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AI and Financial Systemic Risk in the Global Market*

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Abstract

As artificial intelligence (AI) emerges as a key driver of Industry 4.0, nations are vying for a competitive edge in AI advancements, innovation, and applications. This study investigates AI's role in the financial system by delving into the intricate relationship between AI and financial systemic risk (FSR) across diverse contexts. The results show that, first, AI investment is generally associated with increased FSR. Second, global risk spillover is observed in the FSR of various countries. Extreme events can lead to a sharp and simultaneous increase in FSR across nations. In addition, after removing global risk spillover, the FSR dynamics of countries do not strictly conform to geographical proximity. Third, mechanism analysis reveals that AI increases FSR by enhancing the interconnectedness between entities and raising unemployment.

JEL classification: O16; O33; G20; G32
Keywords: Artificial intelligence; Financial systemic risk; Bayesian dynamic factor model; Global risk spillover; Cross-nation analysis

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1 Introduction

Ensuring financial stability has remained a focal point of international regulatory efforts. From the oil crisis of the 1970s and financial crises of 1997 and 2008 to the global financial market turbulence sparked by the COVID-19 pandemic in 2020, every external shock and economic upheaval has been closely tied to fluctuations in financial markets. For governments, financial institutions, or individuals, predicting and analyzing macroeconomic trends have become a crucial focus for policy adjustments and prudent financial decision-making.

In this regard, integrating macroprudential policy into the financial stability framework has emerged as a prominent topic among governments and scholars worldwide (Frait and Komárková, 2010; Ellis et al., 2014; Apergis et al., 2022). Čihák (2007) argues that the failure rate of individual financial institutions, the extent of losses, and interconnectedness between enterprises are the three major factors determining financial stability and cumulative systemic risk. Acemoglu et al. (2015) emphasize that internal interconnectedness within financial enterprises is a significant factor influencing financial stability. While high interconnectedness allows financial institutions to share high resilience, it also increases the financial system's vulnerability and potentially amplifies systemic risk. Advocating for establishing relevant policies before introducing innovations, Adrian et al. (2015) suggest that identifying and tracking systemic risk can effectively promote financial stability. Since financial stability and financial systemic risk (FSR) are closely intertwined, effectively managing FSR and identifying the sources of FSR, particularly in today's rapidly evolving technological landscape, are vital.

Indeed, measuring FSR has emerged as a focal point of intense discussion and research. The conditional value at risk (CoVaR) method (Adrian and Brunnermeier, 2008) has been widely adopted, further explored, and integrated with other techniques that more accurately capture tail risk and interconnections between financial institutions (Wang et al., 2014; Karimalis and Nomikos, 2018). Striving to grasp the essence of FSR and enhance control measures, Frait and Komárková (2010) highlight that systemic risk manifests through temporal accumulation within economic cycles and cross-sectional contagion. Markose et al. (2012) and Laeven et al. (2016) demonstrate the interconnectedness between financial institutions plays an important role in shaping FSR dynamics. Cross-national research (Chen et al., 2021) shows that the similarity of banking systems amplifies systemic risk, with banks contributing more substantially to systemic risk within the financial system than other sectors, like insurance (Cummins and Weiss, 2014). Likewise, the financial network structure influences FSR

(Acemoglu et al., 2015). Furthermore, factors such as size, global activities, and engagement in non-traditional banking activities contribute to the accumulation of FSR (Laeven et al., 2016; Qin and Zhou, 2019; Duan et al., 2021).

Numerous scholars have also noted the variations in and diversification in the manifestations of FSR across different countries. Engle et al. (2015) study FSR in European Union (EU) countries from 2000 to 2012, and find that the FSR in France, Germany, and the UK was significantly higher than that in other countries. This is because Germany and France have higher leverage ratios, while the UK has a relatively lower leverage ratio but a larger market capitalization. Countries with higher levels of collectivism, social trust, and power distance also demonstrated better regulatory capabilities to manage sudden and significant fluctuations in FSR (Hofstede, 2001).

Meanwhile, as an intricately sophisticated tool, artificial intelligence (AI) is revolutionizing entire industry processes and social structures (Acemoglu and Restrepo, 2018; Graetz and Michaels, 2018). While governments and businesses concentrate on advancing and developing AI-related products and systems, stakeholders are becoming increasingly aware of the potential risks and significant impacts on human well-being associated with AI technology. Discussions about restraining and controlling AI development regarding labor structures, employment, ethics, information security, and human rights protection have garnered widespread attention from scholars and the public (Mantelero, 2018). However, the role of AI technologies in the financial network, particularly its effect on FSR, remains relatively under-explored. As the outbreak of FSR cannot be effectively mitigated by individual institutions or countries acting alone, examining the impact of AI on FSR within a macroprudential framework and across countries is important.

Building upon the previous studies, we comprehensively explore the relationship between AI adoption and FSR across 27 countries. These countries encompass a diverse array of economic backgrounds, policy systems, trade partnerships, financial frameworks, and geographical placements, allowing us to delve into AI's varying impacts across a spectrum of nations with their distinct economic environment. We first summarize the literature regarding financial innovation's influence and AI technologies' application on FSR. Then, we employ a Bayesian dynamic factor model to decompose FSR into global and regional components and conduct full-sample and grouping regression analyses to explore AI's impact on systemic risk. Finally, we also explore two mediators between AI and FSR: interconnectedness and unemployment. Our methodology provides an empirical assessment of the impact of AI on FSR in the international market, providing a comprehensive global perspective on the influence of AI on FSR.

2 Research Background

Defining AI's role within regulations, gaining human trust in financial AI, and understanding how new policies related to AI participation affect the financial system are three important conceptual issues when considering the integration of AI in the financial industry (Danielsson et al., 2022). Like other innovation tools, the impact of AI on FSR can be discussed within the framework of financial innovation.

In discussions surrounding financial innovations and systemic risk, some studies approach the topic from a risk-sharing perspective. Merton and Bodie (1995) and Vallascas and Keasey (2012) believe that financial innovation can enhance a financial system's risk-sharing ability and increase financial stability. Gai et al. (2008) argue that financial innovation reduces the likelihood of financial crises in developed countries under decent regulation. Crockett and Cohen (2001) and Wu (2023) propose a U-shaped relationship between financial technology development and FSR. These authors believe that rapid technological changes in the financial industry may introduce instability in the short term. However, innovations can mitigate systemic risk in the long term by diversifying assets and business models.

However, financial innovation may also promote asset liquidity and interconnection between financial institutions. This viewpoint suggests that financial innovation destabilizes the financial system, increases FSR, and triggers financial crises (Kim et al., 2013; Instefjord, 2005; Dewally and Shao, 2013). Aghion et al. (2005) and Li et al. (2020) explain the innovation effect on FSR from a corporate strategy angle. Innovation efforts from peer firms may increase competition and information asymmetry within the financial market, exacerbating FSR spillover from the non-financial sector to the financial sector. Additionally, continued globalization and the increasing complexity of financial networks, driven by financial innovation, have rendered the financial system more fragile, amplifying the outbreak of systemic risks and financial crises. Meanwhile, current financial institutions and regulators have struggled to keep pace with the ongoing reforms driven by financial innovation to address the accumulation of systemic risks, underscoring the urgent need for structural changes in global governance (Goldin and Vogel, 2010).

As one of the most crucial innovative technologies in Industry 4.0, the widespread adoption of AI brings new operational structures and opportunities to the financial industry. Like financial innovation, AI may introduce numerous potential risks to the financial system (Svetlova, 2022). The inaccurate information provided by chatbots (Yigitcanlar et al., 2020) and the absence of privacy protection during personal data collection may potentially give rise to new types of risks in AI applications (Galaz et al., 2021). Simultaneously, the risks generated by AI may combine with other types of risks, such as market and compliance risks, resulting in new risks like digital sovereignty and innovation risks (Novelli et al., 2023). Therefore, constructing trustworthy financial AI systems and products can help mitigate AI-related risks. Dastin (2022) focuses on identifying the drivers that could exacerbate the risks introduced by AI, such as privacy information leaks, inadequate regulation and corresponding policies, and the emergence of ethical and moral concerns in machine learning, including discriminatory notions related to race, income, and gender. In the future development of AI, higher demands will be placed on the impartiality, privacy, compliance, robustness, and accuracy that AI systems can achieve (Alzubaidi et al., 2023). Thus, against this backdrop of the widespread adoption of AI products and systems by various institutions, the impact of AI on systemic risk has become an important research topic. While the literature has expressed concerns about the potential impact of AI on FSR, only a few researchers have substantiated these theories through empirical analysis by directly examining AI's impacts on FSR with diverse indicators.

This study makes important contributions by introducing notable innovations and novel insights. First, our analysis provides clear statistical evidence linking FSR and AI from a panel of various countries in different regions. This broad geographical scope offers a universal overview of the impact of AI technologies on systemic risk in the global financial system. Second, we creatively decompose FSR in each country and extract the global spillover effect and regional factors. This unique approach allows us to observe the idiosyncratic changes in FSR within a nation after excluding the global spillover effect. We also introduce global and regional FSRs, deviating from the traditional use of time-fixed effects. The decomposition enables us to directly explore the relationship between AI and FSR while controlling for global spillover effects and other macroeconomic variables. Finally, our study substantiates the theory proposed by Kero (2013), Chen and Du (2016), and Wagner (2010), affirming that unrestrained financial innovation may potentially increase FSR in a country or the global market. This empirical work adds a practical dimension to existing theoretical frameworks, offering insights into the implications of innovation and diversification strategies inside financial institutions.

3 Theoretical Basis

Our theoretical framework draws upon Kero (2013), Tobias and Brunnermeier (2016), and Chen and Du (2016), who elucidate the intricate interplay between financial instability, systemic risk, and financial innovation. Assume that a financial institution i initially distributes its assets between risky and risk-free assets based on its risk preference. With the advent of AI-based systems and products, the institution can leverage AI to develop new financial products, investing in these AI-related assets—either developed internally or purchasing from other firms—and earning profits from these innovative assets (hereafter, financial innovation assets).[1] On the one hand, the institution may allocate some funds to financial innovation assets to hedge the risk associated with risky investments or enhance profits, as the returns from innovation assets may surpass those from risky assets. On the other hand, the rational institution aims to minimize its allocation to risk-free assets due to their comparatively lower returns. Under these assumptions, the total assets of a financial institution can be defined as follows:

Definition 1 *The total assets of a financial institution (P_A) comprise three primary components: the risky assets (P_R), the risk-free assets (P_F), and newly introduced financial innovation assets (P_{Inno}). These are appropriately utilized by financial enterprises for optimizing profit: $P_A = P_R + P_F + P_{Inno}$. P_{Inno} represents the innovation level since R&D funding increases the likelihood of innovation (Heimonen, 2012). A larger P_{Inno} suggests that financial institutions put more effort into innovation development, thus suggesting a higher innovation level.*

These three types of assets generate different returns for the firm. Based on the high-risk, high-return principle, we assume that the returns from risky and innovation assets will exceed those from risk-free assets. However, it is uncertain whether the returns from innovation assets exceed those of risky assets.

In real world, AI-based innovation assets and traditional risky assets usually operate in the same financial market. Their returns are significantly influenced by overall market trends and macroeconomic factors, such as economic cycles, inflation, and policy changes. Essentially, innovation assets can be considered a new type of risky asset. To reflect the

[1] Investing in financial innovation-driven assets, such as AI-related systems and financial products, can improve operational efficiency and reduce costs for financial institutions. Consequently, this may indirectly bolster returns and profits. Moreover, utilizing AI-driven asset allocation and introducing innovative, customizable financial products tailored to diverse customer needs may result in distinct outcomes compared to traditional businesses.

impact of newly added AI-based innovation assets, we distinguish them from traditional risky assets. In addition, investors may choose between financial innovation assets and risky assets, unintentionally creating a substitution effect between innovation assets and traditional financial assets (Gennaioli et al., 2012). With the integration of global financial markets, the boundaries between different types of financial assets have become blurred, which leads to an increase in return correlation between different types of assets. For these reasons, we assume there is a correlation between our innovation assets returns and risky assets returns. However, since the returns from risk-free assets remain constant, we assume it is not correlated with risky or innovation assets. Then, we have two more definitions:

Definition 2 *Each type of asset earns a specific return.* R_f *and* R_{inno} *represent the returns of the risk-free and financial innovation assets. The yield from the risky asset is* R_r*.* R_r*,* R_f*, and* R_{inno} *are all normally distributed.* R_{inno} *is independent of* R_f *but correlated with* R_r*, indicating that financial institutions utilize financial innovation assets to adjust or hedge against risky assets.*

Definition 3 *The correlation between risky and innovation assets is quantified as follows (Kero, 2013; Chen and Du, 2016):*

$$\beta = \frac{\operatorname{cov}\left(R_{inno}, R_r\right)}{\sqrt{\operatorname{Var}\left(R_{inno}\right) \cdot \operatorname{Var}\left(R_r\right)}}, \quad \beta \in [-1, 0) \cup (0, 1] \tag{1}$$

The correlation between the returns of financial innovation and risky assets can be positive or negative. The higher the absolute value of β, the stronger the correlation between R_{inno} and R_r.

Utilizing the previously defined terms, the total asset growth (G) can be expressed as the sum of the product of the quantity of each type of asset and its respective return yield:

$$G = P_R R_r + P_F R_f + P_{Inno} R_{inno} \tag{2}$$

The expectation of total asset growth and variance of G is:

$$E(G) = P_R R_r + P_F R_f + P_{Inno} R_{inno} \tag{3}$$

Definition 4 *The variance of total asset growth (Var(G)) signifies the volatility of profits, where a higher* $Var(G)$ *indicates greater earnings instability within the financial institution. We define* $Var(G)$ *as a measure of financial instability.*

$$
\begin{aligned}
\operatorname{Var}(G) &= P_R^2 \operatorname{Var}\left(R_r\right)+P_{\text{Inno}}^2 \operatorname{Var}\left(R_{\text{inno}}\right)+2 P_R P_{\text{Inno}} \operatorname{Cov}\left(R_r, R_{\text{inno}}\right) \\
&= P_R^2 \operatorname{Var}\left(R_r\right)+P_{\text{Inno}}^2 \operatorname{Var}\left(R_{\text{inno}}\right)+2 P_R P_{\text{Inno}} \beta \sqrt{\operatorname{Var}\left(R_r\right) \operatorname{Var}\left(R_{\text{inno}}\right)}
\end{aligned} \tag{4}
$$

The financial institution i will maximize its profit and minimize the risk by selecting the optimal portfolios to enhance its earnings. Following Kero (2013), we define the utility function of G as the expression of total profits and its variance.

Definition 5 *The utility function for financial enterprises' assets is defined as* $U(G) = G - \frac{1}{2}\rho Var(G), where \rho \in [0,1]$ *represents the coefficient of absolute risk aversion.*

Financial institutions aim to optimize the utility of total asset growth. Then, we have:

$$
\begin{gathered}
\max_{P_R, P_F, P_{Inno}} E[U(G)] = E(G) - \frac{1}{2}\rho \operatorname{Var}(G) \\
\text{s.t. } P_A = P_R + P_F + P_{Inno} \\
= P_R R_r + P_F R_f + P_{\text{Inno}} R_{\text{inno}} - \frac{1}{2}\rho P_R^2 \operatorname{Var}\left(R_r\right) \\
-\frac{1}{2}\rho P_{\text{Inno}}^2 \operatorname{Var}\left(R_{\text{inno}}\right) - \rho P_R P_{\text{Inno}} \beta \sqrt{\operatorname{Var}\left(R_r\right)} \sqrt{\operatorname{Var}\left(R_{\text{inno}}\right)}
\end{gathered} \tag{5}
$$

To optimize P_R and P_{Inno}, we take the first order partial derivatives of P_R and P_{Inno}, respectively:

$$
\begin{aligned}
\frac{\partial E\left[U(G)\right]}{\partial P_R} &= E(R_r) - \rho\left[P_R \operatorname{Var}(R_r) + P_{Inno}\beta\sqrt{\operatorname{Var}\left(R_r\right)\operatorname{Var}\left(R_{inno}\right)}\right] = 0 \\
P_R &= \frac{E(R_r) - \rho P_{Inno}\beta\sqrt{\operatorname{Var}\left(R_r\right)\operatorname{Var}\left(R_{inno}\right)}}{\rho \operatorname{Var}(R_r)}
\end{aligned} \tag{6}
$$

$$
\begin{aligned}
\frac{\partial E\left[U(G)\right]}{\partial P_{Inno}} &= E\left(R_{Inno}\right) - \rho\left[P_{Inno} \operatorname{Var}\left(R_{inno}\right) + P_R\beta\sqrt{\operatorname{Var}\left(R_r\right)\operatorname{Var}\left(R_{inno}\right)}\right] = 0 \\
P_{Inno} &= \frac{E(R_{Inno}) - \rho P_R\beta\sqrt{\operatorname{Var}\left(R_r\right)\operatorname{Var}\left(R_{inno}\right)}}{\rho \operatorname{Var}(R_{inno})}
\end{aligned} \tag{7}
$$

Incorporating equation (6) into equations (3) and (4), we obtain:

$$
E(G) = \frac{E\left(R_r\right) - \rho P_{\text{Inno}} \beta \sqrt{\operatorname{Var}\left(R_r\right)\operatorname{Var}\left(R_{\text{inno}}\right)}}{\rho \operatorname{Var}\left(R_r\right)}\left[E\left(R_r\right) - R_f\right] + P_{\text{Inno}}\left[E\left(R_{\text{inno}}\right) - R_f\right] + P_A R_f \tag{8}
$$

$$\operatorname{Var}(G)=\left[\frac{E\left(R_r\right)-\rho P_{\text{Inno}}\, \beta \sqrt{\operatorname{Var}\left(R_r\right) \operatorname{Var}\left(R_{\text{inno}}\right)}}{\rho \operatorname{Var}\left(R_r\right)}\right]^2 \operatorname{Var}\left(R_r\right)+P_{\text{Inno}}^2 \operatorname{Var}\left(R_{\text{inno}}\right)+ \\ 2\left[\frac{E\left(R_r\right)-\rho P_{\text{Inno}}\, \beta \sqrt{\operatorname{Var}\left(R_r\right) \operatorname{Var}\left(R_{\text{inno}}\right)}}{\rho \operatorname{Var}\left(R_r\right)}\right] P_{\text{Inno}}\, \beta \sqrt{\operatorname{Var}\left(R_r\right) \operatorname{Var}\left(R_{\text{inno}}\right)} \tag{9}$$

Equation (9) illustrates the relationship among financial instability ($Var(G)$), the correlation between risky and innovation assets (β), and the level of financial innovation (P_{Inno}). Based on this equation, we posit the following propositions:

Proposition 1 *Regardless of how the correlation between risky and innovative assets changes, the degree of financial innovation consistently exhibits a positive correlation with financial instability.*

To prove this proposition, we take the partial derivative of P_{Inno} to $Var(G)$:

$$\frac{\partial Var(G)}{\partial P_{Inno}}=(2-2\beta^2)Var(R_{inno})P_{Inno} \tag{10}$$

Given that $\beta \in [-1,0) \cup (0,1]$, $\beta^2 \leq 1$, and both $Var(R_{\text{inno}})$ and P_{Inno} always hold positive values, we can prove that $\frac{\partial \operatorname{Var}(G)}{\partial P_{\text{Inno}}} \geq 0$. This signifies that P_{Inno} consistently maintains a positive association with $\operatorname{Var}(G)$. Thus, Proposition 1 is confirmed.

Next, we proceed to determine the definition and expression of FSR. As delineated by Tobias and Brunnermeier (2016), FSR is characterized as the alteration in the financial system's value at risk (VaR), contingent upon an institution experiencing distress relative to its median state ($\Delta CoVaR$ approach). The systemic risk contributed by the individual institution to the financial system is expressed as follows:

$$\Delta \operatorname{CoVaR}_q^{m|i}=\operatorname{CoVaR}_q^{m|X^i=\operatorname{VaR}_q^i}-\operatorname{CoVaR}_q^{m|X^i=\operatorname{VaR}_{50}^i} \tag{11}$$

where X^i is the loss of financial institution and VaR_q^i expresses VaR in $q\%$ quantile in financial institution i. $CoVaR_q^{m|X^i}$ represents the VaR of the financial market conditional on the VaR of financial institution i. The calculation process under the $\Delta CoVaR$ approach is as follows:

$$\begin{aligned} \operatorname{CoVaR}_q^i &= \operatorname{VaR}_q^{\mathrm{m}\ |X^i=\operatorname{VaR}_q^i}=\hat{\lambda}_q^i+\hat{\eta}_q^i \operatorname{VaR}_q^i \\ \Delta \operatorname{CoVaR}_q^i &= \operatorname{CoVaR}_q^i-\operatorname{CoVaR}_q^{\mathrm{m}\ |\operatorname{VaR}_{50}^i}=\hat{\eta}_q^i\left(\operatorname{VaR}_q^i-\operatorname{VaR}_{50}^i\right) \end{aligned} \tag{12}$$

Typically, the value of $q\%$ is set at either 95% or 99%, signifying that when the loss of a financial institution reaches 95% or 99%, the company faces a significant risk of failure. Here, we adopt the 95% threshold. Moreover, our scenario assumes that the total asset growth (G) of all financial institutions follows an identical normal distribution.[2] This distribution of G across the financial market mirrors that of a single financial firm. Consequently, following equation (12), the FSR can be defined as follows:

$$FSR = \eta^i \left(\mathrm{VaR}_q^i - \mathrm{VaR}_{50}^i\right) = \eta^i \left[\phi_i^{-1}(50\%) - \phi_i^{-1}(5\%)\right] \tag{13}$$

where ϕ_i^{-1} is the inverse function of G's distribution, which represents the value at risk of G in the 50% and 5% quantiles.[3] $\phi_i^{-1}(5\%)$ implies the profits are on the lower 5% quantile, meaning that the lower end of the earning that is very unlikely to happen. We assume that the VaR is when an unlikely-to-happen loss occurs; therefore, $\phi_i^{-1}(50\%) - \phi_i^{-1}(5\%)$ indicates the deviation from expected return. η^i measures individual companies' contribution to FSR in the financial market.

Proposition 2 *Financial innovation results in a corresponding rise in FSR.*

As ϕ_i^{-1} represents the inverse function of a normal distribution, it cannot be precisely expressed with a concrete formula. To explore the relationship between FSR and P_{Inno}, we assign specific values to the variables other than FSR, P_{Inno}, and β, and then simulate a three-dimensional graph based on this model. Figures 1(a) and (b) illustrate the relationship between FSR and P_{Inno} under different β. Irrespective of the changes in β, FSR shows an upward trend with the increase in P_{Inno}. As β approaches -1, financial innovation assets act as ideal hedging tools for diversification, resulting in a slower increase in FSR. Conversely, when β approaches 1 indicating a high correlation between risky and innovation assets, since they share a similar trend in yield of returns, the latter can be roughly regarded as investments in risky assets; thus, innovation assets do not introduce new risks into the financial system. However, when β approaches zero, signifying a weak correlation between risky and innovation assets, the absence of proper regulation and risk control measures may lead to a rapid increase

[2] The normal distribution adopted here is used to simplify calculations and maintain consistency with the model employed in the empirical analysis. While asset growth distributions may exhibit fat-tail characteristics, such as the Pareto distribution, we have also simulated the relationship between FSR and P_{Inno} using the computer program. The results still support our subsequent proposition.

[3] Here, we use the 5% quantile instead of the 95% because Tobias and Brunnermeier (2016) calculate VaR in return loss (negative return multiple market values). However, our G is the profit (positive return multiple asset amount), which is the opposite value of VaR. Thus $\phi_i^{-1}(50\%) - \phi_i^{-1}(5\%)$ convey the same meaning with $(VaR_{95}^i - VaR_{50}^i)$

in FSR as new types of financial innovations emerge. Proposition 2 is confirmed under both positive and negative β.

[Figure 1]

4 Empirical Analysis

4.1 Data

The 27 selected countries include Australia, Austria, Belgium, Brazil, Canada, China, Denmark, Finland, France, Germany, India, Ireland, Israel, Italy, Japan, Malaysia, the Netherlands, Norway, Poland, Portugal, the Russian Federation, Singapore, South Korea, Spain, Sweden, Switzerland, Turkey, the UK, and the US. Most of these countries belong to the OECD, while four are part of BRICS.

This study utilizes the venture capital (VC) investment in AI and the government spending on R&D as a pivotal metric, and Global AI Vibrancy tools, AI-related publications index, AI knowledge flow index, and AI patent index as a robustness check for assessing the extent of AI concentration, adoption, and penetration within each country. All AI-related indices are sourced from the OECD database.[4] The dimension of AI investment mirrors the VC poured into AI development, directly influencing the tangible advancement of AI endeavors and providing valuable insights into commercial investments in the field. Additionally, some portions of government domestic spending on R&D are allocated to AI projects. While we cannot precisely separate the funds dedicated to AI projects, as Heimonen (2012) indicates, public R&D investment can promote innovation success. Therefore, we include this spending to supplement our AI index to reflect governments' efforts in AI development.

In our assessment of FSR, we adopt a weighted average approach to estimate FSR. Our process commences with identifying the top five financial companies in each country,[5] ranked by their turnover rate and market value.[6] Subsequently, we collect their monthly stock price data and incorporate the composite index in each country as our market index. By calcu-

[4]See the office website of OECD.AI: https://oecd.ai/en/data and OECD database: https://data.oecd.org/rd/gross-domestic-spending-on-r-d.htm

[5]Notably, we encountered unique circumstances in Portugal. Hence, we are limited to data from three actively listed stocks within its financial sector.

[6]Some financial enterprises, characterized by substantial market values, tend to experience stable stock prices and lower turnover rates. However, this might not accurately capture the level of investor attention they garner. Therefore, we adopt a discerning approach by opting for financial companies with similar market values marked by relatively high turnover rates. These selections serve as the representative stocks for each country in our calculations. By doing so, we aim to ensure that our assessment considers the market value and dynamic investor interest, thus providing a more nuanced representation of the financial market trend within each country.

lating the returns of these selected stocks and applying the Copula-CoVaR methodology[7], as outlined in Reboredo and Ugolini (2015), we effectively measure FSR for each country. Given the constraints imposed by the limited availability of AI index data, and to preserve the precision of volatility and the distinctive attributes of FSR data, we examine FSR and apply a dynamic factor model to a data set spanning from January 2000 to December 2022. However, we convert the monthly FSR data into an annual format for benchmark regression purposes to keep consistency with the core explanatory and control variables.

Regarding the control variables, given the country-level focus of our analysis, we include the gross domestic product (GDP), inflation rate (CPI), the foreign exchange rate to USD (FX), unemployment rate (UNEM), and the Human Development Index (HDI)[8] as our control variables. We believe these selected control variables aptly capture a country's economic and developmental landscape, and serve as effective indicators of their influence on FSR. More specifically, GDP and CPI mirror a country's economic health, quality of life, and the resilience of its financial buffer when confronted with the potential risks of a capital shock. A higher GDP and suitable CPI empower a country to stabilize its economy and financial system, granting greater flexibility to attenuate abnormal volatility to its original trajectory and thereby diminishing systemic risks within the nation (Angelini and Farina, 2012; Chu et al., 2020). In terms of FX, as highlighted by Brunnermeier and Oehmke (2013), tumultuous fluctuations in exchange rates often accompany financial crises. Furthermore, as demonstrated in Figure 2, FSR exhibits larger values during financial crises, indicating a positive correlation between FSR and foreign exchange rates. Therefore, we include FX as one of our control variables. UNEM depicts the population and employment pressure experienced by a country. A high unemployment rate combined with a rapid population increase signifies an escalation in systemic risk. In line with Epstein et al. (2019) and Giesecke and Kim (2011), we include UNEM in our research. Specifically, as noted in Schneider et al. (2023), financial institutions with a substantial need for high-skill talent tend to exhibit lower risk. In response, we include the HDI index for each country in our models, serving as a representative measure of the demand for high-skill talent within each country. Furthermore, we augment

[7]Our Copula-CoVaR calculation is based on DCC-GARCH(1,1) and student-t copula.

[8]The HDI is a comprehensive index used for gauging and comparing the overall development and well-being of countries. It considers various key indicators related to health, education, and standard of living, providing a more comprehensive evaluation of human development compared to traditional economic measures. Based on the HDI index criteria, Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Japan, Malaysia, the Netherlands, Norway, Poland, Portugal, Russia, Singapore, South Korea, Spain, Sweden, Switzerland, Turkey, the UK, and the U.S. fall into the very high HDI category, while Brazil and China are classified as having a high HDI level, with India in the medium HDI category.

our regression equation by including the global FSR and regional factors,[9] to address potential cross-sectional dependence, and separate individual FSR characteristics from the global and regional risk spillover effect.

[Figure 2]

The data for dependent, core explanatory, and control variables are collected from the Datastream database, the OECD official database, the International Monetary Fund (IMF) database, the website of the Human Development Index developed by the United Nations Development Programme, and the World Bank. We have a maximum of 621 observations for regressions and 7452 for factor analysis. The specific data description, data sources, and time periods for each variable are provided in Appendix (Table A1) and Table 1.

[Table 1]

Table 2 presents the basic descriptive statistics of the data. We can discern a notable disparity across different dimensions of the AI index in terms of their number of observations and value ranges. For instance, AI investment in some countries nearly approaches zero, signifying limited AI development in specific years, whereas the maximum value can surge as high as 114.4 billion US Dollars. Similarly, the logarithm of FSR spans from -3.964 to -0.748, with a standard deviation of 0.474, underscoring significant variations among countries or considerable fluctuations in FSR over the period.

[Table 2]

4.2 Global and regional FSR

Our methodology unfolds in a structured manner. Initially, we apply a dynamic factor model to categorize the 27 countries into distinct groups and unveil underlying factors that may account for the similar trends observed in the fluctuations of their FSR. Subsequently, we conduct benchmark and grouping regression analyses for the AI index and FSR, which allows us to delve into their intricate relationship from various perspectives. Additionally, we introduce the global FSR and potential factors into the regression. Finally, we investigate the possible mediating effect between AI and FSR to uncover the underlying mechanisms.

With the increasing interconnectedness of economic activities among countries, the global economy prominently exhibits interdependence. As depicted in Figure 2, we discern a degree of consistency in the fluctuations of FSR across different countries spanning two decades. Consequently, risk spillover becomes a non-negligible factor in analyzing FSR across multiple

[9] We introduce the concept of "global FSR" and "regional FSR" in place of time dummies, which are derived from the factor model.

countries.

[Figure 2]

Regarding the underlying origins of the risk spillover effect in FSR across nations, Betz et al. (2016) posits that risk spillover is mainly extensive via the interconnections between financial institutions. The relationships among international banks also play a significant role in facilitating risk spillover. When an international bank conducts operations and holds assets in several nations, its international business ties can trigger risk spillover. Furthermore, owing to their adaptable characteristics and the high liquidity, capital, currencies, and financial instruments can easily facilitate risk transmission between countries (Paltalidis et al., 2015). Likewise, fluctuations in exchange and interest rates can potentially initiate risk spillover. These variations may result in oscillations in the value of assets and liabilities, consequently influencing the financial systems of multiple countries (Wang and Zong, 2020). Additionally, global political and geopolitical events can act as catalysts for disseminating financial risks. For instance, international conflicts or trade disputes may induce market instability across multiple countries (Blasques et al., 2016).

Kose et al. (2008) construct a Bayesian potential dynamic factor model to investigate the common components in the international business cycle among G7 countries[10]. This method effectively addresses the challenge of concurrently extracting multiple levels of dynamic factors. Recognizing the remarkable advantages of this approach in studying the spillover effects among macroeconomic variables, this paper employs a Bayesian multi-dynamic factor model to explore the global risk spillover effects on FSR and categorize 27 countries into different latent factors for further analysis. The methodology's strength lies in its capacity to isolate the global risk spillover effects from each country, allowing us to discern their inherent characteristics in FSR. Consequently, we can classify these countries based on their original FSR volatility, unaffected by spillover effects, for more in-depth analysis. In addition, our FSR is computed using a dynamic Copula-CoVaR approach. To maintain consistency and consider the influence of historical data on current figures, a dynamic factor model is the most suitable choice for our analysis. Following this idea, we construct our dynamic factor model as follows:

$$FSR_{i,t} = \beta_i^W f_t^W + \beta_i^L f_{j,t}^L + \varepsilon_{i,t} \tag{14}$$

[10]The G7 is an intergovernmental political forum composed of the world's seven largest developed economies. The official members are the US, Germany, the UK, France, Japan, Italy, and Canada, and the EU is an informal member.

where β_i^W and β_i^L represent factor loadings, quantifying the sensitivity of the FSR in country i to fluctuations in global FSR factors and other potential factors. The error term $\varepsilon_{i,t}$ represents the heterogeneous component of FSR for country i at time t. f_t^W represents the global dynamic factor to characterize the risk spillover effects among all countries. $f_{j,t}^L$ accounts for regional dynamic factors, which estimate the influence of geographic regional factors on $FSR_{i,t}$. In this context, we assume five regional dynamic factors ($j = 1, 2, ..., 5$) grounded in our assumption of regional interconnectedness among countries. Our sample encompasses 27 countries spanning North America, South America, Oceania, Asia, and Europe. In light of this, we outline our assumptions about grouping details in Appendix (Table A2). According to Kose et al. (2008), $\varepsilon_{i,t}$ follows an autoregressive process of order p (AR(p)), and both the global FSR and the latent dynamic factors adhere to autoregressive processes of order q (AR(q)). Then, we further have:

$$\begin{aligned} f_t^W &= \phi_1^W f_{t-1}^W + \ldots + \phi_q^W f_{t-q}^W + u_t^W \\ f_{j,t}^L &= \phi_{j,1}^L f_{j,t-1}^L + \ldots + \phi_{j,q}^L f_{j,t-q}^L + u_{j,t}^L \\ \varepsilon_{i,t} &= \phi_{i,1}\varepsilon_{i,t-1} + \ldots + \phi_{i,p}\varepsilon_{i,t-p} + u_{i,t} \end{aligned} \tag{15}$$

where $u_{i,t} \sim N\left(0, \sigma_i^2\right)$, $u_t^W \sim N\left(0, \sigma_W^2\right)$, and $u_{j,t}^L \sim N\left(0, \sigma_{j,L}^2\right)$. ϕ_q^W, $\phi_{j,q}^L$, and $\phi_{i,p}$ are all coefficients. This model effectively dissects the co-movement of FSR in diverse countries worldwide into two distinct components: global FSR and regional factors, each delineated by their respective factor loadings β_i^W and β_i^L. If both β_i^W and β_i^L are equal to zero, it signifies that FSR for the particular country is entirely of its own FSR and idiosyncratic ($FSR_{i,t}= \varepsilon_{i,t}$). Additionally, σ_W^2 and $\sigma_{j,L}^2$ for the error terms of the factors are set as one to standardize the scale.

Given that the latent factors are not directly observable, we employ a Bayesian-based Expectation-Maximum algorithm (EM) method. After establishing the conditional distribution of a factor in relation to the available data and model parameters, we can directly generate random samples from this conditional distribution. We apply a Markov Chain Monte Carlo (MCMC) procedure to generate random samples from the joint posterior distribution, considering both the potential parameters and the unobserved factors (Chib and Greenberg, 1996; Kose et al., 2008).

We initiate the process in our calculations by setting the initial values for the parameters and factors and sampling the posterior distribution of the parameters based on the factors. Subsequently, we sample the posterior of global FSR distribution using sampled parameters and other potential factors. This aids in determining the posterior distribution of the dynamic factor. Finally, we complete the first stage of the MCMC by sampling the global FSR factor and obtaining the posterior distribution of the other four potential factors (i.e., Gibbs Sampling). Finally, we repeat the MCMC process until the generated Markov chain exhibits convergence.

Following the parameter settings referenced from Kose et al. (2008), this study employs the prior distribution of the normal distribution $N(0,1)$ for both dynamic factors and autoregressive coefficients. The order of autoregressive process for white noise (p) and potential factors (q) is set to 2. The Inverted Gamma $(3, 0.001)$ is used as the prior distribution for the σ_i^2. This configuration ensures that as the lag order increases, the distribution becomes tightly concentrated around 0, simultaneously ensuring the stationarity of the autoregressive process. In this paper, sampling was performed 45,000 times, with the first 5,000 results discarded as a burn-in period to ensure the robustness of the model.

Finally, we apply a K-means clustering algorithm[11] to analyze the FSR in these countries and assign them to specific groups. Following Hartigan and Wong (1979), the general steps of the K-means algorithm are introduced as follows: (1) Select an initial set of n samples as the initial clustering centroid, $k = k_1, k_2, ...k_n$. (2) For each data point X_i in the data set, calculate its distance to the n centroid and assign it to the cluster associated with the nearest centroid. (3) For each cluster k_n, recalculate its clustering center $K_n = \frac{1}{|c_i|}\sum_{x \in c_i} x$, c_i is the number of data points in the cluster k_n. (4) Repeat steps 2 and 3 above until a stopping condition is met, such as a maximum number of iterations or minimal error change.

Table 3 and Table A2 present our factor analysis results. Table 3 displays the factor loadings for each country across six latent factors. Excluding global factors from other factors enables a more precise examination of each country's unique FSR change characteristics, free from the standardization effects of risk spillover. Following Kose et al. (2003), our approach to identifying global and regional factors is as follows:

(1)The global factor is positive for all countries.

(2)The North American factor is positive for both the U.S. and Canada.

(3)The Asian factor is positive for the vast majority of Asian countries.

(4)The Latin American factor is positive for Brazil.

[11]K-means clustering is a widely recognized unsupervised machine learning algorithm employed to partition a data set into N distinct, non-overlapping clusters. This algorithm's primary objective is to group data points with similar characteristics, where each cluster is symbolized by its centroid—a representative point corresponding to the mean of all data points within that cluster. K-means clustering has been extensively applied in data analysis in recent years.

(5)The European factor is positive for more European countries.

(6)The Oceania factor is positive for Australia, with a larger coefficient.

[Table 3]

Except for India, we observed positive and negative factor loadings in these countries. India stands out with all six-factor loadings being positive, signifying that even after excluding the global FSR spillover effect, the trends in FSR changes within India remain consistent with FSR changes in all other regions. The global factors in these 27 countries are positive, suggesting a robust and positive connection between the global FSR movement and FSR in a single country. This observation indicates that the volatility of FSR is predominantly influenced by the global FSR spillover effect, especially during these unique and challenging circumstances.

The global spillover and regional clustering effects can alter the trend of FSR changes within a country. To compare the relative importance of these dynamic factors in specific countries, we measure the contribution of each factor based on their variance ratios. The variance of FSR can be expressed as:

$$Var(FSR_{i,t}) = (\beta_i^W)^2 Var(f_t^W) + (\beta_i^L)^2 Var(f_{j,t}^L) + Var(\varepsilon_{i,t}) \tag{16}$$

where $Var(f_t^W)$ is the variance for global factor, $Var(f_{j,t}^L)$ represents the variance of potential regional factors. $Var(\varepsilon_{i,t})$ is the variance for white noise. Based on this equation, the relative importance of global factors ρ_i^W and regional factors ρ_i^L on the FSR of a specific country can be expressed as:

$$\begin{aligned} \rho_i^W &= \left(\beta_i^W\right)^2 \operatorname{Var}\left(f_t^W\right) / \operatorname{Var}\left(FSR_{i,t}\right) \\ \rho_i^L &= \left(\beta_i^L\right)^2 \operatorname{Var}\left(f_t^L\right) / \operatorname{Var}\left(FSR_{i,t}\right) \end{aligned} \tag{17}$$

Table 4 displays the contribution of each factor to FSR for 27 countries. The global factor's contribution is far more significant than regional factors in all countries. Most European countries exhibit a variance contribution value exceeding 0.85 for the global factor. In particular, the UK's global factor weight is close to 0.95 among all factors, indicating that changes in the UK's FSR closely follow the global trend. Conversely, the majority of Asian countries, Latin American countries, and some parts of North America exhibit a relatively lower weight in the global factor's contribution, which indicates a more idiosyncratic characteristic in their FSR changes when floating with the global trend.

[Table 4]

We ascertain the grouping of countries with common factor characteristics by conducting a K-means cluster analysis based on factor loadings. The results are presented in Figure 3. We initially hypothesized that changes in FSR may exhibit regional convergence alongside global factors. Indeed, certain countries demonstrate a regional convergence characteristic, as evidenced by similar patterns in FSR changes observed in China, Japan, and South Korea. Moreover, countries in the North American region and parts of the EU also cluster together in Figure 4. However, our results do not perfectly group countries from the same regions together.[12] Consequently, we posit that, beyond global spillover effects and regional considerations, other factors exist and exert some influence on FSR volatility, such as economic scale, natural disaster, political decision, capital requirement, cultural communications, and institutional quality (Zhou, 2013; Rizwan et al., 2020; Ellis et al., 2014).

[Figure 3 and 4]

4.3 FSR and AI

Having identified the distinctive FSR characteristics in these 27 countries, our primary objective remains to explore the relationship between systemic risk and AI. Before conducting the regression analysis, we visualize the relationship between the AI index and FSR for the AI investment index and research expenditure metric. Given the substantial disparities across countries, only presenting the overall regression results may unintentionally overlook valuable information and potentially introduce inaccuracies. We initially perform a regression analysis using the full samples. Subsequently, we conduct grouping regressions by economic development level, human capital development level, and special crisis period. These grouping results enable a more intricate examination and yield additional insights.

We investigate the impact of AI technologies on FSR using the following semi-logarithm regression model:

$$\mathrm{LnFSR}_{it} = \alpha_{it} + \beta\,\mathrm{AI}_{it} + \gamma X_{it} + \phi_1 global\_FSR + \phi_2 regional\_FSR + \varepsilon_{it} \tag{18}$$

where $LnFSR_{it}$ represents the logarithm of FSR calculated based on the copula-CoVaR approach for each country at time t; AI_{it} denotes the AI index for each country i at time t; α_{it}, β, γ, ϕ_1, and ϕ_2 are coefficients. X_{it} denotes the country-level control variables, $global\_FSR$ and $regional\_FSR$ are the global (f_t^W) and regional factors (f_t^L), respectively, derived from $LnFSR_{it}$ using the factor model; and ε_{it} signifies the stochastic disturbance term. To further

[12]The detailed grouping results are shown in Appendix A Table A2.

assess the variations in the impact of AI on FSR across countries, we conduct regression analyses on the full sample and grouping sample using time and individual fixed effects. The results are presented in Table 5.

[Table 5]

Models (1) and (8) provide insights into the AI index and FSR relationship across the full sample. VC investments in AI projects serve as an indicator of public interest in AI technologies. Government research expenditures reflect the focus of national decision-makers on AI development. These two indices play a pivotal role in driving AI development within a nation. The coefficients for VC investments and research expenditures show a positive correlation with FSR. Thus, current investments in AI technologies increase systemic risk in the financial system. This result is consistent with Ho et al. (2004), who argue that research expenditure and investments contribute to increased systemic risk in financial stock markets possibly due to operational risks associated with the R&D process. Consequently, companies with incomplete risk control measures and weaker financial support may not benefit from the advancement of AI technologies. In addition, investments can lead to the dominance of certain companies or sectors in the AI field. If these dominant players encounter issues, it can potentially disrupt the entire market or industry, increasing systemic risk.

Models (2)—(7) and (9)—(14) present the results of grouped regression analyses by economic development level, human capital development level, and special crisis periods.[13] The impact of AI on FSR is more significant in developed countries and countries with higher HDI scores. Additionally, the effect of AI on systemic risk persists during tranquil periods rather than when the world is facing disasters or significant challenges. Interestingly, VC investments in AI have a less significant impact on FSR in developing countries and during crisis periods. However, government spending on R&D consistently affects FSR across periods and all countries regardless of their level of economic development.

Among control variables, the unemployment rate and FSR in most models, and exchange rate and FSR are positively correlated. Thus, countries with higher unemployment rates and volatile currency depreciation tend to experience higher systemic risk overall, affirming the conclusions drawn by Epstein et al. (2019) and Giesecke and Kim (2011). Although the relationships between GDP and FSR are insignificant across all groupings, there is a general tendency for a negative association with FSR. This implies that economies with robust GDP

[13]Considering significant events that may affect systemic volatility, we selected the outbreak of the 2008 financial crisis (years 2008 and 2009) and COVID-19 (years 2020 and 2021) as crisis period samples. Samples from other periods are classified as tranquil period samples.

tend to manifest lower levels of systemic risk in most conditions (Angelini and Farina, 2012; Chu et al., 2020). Global_FSR and Regional_FSR consistently exhibit positive and strong correlations with FSR in each country, indicating a pronounced international spillover and regional clustering effects among these 27 nations.

The proliferation of AI and its potential risks, particularly regarding labor displacement, has been a topic of extensive discussion among scholars (Zhou et al., 2020; Yang, 2022; Buckley et al., 2021). Our results remind us that while the simultaneous adoption of AI technologies can bring numerous benefits, it can also potentially lead to the accumulation of systemic risks. If not managed and mitigated effectively, they can increase the interconnection between financial institutions, thereby raising the possibility of systemic risk outbreaks. Additionally, unregulated AI use can exacerbate wealth inequality, depress labor wages, induce employment anxiety, and amplify potential risks in the financial industry.

4.4 Endogenous and Robustness Tests

Endogenous problems always persist as inherent challenges in data collection and OLS model analyses. To address this concern, we first implement a comprehensive robustness check by replacing the core explanatory variables and changing the calculation method of FSR. Additionally, we incorporate instrumental variables (IV) into our analytical framework to enhance the reliability of our results.

We undertake a verification process by substituting our primary explanatory variables with the AI index derived from an alternative source. Specifically, we integrate our AI indices with the Global AI Vibrancy Tool, an index meticulously curated by Stanford University. The Global AI Vibrancy Tool is a comprehensive metric for assessing national AI development across countries from 2017-2021. Recognizing the limited observations in the Global AI Vibrancy Tool, we gauge AI development from a research knowledge perspective. We include the number of AI-related publications, AI patents, and knowledge concerning AI techniques to reflect AI development in research. These metrics reflect general interest in AI technology and provide insights into the actual outcomes related to creating AI systems and associated products. We believe our selected supplemental AI index complements our benchmark results, providing an effective input-output robustness check.

The regression results are displayed in Table 6. Models (15) to (20) consistently reveal a robust and positive association between the AI index and FSR. In Models (15)-–(18), we replace our AI index with other related indices and find positive outcomes with high significance levels, consistent with our benchmark regression results. In Models (19) and (20), we replace the FSR calculation method with $\Delta CoVaR$, as discussed in the theoretical section of this article. These results reaffirm our propositions, indicating that as the level of financial innovation increases, FSR increases.

[Table 6]

To address the endogeneity issue, we follow Liu et al. (2021) by incorporating the logarithm of the total number of industrial robots in stock and use it as our IV. The prevalence of industrial robots indicates a nation's automation level, with a higher count suggesting a more robust automation infrastructure. Notably, especially in the early stages, AI technologies were often conceptualized as automated tools in various studies (Acemoglu and Restrepo, 2018). Given that the number of industrial robots is a crucial indicator in the manufacturing industry, its direct correlation with the FSR is not apparent. Thus, our IV selection is appropriate for this research context. The under-identification test with its p-value and weak identification test help verify our IV's effectiveness. Employing the 2SLS approach, we systematically reevaluate the relationship between our AI index and FSR. All robustness test results are listed in Table 7. Both 2SLS regressions achieve the highest levels of statistical significance, highlighting a positive relationship between the AI index and FSR.

[Table 7]

As our robustness check and endogenous test affirm the assumptions embedded in our benchmark regression, we posit that the widespread application of AI technologies can potentially increase FSR in each country. The substantial integration of AI technologies into financial institutions may heighten interconnectedness among them and introduce potential risks to the financial system, as suggested by Temelkov (2018); Chaudhry et al. (2022).

4.5 Mechanism Analysis

Here, we explore the underlying mechanism between AI and FSR. Interconnectedness has always been considered a critical factor in the accumulation of systemic risk in financial systems (Tobias and Brunnermeier, 2016; Wu et al., 2021; Markose et al., 2012). Interbank lending, similar asset structures, and analogous business operating methods link financial institutions together. These interconnections allow financial companies to support each other during crises yet make them vulnerable to similar risks and potential weaknesses. It can trigger chain reactions and lead to systemic risk in the financial ecosystem. Applying AI technologies brings new opportunities and potential profits to financial enterprises. However, it also introduces new risks into the current financial network. AI can potentially strengthen interconnectedness between institutions by promoting similar operating strategies or amplifying companies' ambitions to earn more profits with the presence of AI's benefits. In turn, it generates more potential risks and increases the accumulation of systemic risk. We posit that:

Hypothesis 1 *AI can increase FSR by strengthening the interconnectedness between entities.*

To substantiate this hypothesis, we measure interconnectedness in two dimensions: the global spillover effects and international cooperation in AI research. The interconnectedness of the global financial market is represented by the global factor extracted through Bayesian factor modeling. The interdependencies between countries are measured by the number of cross-country collaborations in AI research conducted by each country. We believe these two indices reasonably reflect the connections between countries in the capital market and research.

In addition to interconnectedness, the potential risks introduced by AI through social changes are equally evident. Nguyen and Vo (2022) conduct an empirical analysis based on 40 countries, and find a non-linear relationship between AI and unemployment. Specifically, AI increases unemployment within a certain range of inflation rates. Similarly, Bordot (2022) indicates a positive relationship between AI and the unemployment rate at all education levels. Mutascu (2021) also argues that the contribution of AI in reducing unemployment only occurs in the low-inflation regions. McClure (2018) points out that introducing AI technology intensifies workers' concerns about the risk of unemployment. This anxiety stems partly from fears of automation and the replacement of traditional labor by intelligent technologies, especially for those professions that technological advancements may directly impact. Zhou et al. (2020) indicate a correlation between the widespread application of AI, and an increase in salaries for highly educated employees and a decrease in salaries for those with lower professional knowledge. Their research suggests that elders and those with lower educational attainment are often more susceptible to being replaced by jobs driven by AI technology, which raises a potential societal concern: the potential widening of income disparities, higher unemployment, and rising poverty (Agrawal et al., 2018). To mitigate these concerns, governments and businesses are providing support and resources for employees, aiming to help individuals acquire the necessary skills to better cope with the rapid evolution of AI technology, alleviate concerns about unemployment risks, and offer them broader prospects for professional development (Jaiswal et al., 2022).

Gertler and Grinols (1982) discover a correlation between unemployment and FSR when examining stock returns on the New York Stock Exchange from 1970 to 1980. Their empirical results suggest that a higher unemployment rate is associated with higher systemic risk due to the effect of short-term interest rates and other potential factors. Using U.S. data and cross-country panels, Bai (2021) argues that unemployment has a strong positive effect on credit risk, which weakens the solvency of enterprises and triggers significant risks in the financial system. Similarly, Festic et al. (2011) also argue for a significant negative effect between unemployment and loan portfolio quality, thereby posing risks to macroeconomic stability. Unemployment also alters the general accessibility of loans to the population. With the emergence of microfinance specifically for low-income individuals, instances of default have become a threat and contribute to the accumulation of systemic risk (Imai et al., 2010). Accordingly, we propose another hypothesis:

Hypothesis 2 *AI can elevate FSR by increasing unemployment in a nation.*

Table 8 presents the mechanism analysis results. Models (1) and (3) test Hypothesis 1 from two perspectives. Model (1) examines the mediating effect of interconnectedness in international collaborative research. According to the Sobel-Goodman mediation tests, the total effect of the research expenditure index on FSR is 0.001 ($p < 0.01$). Model (3) tests the mediating effect of interconnectedness in the global financial market perspective. We observe positive relationships between the AI index, the global interconnectedness factor, and FSR in all three regressions in Model (3), with the highest significance level. The total effect in Model (3) is 0.01, while the indirect effect accounts for 70% of the total effect. Thus, AI impacts FSR primarily by increasing interconnectedness between countries and financial institutions rather than directly increasing FSR. In Model (2), we examine the mediating role of unemployment. The mechanism test shows a significant and positive relationship. However, the indirect effect accounts for only a small portion of the total effect, indicating that unemployment plays a less significant mediating role than interconnectedness. Accordingly, both hypotheses 1 and 2 are both supported. Our mediating effect results align with the findings of Bordot (2022); Gertler and Grinols (1982) and Danielsson et al. (2022). Thus, AI increases FSR by enhancing interconnectedness between entities and raising unemployment.

[Table 8]

5 Conclusions

This study examines the intricate relationship between AI and FSR across diverse contexts. We report several crucial findings. First, we find global risk spillovers of FSR in various countries. Extreme events, such as the 2008 financial crisis and the initial outbreak of the COVID-19 pandemic in 2020, led to a sharp and simultaneous increase in FSR across different nations. Meanwhile, the changes in FSR are more strongly influenced by global risk spillover rather than regional factors. The K-means clustering results show that after removing global risk spillover, the FSR dynamics of countries do not strictly conform to geographical proximity. In other words, neighboring countries may not necessarily exhibit similar FSR dynamics, indicating that various factors beyond regional considerations contribute to the diverse FSR patterns observed across nations. This heterogeneity may be attributed to the country's culture, policies, and economic development characteristics.

Second, we assess the impact of AI-related investment on FSR, including VC investment in AI projects, and the government spending on R&D that may go to AI development. We find that increased government and private investments in AI projects may amplify FSR. Specifically, increased R&D investments may inadvertently bolster interconnectedness between entities, escalate operational risks, and foster technological monopolies. Furthermore, the impact of AI on FSR is more significant in developed countries and countries with higher HDI scores. Additionally, the effect of AI on systemic risk persists during tranquil periods rather than when the world is facing disasters or significant challenges. Our results hold even after using other AI-related indices.

Lastly, building on the previous chapter, we delve into the mechanisms and mediating effects of AI's impact on FSR. Our mechanism analysis results suggest that AI can increase FSR by enhancing interconnectedness between entities and raising unemployment. Interconnectedness' mediating effect is stronger than that of unemployment. Our mechanism analysis underscores the complexity of AI's role in shaping FSR dynamics.

Based on our findings, we propose several policy recommendations: 1) Prudent approach to AI development and application: Given the diverse impacts of AI on systemic risk across various dimensions, countries should adopt a cautious stance towards AI development and application. Recognizing global risk spillover effects, nations should strengthen monitoring mechanisms to promptly identify early signs of systemic risk transmission. 2) Regulatory oversight of AI investments: Governments should exercise regulatory oversight to ensure responsible and sustainable investment in AI projects. This entails monitoring government and private investments in AI to prevent the concentration of technological monopolies and mitigate potential systemic risks arising from increased investment activities. Policymakers may also encourage diversity and dispersion within the AI market to alleviate systemic risk. For instance, developing a diverse range of AI projects and patents can be promoted, thereby preventing the dominance of a single AI tool or technology, and enhancing market resilience. 3) Exercise caution regarding the interconnectedness and unemployment resulting from AI applications: As AI is implemented across various industries, governments and enterprises should consider prioritizing workforce capabilities, creating new opportunities for workers to prevent exacerbating unemployment, and diversifying business operations to avoid over-reliance on AI technologies.

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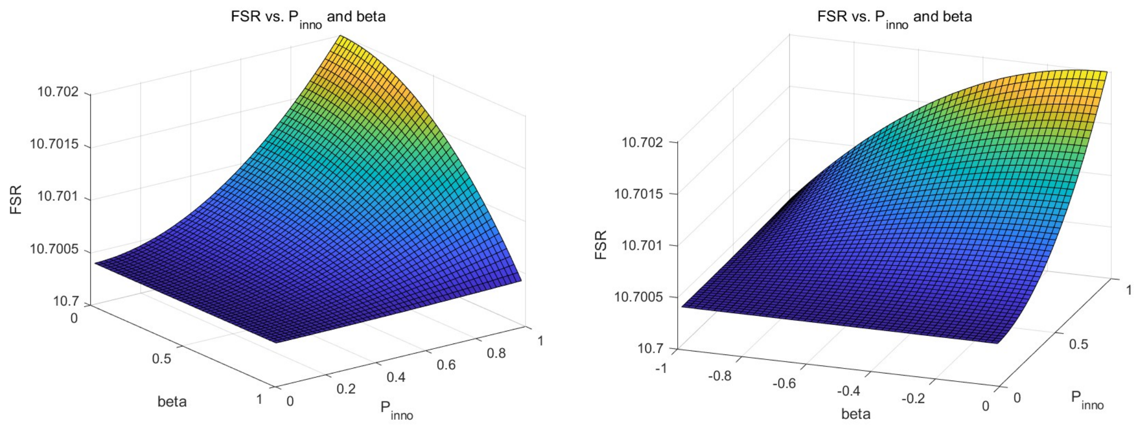
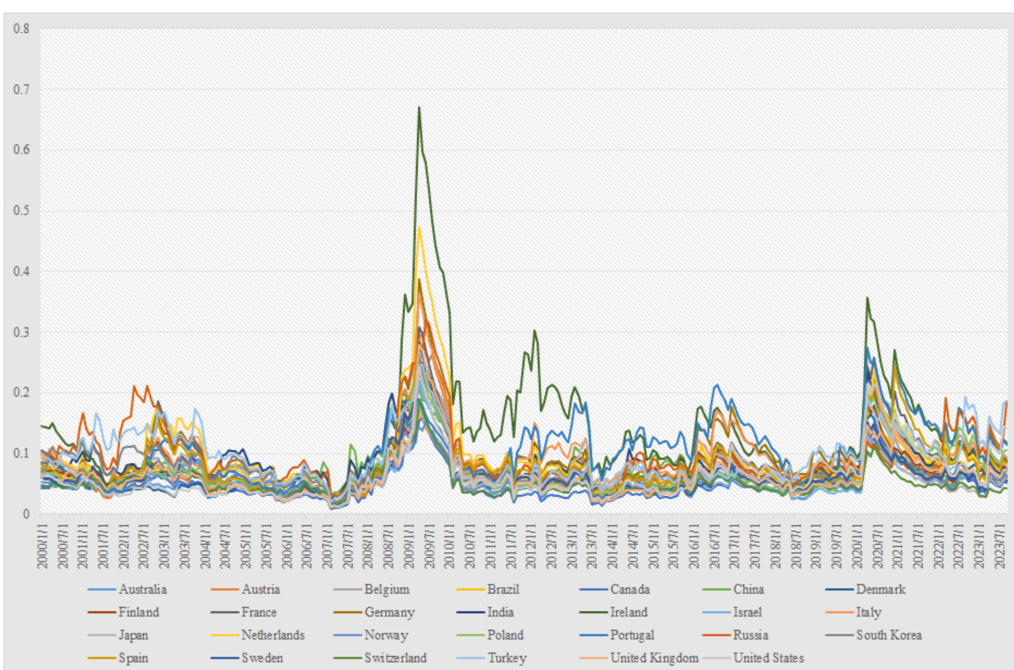
Figure 1: Relationship between financial systemic risk and financial innovation level



(a) when $\beta > 0$ (b) when $\beta < 0$

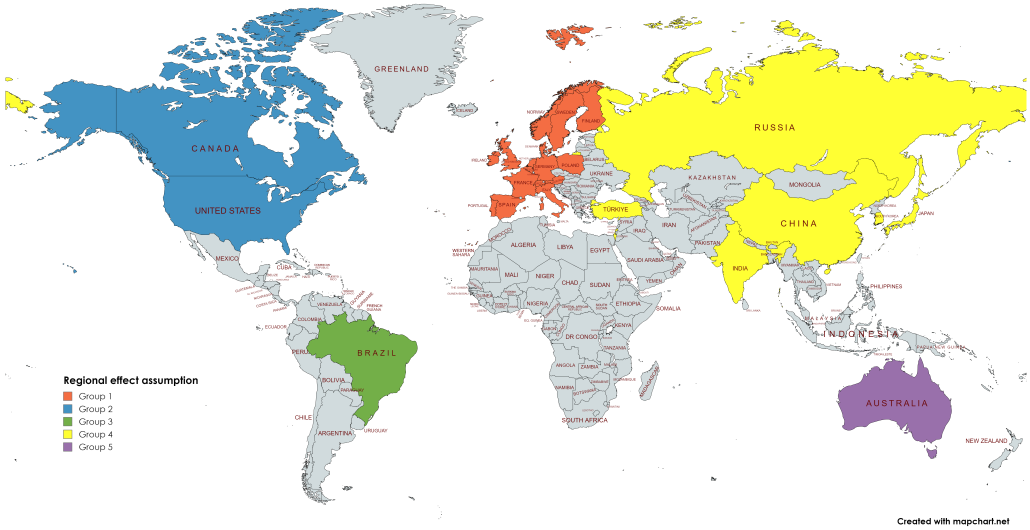
Note: (1) During the simulation, we set the following parameters: $E(R_{Inno}) = 0.3$, $E(R_r) = 0.23$, $R_f = 0.05$, $Var(R_i) = 0.005$, $Var(R_{Inno}) = 0.013$, and $\rho = 0.5$. We determine the value of $E(R_r), R_f, Var(R_i) and Var(R_{Inno})$ based on real ratio. $E(R_r)$ and $Var(R_i)$ are derived from the average returns and variance of S&P 500 financial sector from 2000 to 2023. R_f is determined by the one-year U.S. treasury bond yield rate in 2023. As for the value of $Var(R_{Inno}$, Kero (2013) consider credit derivatives as financial innovation assets. Following this idea, our $Var(R_{Inno}$ is calculated from the Options Price of the S&P 500 Index. We give a neutral risk aversion ratio ($\rho = 0.5$) in our plot. (2) We also tested this model under varying values of $E(R_{Inno})$, ensuring it is larger or smaller than $E(R_r)$. The results remain robust, with the figure strikingly similar to the one presented. Therefore, we opt not to include additional simulation plots in this paper.

Figure 2: Financial systemic risk for 27 countries



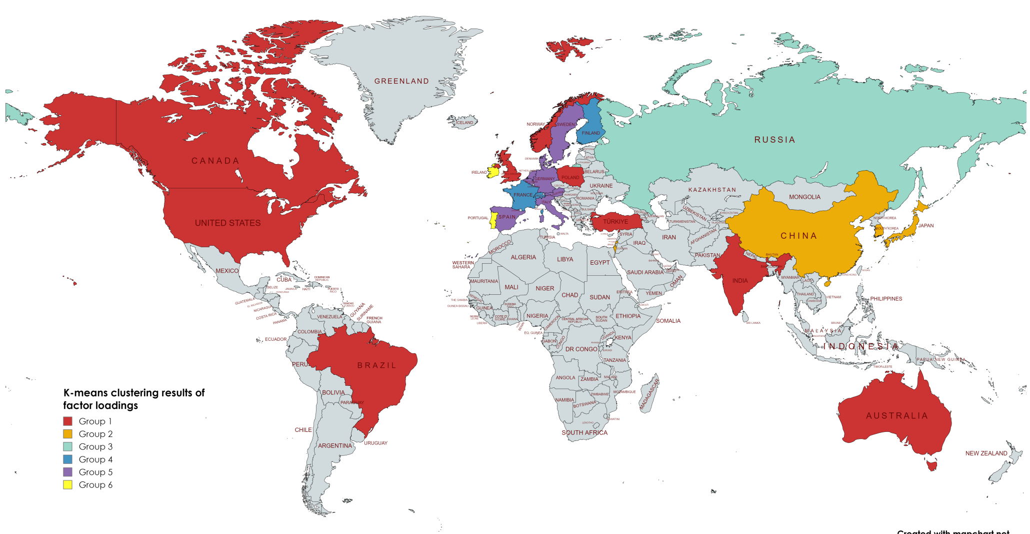
Note: The FSR values for each country are computed using stock returns sourced from Datastream.

Figure 3: Regional effect assumption



Note: Group A is organized based on our assumption that the FSR for each country will display a regional similarity after subtracting the global spillover effect.

Figure 4: K-means clustering results of factor loadings



Note: Group B shows the grouping results under K-means.

Table 1: Variables description

Observation Period	Variables		Description
2000-2022	Dependent variable	LnFSR	The logarithm of Financial Systemic Risk
2012-2022	Core explanatory variable	AI_investment	VC investment in AI projects (Billions of U.S. dollars)
2000-2022	Core explanatory variable	Research_expenditure	Government spending on R&D (Billions of U.S. dollars)
2017-2021	(for robustness check)	Global_Vibrarcy_AI_index	The global vibrancy tool developed by Stanford University for measuring AI development in each country.
2000-2022	(for robustness check)	AI_publications	The logarithm of AI-related publications per capita
2005-2017	(for robustness check)	AI_patent	The logarithm of the count of AI-related patents' applications to the US Patent and Trademark Office (USPTO)
2000-2022	(for robustness check)	AI_knowledge_flow	The logarithm of AI-related publications per capita
		FX	The percentage change of foreign exchange rate
		LnGDP	The logarithm of gross domestic product(Billions of U.S. dollars)
2000-2022	Control variables	CPI	Inflation rate
		UNEM	Unemployment rate
		HDI	Human development index
		Global FSR	The potential global factors obtained from the dynamic factor model
		Regional FSR	The potential factors obtained from the dynamic factor model

Note: The stock returns that are used to estimate FSR are obtained from Datastream, while the AI index data is sourced from the OECD database (https://oecd.ai/en/data and https://stats.oecd.org/Index.aspx?DataSetCode=PATS_IPC). As for the control variables, FX, GDP, CPI, and UNEM data are sourced from the IMF database (https://www.imf.org/external/datamapper/datasets/WEO) and World Bank (https://data.worldbank.org/). HDI data are derived from the research conducted by the United Nations Development Programme (https://hdr.undp.org/data-center/human-development-index#/indices/HDI.). The Global FSR and Regional FSR are derived from the Bayesian dynamic factor model.

Table 2: Descriptive Statistics

Variable	Observations	Mean	P50	SD	Min	Max	Skewness	Kurtosis
LnFSR	621	-2.703	-2.748	0.474	-3.964	-0.748	0.524	3.436
Research_expenditure	522	58.94	18.51	113.0	1.925	709.7	3.340	14.35
AI_investment	293	2.461	0.103	9.757	0.000	114.4	7.174	68.41
Global_Vibrarcy_AI	135	14.25	9.151	16.21	0.789	78.16	2.408	8.524
AI_publications	621	5.024	5.334	1.182	-0.061	6.890	-1.421	5.233
AI_knowledge_flow	403	628.3	211.0	1268	1.000	9609	4.333	24.48
AI_patent	347	3.469	3.266	1.836	-1.386	8.567	0.274	3.072
LnTotal_Robots	608	9.280	9.045	1.943	2.079	14.05	-0.009	3.091
FX	594	0.011	-0.001	0.103	-0.169	0.967	3.113	24.77
LnGDP	621	6.849	6.707	1.153	4.608	10.14	0.543	2.864
CPI	621	0.033	0.022	0.054	-0.017	0.723	7.216	74.53
UNEM	621	7.129	6.500	3.519	1.700	26.10	1.688	7.554
HDI	621	0.867	0.898	0.089	0.491	0.964	-1.910	6.496
Global_FSR	621	0.001	-0.243	0.825	-1.038	3.031	2.218	8.522
Regional_FSR	621	-0.002	-0.014	0.134	-0.366	0.424	0.071	4.011

Table 3: Factor loading matrix

	Potential factors					
Country	Global	Asia	North America	Latin America	Oceania	Europe
Australia	1.055	-0.886	0.366	0.229	0.497	0.1816
Austria	1.053	-0.451	-0.892	-0.076	1.155	-1.2997
Belgium	1.069	0.183	-1.114	-0.417	0.012	-0.1306
Brazil	0.966	-0.552	2.208	0.547	-0.095	0.7531
Canada	1.059	0.328	1.064	-0.450	0.021	0.7177
China	0.909	0.807	0.110	2.120	1.731	-2.5710
Denmark	1.022	-0.468	0.056	-0.361	1.443	-2.4627
Finland	1.068	0.154	0.137	-0.104	-0.811	0.8305
France	1.046	-0.800	-0.017	-0.440	-0.826	0.4226
Germany	1.045	-0.382	-0.659	-0.716	-0.874	-0.1914
India	0.991	0.348	0.867	1.703	1.391	0.6412
Ireland	0.962	-0.650	-2.206	-0.020	1.035	-0.4049
Israel	1.018	1.029	-0.715	0.463	0.518	-0.4584
Italy	1.019	-0.806	-1.531	-0.501	-0.769	0.2118
Japan	0.869	0.073	-0.533	2.888	-2.648	1.4822
Netherlands	1.053	0.531	-1.048	-0.219	-0.308	0.0454
Norway	1.049	-0.146	0.920	0.840	-0.063	-0.0206
Poland	1.026	-0.275	0.961	-1.166	0.937	-0.5461
Portugal	0.748	-2.858	0.429	0.461	-1.389	0.5375
Russia	0.852	2.136	-0.413	-1.504	-1.005	-0.9537
South Korea	0.975	1.743	0.123	0.266	-0.478	0.7173
Spain	1.034	-0.754	0.162	-0.789	-0.823	1.1258
Sweden	1.068	0.484	-0.677	-0.266	0.603	-0.2372
Switzerland	1.036	0.947	0.180	0.908	-0.132	0.2930
Turkey	0.874	1.411	2.123	-1.355	-1.038	1.9276
United Kingdom	1.072	0.048	-0.496	-0.720	0.132	0.3989
United States	0.973	-1.337	1.042	-0.833	1.024	-0.5230

Note: (1) The factor loading matrix records the factor loadings for individual countries across five regional factors and one global spillover factor; (2) Our approach to identifying global and regional factors is as follows: The global factor is positive for all countries. The North American factor is positive for both the United States and Canada. The Asian factor is positive for the vast majority of Asian countries. The Latin American factor is positive for Brazil. The European factor is positive for more European countries. The Oceania factor is positive for Australia, with a larger coefficient.

Table 4: Global and regional variance contribution

		Global and regional variance contribution					
Country	Region	Global	Asia	North America	Latin America	Oceania	Europe
Australia	Oceania	0.9152	0.0386	0.0040	0.0013	0.0048	0.0010
Austria	Europe	0.9116	0.0100	0.0236	0.0001	0.0259	0.0057
Belgium	Europe	0.9394	0.0016	0.0368	0.0042	0.0000	0.0000
Brazil	Latin America	0.7668	0.0150	0.1444	0.0072	0.0002	0.0086
Canada	North America	0.9219	0.0053	0.0335	0.0048	0.0000	0.0120
China	Asia	0.6796	0.0320	0.0004	0.1077	0.0582	0.0712
Denmark	Europe	0.8578	0.0108	0.0001	0.0031	0.0405	0.0009
Finland	Europe	0.9371	0.0012	0.0006	0.0003	0.0128	0.0107
France	Europe	0.8992	0.0315	0.0000	0.0046	0.0133	0.0006
Germany	Europe	0.8983	0.0072	0.0129	0.0123	0.0148	0.0056
India	Asia	0.8074	0.0059	0.0223	0.0695	0.0376	0.0064
Ireland	Europe	0.7610	0.0208	0.1441	0.0000	0.0208	0.0057
Israel	Asia	0.8526	0.0521	0.0151	0.0051	0.0052	0.0007
Italy	Europe	0.8536	0.0320	0.0694	0.0060	0.0115	0.0001
Japan	Asia	0.6214	0.0003	0.0084	0.1999	0.1362	0.0023
Netherlands	Europe	0.9120	0.0139	0.0325	0.0011	0.0018	0.0013
Norway	Europe	0.9050	0.0010	0.0250	0.0169	0.0001	0.0001
Poland	Europe	0.8657	0.0037	0.0274	0.0326	0.0170	0.0141
Portugal	Europe	0.4601	0.4017	0.0054	0.0051	0.0375	0.0588
Russia	Asia	0.5965	0.2244	0.0051	0.0542	0.0196	0.0412
South Korea	Asia	0.7820	0.1494	0.0004	0.0017	0.0044	0.0184
Spain	Europe	0.8794	0.0279	0.0008	0.0149	0.0131	0.0012
Sweden	Europe	0.9384	0.0115	0.0136	0.0017	0.0071	0.0015
Switzerland	Europe	0.8823	0.0441	0.0010	0.0198	0.0003	0.0004
Turkey	Europe	0.6278	0.0979	0.1335	0.0440	0.0209	0.0084
United Kingdom	Europe	0.9455	0.0001	0.0073	0.0124	0.0003	0.0085
United States	North America	0.7780	0.0879	0.0321	0.0166	0.0204	0.0141

Table 5: Benchmark Regression Results

	Model (1) All	Model (2) Developing Countries	Model (3) Developed Countries	Model (4) HDI Level: high	Model (5) HDI Level: very high	Model (6) Tranquil period	Model (7) Crisis period
Variables	LnFSR	LnFSR	LnFSR	LnFSR	LnFSR	LnFSR	LnFSR
AI_investment	0.003**	-0.004	0.004**	-0.003	0.005**	0.005*	0.000
	(0.002)	(0.485)	(0.013)	(0.670)	(0.014)	(0.066)	(0.879)
FX	0.073	0.152	-0.190	-0.259	0.042	0.004	-0.088
	(0.125)	(0.495)	(0.307)	(0.649)	(0.768)	(0.976)	(0.907)
LnGDP	-0.226***	0.063	-0.224*	-0.032	-0.158	-0.336***	0.207
	(0.059)	(0.789)	(0.073)	(0.938)	(0.180)	(0.005)	(0.730)
CPI	0.170	-0.043	-0.158	0.522	-0.140	0.012	0.007
	(0.185)	(0.957)	(0.281)	(0.678)	(0.363)	(0.973)	(0.949)
UNEM	0.020***	0.059**	-0.012	0.051	-0.001	0.006	-0.033
	(0.005)	(0.035)	(0.182)	(0.149)	(0.936)	(0.426)	(0.430)
HDI	2.791***	0.845	-3.397	-	-	-0.706	6.468
	(0.776)	(0.699)	(0.121)	-	-	(0.587)	(0.361)
Global_FSR	0.433***	0.312***	0.533***	0.321***	0.509***	0.627***	0.447***
	(0.013)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)	(0.000)
Regional_FSR	0.379***	0.126	0.362***	0.160	0.323**	0.282**	0.312
	(0.090)	(0.685)	(0.007)	(0.713)	(0.014)	(0.038)	(0.703)
Individual fixed effect	YES	YES	YES	YES	YES	YES	YES
Observations	293	54	239	22	260	239	54
adj. R2	0.707	0.641	0.783	0.738	0.751	0.557	0.904

Table 5: Benchmark Regression Results (continued)

	Model (8) All	Model (9) Developing Countries	Model (10) Developed Countries	Model (11) HDI Level: high	Model (12) HDI Level: very high	Model (13) Tranquil period	Model (14) Crisis period
Variables	LnFSR	LnFSR	LnFSR	LnFSR	LnFSR	LnFSR	LnFSR
Research_expenditure	0.001***	0.001***	0.002***	0.000	0.003***	0.001***	0.001*
	(0.000)	(0.007)	(0.000)	(0.574)	(0.000)	(0.007)	(0.078)
FX	0.073	0.375*	-0.216	-0.592	0.193	0.390***	-0.424
	(0.125)	(0.055)	(0.159)	(0.673)	(0.105)	(0.001)	(0.277)
LnGDP	-0.226***	-0.157	-0.303***	0.142	-0.080**	-0.054	-0.550***
	(0.059)	(0.150)	(0.000)	(0.390)	(0.044)	(0.401)	(0.002)
CPI	0.170	0.401	0.023	-0.447	0.219	-0.308	0.081
	(0.185)	(0.649)	(0.896)	(0.748)	(0.237)	(0.399)	(0.637)
UNEM	0.020***	0.054*	0.025***	0.657*	0.023***	0.028***	-0.013
	(0.005)	(0.078)	(0.000)	(0.065)	(0.000)	(0.000)	(0.413)
HDI	2.791***	-1.110	6.137***	-	-	0.227	3.114**
	(0.776)	(0.339)	(0.000)	-	-	(0.786)	(0.024)
Global_FSR	0.433***	0.292***	0.452***	0.203***	0.435***	0.717***	0.315***
	(0.013)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)	(0.000)
Regional_FSR	0.379***	0.231	0.421***	0.909*	0.297***	0.297***	0.237*
	(0.090)	(0.276)	(0.000)	(0.071)	(0.001)	(0.003)	(0.096)
Individual fixed effect	YES	YES	YES	YES	YES	YES	YES
Observations	500	62	438	21	479	406	94
adj. R2	0.725	0.771	0.779	0.780	0.751	0.631	0.830

Note: (1) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; (2) The LnFSR here is estimated by copula-CoVaR approach.

Table 6: Robustness Test

	Model(15)	Model(16)	Model(17)	Model(18)	Model(19)	Model(20)
	LnFSR	LnFSR	LnFSR	LnFSR	LnFSR2	LnFSR2
Global_Vibrarcy_AI	0.013**					
	(0.006)					
AI_publications		0.186***				
		(0.038)				
AI_patent			0.069**			
			(0.028)			
AI_knowledge_flow				0.000***		
				(0.000)		
Research_expenditure					0.001**	
					(0.000)	
AI_investment						0.004***
						(0.002)
FX	-0.210	0.040	-0.054	-0.125	0.282***	0.296**
	(0.326)	(0.107)	(0.161)	(0.118)	(0.104)	(0.115)
LnGDP	0.215	-0.215***	-0.169*	-0.234***	-0.164***	0.004
	(0.230)	(0.050)	(0.094)	(0.077)	(0.050)	(0.094)
CPI	-0.029	0.090	0.492	0.105	-0.385**	-0.214
	(0.140)	(0.176)	(0.405)	(0.151)	(0.151)	(0.136)
UNEM	0.018	0.017***	0.040***	0.003	0.016***	-0.013**
	(0.020)	(0.004)	(0.006)	(0.006)	(0.004)	(0.006)
HDI	4.464	-0.073	1.919	1.322	-0.800	-0.840
	(4.200)	(0.893)	(1.294)	(0.805)	(0.633)	(1.110)
Global_FSR	0.484***	0.413***	0.409***	0.377***	0.261***	0.193***
	(0.023)	(0.012)	(0.013)	(0.011)	(0.012)	(0.015)
Regional_FSR	0.358**	0.308***	0.176	0.206**	0.047	0.105**
	(0.173)	(0.076)	(0.119)	(0.082)	(0.050)	(0.045)
Individual fixed effect	YES	YES	YES	YES	YES	YES
Obseravtions	135	594	347	403	500	293
adj. R2	0.828	0.725	0.770	0.779	0.527	0.384

Note: (1) Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$; (2) Global AI Vibrancy Tool is an AI index crafted by Stanford University, serves as a metric for gauging national AI development across 27 countries from 2017 to 2021.

Table 7: Endogenous test

	2SLS(1)	First stage	2SLS(2)	First stage
	LnFSR	Research_expenditure	LnFSR	AI_investment
lnTotal_Robots		17.405***		5.122***
		(6.294)		(1.463)
Research_expenditure	0.003*			
	(0.002)			
AI_investment			0.093***	
			(0.031)	
Underidentification test	7.316		13.972	
P-value	(0.000)		(0.000)	
Weak identification test	19.562		6.854	
Hansen J statistic_p-value	0.000		0.000	
Observation	489		293	

Note: (1) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; (2) Our IV variable lnTotal_Robots represents the natural logarithm of the sum of industrial robots currently in use and newly installed each year. This data is obtained from the report published by the International Federation of Robotics (IFR), accessible on their website: https://ifr.org/worldrobotics/.; (3) Underidentification test refers to the Anderson LM statistics. The estimated results reject the null hypothesis, indicating a correlation between the instrumental and explanatory variables; (4) A Weak identification test is established based on Cragg-Donald Wald F-statistics. The result of the weak identification test is larger than 5, indicating a strong correlation between IV and endogenous variables, which suggests the absence of weak instrumental variables.

Table 8: Mechanism test

	Model(1)			Model(2)			Model(3)		
VARIABLES	LnFSR	# of collaborate_research	LnFSR	LnFSR	UNEM	LnFSR	LnFSR	Global_FSR	LnFSR
Researcher_expenditure	0.001***	0.332***	-0.001	0.0014***	0.013***	0.001***			
	(0.0003)	(0.008)	(0.0006)	(0.0003)	(0.003)	(0.0003)			
# of collaborate_research			0.006***						
			(0.0017)						
UNEM						0.0195***			
						(0.0045)			
AI_investment							0.010***	0.0138***	0.003**
							(0.003)	(0.005)	(0.0017)
Global_FSR									0.505***
									(0.021)
_cons	-3.676***	-72.33***	-3.808***	2.115***	13.105*	1.767**	-7.382***	-13.398***	-0.618
	(0.466)	(12.51)	(0.532)	(0.705)	(7.305)	(0.760)	(1.867)	(3.067)	(1.083)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sobel-Goodman Tests			0.002***			0.002***			0.007***
			(0.001)			(0.000)			(0.002)
Total effect			0.001			0.001			0.010
Indirect effect			0.002			0.0003			0.007
Observations	500	500	500	500	500	500	293	293	293
R-squared	0.7922	0.9360	0.7971	0.8474	0.6885	0.8537	0.4983	0.2925	0.8433

Notes: (1)Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; (2) # of collaborate_research refers to the total number of international collaborate research (in thousands) summarized by OECD from the OpenAlex. From an AI research perspective, we use this index to reflect the interconnections between countries. (3) The Sobel-Goodman Mediation Test is a widely employed method for evaluating the significance of a mediation effect within linear regression models. In the presented table, we provide estimations, standard errors, and the associated p value for the Sobel-Goodman test. The p value, which is less than 0.05, strongly suggests a mediating effect among the variables; (4) The total effect signifies the overall impact of the AI index on FSR, while the indirect effect represents the impact mediated through the mediating variable.

A Appendix

Table A1: The brief code of the top 5 financial institutions and their market index in 27 countries

Country	Individual financial stock 1	Individual financial stock 2	Individual financial stock 3	Individual financial stock 4	Individual financial stock 5	Market Index
Australia	COMMONWEALTH BK.OF AUS.	NATIONAL AUS.BANK	WESTPAC BANKING	ANZ GROUP HOLDINGS	COMPUTERSHARE	S&P/ASX 200 INDEX
Austria	OBERBANK	BANK FUR TIROL UND VBG.	BKS BANK	ERSTE GROUP BANK	FRAUENTHAL HOLDING	AUSTRIAN TRADED INDEX
Belgium	KBC GROUP	BANQUE NATIONALE DE BELGIQUE	GIMV	GBL NEW	BREDERODE	BEL 20 INDEX
Brazil	AMAZONIA ON	BANCO DO NORD ON	BNCO ALFA INVEST PN	BANCO BRADESCO PN	ITAU UNIBANCO HOLDING PN	BRAZIL BOVESPA
Canada	LAURENTIAN BK.OF CANADA	BANK OF MONTREAL	NATIONAL BANK OF CANADA	CI FINANCIAL	BK.OF NOVA SCOTIA	S&P/TSX 60 INDEX
China	PING AN BANK	SHAI.PUDONG DEV.BK.	SHAANXI INTL.TRUST	SHANGHAI AJ GP.	SHANGHAI CHINAFORTUNE	SHANGHAI SE A SHARE INDEX
Denmark	LAN & SPAR BANK	GROENLANDSBANKEN	KREDITBANKEN	SPAR NORD BANK	SYDBANK	OMX 20 INDEX
Finland	NORDEA BANK	ALANDSBANKEN A	PANOSTAJA	EQ	KH GROUP	RF FINLAND FINANCIALS L INDEX
France	CARDE.CAMU.IEV.	BNP PARIBAS	CAISSE REG CRED AGRIC MUT TOURAIN POITOU	CARDE.CAMU.APR.PAR	CREDIT AGR.ILE DE FRANCE	FRANCE CAC 40 INDEX
Germany	MERKUR PRIVATBANK	DEUTSCHE BANK	COMMERZBANK	BAADER BANK	DEUTSCHE BETEILIGUNGS	DAX PERFORMANCE INDEX
India	KOTAK MAHINDRA BANK	STATE BANK OF INDIA	FEDERAL BANK	AXIS BANK	JAMMU	KASHMIR BANK & S&P/BNY MELLON INDIA ADR INDEX
Ireland	FBD HOLDINGS	BANK OF IRELAND GROUP	AIB GROUP	PERMANENT TSB GHG.	RECONSTRUCTION CAP.II	S&P/BNY MELLON IRELAND ADR INDEX
Israel	FIRST INTL.BK.OF ISR.	MIZRAHI TEFAHOT LTD.	LEUMI LTD.	BANK HAPOALIM B M LTD.	DISCOUNT	S&P/BNY MELLON ISRAEL ADR INDEX
Italy	BPER BANCA	INTESA SANPAOLO	BANCA MEDIOLANUM	UNICREDIT	MEDIOBANCA BC.FIN	FTSE MIB INDEX
Japan	DAITO BANK	BANK OF NAGOYA	SUMITOMO MITSUI TST.HDG.	AEON FINANCIAL SERVICE	ACOM	NIKKEI 225 INDEX
Netherlands	ING GROEP	VAN LANSCHOT KEMPEN	VALUE8	HAL TRUST	AEGON	AEX INDEX (AEX) INDEX
Norway	SPAREBANK 1 SMN ORDS	SPAREBANK 1 NORDNORGE	SPAREBANK 1 SR-BANK	SPAREBANKEN VEST	ABG SUNDAL COLLIER HOLDING	OSLO EXCHANGE ALL SHARE
Poland	ING BANK SLASKI	MBANK	BANK MILLENNIUM	BANK POLSKA KASA OPIEKI	BANK HANDLOWY W WARSZAWIE	RF POLAND BNKING/INV SVS L INDEX
Portugal	BANCO COMR.PORTUGUES	PATRIS INVESTIMENTOS	RAIZE-INSTITUICAO DE PAGAMENTOS			PSI20
Russia	SBERBANK OF RUSSIA	URAL-SIBERIAN BANK	ROSBANK	BANK SAINT PETERSBURG	IRKUT	S&P/BNY MELLON RUSSIA ADR INDEX
South Korea	INDUSTRIAL BANK OF KOREA	SHINHAN FINL.GROUP	JEJU BANK	KB FINANCIAL GROUP	SBI INVESTMENT KOREA	KOREA SE COMPOSITE (KOSPI) INDEX
Spain	BANCO SANTANDER	BANKINTER	BBV.ARGENTARIA	ALANTRA PARTNERS	CORPORACION FINCA.ALBA	IBEX 35 INDEX
Sweden	SWEDBANK A	SKANDINAVISKA ENSKILDA BANKEN A	SVENSKA HANDELSBANKEN A	BURE EQUITY	ORESUND INVESTMENT	OMX STOCKHOLM 30 (OMXS30) INDEX
Switzerland	WALLISER KANTONALBANK	BANQUE CANTON.DE GENEVE	BASLER KB	VONTOBEL HOLDING	LIECHTENSTEINISCHE LANDESBANK	FTSE Switzerland
Turkey	TKI.GARANTI BKSI.	TURKIYE IS BANKASI	AKBANK	SEKERBANK	GLOBAL YATIRIM HLDG.	TR-ISE 100 INDEX
United Kingdom	HSBC HOLDINGS	BARCLAYS	STANDARD CHARTERED	CLOSE BROTHERS GROUP	MAN GROUP	FTSE 100 INDEX
United States	LANDMARK BANCORP	AMERIS BANCORP	HMN FINANCIAL	WCF BANCORP	MIDWESTONE FINL.GP.	S&P 500 COMPOSITE Index

Table A2: Regional effect assumption and K-means clustering results

Group A	Component list (based on regional distribution)
1	Austria, Belgium, Denmark, France, Finland, Germany, Ireland, Italy, Norway, Netherlands, Poland, Portugal, Spain, Sweden, Switzerland, United Kingdom.
2	Canada, United States.
3	China, India, Israel, Japan, Russia, South Korea, Turkey.
4	Australia.
5	Brazil.
Group B	**Component list (K-means clustering results of factor loadings)**
1	Australia, Brazil, Canada, India, Norway, Poland, Turkey, United Kingdom, United States.
2	China, Israel, Japan, South Korea.
3	Russia.
4	Finland, France, Switzerland.
5	Austria, Belgium, Denmark, Germany, Italy, Netherlands, Spain, Sweden.
6	Ireland, Portugal.

Note: Group A is based on our assumption that the FSR for each country will display a regional similarity after subtracting the global spillover effect. Group B shows the results under K-means based on the coefficient of potential factors.