risk is complex and cannot be simply classified as promoting or inhibiting effects. To further observe the relationship between FSR and AI across different stages, we use some parameter values and draw the function of Equations (7) and (8).

Assuming that we have one unit of funds invested in different assets ($p = 1$) and the proportion of the deposit is 0.2 ($d = 0.2$), the proportion of financial innovation assets

(w_i) ranges between 0.1 and 0.9.[5] Figure 3 displays the individual risk of a single financial institution, while Figure 4 depicts the relationship between w_1, w_2, and R^S. According to the numerical simulation, it is evident that diversifying funds and investing in new types of assets (particularly financial technology and AI-related assets) effectively reduce individual risk. Moreover, the risk is minimized when funds are fully diversified into two parts ($w_i = 0.5$). Regarding FSR, an increase in w_1 and w_2 initially reduces risk, but R^S increases once the proportion of financial innovation assets becomes sufficiently large. In the figures, the maximum value of R^S lies with the corresponding values of $w_1 = 0.10$ and $w_2 = 0.90$, or $w_1 = 0.90$ and $w_2 = 0.10$. The minimum value of R^S corresponds with $w_1 = w_2 = 0.50$.

[Figure 3] & [Figure 4]

It should be emphasized that the figure of R^S in the case of $w_1 = 0.10$ and $w_2 = 0.90$ is higher than that of $w_1 = 0.10$ and $w_2 = 0.10$. This implies that the risk associated with two firms holding entirely different types of financial assets does not necessarily decline compared to the scenario where both firms hold identical types of assets. This conclusion aligns with the findings of Wagner (2010) and Liang et al. (2020), who argue that intensified diversification is accompanied by higher systemic risk. The numerical simulation of the two-sector model indicates that engaging in new types of businesses, such as investing in innovative financial assets and AI systems, may introduce new risks to the financial system and trigger the transmission of individual risks throughout the whole sector due to the unfamiliarity with new types of business and incomplete regulations.

We can also see from Equations (7) and (8) that a higher value of p and a lower value of d are associated with a decrease in both individual and systemic risks. Financial institutions with larger total financial assets possess a greater capacity to withstand risks, consequently contributing less to overall financial risk. In addition, institutions with a higher proportion of current liabilities in their financial structure touch the bankruptcy bottom threshold more easily ahead of other institutions, thereby triggering systemic financial crises.

[5] We avoid expanding the range close to $[0, 1]$ because as the values of w_i approach 0 or 1, the value of individual and financial systemic risk will become infinitely large, making it inconvenient for us to observe changes.

Wagner's two-sector model and the theory of diversified investment are important theories in finance concerning systematic risk and portfolio optimization. These models and discussions on systemic risk and diversification apply to interbank scenarios and have practical relevance for financial institutions beyond banks (Wagner, 2010). The securities and insurance industries face market volatility and the complexity of various investment tools, where risk diversification is crucial. Wagner's model and diversified investment theory can be used to determine the investment portfolio, minimizing systemic risk and increasing returns. For both individual and institutional investors, the two-sector model and implications of diversification on FSR more accurately consider the correlation and risk between different asset classes, helping investors construct more balanced and effective investment portfolios (Ibragimov et al., 2011; Wagner, 2011). Moreover, even non-financial enterprises confront challenges in fund management and risk regulation. By introducing Wagner's theory into corporate financial decision-making, Dungey et al. (2022) found that a company's size, credit, and other aspects are closely related to the two dimensions of FSR.

Another theoretical framework relevant to this study is the Circumventive Innovation Theory (CIT), which has greatly influenced numerous researchers in the financial industry (Kane, 1984). CIT suggests that one of the motivations for financial institutions to engage in financial innovation is to circumvent regulation. When there are enough profit opportunities outside of regulatory control, financial institutions promote innovation, thus bypassing current regulatory restrictions and achieving greater benefits. Rapid AI advancement has facilitated cost reduction and increased enterprise profit generation, enabling them to operate with fewer rules and reporting obligations. Note that this progress has outpaced the development of regulatory frameworks. Without updated legislation, the accumulation of potential risks has intensified, amplifying systemic risk. For instance, introducing AI-based automated credit review systems has lowered the loan acquisition criteria for small and medium enterprises (SMEs) and individuals, expanding the lending business and broadening firms' client acquisition channels. Nevertheless, this development has also heightened the risk of default among individuals. In another case, the algorithmic mechanisms employed in the prevalent AI-driven investment services within the financial industry have raised concerns. These AI technologies often utilize similar or identical algorithms for clients with varying risk tolerances. If errors exist within the underlying algorithms, they can propagate a "domino effect" of risk contagion, triggering interconnected adverse consequences and exacerbating systemic risk (Shah, 2014; Alexander, 2006). CIT applies to both banking and non-banking sectors—supporting business innovation and expansion—and offers valuable insights into product innovation, policy monitoring adjustments, and overall firm performance (Funk and Hirschman, 2014; Kane, 2010). These theoretical perspectives provide a comprehensive understanding of the risks associated with financial institutions and their activities.

4 Methodology

4.1 A Measurement of AI

The financial AI index in China can be divided into three categories. First, the digital inclusive financial index developed by Peking University is widely adopted by researchers as the standard to reflect the development of financial technology in China (Sun and Tang, 2022). However, this index is compiled using user-level data from Alipay, China's leading digital payment platform. Most customers using this application are individual customers, which may not represent financial institutions and other enterprises. Second, Pin and Yue (2015) has constructed a financial AI index based on the statistics of news terms recorded by Google or Baidu search engine on keywords, such as "artificial intelligence," "financial technology," and "big data and machine learning". The third approach involves constructing the AI index with relatively objective indicators. Some researchers employ metrics such as the number of industrial robots (Qian et al., 2022), the number of AI patents (Yang, 2022), or the AI adoption rate gathered from corporate surveys as indicators to portray the utilization of AI technologies across various industries and enterprises.[6]

Given the suitability of the data set to our research objectives, we follow the idea of the third approach and utilize established indices and indicators to construct our financial AI index for each financial institution. Specifically, we use the China Fintech Innovation

[6]Please see the work done by the International Business Machines Corporation (IBM):https://www.ibm.com/watson/resources/ai-adoption.

Index (CFII) developed by the China Center of Fintech Research (CCFR) at the Central University of Finance and Economics as our firm-level AI index. The CFII serves as the basis for measuring the financial innovation capability of individual financial enterprises. The quantitative assessment of CFII in Chinese financial enterprises is primarily conducted at four levels: the foundation of financial technology endowment, development of financial technology business, awareness of financial technology, and its core capabilities. Among the detailed indicators, the assessment of AI development encompasses the proportion of enterprise investment in research and development or acquisition of AI-related products and systems, number of different AI products, investment in virtual branches and online business, quantity of AI-related patents, and feedback from the company's managers on AI products. A detailed scoring system is applied based on how much each financial institution utilizes AI.

To capture the actual level of AI application and address any missing values, we supplement the data set with additional indicators such as the number of R&D personnel within financial institutions, new patent applications for financial products, and proportion of R&D expenditure in total operating expenditure. By incorporating these innovation-related financial indicators, we strengthen the data set and enhance its ability to reflect the utilization of AI within financial enterprises. Moreover, this method enables us to obtain firm-level data for the AI index, providing a micro perspective on AI adoption and facilitating the exploration of interconnections between institutions for further analysis.

4.2 A Measurement of Financial Systemic Risk

This section presents the dynamic time-series CoVaR-Copula approach for calculating FSR. The copula family consists of diverse types, broadly classified into elliptical copulas (such as Gaussian and Student's t) and Archimedean copulas (including Clayton, Gumbel, and SJC)(see Table 1). In the literature related to the financial market, elliptical copulas are commonly utilized, while Archimedean copulas are more effective in capturing asymmetric lower and upper tail dependence. The selection of the most suitable copula model among various options is based on the Akaike information criterion (AIC), which is widely used in previous studies (Zhang et al., 2021; Karimalis and Nomikos, 2018).

[Table 1]

Here, the estimation of FSR is based on the calculation of ΔCoVaR, and the measurement procedures are outlined as follows. First, we estimate the VaR[7] for each financial institution using time series data and marginal distribution models. Given the accuracy of marginal distribution calculations and the characteristics of our data, we adopt the AR(1)-GARCH(1,1) model[8] to estimate the volatility of the financial asset portfolio and the marginal distributions of each financial institution. This model choice strikes a balance between estimation efficiency and accuracy. Follow the work of Glosten et al. (1993), we estimate:

$$\begin{aligned} \mathrm{R_t} &= \mu + \varnothing \mathrm{R_{t-1}} + \xi_\mathrm{t} \\ \xi_\mathrm{t} &= \sigma_\mathrm{t} \cdot \mathrm{z_t} \\ \sigma_\mathrm{t}^2 &= \omega_1 + \alpha_1 \xi_{\mathrm{t}-1}^2 + \beta_1 \sigma_{t-1}^2 \end{aligned} \tag{9}$$

R refers to the market return for financial institutions. $\mu, \varnothing, \omega_1, \alpha_1$, and β_1 are the estimated parameters, σ_t^2 is the conditional variance, and $\xi_\mathrm{t} \sim$ i.i.d.N $(0, 1)$. Moreover, we consider $\Pr(R_t \leq \mathrm{VaR}) = \alpha$, where α represents the desired confidence level. This can be further expressed as: $\Pr\left(z_t \leq \frac{\mathrm{VaR}-\mu_t}{\sigma_t}\right) = \alpha$. By solving this equation, the VaR value can be obtained using the following equation.

$$\mathrm{VaR}_{\alpha,t} = \mu_t + \sigma_t z_{\nu,\eta}^{-1}(\alpha) \tag{10}$$

where $z_{\nu,\eta}$ represents the skewed Student's t distribution with ν and η as parameters. The values of μ_t and σ_t represent each financial institution's mean and standard deviation at time t.

Second, we transfer the expression of CoVaR to coordinate with the copula function.

[7]Value at Risk (VaR) was extensively employed as a prevalent approach for identifying systemic risk in previous studies. It calculates the potential monetary losses incurred within a specified confidence level. This approach is improved by a more comprehensive measure, conditional Value at Risk (CoVaR)(Tobias and Brunnermeier, 2016). By considering the conditional nature of risk, CoVaR provides insights into the potential contagion effects and systemic vulnerabilities that can arise within the financial sector.

[8]Hansen and Lunde (2005) compared the performance of 330 ARCH models in describing conditional variance and found that the AR(1)-GARCH(1,1) demonstrated superior performance compared to other models in analyzing exchange rate volatility.

The CoVaR method is implemented as follows. Considering $R_{i,t}$ as the return for financial institution i at time t, and $R_{m,t}$ as the return for the overall financial market, the CoVaR can be defined as the β-quantile of the distribution of $R_{m,t}$ based on the following conditional probability:

$$\Pr\left(R_{m,t} \leq \mathrm{CoVaR}_{\beta,t}^{m|i} \mid R_{i,t} \leq \mathrm{VaR}_{\alpha,t}^{i}\right) = \beta \tag{11}$$

where α and β represent the confidence level, typically set by financial regulators at 1% or 5%. Formulating Equation (11) as an unconditional bivariate distribution, we have:

$$\Pr\left(R_{m,t} \leq \mathrm{CoVaR}_{\beta,t}^{m|i} \mid R_{i,t} \leq \mathrm{VaR}_{\alpha,t}^{i}\right) = \alpha\beta \tag{12}$$

The third step involves incorporating the copula equation into the expression. Equation (12) is rewritten in terms of the joint marginal distribution function of $R_{m,t}$ and $R_{i,t}$ as follows:

$$C_{R_{m,t},R_{i,t}}\left(\mathrm{CoVaR}_{\beta,t}^{m|i}, \mathrm{VaR}_{\alpha,t}^{i}\right) = \alpha\beta = c(u,v) \tag{13}$$

where $C_{R_{i,t}}$ and $C_{R_{m,t}}$ represent the marginal densities of $R_{i,t}$ and $R_{m,t}$, respectively. The function $c(u,v)$ denotes the copula function from the selected copula family and can generally be expressed as $c(u,v) = \frac{\partial^2 C(u,v)}{\partial u \partial v}$.

Finally, we use the maximum likelihood method to solve for the parameters of the marginal distributions and estimate ΔCoVaR. We incorporate the time-varying parameters calculated previously into the copula functions at each time t. By solving the equation $u = C_{R_{m,t}}\left(\mathrm{CoVaR}_{\beta,t}^{m|i}\right)$, we can obtain the final estimation of FSR represented by the ΔCoVaR measure (Equation (14)):

$$\Delta\,\mathrm{CoVaR}_{\beta,t}^{m|i} = \left(\mathrm{CoVaR}_{\beta,t}^{m|i} - \mathrm{CoVaR}_{\beta,t}^{m|i,\alpha=0.5}\right) / \,\mathrm{CoVaR}_{\beta,t}^{m|i,\alpha=0.5} \tag{14}$$

By combining the copula function with the dynamic CoVaR approach, the calculation offers several notable advantages. First, the dynamic time-series CoVaR-Copula approach surpasses the traditional CoVaR approach by considering the impact of risk spillover effects between institutions and incorporating the interference of residual terms from the

GARCH model into the analysis. This approach's integration of copula functions demonstrates its superiority in capturing the independence and correlation between financial institutions and systems. Second, incorporating copula functions offers greater flexibility in estimating marginal and dependence structures, mitigating potential specification deviations during risk measurement calculations. Notably, the copula function effectively addresses issues related to tail independence, symmetry, and asymmetric tail dependence, which are associated with the CoVaR method. This flexibility enables a precise depiction of the dependence structure. Third, the Copula-CoVaR approach surmounts the limitations of connecting two non-normal distributions and describing the dependence structure solely through linear correlation coefficients inherent in the traditional CoVaR approach. The copula function provides a robust framework for capturing the complex dependence patterns between variables, allowing for accurate systemic risk analysis. Lastly, the dynamic nature of the time series CoVaR-Copula approach is particularly valuable in capturing the evolving interconnections among financial institutions, especially during crisis scenarios. The traditional static models may lead to deviations or even invalidity of the calculated results in such dynamic situations. The dynamic time series CoVaR-Copula approach yields more precise and reliable estimation results by accounting for changes over time.

We gathered monthly closing stock prices for 83 financial companies from the Shanghai Stock Exchanges, Shenzhen Stock Exchanges, and National Equities Exchange and Quotations (NEEQ)[9], along with the CSI 300 Index.[10] The data set covers the period from January 2017 to December 2020. Subsequently, we compute the returns for each stock, wherein each company's return is designated as $R_{i,t}$, and the return of the CSI 300 Index is denoted as the market return $R_{m,t}$. These values are subsequently employed in the calculation of ΔCoVaR.

[9]National Equities Exchange and Quotations (NEEQ) is the third national securities trading venue established with the approval of the Chinese government. It is primarily designed for companies with relatively smaller market capitalization than those listed on the main board. Some high-quality stocks listed on the NEEQ have gradually been transferred to the Beijing Stock Exchange.

[10]The CSI 300 Index is a constituent stock index compiled from 300 A-shares with large market capitalization and good liquidity selected from the Shanghai and Shenzhen stock markets. It is weighted by market capitalization and effectively reflects the state and fluctuations of the Chinese stock market.

4.3 Control Variables

Real Estate Climate Index ($RECI$) is derived from the national real estate industry, with real estate development investment serving as the underlying benchmark. It offers insights into the national real estate market and is a reference for development and investment decisions. $RECI$ is crucial in influencing FSR from a macroeconomic standpoint (Wu et al., 2021). We employ a monthly $RECI$ to capture investor sentiments and provide an outlook on the future economy.

Money Supply ($M2$) is an intermediate target for a country's monetary policy. It refers to currency in circulation and is regulated by governments and financial authorities to manage inflation or deflation. A higher growth rate of $M2$ can increase inflationary pressures, particularly during economic booms. Such inflationary pressures escalate systemic risks within the financial industry (Xu et al., 2018). We use the monthly growth rate of $M2$.

Consumer Price Index (CPI) is a key indicator of domestic inflation. A significant increase in the CPI suggests the presence of inflation, which becomes an economically destabilizing factor and contributes to the heightened systemic risk within the overall market. Following the approach of Wu et al. (2021), we use the growth rate of the CPI in the analysis.

Gross Domestic Product (GDP) indicates a country's economic performance and overall economic environment. A moderate increase in GDP signifies a stable and positive economic growth trajectory. A more stable macroeconomic environment tends to mitigate the likelihood of generating systemic risks (Chu et al., 2020). This study applies the GDP growth rate as a control variable.

Scale of financial institutions ($SIZE$) is important in risk management (Shleifer and Vishny, 2010). Large companies typically have more liquid assets and a more stable asset structure to withstand external risks. In this study, the size of financial institutions is represented by the logarithm of total assets.

Debt Ratio (DR) is the total debt ratio to total assets. It reflects the level of debt repayment capacity of a bank. A lower debt ratio indicates that financial institutions allocate more reserves to mitigate and withstand the risks associated with bad debts, thus enhancing their resilience against losses from non-performing loans. In other words, a lower debt ratio is generally associated with lower levels of FSR.

Return on Assets (ROA) is a financial metric that measures a company's profitability by calculating the after-tax net profit relative to its total assets. Companies with higher profitability often possess advantages in organizational structure, business decision-making, and risk control. However, a financial institution with higher profits may also engage in high-risk activities, potentially increasing systemic risks under adverse conditions.

Cash to Asset Ratio (CTA), obtained by dividing cash by current assets, measures short-term solvency. A financial institution with a higher cash-to-asset ratio is better equipped to respond to credit risks and potential crises. It has a stronger capacity to withstand risk and is less likely to be affected by risk spillover from other financial institutions, thus reducing the possibility of systemic risk (Lee et al., 2020).

5 Empirical Results

5.1 Descriptive Statistics

We analyze the correlation between AI and FSR within the Chinese financial sector from January 2018 to December 2020.[11] Our data are sourced from the CSMAR database, the China Statistical Yearbook, financial reports posted by listed companies on the stock exchange website, the website of the National Bureau of Statistics of China, and the Financial Technology Research Center of the Central University of Finance and Economics. Any abnormal or extreme values are excluded by applying the winsorization technique at the 1% and 99% quantiles to ensure data integrity. We gathered data from 83 financial companies in China and expanded them into monthly data, comprising 2988 observations. Table 2 presents the descriptive statistics of the data set. Following winsorization at the

[11] We focus on the period from 2018 to 2020 for two primary reasons. First, our access to data is limited to the information provided by the China Financial Science and Technology Research Center at the Central University of Finance and Economics and the China Stock Market and Accounting Research (CSMAR) database. Our data analysis heavily relies on their published data sets, making it challenging to extend the study to a longer period. Second, the field of financial technology in China had a late start—beginning in the year 2017—compared to other developed countries. As a result, it is difficult for us to collect data from earlier periods.

1% and 99% levels, the average Variance Expansion Factor Value (VIF) for all variables is less than 2, indicating no significant collinearity among the explanatory variables. The average FSR value is 0.117, with a standard deviation of 0.048. The FSR values range from 0 to 0.564, indicating substantial volatility in FSR during the sample period.

[Table 2]

5.2 Benchmark Regression Results

To explore the impact of AI on FSR, we construct the following panel data regression model:

$$\mathrm{FSR}_{it} = \alpha + \beta\, \mathrm{AI}_{it} + \gamma X_{it} + \varepsilon_{it} \tag{15}$$

where FSR_{it} refers to the financial systemic risks (ΔCoVaR) for each financial institution i at time t. AI_{it} represents the financial AI index, and α, β, and γ are coefficients. X_{it} are control variables related to both macroeconomic and firm-level financial factors, and ε_{it} is a random disturbance term.

Figure 5 illustrates the FSR of banks, securities companies, insurance companies, and other financial institutions (e.g., Private Equity (PE) & Venture Capital (VC) firms, financial consulting firms, and financial information services companies). Notably, the banking industry's FSR experienced a decline, whereas securities companies, insurance companies, and other financial institutions witnessed a slight increase. Furthermore, the figure highlights that, in general, the FSR in the insurance and banking industries is lower than in securities and other financial companies. The yellow and red lines exhibit more pronounced fluctuations, indicating that securities companies and PE/VC firms are more susceptible to external impacts and crises, leading to more volatile changes in FSR. Additionally, abnormal fluctuations in the overall FSR can be observed from early 2019, attributable to the sustained impact of the stock market crash in April 2015. Another significant swing occurred in January 2020 due to the outbreak of the COVID-19 pandemic.

[Figure 5]

Table 3 presents estimation results from the fixed effects regression models, and Figures 6 and 7 depict the relationship between FSR and AI. The results indicate that AI technologies play a significant role in restraining the growth of FSR, as evidenced by passing the significance test at the 1% level. Specifically, for every 1% increase in AI, FSR in China decreases by 5.6%. Models (2) and (3) are additional individual fixed effects models, but the sample has been divided into two periods: the crisis and non-crisis periods. The Chinese financial market experienced significant turbulence starting in March 2019, mainly due to the lingering impact of the severe stock crash in 2015 along with other major events.[12] Regression results from both periods reveal that AI continues to significantly suppress the growth of FSR, indicating its enduring impact on systemic risk reduction.

[Figure 6], [Figure 7] & [Table 3]

There may be several reasons accounting for this phenomenon. First, AI improves efficiency by automating tasks and reducing errors, allowing employees to focus on more valuable work. Second, AI enables intelligent monitoring, helping financial institutions detect and prevent risks such as expired loans, suspicious transactions, and cyber threats. The results also indicate that the impact of explanatory variables on FSR is different during the crisis and non-crisis periods. The variables related to the company's liquidity—such as the ROA and the cash-to-asset ratio—are significant at the 1% and 5% levels, respectively, during the non-crisis period but become insignificant during the crisis period. This indicates that financial institutions in China can manage the proportion of profits and cash to total assets and keep them relatively stable even though their total assets fluctuate with market systemic risks.

Models (4) and (5) examine the impact of AI on FSR in different types of institutions. The results consistently show that implementing AI reduces systemic risk across various financial sectors. Notably, the RECI affects systemic risk only in the non-banking industry, while banks' debt ratio is more closely related to systemic risk than in other financial companies. The different business scopes and priorities of these institutions can explain this. Banks benefit from machine learning technology for precise deposit-taking

[12]On March 21, 2019, Beijing Bank's announcement of establishing a foreign-owned joint-venture bank with ING Bank N.V., one of the largest banks in Holland, attracted widespread attention from financial practitioners and had a considerable impact on the stock market at that time. The intense fluctuations in the Chinese stock market subsided around March 2020.

and credit risk management, while securities and investment companies focus on building investment trend models and providing intelligent investment advisory services using knowledge graphs. Additionally, non-bank companies are more involved in real estate projects, leading to a stronger connection between RECI and systemic risk in this sector.

5.3 Robustness Tests

To address the potential endogeneity issues caused by interdependent economic variables, omitted variables, and sample selection bias, this study uses Two-Stage Least Squares (2SLS) regression and system generalized method of moments (GMM). System GMM is a widely used econometric estimation method in panel data analysis. This method extends the standard GMM by incorporating both the levels and first differences of the variables in the model simultaneously, effectively addressing the endogeneity issue. Furthermore, System GMM utilizes lagged dependent variables as instruments, enhancing the identification of model parameters and yielding more efficient estimation. Incorporating these features provides a robust framework for estimating panel data models and helps mitigate endogeneity concerns.

For the method of 2SLS, the regression models are as follows:

$$AI_{it} = \alpha_1 + \beta_1 IV_{it} + \gamma_1 X_{it} + \varepsilon_{it} \tag{16}$$

$$FSR_{it} = \alpha_2 + \beta_2 \widehat{AI}_{it} + \gamma_2 X_{it} + \mu_{it} \tag{17}$$

where AI_{it} represents the AI index, and $\widehat{AI}_{it}$ denotes the fitted value. The remaining symbols have the same definitions as mentioned earlier. The relationship between FSR and AI adoption has received limited attention in previous research, resulting in a scarcity of effective instrumental variables for reference. We choose the ratio of research expenditures to total expenses within financial institutions as the instrument variable. Financial institutions in China currently acquire AI systems through foreign purchases or by developing them internally with the help of in-house technicians. The expenses allocated to support AI development are classified as "research expenditure" in the financial statements. A higher proportion of research expenditure indicates a greater likelihood of AI development within the financial institution. The allocation of research funds for technology development and system construction is determined by management's decision-making, which can be considered an exogenous factor with no direct relationship to FSR. Therefore, we assert that the ratio of research expenditures to total expenses qualifies as a suitable instrumental variable for this study.

Table 3 shows the 2SLS regression results in the columns of Models (6) and (7). We can see from the results that the impact of AI on FSR is still significant even though the endogenous problems have been eliminated. Model (6) shows that the higher the proportion of research expenditure, the higher the AI adoption rate will be for financial institutions. Furthermore, following Andrews et al. (2019), we conduct several tests on instrumental variables. The results indicate that IV has passed the robustness test for weak instruments, reflecting that our selection for IV is effective.

The results under System GMM are presented in Models (8) and (9). Model (8) displays the estimated results of System GMM without incorporating control variables. Model (9) presents the results of System GMM with control variables. The coefficients of AI in both models remain negative and significant, indicating that AI technologies effectively reduce FSR. The results are consistent with the findings of the benchmark regression. Several tests are conducted to assess the validity of IVs. The autocorrelation of the disturbance term is examined using AR(1) and AR(2) statistics, while the exogeneity of the IVs is assessed using the Hansen test. The P-value of the AR(1) and AR(2) indicates the presence of first-order autocorrelation and the absence of second-order autocorrelation. Meanwhile, the P-value of the Hansen test is greater than 0.1, suggesting the effectiveness of the IVs applied in System GMM.

We also implement the robustness test by replacing the measurement method of the dependent variable and core explanatory variable while controlling for the interference of crisis periods. For the indicator of FSR, Festic et al. (2011) adopt the Non-performing Loan (NPL) rate[13] to reflect the contribution of financial institutions in systemic risk. However, Li et al. (2020) choose the Z-score value[14] as the indicator of potential risk.

[13]The NPL rate is calculated as the non-performing loans to total gross loans.

[14]For the calculation of the Z-score, we follow Altman et al. (1994), and the expression is $Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5$, where X_1=working capital/total assets, X_2=retained earnings/total

Therefore, financial institutions' Z-value and NPL ratio are selected as substitute variables for FSR. Moreover, we introduce an alternative core explanatory variable: the number of AI systems adopted by the listed financial institutions. This variable, denoted as $AI2$, encompasses various forms of AI systems' generation, including outsourcing, independent research and development, and collaborative development. The results for the robustness test are shown in Table 4. Models (10) and (11) replace FSR with Z-score and NPL ratio, respectively, while Model (12) changes the AI index to the number of AI systems adopted by each company. Even though the core explanatory variables impact systemic risk in varying degrees after replacing the variables, their impact on FSR remains the same. Therefore, we confirm our models' robustness and AI's significant role in FSR.

[Table 4]

5.4 Heterogeneity Analysis

We add the interaction terms of size and AI ($AI \times SIZE$), dummy variables of the special period and AI ($AI \times Crisisperiod$, where crisis periods equal one, otherwise zero), and dummy variables of business nature and AI ($AI \times industry$) to explore the mediating effect of the scale, particular market environment and business nature on the role of AI in FSR. All the results are presented in Table 4.

Model (13) demonstrates the statistically significant impact of the interaction term $AI \times SIZE$ at the 1% significance level, suggesting that the influence of AI on systemic risk varies depending on the size of financial institutions. Specifically, larger financial institutions exhibit a stronger relationship between AI adoption and the reduction of FSR. This can be ascribed to larger institutions often having greater systemic importance and engaging in higher-risk activities. They are more susceptible to liquidity issues and market failures during crises, leading to higher systemic risk levels. These larger institutions can effectively mitigate systemic risk and enhance stability by adopting AI systems. This result is consistent with Gennaioli et al. (2013) and Wu et al. (2021).

assets, X_3=earnings before interest and tax/total assets, X_4=market value of equity/book value of total debt, and X_5=revenue/total assets. When the Z-value exceeds 2.9, the enterprise is considered safe with a low risk of bankruptcy; otherwise, it indicates a high credit risk and instability.

Model (14) examines the effect of AI on FSR in different economic conditions. The positive coefficient of $AI \times Crisisperiod$ suggests that the role of AI in influencing FSR becomes more pronounced during unfavorable market conditions. This finding implies that higher AI adoption rates may limit the flexibility of companies' business operations during crises, thereby exacerbating their contribution to FSR within financial institutions. Model (15) reveals the role of business nature on the relationship between AI and FSR. The coefficient is at the highest significance level for banks and insurance companies, suggesting that the impact of AI adoption on mitigating FSR is more pronounced in the banking and insurance industries compared to other types of financial institutions. As for securities companies, the effect of AI in suppressing FSR is not stronger than in other financial service companies.

5.5 Mechanism Test

The rapid development of AI has influenced workforce composition and organizational structure inside the firm. With increasing demands on new technology for human capital, AI as an advanced technology is positively associated with productivity and employment (Yang, 2022). Adopting robots in industries has improved labor and total factor productivity while reducing job opportunities for low-skilled workers (Graetz and Michaels, 2018). Wang et al. (2021) examine the impact of skill-biased technological change on employment and wages in 33 industries in China. The results indicate that technological advancements, such as AI and machine learning, have a significant positive effect on the wages and employment in positions that require mastery of core technologies and minimal labor but no perceptible impact on the wages and employment of workers with moderate technical skills who are not at the cutting edge. Ballestar et al. (2020) also find links between applying digital techniques, productivity, and employment rates.

In the relationship between human capital and FSR, Schneider et al. (2023) point out that the demand for highly skilled talent in the banking industry is typically associated with lower systemic risk and profitability. Marek et al. (2020) study the effects of the COVID-19 pandemic on human capital and indicate that the pandemic has led to the optimization of workloads and the simplification of non-essential processes, which has further promoted financial inclusion and resulted in increased FSR. For instance, during the COVID-19 outbreak, banks' capacity to provide cash withdrawals was limited, and more employees were distributed to support online services. This change in the employment structure, the widespread use of financial AI and digital products, and the demand for capital inflow have led banks to accept customers with poor credit ratings. As a result, systemic risks increased under this series of mechanisms.

As the transformed employment structure is closely related to the risks in society as a whole and considering the effect of labor substitution brought by the massive application of the financial AI system, whether human capital can be treated as a mediator between AI and FSR will be explored in this section. Accordingly, we propose the hypothesis: *AI depresses the increase of financial systemic risk by enhancing the human capital of financial institutions.*

We explore the existence of the mediation effect by conducting the Sobel-Goodman Mediation Test to verify the results (Table 5). Models (16) and (17) present the regression analyses between FSR and AI and human capital and AI, respectively. Model (18) demonstrates the mechanism tests that utilize EDU as the mediator. The mediation test shows a high significance level, indicating that AI technologies reduce FSR by raising the average education level of financial institution employees. Furthermore, the coefficients for $LnAI$ and EDU are statistically significant, suggesting no complete mediation of human capital in the relationship between AI and FSR. In other words, even after controlling for the mediating variable's influence, AI's direct effect on FSR still persists, confirming our hypothesis.

[Table 5]

This finding aligns with the conclusions drawn by previous studies (Wang et al., 2021; Innocenti and Golin, 2022). These studies posit that the advent of AI technologies serves as an impetus for individuals to seek higher education, leading to an increase in the proportion of high-skilled labor; this shift in labor market composition is positively associated with a reduction in systemic risk. In contrast to Qian et al. (2022), which primarily focuses on the mediating effect of AI on green economic growth, we innovatively establish a link between AI and systemic risk through the mediating effect of human capital. By examining this mediating relationship, the present research contributes to the existing literature and extends our understanding of the implications of AI in the context of systemic risk.

6 Conclusions

We investigate the impact of AI on systemic risk in the financial industry, and this paper contributes practical significance to the current literature and offers a unique review of the adoption of AI technologies. While previous studies have predominantly focused on the impact and application of AI on productivity, firm performance, and employment structure, we provide a novel review of the non-diversifiable risk associated with widespread AI adoption to fill this knowledge gap. Meanwhile, recognizing that past studies were primarily conducted based on theoretical derivation, industrial surveys, and case studies, we support the previous studies with an empirical analysis based on a firm-level AI index, offering a comprehensive and quantitative understanding of the relationship between AI and FSR.

The results reveal several important findings. First, the systemic risk in China's banking and insurance sectors is lower than in securities and other financial companies. Moreover, FSR decreases in the bank sector while increasing in securities, insurance, and other financial institutions. The analysis also indicates extreme events significantly elevate FSR during the corresponding period. This highlights that FSR tends to increase under such extreme circumstances while exhibiting relatively lower fluctuations in more stable economic environments. Second, we show that adopting AI technologies and systems in the financial industry helps mitigate the escalation of FSR. The robustness tests conducted further confirm the validity and reliability of this result. However, when considering the influence of AI on FSR across different financial sectors, the results show distinct patterns. More specifically, the application of AI in the banking and insurance industries exhibits greater effectiveness in reducing FSR compared to other types of financial institutions. Conversely, the impact of AI on FSR in the securities industry does not appear to be stronger than in PE/VC and other financial agent companies. Third, using the mediating effect model, this study concludes that AI can reduce FSR by improving the human capital of financial firms. However, even after controlling for the mediating variable's influence, AI's direct effect on FSR persists.

Despite the initial findings indicating that the current utilization of AI technologies in China's financial industry effectively helps decrease systemic risk, it is crucial to exercise caution due to the relatively low development and adoption of AI systems and related products. The two-sector model employed in this study is a reminder that the excessive introduction of financial AI in the future may still pose the potential chance of increasing FSR. This highlights the demand for a balanced approach in integrating AI technology to maximize benefits while minimizing potential adverse effects on systemic stability. Further research and monitoring are necessary to assess the long-term implications of widespread AI implementation and its impact on the entire financial industry.

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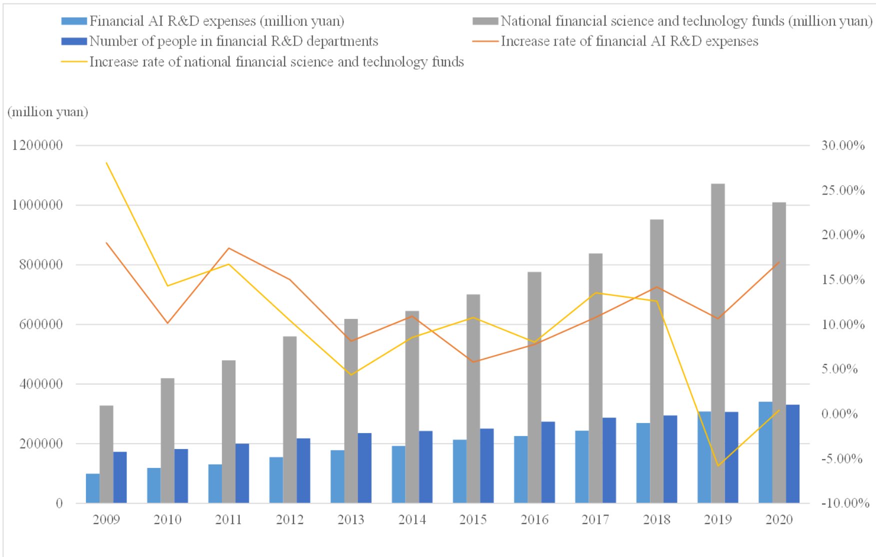
Figure 1: AI related R&D expenditure of financial institutions and government



Note: The data are obtained from CSMAR database (https://cn.gtadata.com/).

Figure 2: Financial innovation and default or bankruptcy of financial institutions

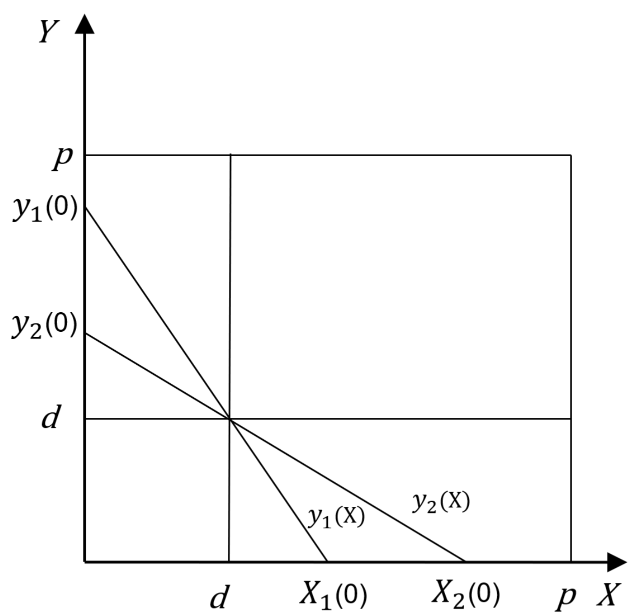


Figure 3: Individual risk of financial institution

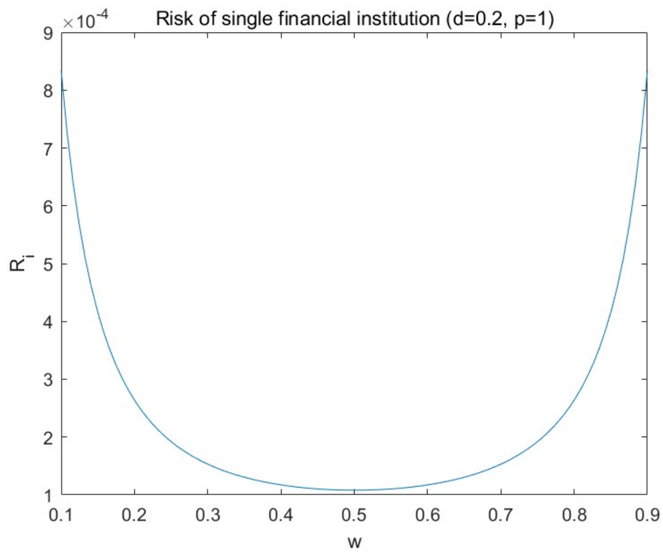


Figure 4: Systemic risk of financial system

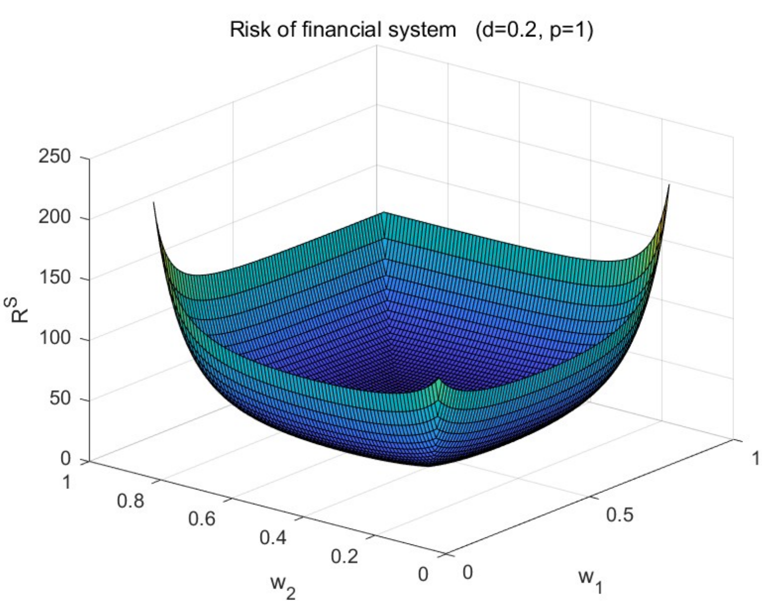


Figure 5: Systemic risk of the financial industry in China (2018-2020)

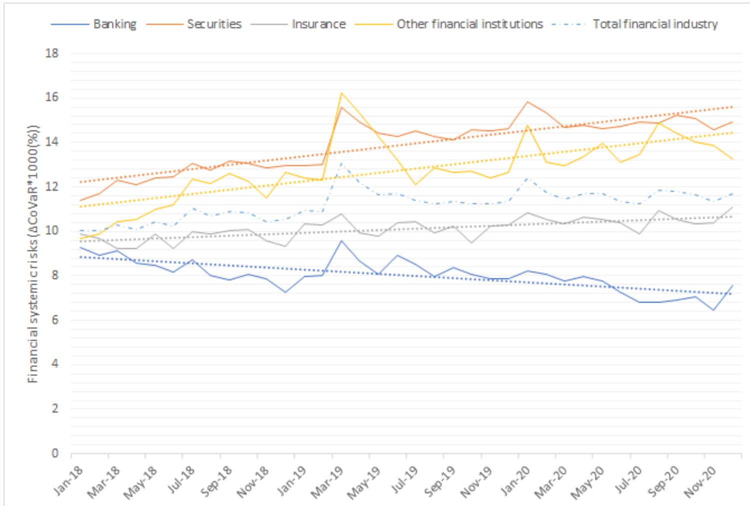


Figure 6: Systemic risk of the financial industry and AI in China (2018-2020)

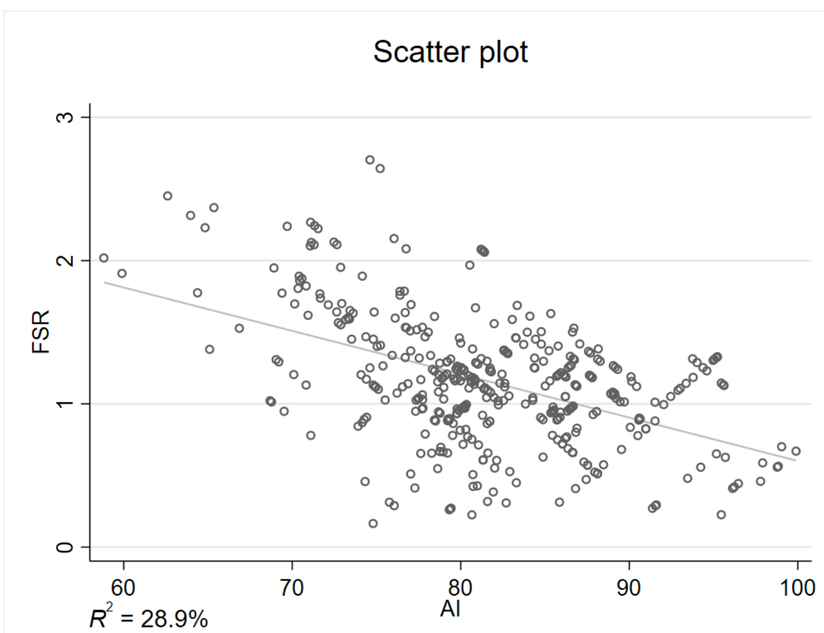
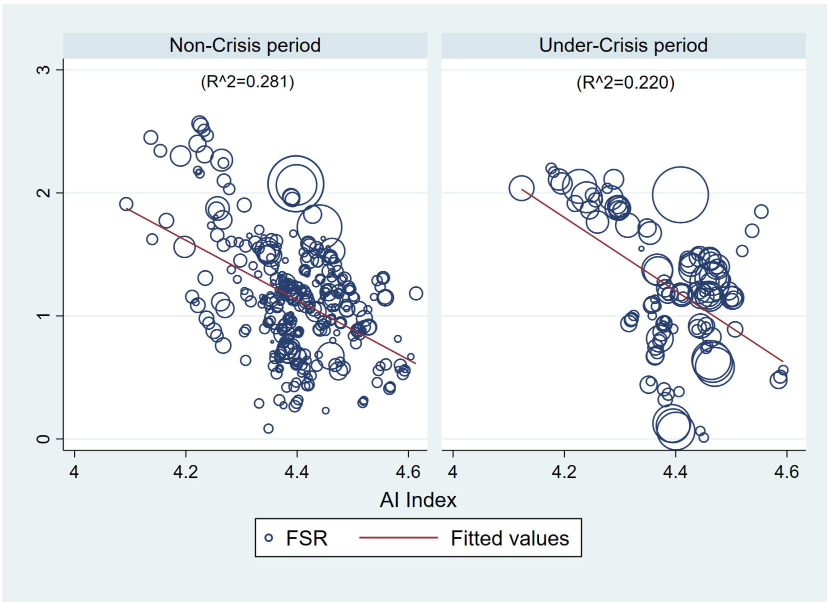


Figure 7: FSR and AI under Crisis and non-Crisis period in China (2018-2020)



Note: We adopt return on assets (ROA) as a weight to create this figure. Each bubble's size corresponds to the companies' profitability, with larger bubbles representing higher profit rates. We can see from the figure that a negative relationship exists between AI and FSR during both periods.

Table 1: Different copula functions and their definitions

Copula type	Expression	Characteristic
Gaussian Copula	$C_{\mathrm{GA}}(u, v; \rho) = \Phi_\rho\left(\Phi^{-1}(u), \Phi^{-1}(v)\right).$	a symmetric copula with zero tail dependence
Student's t Copula	$C_{\mathrm{ST}}(u, v; \rho, n) = T_{\rho,n}\left(t_n^{-1}(u), t_n^{-1}(v)\right)$	a symmetric copula with symmetric tail dependence
Gumbel Copula	$C_{\mathrm{GU}}(u, v; \delta) = \exp\left(-\left((-\log u)^\delta + (-\log v)^\delta\right)^{\frac{1}{\delta}}\right).$	an asymmetric copula with an upper tail dependence
180 Rotated Gumbel Copula	$C_{\mathrm{RGU}}(u, v; \delta) = u + v - 1 + C_{\mathrm{GU}}(1-u, 1-v; \delta).$	an asymmetric copula with a lower tail dependence
Clayton Copula	$C_{\mathrm{CL}}(u, v; \delta) = \max\left\{\left(u^{-\delta} + v^{-\delta} - 1\right)^{-\frac{1}{\delta}}, 0\right\}$	an asymmetric copula with an lower tail dependence
Rotated Clayton Copula	$C_{\mathrm{RCL}}(u, v; \delta) = u + v - 1 + C_{\mathrm{CL}}(1-u, 1-v; \delta).$	for upper tail dependence
SJC Copula	$C_{\mathrm{SJC}}\left(u, v; \tau^U, \tau^L\right) = 0.5\left(C_{\mathrm{JC}}\left(u, v; \tau^U, \tau^L\right) + C_{\mathrm{JC}}\left(1-u, 1-v; \tau^U, \tau^L\right) + u + v - 1\right)$	both for asymmetric and symmetric tail dependence

Table 2: Descriptive statistics

Variable	Obs	Mean	P50	S.D	Min	Max	Skewness	Kurtosis	Vif
FSR	2988	0.117	0.116	0.048	-0.218	0.346	0.363	4.219	—
AI	2988	81.44	80.58	6.920	58.39	100.0	0.092	3.224	1.48
$RECI$	2988	100.9	101.1	1.049	97.44	102.0	-1.468	5.081	1.85
$M2$	2988	0.682	0.653	0.724	-0.664	2.467	0.371	2.821	1.09
CPI	2988	0.002	0.001	0.036	-0.136	0.165	0.960	17.31	1.04
GDP	2988	0.057	0.063	0.013	0.023	0.069	-0.012	3.159	1.50
$SIZE$	2988	26.15	25.82	2.354	20.62	31.14	0.087	2.620	4.46
DR	2988	0.753	0.777	0.196	0.014	0.943	-1.675	5.734	3.48
ROA	2988	0.010	0.007	0.016	0.044	0.241	6.982	7.992	1.33
CTA	2988	0.151	0.125	0.114	0.010	0.609	0.623	2.787	1.29
time	2988	18.50	18.50	10.39	1	36	0	1.798	—
id	2988	42.69	43	24.34	1	83	-0.0200	1.794	—

Note: FSR refers to the financial systemic risk; AI is the artificial intelligence; $RECI$ represents the Real State Climate Index; $M2$ is the money supply; CPI is the growth rate of the Consumer Price Index; GDP represents the growth rate of GDP; $SIZE$ is the logarithm of total asset; DR refers to the debt ratio; ROA and CTA represent the return on asset and cash to asset ratio respectively.

Table 3: Regression results

	Model(1)	Model(2)	Mode(3)	Mode(4)	Model(5)	Model(6)	Model(7)	Model(8)	Model(9)
	All samples(FE)	No crisis	Under crisis (2019.03-2020.03)	Banking	Non-banking	First stage	Second stage	Sys GMM	Sys GMM
Variables	FSR	FSR	FSR	FSR	FSR	AI	FSR	FSR	FSR
IV						150.967***			
						(5.77)			
FSR_{t-1}								0.068**	-0.048**
								(0.54)	(-0.65)
AI	-0.056***	-0.061***	-0.064***	-0.098***	-0.095***		-0.134***	-0.084***	-0.065***
	(-35.36)	(-31.27)	(-27.14)	(-23.71)	(-14.16)		(-6.20)	(-6.05)	(-3.00)
$RECI$	-0.016***	-0.016**	-0.021***	-0.002	-0.005**	0.129	-0.002*		-0.004
	(-3.96)	(-2.48)	(-2.38)	(-0.21)	(-2.52)	(1.06)	(-0.13)		(-0.49)
$M2$	-0.003	-0.006	0.010	-0.007	0.0002	0.071	0.004		-0.009
	(-0.72)	(-0.89)	(1.44)	(-1.08)	(0.79)	(0.47)	(0.22)		(-1.53)
CPI	-0.483***	-0.058**	-0.503***	0.031**	-0.061***	3.435	-0.221		-0.310**
	(-4.88)	(-0.46)	(-3.74)	(2.33)	(-1.35)	(1.17)	(-0.59)		(-2.24)
GDP	-0.012***	-0.008***	-0.094**	-0.001**	-0.004**	0.736***	-0.094***		-0.713
	(-3.31)	(-2.10)	(-2.80)	(-1.41)	(-2.30)	(7.70)	(-4.98)		(-1.08)
$SIZE$	-0.034*	-0.066**	0.014	-0.006	-0.004*	2.501***	0.256***		-0.455
	(-1.72)	(-2.95)	(0.43)	(-1.44)	(-1.56)	(30.39)	(4.71)		(-2.03)
DR	0.130*	0.176*	-0.006	-0.026**	0.023	-11.613***	-1.155***		1.667
	(1.15)	(1.38)	(-0.03)	(-2.09)	(0.54)	(-11.82)	(-3.87)		(1.12)
ROA	0.783**	1.795***	-0.352	-0.082	-0.017	-120.352***	9.979***		-2.381
	(2.37)	(4.06)	(-0.92)	(-0.07)	(-0.13)	(-4.09)	(7.59)		(-1.18)
CTA	0.042***	0.048***	-0.019	0.023***	0.002***	0.521***	0.237***		-0.057***
	(4.35)	(4.46)	(-1.30)	(0.98)	(0.39)	(5.00)	(14.47)		(-0.62)
_cons	8.045***	9.237***	7.669***	-7.126***	9.520***	5.957	5.477***	7.963	10.83***
	(11.84)	(10.28)	(6.59)	(-28.23)	(35.05)	(0.49)	(3.62)	(6.41)	(1.02)
CompanyFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	2988	1,909	1,079	936	2052	2,988	2,988	2,988	2,988
R2	0.289	0.281	0.220	0.281	0.255	0.321	0.342		
Number of companies	83	83	83	26	57	83	83	83	83
Underidentification test							11.553***		
							(0.00)		
Weak instrumental variable test							20.017		
AR(1)-P value								0.025	0.024
AR(2)-P value								0.156	0.159
Hansen test-p value								0.102	0.117

Notes: (1) t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1 (2) The Underidentification test refers to the Kleibergen-Paap rk LM statistic. The P-value is less than 1%, indicating that the null hypothesis of "insufficient identification of instrumental variables" is rejected at the 99% level. (3) A weak instrumental variable test is conducted based on minimum eigenvalue statistics. The instrumental variables should meet the conditions of relevance and exogenous. When the correlation is weak, the problem of "weak instrumental variables" will arise. We use the F-statistic to test for the significance of excluded instruments. If the first-stage F-statistic is smaller than 10, it indicates the presence of a weak instrument. (4) Models (8) and (9) take the 1st to 4th order lag terms of FSR, 1st to 3rd order lag terms of core explanatory variable and control variables as GMM-type instrument variables, and set time (month) as IV-type instrument variables. (5) AR(1)-p value and AR(2)-p value is derived from the Arellano-Bond test for AR(1) and AR(2) in first differences. (6) The Hansen test-p value is derived from the Hansen J statistic, which tests the exogenous of instrumental variables. The p-value is larger than 0.1, indicating that the null hypothesis of 'all instrumental variables are exogenous' can not be rejected at the 90% level.

Table 4: Robustness test and heterogeneity analysis

	Model(10)	Model(11)	Model(12)	Model(13)	Model(14)	Model(15)
VARIABLES	Z-Score	NPL ratio	FSR	FSR	FSR	FSR
AI	-0.417**	-0.007*		-0.602***	-0.054***	-0.096***
	(-28.77)	(-2.01)		(-41.73)	(-34.62)	(-16.13)
$AI2$			-0.054*			
			(-33.53)			
$AI \times SIZE$				0.021***		
				(38.02)		
$AI \times CrisisPeriod$					0.0006***	
					(5.80)	
$AI \times Industry1$						-0.197***
						(-22.89)
$AI \times Industry2$						0.001
						(1.36)
$AI \times Industry3$						-0.172***
						(-60.28)
_cons	69.050***	-28.551***	7.223***	0.041***	0.039***	0.003***
	(11.02)	(-7.78)	(10.46)	(40.41)	(10.46)	(22.89)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
CompanyFE	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,988	2,988	2,988	2,988	2,988	2,988
R-squared	0.3269	0.1803	0.2956	0.5614	0.2921	0.2694

Note: (1) t-statistics in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$; (2) $AI2$ is the number of listed financial institutions reporting the adoption of AI technologies and systems. The type of AI technologies reported by listed companies includes outsourcing, independent R&D and cooperate development; (3) $SIZE$ denotes the total asset scale of companies;(4) $CrisisPeriod$ refers to the period from March 2019 to March 2020 since China was experiencing a financial crisis and COVID-19 pandemic. The rest of the period is treated as a non-crisis period. (5) $Industry1$, $Industry2$, and $Industry3$ refer to the banking, securities, and insurance companies. In the analysis, We treat $Industry1$, $Industry2$, and $Industry3$ as the experimental group, while other types of financial companies - such as PE, VC, and other financial service companies - are considered the control group.

Table 5: Mechanism test

	Model(16)	Model(17)	Model(18)
VARIABLES	FSR	EDU	FSR
$LnAI$	-4.672***	2.039***	-4.635***
	(0.114)	(0.045)	(0.168)
EDU			0.185***
			(0.051)
_cons	21.710***	-6.517***	20.387***
	(0.499)	(0.196)	(0.659)
CountryFE	Yes	Yes	Yes
YearFE	Yes	Yes	Yes
Sobel-Goodman Mediation Tests			0.640***
			(0.340)
Observations	2988.00	2760.00	2760.00
R-squared	0.2322	0.4425	0.8578

Notes: (1)Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; (2) $LnAI$ refers the logarithm of AI index; (3) EDU is the human capital of a financial institution, represented by the per-capita education level of the total employees in each firm; (4) Sobel-Goodman Mediation Test is developed to test the mediating effect among variables. The P-value of the Sobel test is smaller than 0.01, indicating human capital is an effective mediator; (5) There are only 2760 observations available for Model (17) and Model (18) due to missing variables in the human capital data. As a result, the data set was reduced in size for these two models.