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Original Paper

Quantile-based Nonlinear Impact of Artificial Intelligence and Economic Policy Uncertainty on Education and Training Market in China

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Abstract

In recent years, with the rapid development of artificial intelligence (AI) technology and the intensification of global economic policy uncertainty (EPU), China's education and training market (ETM) is facing unprecedented challenges and opportunities. This paper analyzed the quantile-based nonlinear impact of AI and EPU on ETM in China, and the results are as follows: 1. The nonparametric quantile causality test shows that there is a unidirectional causal relationship between AI and EPU, AI and ETM, as well as EPU and ETM; 2. The cross-quantilogram indicates that there is a quantile dependence among the three: the positive predictive effect of AI on ETM is mainly concentrated in bullish markets, the negative predictive effect of EPU on ETM is mainly concentrated in periods of policy stability, and there is an interaction between AI and EPU (AI promotes EPU in bullish markets, while EPU promotes AI during periods of economic stability); 3. The GARCH-Conditional quantile regression-model reveals the asymmetry of risk spillovers—the intensity of upside risk spillovers is far greater than that of downside ones. The risk spillover from AI to ETM is characterized by high volatility and strong extremeness, while the impact of EPU is relatively moderate but more persistent. The results suggested that policy makers, education and training organizations should comprehensively consider AI and EPU to cope with market uncertainty and ensure the stability and sustainability of ETM in China.

Keywords

Artificial intelligence, Economic policy uncertainty, Education and training market, Nonparametric quantile causality test, Cross-quantilogram method, GARCH copula quantile regression-based CoVaR model

1. Introduction

Artificial intelligence (AI), as a booming technology, is profoundly affecting all aspects of our social life. It has generated a whole new way of teaching and learning in the field of education, and the change may imply that the field of education could be one of the fields most profoundly impacted by AI (Zouhaier et al., 2023). It can be said that the future of education is inextricably linked to the development of intelligent machines (Pedro et al., 2019). Many developed countries have already incorporated AI in their education systems. Among the proportions of educational institutions worldwide using educational robots in 2018, 26% of educational institutions in the United States utilized robots. Japan and the United Kingdom followed closely, with both having an adoption rate of 12%. South Korea and the Netherlands came next, with adoption rates of 10% and 7% respectively (Osetskyi et al., 2020). As the largest developing country, China has also demonstrated unique advantages in terms of technological development and economic growth. In 2017, the Chinese government released the New Generation Artificial Intelligence Development Plan[1], which proposes to China to become one of the world's leading AI innovation centers by 2030. As part of this vision, China has formulated a national strategy for AI education. In 2024, China's Ministry of Education launched four specific actions[2] aimed at using AI to promote the integration of teaching and learning applications, to improve the digital education literacy and skills of the entire population, and to develop large AI model for education, as well as regulating the use of AI in science ethics.

AI plays a key role in improving teaching efficiency and optimizing the learning experience. It can analyze students' learning behaviors based on their historical performance and generate personalized learning programs to improve learning outcomes (Luckin and Holmes, 2016). AI also changes the business model and market structure of education and training. Many Chinese education technology companies, such as Xueersi International Education Group and New Oriental Education and Technology Group, have begun to explore the application of AI to personalized learning and intelligent tutoring, thereby improving students' learning effects and teachers' teaching efficiency (Renz and Hilbig, 2020). According to the China's Education and Training Market Report[3] in 2023, with the gradual popularization of AI technology, the size of the AI-driven education and training industry is expected to reach 236.14 billion RMB by 2025, with huge growth potential. This trend not only brings new opportunities for educational institutions, but also prompts them to rethink the effectiveness and future direction of the traditional education model.

In the context of globalization and the rapid development of information technology, national economic policies often play an important role in guiding and regulating the market (Easterly, 2005). However, in recent years, the economic policy environment of countries around the world has become more and more

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[1] For this, refer to: https://www.gov.cn/zhengce/content/2017-07/20/content_5211996.htm.

[2] See: http://www.moe.gov.cn/jyb_xwfb/xw_zt/moe_357/2024/2024_zt05/mtbd/202403/t20240329_1123025.html

[3] For this, see: https://www.chinabgao.com/k/jiaoyupeixun/67618.html

uncertain due to the combined effects of multiple factors, such as the COVID-2019, the U.S.-China trade war, the U.S.-China technological war, the Russian-Ukrainian war, and other international complexities. Economic policy uncertainty (EPU) has become one of the important variables affecting various industries (Baker et al., 2016). China's economic development has made remarkable achievements in the past decades, and the updating rate of the required knowledge competencies in various industries is getting faster and faster. In this context, the education and training industry has become an integral part of Chinese society that cannot be ignored. With the increasing investment in education by Chinese families, the education and training industry has developed rapidly, especially in the areas of out-of-school tuition, vocational training and quality education (Guo et al., 2019; Fan et al., 2024). However, as an industry highly dependent on the policy environment and market demand, education and training organizations are not only affected by market supply and demand, but also directly constrained by changes in national education policies and economic policies (Azizi and Lasonen, 2006). In recent years, with the introduction of the "Double Reduction" policy[4] (i.e., the policy to reduce the burden of students' homework and the burden of out-of-school training) and China's stringent restrictions on the entry of capital into the education industry, the operating environment of education and training institutions has changed significantly, which has made the study of the impact of EPU on the education and training industry increasingly urgent and necessary (Yin and Lai, 2021; Guo, 2022). The education and training industry, as an important supporting force for China's economic transformation and human capital enhancement, faces an increasingly complex policy environment. On the one hand, the state's emphasis on educational fairness and policy adjustments have led to a greater impact on certain segments of the industry, especially subject-based training organizations in the compulsory education stage (Lu et al., 2023; She et al., 2023); on the other hand, in China, the education and training industry is not only an important supplement to the education system, but also an important source of household expenditure and social investment of an important area. Parents' emphasis on education and demand for high-quality educational resources make the education and training market (ETM) a huge potential. While existing studies have revealed that EPU can have a profound impact on the financing, expansion and innovation capabilities through a variety of policies such as capital market, industry regulation, taxation, and a wide range of impacts on firms' behaviors and macroeconomics (Wang et al., 2014; He et al., 2020; Zhang et al., 2022; Liu and Gao, 2024), research about its influence on ETM is still relatively limited (Al-Thaqeb and Algharabali, 2019). To characterize the properties of nonlinearity, heterogeneity, tail risk, and quantile dependence, thereby enabling the derivation of targeted conclusions for implementing differentiated policies based on distinct market conditions, this paper examines the quantile-based impact of China's AI and EPU on the ETM.

The innovations of this paper are as follows. Firstly, a large number of studies have considered AI or EPU as a single variable and examined the impact of AI/EPU on China's education industry qualitatively.

[4] see http://www.moe.gov.cn/jyb_xwfb/ gzdt_gzdt/s5987/202107/t20210724_546566.html

Little attention has been paid to the impact of these two variables on China's ETM quantitatively. And the interaction between EPU and AI on ETM has also received little attention. Second, unlike previous studies that mainly focus on the linear relationship between AI and ETM, our study provides more insight into the nonlinear relationship. Finally, the existing literature mainly focuses on education research in the developed western countries with fairly mature education systems such as the U. S. (Marginson, 2018). However, as the world's second-largest economy and the largest developing country, although there is a certain gap between China's education and training system and that of developed countries, it has also expanded rapidly in recent years (Mok and Jiang, 2018). This rapid development is particularly reflected in the expansion of the scale of education, the gradual equalization of educational resources and the government's continuous investment in education and training (Cai, 2020). Hence, this paper focuses on analyzing the quantile-based impact of AI and EPU on ETM in China. To be specific, we applied the nonparametric causality-in-quantiles test to study the causality, and the cross-quantilogram method to show the quantile dependence relationship, and the GARCH-CQR-CoVaR to reveal the asymmetry of risk spillover among them.

The paper is structured as follows: Section 2 summarizes the relevant literature and presents the research hypotheses; Section 3 discusses the methods used in this study; the empirical results and their discussion are presented in Section 4; the final section includes the conclusions and recommendations.

2. Literature Review

2.1 Artificial Intelligence and Education & Training Market

With the rapid progress of science and technology, the application of AI in ETM has become increasingly deep. The introduction of AI technology has brought new and unprecedented changes to the education and training industry, especially in personalized learning and teaching management. For example, online education platforms such as Bytedance Education and Homework Help are able to provide personalized learning content and paths based on students' learning behaviors and performances, which improves the efficiency and effectiveness of learning, and reduces the education costs for both students and parents (Li and Lalani, 2020; Harry and Sayudin, 2023). AI technology also plays an important role in the field of adult education and vocational training (Chen and Zhang, 2022). By analyzing trainees' individual profiles through data analytics tools, the most suitable combination of courses can be recommended for trainees to help them improve their vocational skills and competitiveness (Rott et al., 2022). Thanks to the assistance of AI technology, education and training have become more flexible, allowing for efficient learning regardless of time and location. Hence, the following two hypotheses are proposed.

Hypothesis 1a: There is a dynamic causal link between AI and ETM

Hypothesis 1b: AI promotes ETM during bullish periods

2.2 Economic Policy Uncertainty and Education & Training Market

Since the financial crisis in 2008, more and more scholars have begun to refocus on the impact of EPU on economic activities. Firstly, EPU leads to investment market volatility (Chen et al., 2022), which in turn affects financial flows and strategic development in ETM. Second, uncertainty in economic policies can prompt households to spend more on education and training to enhance their ability to cope with future risks, which directly contributed to the development of the vocational training market in China. With the instability in the labor market, many people maintain their competitiveness by upgrading their skills. There is a positive correlation between policy uncertainty and vocational training because individuals and firms want to respond to the changing policy environment by upgrading their skills (Ding et al., 2023). In addition, particularly in China, households tend to increase their investment in education to ensure that the next generation gains a competitive advantage in an uncertain economic environment (Zhou, 2013; Luun and Kornrich, 2017). Moreover, in response to the severe economic situation, the Chinese government has often promoted social stability and employment by introducing policies that support education and training. For example, in the context of increasing EPU, government intervention in the ETM effectively promotes the expansion of vocational education (Nilsson, 2010). Finally, economic policy turbulence not only affects ETM, but also has an indirect impact on the employment market. In the context of increasing policy uncertainty, vocational training and the job market are more closely linked, and skill upgrading becomes an important way to cope with uncertainty (Li et al., 2024). Therefore, we propose the following two hypotheses.

Hypothesis 2a: There is a dynamic causal link between EPU and ETM

Hypothesis 2b: EPU will boost ETM in times of economic turbulence

2.3 Artificial Intelligence and Economic Policy Uncertainty

The relationship between AI and EPU has been a hot issue in academic discussions in recent years. The relationship between AI and EPU is a complex two-way process. AI can affect EPU. The widespread use of AI is changing the way traditional industries operate and challenging the existing laws and frameworks. For example, the development of AI raises privacy, data security, and employment concerns that require new responses from policymakers (Prezgalinska, 2019). However, policies often lag behind when responding to changes in AI technology, which will lead to a mismatch between policy and technology development, which in turn will exacerbate the uncertainty of economic policy. The development of AI technology affects the loss of jobs (Giuntella et al., 2022; George et al., 2023), which puts more pressure on policymakers to formulate economic policies, labor regulations and social security policies. The uncertainty of these policies, in turn, affects enterprises' investment decisions. Enterprise decision-makers may postpone or reduce investments in the AI industry due to concerns about future policy changes. When the policy environment is uncertain, the firms in the AI industry tend to adopt a more conservative investment strategy, who may delay or reduce investment in AI due to concerns about future policy changes. When faced with high-risk and cutting-edge technology investment areas, firms may postpone the investment and application of AI technology (Carriere-Swallow and Cespedes, 2013; Katayama and Kim, 2018). And the fluctuations in the EPU can affect the AI technology research and development direction. For example, companies may avoid R&D involving large amounts of personal data in favor of other projects before data protection laws are clear (Gholipour, 2019). This not only affects the breadth of applications of AI technologies, but also limits their innovation potential. The increase of uncertainty in economic policies also leads to AI brain drain, especially in countries with unstable economic policy environments, where top AI talents may choose to work in countries with clearer policies, thus affecting the development of AI in the country to which the talent belongs (Frank et al., 2019; Zwetsloot et al., 2021). Hence, the following hypothesizes are proposed.

Hypothesis 3a: EPU promotes/hampers AI when EPU is in a smooth/turbulent state

Hypothesis 3b: AI promotes EPU when it is in bullish.

3. Methodology

This study first uses the nonparametric quantile causality test (Balcilar et al., 2016) to explore the causal relationships among the three markets of China's AI, EPU, and ETM, then employs the cross-quantilogram method (Han et al., 2016) to analyze the responses of one market to changes in different quantiles and market states of another market, and subsequently applies the GARCH-CQR-CoVaR model (Tian et al., 2022) to examine the risk spillover among them.

3.1 Non-parametric Causality-in-quantiles Test

For the observable time series $\{x_t, y_t\}$, we say that x_t does not have a causal effect on y_t in the θ-quantile with respect to the lag vector of $\{y_{t-1}, \cdots, y_{t-p}, x_{t-1}, \cdots, x_{t-p}\}$, if

$$Q_\theta(y_{t-1}, \cdots, y_{t-p}, x_{t-1}, \cdots, x_{t-p}) = Q_\theta(y_{t-1}, \cdots, y_{t-p}). \tag{1}$$

Conversely, x_t is a prima facie cause of y_t in the θ-quantile with respect to $\{y_{t-1}, \cdots, y_{t-p}, x_{t-1}, \cdots, x_{t-p}\}$ if

$$Q_\theta(y_{t-1}, \cdots, y_{t-p}, x_{t-1}, \cdots, x_{t-p}) \neq Q_\theta(y_{t-1}, \cdots, y_{t-p}) \tag{2}$$

Here $Q_\theta(y_t|\cdot)$ is the θ-quantile of y_t depending on t and $0<\theta<1$.

Write $Y_{t-1} \equiv \{y_{t-1}, \cdots, y_{t-p}\}$, $X_{t-1} \equiv \{x_{t-1}, \cdots, x_{t-p}\}$, $Z_t = \{X_t, Y_t\}$. Let $F_{Y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{Y_t|Y_{t-1}}(y_t|Y_{t-1})$ denote the conditional distribution function of y_t given Z_{t-1} and Y_{t-1} respectively. Assume that $F_{Y_t|Z_{t-1}}(y_t|Z_{t-1})$ is absolutely continuous with respect to y_t for almost all Z_{t-1}. If $Q_\theta(Z_{t-1}) = Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) = Q_\theta(y_t|Y_{t-1})$, then the probability that $F_{Y_t|Z_{t-1}}(Q_\theta(y_t|Z_{t-1})|Z_{t-1}) = \theta$ is 1. Therefore, based on Eqs. (1) and (2), the following hypotheses need to be tested.

$$H_0: \ P\{F_{Y_t|Z_{t-1}}(Q_\theta(Y_t)|Z_{t-1}) = \theta\} = 1 \tag{3}$$

$$H_1: \ P\{F_{Y_t|Z_{t-1}}(Q_\theta(Y_t)|Z_{t-1}) = \theta\} < 1 \tag{4}$$

Jeong et al. (2012) introduced a distance measure J to test the original hypothesis, which is defined as

$$J = E\left[\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} - \theta\right\}^2 f_Z(Z_{t-1})\right] \tag{5}$$

Here $f_z(Z_{t-1})$ is the marginal density function of Z_{t-1}. $J = 0$ if and only if H_0 holds, and $J > 0$ holds under H_1. They showed that the feasible kernel-based test statistic for J has the following form

$$\hat{J}_t = \frac{1}{T(T-1)h^2} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{6}$$

where h denotes the bandwidth, $K(\cdot)$ is a known kernel function, k denotes the lag order, T denotes the sample size, and ε denotes the regression error, which is estimated to be $\hat{\varepsilon}_t = 1\{y_t \le Q_\theta(y_{t-1})\} - \theta$.

If the above procedure (i.e., Eqs. (1)-(6)) is applied to y_t, it is called the nonparametric causality-in-mean analysis. Similarly, if it is applied to y_t^2, it is called the nonparametric causality-in-variance analysis.

3.2 Cross-quantilogram Method

Han et al. (2016) proposed the cross-quantilogram (CQ) method, which can identify the responses of one market to changes in different quantiles and market states of another market. Given two stable time series $y_t = (y_{1t}, y_{2t})^T \in R^2, x_t = (x_{1t}, x_{2t}) \in R^{d1} \times R^{d2}$. The conditional quantile function is denoted as $q_{it}(\tau_i) = inf\{v: F_i(v) \ge \tau_i\}$ for $\tau_i \in (0,1), i = 1, 2,$ where $F_i(\cdot)$ is the distribution function of the time series. The CQ method accounts for the serial dependence between two events: $\{y_{1t} \le q_{1t}(\tau_1)\}$ and $\{y_{2t-k} \le q_{2t-k}(\tau_2)\}$, where k is the lag order. The statistic CQ for $\tau = (\tau_1, \tau_2)$ quantile with k lags is

$$\rho_\tau(k) = \frac{E[\psi_{\tau1}(y_{1t} - q_{1t}(\tau_1))\psi_{\tau2}(y_{2t-k} - q_{2t-k}(\tau_2))]}{\sqrt{E[\psi_{\tau_1}^2(y_{1t} - q_{1t}(\tau_1))]}\sqrt{E[\psi_{\tau_2}^2(y_{2t} - q_{2t}(\tau_2))]}} \tag{7}$$

where $y_{i,t}$ denotes the smooth time series, $\psi_a = 1[u < 0] - a$ is the series dependency between events called quantile hit process, and t is the time. If $\rho_\tau(k) = 0$ it indicates that there is no cross-dependence between $\{y_{2t-k} \le q_{2t-k}(\tau_2)\}$ and $\{y_{1t} \le q_{1t}(\tau_1)\}$, making it impossible to conduct directional prediction from $\{y_{2t-k} \le q_{2t-k}(\tau_2)\}$ to $\{y_{1t} \le q_{1t}(\tau_1)\}$. Estimating the change in $\rho_\tau(k)$ for different lag lengths k allows us to identify the change in quantile dependence over different time periods (short, medium, and long). The common lag lengths $k = 1, 5, 22$ represent daily, weekly and monthly lags respectively.

Han et al. (2016) proposed the following Box-Ljung statistic to test the null $H_0: \rho_\tau(k) = 0$ with all k lags, $1 \le k \le p, p \ge 1.$

$$Q_\tau^{(p)} = T(T+2)\sum_{k=1}^{p} \hat{\rho}_\tau^2(k) \Big/ (T-k) \tag{8}$$

Here $\hat{\rho}_\tau(k)$ is the estimates of $\rho_\tau(k)$ which is defined as

$$\hat{\rho}_\tau(k) = \frac{\sum_{t-k+1}^{T} \psi_{\tau1}(y_{1t} - \hat{q}_{1t}(\tau_1))\,\psi_{\tau2}(y_{2t-k} - \hat{q}_{2t-k}(\tau_2))}{\sqrt{\sum_{t-k+1}^{T} \psi_{\tau1}^2(y_{1t} - \hat{q}_{1t}(\tau_1))}\,\sqrt{\sum_{t-k+1}^{T} \psi_{\tau2}^2(y_{2t-k} - \hat{q}_{2t-k}(\tau_2))}} \tag{9}$$

The approximation of CQ statistics is achieved by a smooth bootstrap process, which involves the recalculation of the time series $\{(y_t, k^*)\}_{t=k+1}^T$ and the conditional quantile function $\hat{q}_{tk}(\tau) = [\hat{q}^*{}_{1t}(\tau_1), \hat{q}^*{}_{2t-k}(\tau_2)]$. To ensure the robustness of results, we performed 1000 bootstrap estimates of

$\hat{\rho}_{\tau}^{*}(k)$.

3.3 GARCH Copula Quantile Regression-based CoVaR Model

3.3.1 ARMA(p,q)-EGARCH(m,n)

The ARMA-EGARCH model captures the correlation, volatility, and conditional heteroskedasticity of return series. The ARMA(p,q)-EGARCH(m, n) model is

$$\begin{cases} r_t = \mu_t + a_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i r_{t-1} + \sum_{j=1}^{q} \psi_t a_{t-j} + a_t \\ a_t = \sigma_t \varepsilon_t \\ \ln\, \sigma_t^2 = \omega + \sum_{i=1}^{m} g_i(\varepsilon_{t-i}) + \sum_{j=1}^{n} \beta_j \ln\, \sigma_{t-j}^2 \end{cases} \tag{10}$$

Among them, p and q are non-negative integers; φ_0 is the constant term, φ_i and ψ_t are the autoregressive parameter and moving average parameter, respectively; σ_t^2 denotes the conditional variance that has dynamics as given by the GARCH model in (10); the ε_t series consists of independent and identically distributed (i.i.d.) random variables with mean 0 and variance 1; $\omega > 0, a_i \geq 0, \beta_j \geq 0, \sum_{j=1}^{max(m,n)} (a_i + \beta_j) < 1; g_i(\varepsilon_{t-i}) = a_i\varepsilon + \gamma_i(|\varepsilon_i| - E|\varepsilon_i|)$; $E|\varepsilon_i|$ is the expected value of absolute standardized innovation ε_t; the a_i parameter represents the sign effect; the γ_i parameter denotes the magnitude effect, which reflects the asymmetric effect of positive and negative return volatility.

3.3.2 Conditional Quantile Regression Model

Using Sklar's Theorem (Sklar, 1959), the marginal distribution of random variable X, $u = F_X(x)$, and the marginal distribution of $Y, v = F_Y(y)$, are linked into a multivariate distribution function, i.e. $F_{XY}(x,y) = C(F_X(x), F_Y(y); \delta)$. Let $F_{X|Y}(y|x)$ denote the conditional distribution function of Y given X = x, then

$$\tau = P(Y \leq y|x) = \lim_{\Delta x \to 0} P(Y \leq y|x < X < x + \Delta x) = \frac{\partial C(u,v;\delta)}{\partial u} \stackrel{\text{def}}{=} C_1(\mathrm{v}|u;\delta).$$

Therefore, based on the conditional probability that Y lies at quantile τ given X=x, we can obtain the inverse function of $C_1(\mathrm{v}|u;\delta)$:

$$v = C_1^{-1}(\tau|u;\delta). \tag{11}$$

Eq. (11) represents the τ^{th}copula quantile curve of (u,v). Thus, we can derive the quantile regression (CQR) function of (x,y) at the τ-th quantile:

$$y = F_Y^{-1}\big(C_1^{-1}(\tau|F_X(x);\delta)\big) \tag{12}$$

Based on the definition of upside conditional value at risk (UCoVaR), the $(1-\tau)^{th}$copula quantile curve of (u,v) can be generated as:

$$v = C_1^{-1}(1-\tau|u;\delta) \tag{13}$$

Accordingly, the CQR function of (x,y) at the $(1-\tau)^{th}$ quantile is

$$y = F_Y^{-1}\big(C_1^{-1}(1-\tau|F_X(x);\delta)\big) \tag{14}$$

3.3.3 Conditional Value at Risk (CoVaR) Model

Using the measures of value at risk (VaR) and conditional value at risk (CoVaR) proposed by Adrian and Brunnermeier (2016), we take the spillover from the AI market to the ETM market as an example. Given a confidence level of $1-\beta$, the downside $VaR_{\beta,t}^{AI}$ and upside $VaR_{1-\beta,t}^{AI}$ of AI market returns satisfy the following conditions with the downside $DCoVaR_{\tau|\beta,t}^{ETM|AI}$ and $UCoVaR_{1-\tau|1-\beta,t}^{ETM|AI}$ of ETM market returns (given a confidence level of 1−τ):

$$\begin{aligned} &Pr\left(r_{ETM,t} \le CoVaR_{\tau|\beta,t}^{ETM|AI} \middle| r_{AI,t} = VaR_{\beta,t}^{AI}\right)\right) \\ &= Pr\left(r_{ETM,t} \ge CoVaR_{1-\tau|1-\beta,t}^{ETM|AI} \middle| r_{AI,t} = VaR_{1-\beta,t}^{AI}\right)\right) = \tau, \end{aligned} \tag{15}$$

where $r_{AI,t}, r_{ETM,t}$ represent the returns of the AI industry and the ETM market at time t, respectively. Therefore, at a confidence level of $1-\tau$ the risk spillover $\Delta CoVaR_{\tau|\beta,t}^{ETM|AI}$ is

$$\Delta CoVaR_{\tau|\beta,t}^{ETM|AI} = CoVaR_{\tau|\beta,t}^{ETM|AI} - CoVaR_{\tau|0.5,t}^{ETM|AI}. \tag{16}$$

Here, $CoVaR_{\tau|\beta,t}^{ETM|AI}$ and $CoVaR_{\tau|0.5,t}^{ETM|AI}$ denote the VaR of the ETM market when the AI market is in an extreme state and a benchmark state, respectively. Similarly, the upside risk spillover is

$$\Delta CoVaR_{1-\tau|1-\beta,t}^{ETM|AI} = CoVaR_{1-\tau|1-\beta,t}^{ETM|AI} - CoVaR_{1-\tau|0.5,t}^{ETM|AI} \tag{17}$$

3.3.4 GARCH-CQR-CoVaR Model

Let $F_{AI,t}$ and $F_{ETM,t}$ denote the marginal distribution functions of returns $r_{AI,t}$ and $r_{ETM,t}$, respectively. The GARCH copula quantile regression-based CoVaR (GARCH-CQR-CoVaR) model is expressed as follows:

$$\begin{aligned} D_{ETM}\left(\frac{CoVaR_{\tau|\beta,t}^{ETM|AI} - \mu_{ETM,t}}{\sigma_{ETM,t}}\right) &= C_1^{-1}\left(\tau | D_{AI}\left(\frac{VaR_{\beta,t}^{AI} - \mu_{AI,t}}{\sigma_{ETM,t}}\right); \delta\right) \\ &= C_1^{-1}\left(\tau \middle| D_{AI}\left(VaR_{\beta,t}^{\varepsilon_{AI}}\right); \delta\right) \end{aligned} \tag{18}$$

where, D_{ETM} and D_{AI} represent the marginal distribution of $\varepsilon_{ETM,t}$ and $\varepsilon_{AI,t}$ (i.e. the standardized residuals of $r_{ETM,t}$ *and* $r_{AI,t}$), respectively; $\mu_{ETM,t}, \mu_{AI,t}$ and $\sigma_{ETM,t}, \sigma_{AI,t}$ denote the conditional means and standard deviations of returns in the ETM market and AI market, respectively. Therefore, the downside conditional value at risk (DCoVaR) can be estimated as:

$$CoVaR_{\tau|\beta,t}^{ETM|AI} = \mu_{ETM,t} + \sigma_{ETM,t} D_{ETM}^{-1}\left(C_1^{-1}\left(\tau \middle| D_{\mathrm{AI}}\left(VaR_{\beta,t}^{\varepsilon_{\mathrm{AI}}}\right); \delta\right)\right) \tag{19}$$

Here, D_{ETM}^{-1} is the quantile function of $\varepsilon_{ETM,t}$。 The following Eq. (20) represents the embedded algorithm of the nonlinear quantile regression model [51] at the τ-th quantile:

$$Q_\tau\left(\varepsilon_{ETM,t} | \varepsilon_{AI,t}\right) = \theta_\tau + \eta_\tau D_{ETM}^{-1}\left(C_1^{-1}\left(\tau \middle| D_{AI}\left(D_{AI}\left(\varepsilon_{AI,t}\right)\right); \delta_\tau\right)\right) \tag{20}$$

where $Q_\tau(\varepsilon_{ETM,t}|\varepsilon_{AI,t})$ is the τ-th conditional quantile of $\varepsilon_{ETM,t}$ given $\varepsilon_{AI,t}$, η_τ is the scaling parameter, and θ_τ is the translation parameter. Therefore, given confidence levels τ and β, the $DCoVaR_{\tau|\beta,t}^{ETM|AI}$ of the ETM market can be derived under the condition of the downside $VaR_{\beta,t}^{\varepsilon_{\mathrm{AI}}}$ of the AI market:

$$CoVaR_{\tau|\beta,t}^{ETM|AI} = \left(\mu_{ETM,t} + \sigma_{ETM,t}\theta_{\tau}\right) + \sigma_{ETM,t}\eta_{\tau}D_{ETM}^{-1}\left(C_1^{-1}\left(\tau \middle| D_{AI}\left(D_{AI}\left(\varepsilon_{AI,t}\right)\right)\right); \delta_{\tau}\right) \tag{21}$$

which is called the GARCH-CQR-DCoVaR model (Tian and Ji, 2022). Meanwhile, the GARCH-CQR-UCoVaR model (Tian and Ji, 2022) is

$$CoVaR_{1-\tau|1-\beta,t}^{ETM|AI} = \left(\mu_{ETM,t} + \sigma_{ETM,t}\theta_{1-\tau}\right) + \sigma_{ETM,t}\eta_{1-\tau}D_{ETM}^{-1}\left(C_1^{-1}\left(1-\tau \middle| D_{ETMAI}\left(D_{AI}\left(\varepsilon_{AI,t}\right)\right)\right); \delta_{1-\tau}\right) \tag{22}$$

Correspondingly, under the condition that the AI market is in a benchmark state ($\beta = 0.5$), Eqs. (21) and (22) can be used to calculate the DCoVaR and UCoVaR of the ETM market. The expressions for the corresponding downside and upside risk spillovers are as follows:

$$\Delta CoVaR_{\tau|\beta,t}^{ETM|AI} = \sigma_{ETM,t}\eta_{\tau}\left(D_{ETM}^{-1}\left(C_1^{-1}(\tau|\beta;\delta_{\tau})\right) - D_{ETM}^{-1}\left(C_1^{-1}(\tau|0.5;\delta_{\tau})\right)\right) \tag{23}$$

and

$$\Delta CoVaR_{1-\tau|1-\beta,t}^{ETM|AI} = \sigma_{ETM,t}\eta_{1-\tau}D_{ETM}^{-1}\left(C_1^{-1}(1-\tau|1-\beta;\delta_{1-\tau})\right) + \sigma_{ETM,t}\eta_{1-\tau}D_{ETM}^{-1}\left(C_1^{-1}(1-\tau|0.5;\delta_{1-\tau})\right) \tag{24}$$

3.4 Two-sample Bootstrap Kolmogorov-Smirnov (KS) Test

To determine whether AI and EPU make significant contributions to the risk spillover effect on the ETM market, we adopt the two-sample bootstrap KS test proposed by Abadie (2002) to compare the cumulative distribution functions (CDFs) of the benchmark CoVaR and the downside (or upside) CoVaR. The statistical measure for the significance test is defined as follows:

$$D_{mn} = \left(\frac{mn}{m+n}\right)^{0.5} sup|F_m(x) - G_n(x)| \tag{25}$$

where, $F_m(x)$ and $G_n(x)$ are the CDFs of the benchmark CoVaR and the downside (or upside) CoVaR, respectively; m and n represent the sizes of the two samples. The null hypotheses for the significance tests of downside and upside risk spillovers are defined as:

$$H_0: \Delta CoVaR_{\tau|\beta,t}^{ETM|i} = CoVaR_{\tau|\beta,t}^{ETM|i} - CoVaR_{\tau|0.5,t}^{ETM|i} = 0 \tag{26}$$

and

$$H_0: \Delta CoVaR_{1-\tau|1-\beta,t}^{ETM|i} = CoVaR_{1-\tau|1-\beta,t}^{S|i} - CoVaR_{1-\tau|0.5,t}^{ETM|i} = 0. \tag{27}$$

Here i denotes either AI or EPU. Finally, the asymmetry test can assess whether the downside risk spillover from the AI or EPU market to the ETM market is greater than or equal to the upside risk spillover. This asymmetry test can also be implemented via the two-sample bootstrap KS test. The alternative hypothesis for the asymmetry test is defined as:

$$H_1: CoVaR_{1-\tau|1-\beta,t}^{ETM|i} > \left|CoVaR_{\tau|\beta,t}^{\mathrm{ETM|ETM}}\right| \tag{28}$$

4. Empirical Results and Analysis

4.1 Data and Descriptive Analysis

The data collection period for this paper is from January 2, 2019 to June 17, 2022. The starting point of the data is due to the fact that 2019 is a year of rapid development and deep integration of AI in education and training, especially when applications such as personalized learning, adaptive teaching, and automated assessment begin to be deployed on a large scale. And at the beginning of 2019, the Ministry of Education initiated the construction of “Smart Education Demonstration Zone”[5], which encouraged schools to introduce smart education technologies and requires them to enhance the collection, analysis and application of education data through digital means, and to build intelligent smart and personalized teaching and learning system. This policy established an opportunity for cooperation between education technology companies and schools. The outbreak of COVID-2019 further promoted the popularity and innovation of AI applications in education and training, marking AI as an important technological driver of educational change. The end point of the data is the termination time of the EPU daily data we adopted. We used the CSI Artificial Intelligence Industry Index (No.931071) to represent the development of the AI industry in China. The index specializes in tracking major companies engaged in AI research, development, applications and services in the Chinese market, which comprehensively reflects the market performance of the AI industry. It provides a clear reference about investment opportunities in the AI industry by including key market indicators such as market capitalization, stock price and trading volume. Secondly, when measuring the market situation of China's ETM, we used the CSI Global China Education Thematic Index (No. 931456), which covers companies related to China's education listed on all major stock markets around the world, ensuring a broad and representative sample, which comprehensively reflects the overall performance of China's ETM. Both indices are launched by the China Securities Index Co., Ltd, which is an authoritative financial market index provider jointly funded by the Shanghai and Shenzhen Stock Exchanges, two of China's stock exchanges. Finally, for the China’s EPU index, we used the one proposed by (Huang and Luk, 2020). Although based on the South China Morning Post, Baker et al. (2016) proposed an EPU index[6] to portray the uncertainties caused by various factors such as the financial crisis, trade conflicts, and the COVID-2019 pandemic, the one developed by Huang and Luk (2020) is more robust which is based on ten mainland Chinese newspapers, and can reflect a greater range of uncertainty more completely and timely. It has several advantages, see https://cbade.hkbu.edu.hk/epu-mainland-china/.

All stock market indices exhibit non-stationarity (Elliott et al., 1992). Non-stationarity implies that the statistical properties (e.g. mean, variance) of these time series data vary over time, which can pose some statistical challenges for subsequent analyses. To cope with this problem, a first-order logarithmic difference method is used in this paper to transform the data into a smooth series. The returns of AI and

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[5] http://www.moe.gov.cn/srcsite/A16/s3342/201901/t20190110_366518.html

[6] http://www.moe.gov.cn/srcsite/A16/s3342/201901/t20190110_366518.html

ETM are calculated as the natural logarithm of the relative change in returns between two continuous days. That is $r_t = 100 \times ln(P_t/P_{t-1})$, where P_t is the price of time t. The volatility is obtained by calculating the square of the returns (Li et al., 2021).

The trend plot of the first-order logarithmic difference variables is shown in Figure 1. Table 1 demonstrates the descriptive statistics of AI, EPU and ETM. It can be seen that EPU exhibits the largest volatility. All the variables except EPU have the characteristics of sharp peaks and thick tails. EPU has a skewness close to zero and a more normal kurtosis close to the normal distribution. The Jarque-Bera test indicates that the distributions of the returns and volatilities of AI and ETM are non-normally distributed at 1 % significance level. The ADF test shows that all variables are smooth series at the 5% significance level.

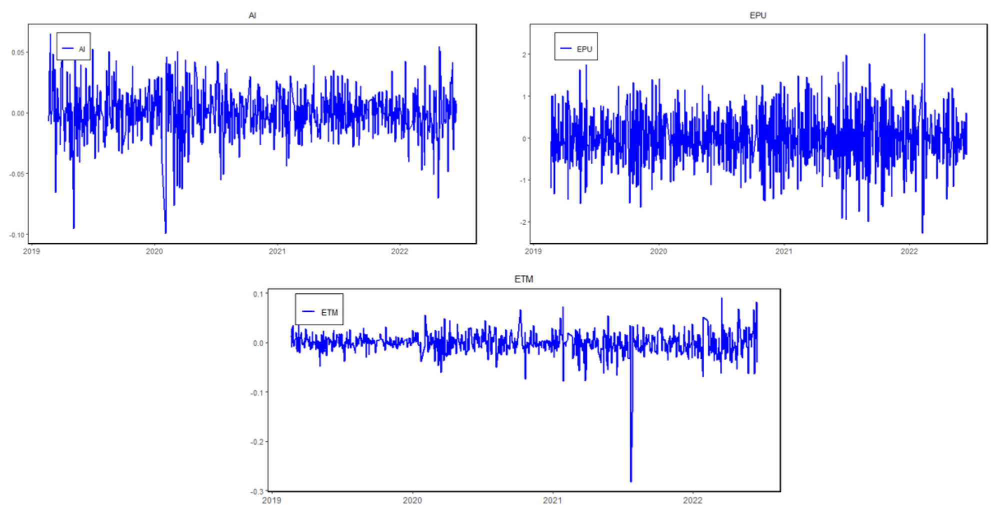

Figure 1. Trend Plot after Difference

Table 1. Descriptive Statistics

Variant	AI returns	AI volatility	ETM returns	ETM volatility	EPU
Observations	837	837	837	837	837
Mean	0.015	3.749	-0.059	5.240	-0.015
Median	-0.027	1.105	0.008	1.171	-1.638
Maximum	6.466	98.972	9.015	801.882	247.749
Minimum	-9.949	5.126E-07	-28.318	0	-228.241
Std. Dev.	1.937	7.649	2.290	29.585	66.610
Skewness	-0.368	6.019	-2.520	23.797	-0.005
Kurtosis	5.170	58.412	32.615	632.022	3.170
Jarque-Bera	183.081***	112136.826***	31472.760***	13877921.482***	1.009
ADF	-8.757**	-7.091**	-8.560**	-9.081**	-14.753**

Note. 1. *** and ** indicate 1% and 5% significance levels, respectively; 2. The values are rounded to 3 decimal places.

4.2 The Non-parametric Causality-in-quantiles Test

In this section, we used the nonparametric causality-in-quantiles test introduced by (Balcilar et al., 2016) to study the interaction between AI and ETM, EPU and ETM, and AI and EPU. Based on the range of the quantile distribution, we can classify the market into the following three types: bullish market (corresponding to the higher quantile), normal market (corresponding to the median, i.e., around 0.5), and bearish market (corresponding to the lower quantile) (Shao et al., 2021; Sohag et al., 2023). Figures 2-4 show the predictability of the distributions between AI and ETM, EPU and ETM, and AI and EPU, respectively. Here the horizontal axis represents the quantiles in the range (0.01, 0.99) and the vertical axis represents the statistics of the nonparametric causality-in-quantiles tests. The causality-in-mean and causality-in- variance tests are represented by blue and green solid lines, respectively. The results depend specifically on the market state reflected by the relevant quantile in the distribution of the dependent variable. The probabilities of significance levels of 10% and 5% are represented by grey and dark yellow lines, respectively. The causality curves indicate the degree of predictability that exists between any two markets, and these quantiles correspond to specific market conditions.

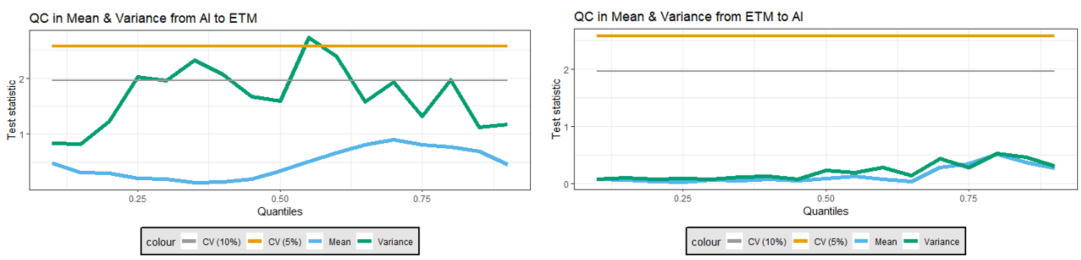

Figure 2. Quantile Causality Diagram between AI and ETM

First, we tested the causal relationship between AI and ETM. Figure 2 illustrates the causality between AI and ETM at different quantiles. In a normal market, AI has a significant unidirectional variance causality on ETM. This implies that AI will have a significant impact on decisions related to the development of ETM. Alam (2023) also found that AI has high potential as a tool for ETM and that AI plays a key role in enhancing learning and improving educational outcomes. ETMs, on the other hand, have a negligible role to play in AI.

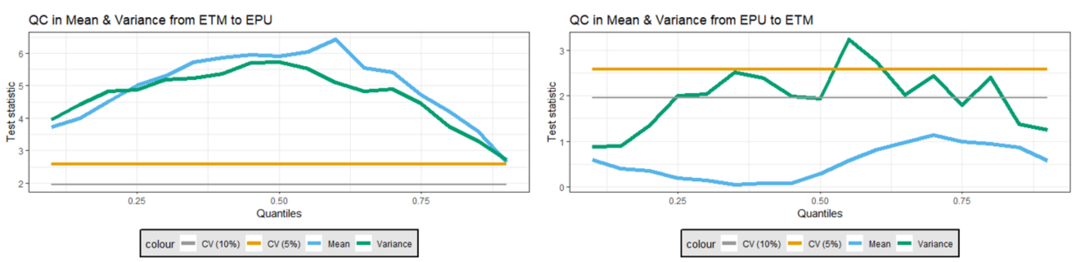

Figure 3. Quantile Causality Diagram between EPU and ETM

Next, Figure 3 illustrates the causal relationship between EPU and ETM at different quantiles. First, the causality from ETM to EPU exists over almost the entire range of quantiles, except in the extreme high quantiles of variance causality. And from EPU to ETM, the variance causality in the quantile range of (0.5, 0.625) is significant at the 10% level, and the variance causality in the quantile ranges of (0.25, 0.43) and (0.75, 0.87) is significant at the 5% level, which suggests that the volatility of the ETM is closely related to the volatility of the EPU. Wang et al. (2023) showed that when uncertainty about economic development increases, individuals may choose to hedge their labor market risks by pursuing education to improve their future employment prospects. This study demonstrates the stabilizing and adaptive role of education and training in the context of EPU. ETM not only enhances individuals' ability to cope in uncertain economic environments, but also contributes to overall economic stability and growth through the development of more rational and informed decision makers.

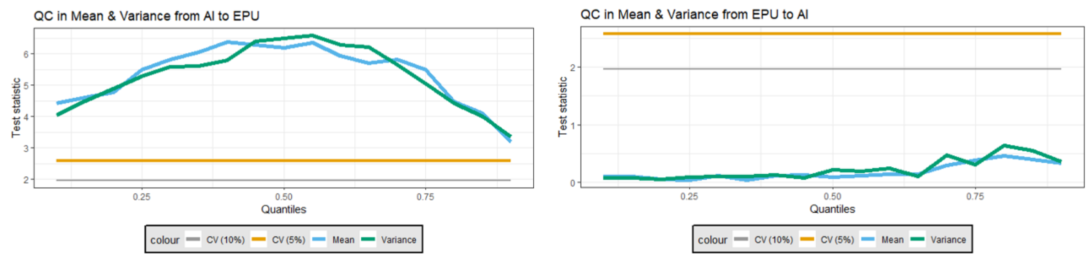

Figure 4. Quantile Causality Diagram between AI and EPU

Finally, we tested the causal relationship between AI and EPU, as shown in Figure 4. We found that the causality from AI to EPU exists in the whole middle quantile range. This means that there is strong predictability from AI to EPU across the entire market state, while the causal effect of EPU on AI is almost negligible.

4.3 Cross-quantilogram Method

In this subsection, we investigated the nonlinear dependencies between AI/EPU and ETM using the cross-quantilogram method and presented them in the form of heatmaps. We divided the 5% - 95% quantiles into 19 cells at 5% intervals, and each heat map consists of 361 cells quantiles representing different combinations of quantiles. In addition, we used asterisks (*) to mark results that reach the 10% significance level. Secondly, the heatmaps contain red and blue squares, where the red squares indicate a positive correlation or the highest degree of dependence, while the blue squares indicate a negative degree of correlation. The intensity of the colors ranges from blue to red indicating a change in correlation from negative to positive. Finally, we considered different lags, including daily (1 day), weekly (5 days), and monthly (22 days). This approach highlights the impact of short (lag 1), medium (lag 5), and long term (lag 22) lags on the market response. These results are based on a bootstrap procedure of 1000 iterations.

4.3.1 AI and ETM

Figure 5 illustrates the predictability from AI to ETM. Panel A demonstrates the transfer from AI to ETM returns with different lags. Both variables show a significant positive correlation at the high quantile (around 0.9 quantiles) under lag 1. This suggests that when AI is in a bullish market, ETM also tends to behave bullishly. This confirms that when AI is in a bullish market, AI promotes ETM (i.e., Hypothesis 1b). Moreover, at the middle (0.45, 0.55) quantiles, the correlation is weak or negative, suggesting that at these extremes, AI is a negative predictor of ETM returns. With lag 5, a significant positive correlation is shown at the high (0.9, 0.95) quantiles, indicating that when AI is in bullish market, AI volatility still significantly affects ETM. Roszkowska (2019) obtained a similar correlation when examining AI and education-technology stocks, suggesting that market volatility in the technology sector can have a direct impact on the ETM market. The pass-through effect with a lag of 22 days shows a more even color distribution and a weakening of the overall correlation. Pedro et al. (2019) observed a similar phenomenon when examining the interaction between the education and training industry and the technology industry, with the negative correlation being more pronounced especially during periods of market correction. These results confirm the existence of a dynamic causal link between AI and ETM (i.e., Hypothesis 1a).

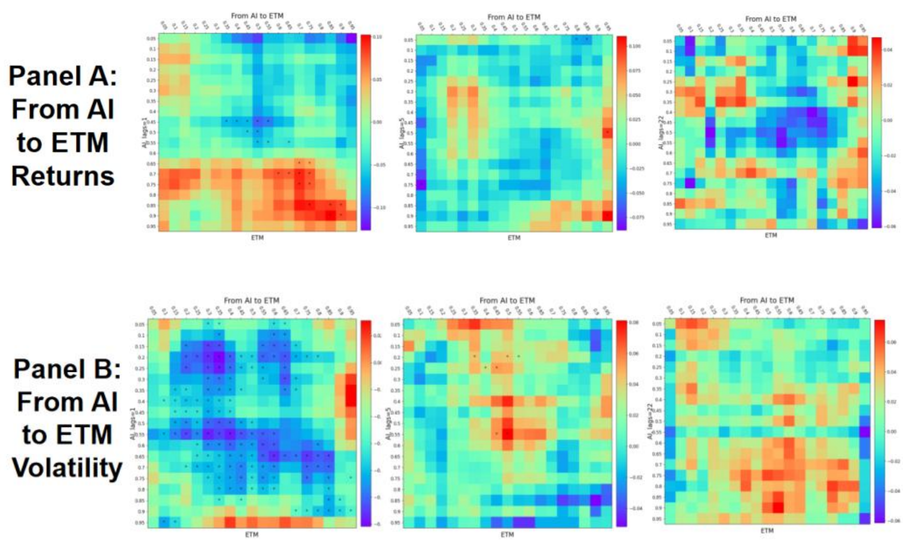

Figure 5. Cross-quantilogram Heatmap between AI and ETM

Panel B shows the volatility risk transfer from AI to ETM. When both AI and ETM are in the (0.1, 0.9) quantiles, AI transmits negative volatility to ETM at daily frequency. Volatility in the AI may negatively affect ETM in the short term. So as the market transforms and policies are optimized, the red area in the graph is likely to expand, driving a positive cycle between AI and ETM in the long term. While when we consider the monthly frequency, the effect of AI volatility on ETM is insignificant.

4.3.2 EPU and ETM

Figure 6 illustrates the predictability from EPU to ETM. Panel A shows the pass-through from EPU to ETM returns at different lags. A large red area is found when EPU is in (0.65, 0.9) quantiles and ETM is at low quantiles with lag 1 day, indicating a positive effect on ETM at these quantiles, which confirms that EPU promotes ETM when EPU is in a turbulent state (i.e., Hypothesis 2b). This may reflect the fact that people tend to improve their competitiveness through education and training when there is an increase in policy uncertainty (Koirala et al., 2024), a move that promotes the development of ETM. A significant negative correlation is shown when EPU and ETM are at the lower quantiles suggesting that EPU has negative impact on ETM when EPU declines. Whereas, with a lag of 5 days it can be seen that there is a decrease in the red areas for EPU at high quantiles, even some blue areas appear. This indicates that the effect of EPU on ETM diminished and showed a negative effect in this time period or condition, which confirms the existence of a dynamic causal link between EPU and ETM (i.e., Hypothesis 2a). The red region is relatively concentrated, especially in the (0.9, 0.95) quantiles, showing that EPU has a significant positive effect on ETM in these quantiles. This suggests that policy uncertainty has a strong driving effect on ETM under specific market conditions. When EPU is increasing, an increase in EPU is often accompanied by an increase in ETM. This may be due to the fact that investors are more concerned about the long-term investment value of the education sector when EPU is at an extremely high level (Wang et al., 2023).

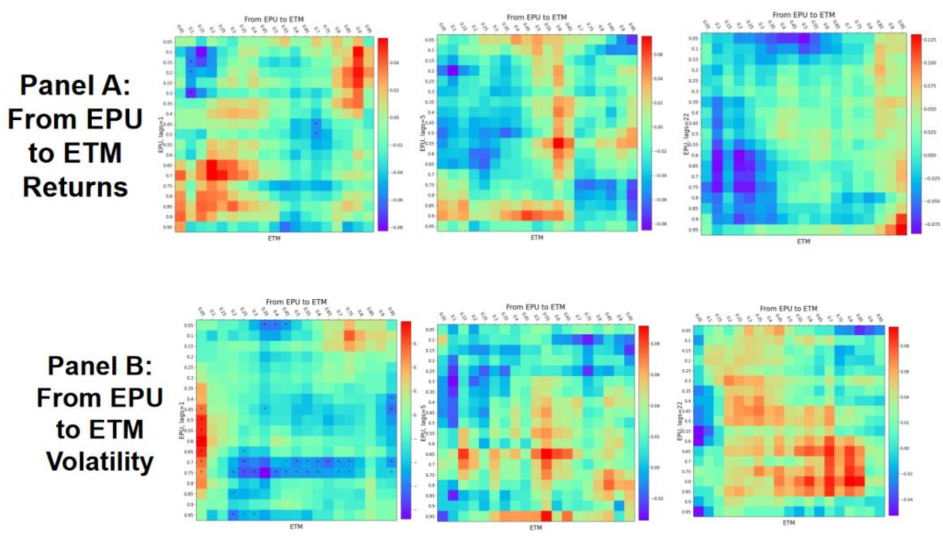

Figure 6. Cross-quantilogram Heatmap between EPU and ETM

Panel B shows the volatility risk transmission from EPU to ETM. At a lag of 1 day, volatility of EPU is positively predictive of ETM when EPU is in the (0.4, 0.75) quantiles and ETM is in the (0, 0.05) quantiles. The volatility of EPU has a negative predictive effect on ETM when EPU is in the (0.7, 0.8) quantiles and ETM is in the (0.2, 0.75) quantiles. However, this negative effect diminishes at a lag of 22 days. Specifically, the volatility of EPU has a positive predictive effect on ETM when EPU is in the middle and high quantiles. The positive predictive effect strengthens at a lag of 22 days when both are around 0.75 quantile. This may be due to the fact that long-term uncertainty may lead to instability in the ETM, as market participants become anxious in the face of long-term policy changes, affecting their investment and consumption decisions. This may lead to greater ETM volatility (Windolf, 1992).

4.3.3 AI and EPU

Figure 7 illustrates the different predictability between AI and EPU. Panel A shows the response from EPU to AI for different lags. Observation of the daily lag plots reveals that the negative response of AI to EPU is evident when EPU is in the low (0.1, 0.25) quantiles and AI is in the middle (0.55, 0.65) quantiles. In addition, when we consider weekly memory, we found a strong negative response of AI to EPU's when EPU is in low quantile and AI is in the middle (0.55, 0.6) quantiles. This suggests that in the normal market, the EPU is relatively stable, thus firms are willing to invest more in AI technologies as a strategy to improve operational efficiency, contributing to the development of AI. As the market demand for AI increases, firms may enhance their competitiveness in uncertain environments by transforming through digital innovation to increase resilience (Zhou, 2023). This confirms that in China, EPU promotes the development of AI when it is stable (i.e., Hypothesis 3a). When we consider the monthly frequency, the effect of EPU on AI is not significant.

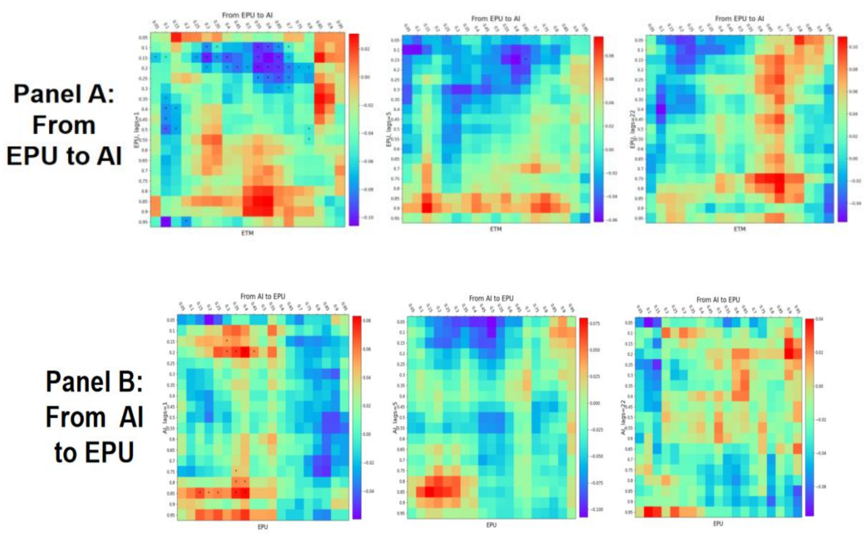

Figure 7. Cross-quantilogram Heatmap between AI and EPU

Panel B shows the cross-quantile correlations from AI to EPU with different lags. Specifically, in the short-term lag (1-day) plots, there is a significant positive correlation effect of AI on EPU when AI is at the low quantiles of (0.15 to 0.25) and EPU is at the low and middle quantiles (0.3 to 0.45). There was a significant positive correlation effect between the low and middle quantiles of AI (0.25 to 0.4) and the high quantiles of EPU (0.75 to 0.85). A positive correlation effect of AI on EPU was found between the high quantile of EPU (0.85 to 0.95) and the high quantile of AI (0.85 to 0.95) at a lag period of 5 days. This suggests that when both EPU and AI are at high levels, an increase in AI leads to an increase in EPU. This confirms that in China, AI promotes EPU under extreme conditions (bullish market) (i.e., Hypothesis 3b). At long lags (22 days), When AI and EPU are both at high quantiles (0.85 to 0.95), AI has a negative effect on EPU.

4.4 GARCH-CQR-CoVaR Model

4.4.1 Estimation of Marginal Distributions

To capture the distributional characteristics of heavy tails, skewness, autocorrelation, and volatility clustering, the marginal distributions of the ETM, AI, and EPU markets are constructed based on the ARMA-EGARCH family of models, with assumptions of the standard normal distribution (Norm), standardized Student's t-distribution (SST), and standardized skewed Student's t-distribution (SSST), respectively. Table 2 presents the criteria of Log-Likelihood Function (LLF) and Akaike Information Criterion (AIC) for model selection.

Table 2. Selection of Marginal Distributions

Variant	Distributions	ARMA(2,2)-EGARCH(1,1)	
		LLF	AIC
	Norm	-1783.367	4.283
ETM	SST	**-1703.181**	**4.094**
	SSST	-1705.146	4.101
	Norm	-1695.494	4.073
AI	SST	**-1685.452**	**4.051**
	SSST	-1685.413	4.054
	Norm	-4463.626	10.687
EPU	SST	**-4462.164**	**10.686**
	SSST	-4470.083	10.707

Note. Norm, SST, and SSST denote the standard normal distribution, standardized Student's t-distribution, and standardized skewed Student's t-distribution, respectively. LLF and AIC represent the log-likelihood function value and Akaike information criterion, respectively; a significant increase in LLF and a significant decrease in AIC together indicate an improvement in the model's goodness of fit.

Based on a comprehensive consideration of the AIC and the same configuration of other indicators, the ARMA(2,2)-EGARCH(1,1) model demonstrates the optimal adaptability for the ETM, AI, and EPU series by comparing the fitting effects of the Norm, SST, and SSST distributions. For ETM, the LLF of the SST distribution (-1703.181) is significantly larger than those of the other two distributions, and its AIC (4.094) is also the smallest. Similarly, the SST distribution (AIC = 4.051) is selected for the AI market: although its LLF (-1685.452) is slightly lower than that of the SSST distribution (LLF = -1685.413), its AIC value is lower than those of the Norm distribution (AIC = 4.073) and the SSST distribution (AIC = 4.054). Considering the consistency of model selection, the SST distribution is ultimately chosen. The EPU series also adopts the SST distribution (AIC = 10.686), whose LLF and AIC values are both superior to those of the other two distributions.

Table 3. Parameter Estimates of ARMA(2,2)-EGARCH(1,1) Model with SST Innovation

Parameters	ETM	AI	EPU
φ_0	-0.015	0.007	-0.048
	(0.017)	(0.057)	(0.145)
φ_1	1.117***	1.615***	-0.877***
	(0.008)	(0.004)	(0.036)
φ_2	-0.120***	-0.982***	0.060**
	(0.008)	(0.005)	(0.028)
ψ_1	-1.021***	-1.618***	0.046
	(2.385e-05)	(0.008)	(0.033)
ψ_2	0.028***	0.972***	-0.893***
	(0.001)	(0.006)	(0.046)
ω	0.036***	0.033***	0.210***
	(0.007)	(0.006)	(0.003)
a_1	0.002	0.003	-0.045**
	(0.025)	(0.020)	(0.019)
β_1	0.974***	0.973***	0.973***
	(3.168e-04)	(0.003)	(1.409e-04)
γ_1	0.193***	0.142***	0.063***
	(0.010)	(0.034)	(0.011)
ν	4.414***	7.890***	24.867
	(0.668)	(2.187)	(15.610)
Lj	5.060	4.292	9.219
	[0.887]	[0.933]	[0.512]
ARCH	0.846	6.654	15.195
	[0.999]	[0.758]	[0.125]

Note. 1. Standard errors are in parentheses, and p-values are in square brackets. 2. *** indicates rejection of the null hypothesis at the 1% significance level, and ** indicates rejection at the 5% significance level.

Figure 8 presents the QQ plots of the residuals from the three models. The results all meet the requirements: the points in the figures are close to a straight line, indicating that the assumption of the studentized t-distribution for the samples is acceptable. This further confirms that the models are adequately fitted.

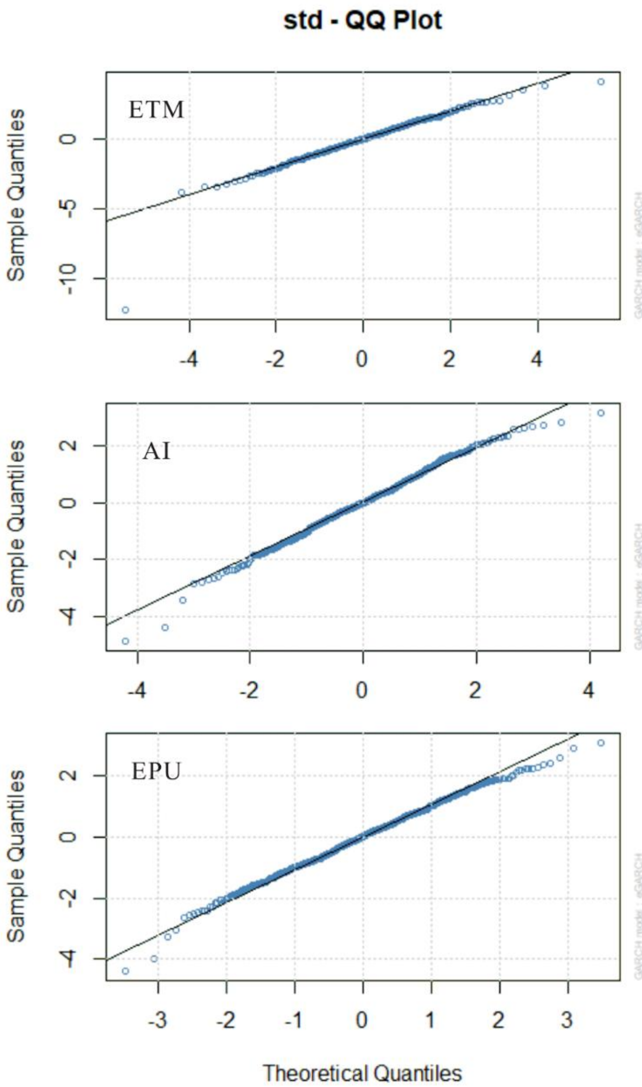

Figure 8. QQ Plots of Residuals from ARMA(2,2)-EGARCH(1,1) Models (Based on SST Distribution) for ETM, AI, and EPU

4.4.2 Copula Model Selection

Based on standardized residuals, we will adopt the marginal inference function method (Nelsen, 2006) to select the optimal copula function for the pairs of AI-ETM and EPU-ETM respectively. LLF provided in the Table 4, the rotated Gumbel copula and the Gumbel copula can optimally capture the downward and upward tail dependence structures between ETM and AI, respectively; whereas for the pair of ETM and EPU, the differences among various copula functions are relatively small. To maintain the consistency of model specification, the rotated Gumbel CQR model and the Gumbel CQR model will be used respectively in the subsequent steps to estimate the downside and upside CoVaR of the stock market.

For the convenience of readers, we have included the copula functions and their corresponding models in the Appendices A and B.

Table 4. Parameter Estimates for Copulas and Model Selection Statistics

Tail dependence	Copulas	AI		EPU	
		$\hat{\delta}$	LLF	$\hat{\delta}$	LLF
Downside	Clayton	0.448	128.216	3.32e-10	0.004
	Rotated Joe	0.505	121.889	1.39e-05	-0.001
	Rotated Gumbel	0.442	154.221	1.39e-05	-0.001
	Rotated Galambos	0.435	149.999	0.002	0.021
	Rotated Hüsler-Reiss	0.395	134.833	0	-9.99e-16
Upside	Rotated Clayton	0.427	115.719	1.55e-10	0.314
	Joe	0.488	104.820	0.029	0.285
	Gumbel	0.437	143.622	0.019	0.240
	Galambos	0.429	142.566	0.018	0.211
	Hüsler-Reiss	0.411	138.960	0	-2.77e-15

4.4.3 Estimation of the CQR Model

The rotated Gumbel CQR and Gumbel CQR model were fitted using residuals at 5% and 95% quantiles to estimate the coefficients δ, θ and η, whose fitting curves are shown in Figure 9 and results are presented in Table 5.

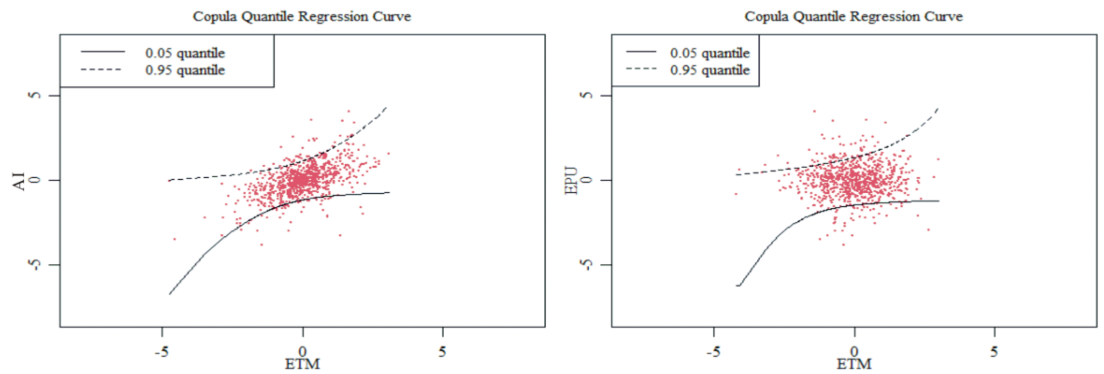

Figure 9. Quantile Regression Curves

Table 5. Coefficient Estimation of the CQR Model

Quantile	Estimated Value	AI-ETM	EPU-ETM
τ=5%	δ_τ	1.522***	1.331***
		(0.523)	(0.477)
	θ_τ	-0.365	-0.737
		(0.388)	(0.518)
	η_τ	0.718***	0.586***
		(0.157)	(0.245)
1−τ=95%	$\delta_{1-\tau}$	2.523**	2.700**
		(1.486)	(1.356)
	$\theta_{1-\tau}$	0.580	0.940***
		(0.504)	(0.262)
	$\eta_{1-\tau}$	0.882***	0.690***
		(0.222)	(0.088)

Note. Standard errors are in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.

For the downside risk (i.e. at the 5% quantile), it is shown that the tail dependence parameters between AI and ETM ($\delta_\tau = 1.522$) and between EPU and ETM ($\delta_\tau = 1.331$) are both significant at the 1% level. This indicates that AI and EPU exhibit a significant synergistic effect on ETM under extreme downside risk. The estimated values of the scaling parameter η_τ are 0.718 for AI-ETM and 0.586 for EPU-ETM, both significantly less than 1 (with p-values of 0.000), suggesting a nonlinear attenuation characteristic in the transmission of risk shocks.

For the upside risk (i.e. at the 95% quantile), the strength of tail dependence increases significantly (AI-ETM: $\delta_{1-\tau} = 2.523$; EPU-ETM: $\delta_{1-\tau} = 2.700$), and both pass the 5% significance test. This shows that the transmission effect of external shocks on ETM is more sensitive under upside risk. Notably, the location parameter $\theta_{1-\tau} = 0.940$ for EPU, which is significantly positive at the 1% level, while $\theta_{1-\tau} = 0.580$ for AI fails the significance test. This implies that the direct impact of EPU on ETM's upside risk is more explicit. In addition, the scaling parameter $\eta_{1-\tau}$ is significant (AI: 0.882; EPU: 0.690), further verifying the nonlinear amplification mechanism of extreme upside risk, which is consistent with the market's characteristic of overreacting to positive signals (such as technological breakthroughs or policy incentives).

4.4.4 Dynamic Risk Spillovers from AI and EPU to the ETM Market

At a 95% confidence level ($\tau = \beta = 5\%$), the downside $CoVaR_{\tau|\beta,t}^{ETM|\mathrm{i}}$ and upside $CoVaR_{1-\tau|1-\beta,t}^{ETM|\mathrm{i}}$, of the ETM market (where i denotes AI or EPU) can be calculated using Eqs. (19) and (20). The parameters required for this calculation have been obtained from the marginal distribution estimation and CQR model estimation in the previous two sections. To determine whether AI and EPU contribute to the ETM market, we use the two-sample bootstrap KS test to compare the dynamic CoVaR of the ETM market. The significance test results in Table 6 indicate that the null hypothesis is rejected at the 1% significance level. Therefore, AI and EPU make significant contributions to the ETM market. The results of the asymmetry test show that the risk spillovers from AI and EPU to the ETM market (hereinafter referred to as "AI risk spillover" or "EPU risk spillover" for short) both exhibit significant asymmetric characteristics, with upside risk spillovers greater than downside risk spillovers.

Table 6. Results of Significance Tests and Asymmetry Tests

Indicator	Statistics		
	Downside $H_0: \Delta CoVaR_{\tau\|\beta,t}^{\text{ETM\|i}}=0$	Upside $H_0: \Delta CoVaR_{1-\tau\|1-\beta,t}^{\text{ETM\|i}}=0$	Asymmetry $H_1: \Delta CoVaR_{1-\tau\|1-\beta,t}^{\text{ETM\|i}} \geq \left\|\Delta CoVaR_{\tau\|\beta,t}^{\text{ETM\|i}}\right\|$
AI	0.639***	0.829***	0.495***
	[0.000]	[0.000]	[0.000]
EPU	0.485***	0.723***	0.575***
	[0.000]	[0.000]	[0.000]

Note. $\mathrm{H_0}: \Delta\mathrm{CoVaR}_{\tau|\beta,t}^{\mathrm{ETM|i}} = 0$ indicates that there is no difference between the dynamic CoVaR of ETM when AI or EPU is in an extreme state versus a benchmark state. $\mathrm{H_1}: \Delta\mathrm{CoVaR}_{1-\tau|1-\beta,t}^{\mathrm{ETM|i}} > \left|\Delta\mathrm{CoVaR}_{\tau|\beta,t}^{\mathrm{ETM|i}}\right|$ indicates that the upside risk spillover is greater than the downside risk spillover. The p-values of the KS test statistics are in square brackets. *** indicates rejection of the null hypothesis at the 1% significance level.

Table 7 presents the descriptive statistics of downside and upside risk spillovers. In terms of downside risk, both the mean value (-1.937) and the absolute median (-1.846) of AI are higher than those of EPU (mean: -1.391; median: -1.326), indicating that the negative impact of AI-driven technological uncertainty on ETM is more intense. Additionally, the variance of AI's downside risk (0.651) is higher than that of EPU (0.468), and its extreme minimum value reaches -6.800 (compared to -4.886 for EPU). This reflects that the tail impact of AI-related risk events is more severe, which may be associated with black swan events such as technological iteration failures or sudden regulatory changes.

Table 7. Summary Statistics of Risk Spillovers

Type	Indicator	Mean	Variance	Maximum	Minimum	Median
Downside Risk Spillover	AI	-1.937	0.651	-0.833	-6.800	-1.846
	EPU	-1.391	0.468	-0.599	-4.886	-1.326
Upside Risk Spillover	AI	2.706	0.910	9.503	1.164	2.579
	EPU	2.127	0.715	7.469	0.915	2.027

Regarding upside risk, the mean value (2.706) and median (2.579) of AI are significantly higher than those of EPU (mean: 2.127; median: 2.027), and AI's maximum value (9.503) is much higher than EPU's (7.469). This highlights that the short-term boosting effect of technological innovation breakthroughs (such as the implementation of generative AI applications) on ETM is more significant. Notably, the variance of AI's upside risk (0.910) is higher than that of EPU (0.715). Combined with its extreme value distribution characteristics, this indicates that there is a stronger nonlinear amplification mechanism in market optimism driven by AI, which may stem from the short-term overshooting response of capital to technological concepts.

Overall, the risk spillovers from AI to ETM exhibit the characteristics of "high volatility and strong extremeness," while the impact of EPU is relatively moderate but more persistent. This difference reflects the distinct action paths of technological variables and policy variables in driving market risks: the former is susceptible to shocks from sudden technological events, while the latter is closely associated with the gradual nature of policy cycle adjustments.

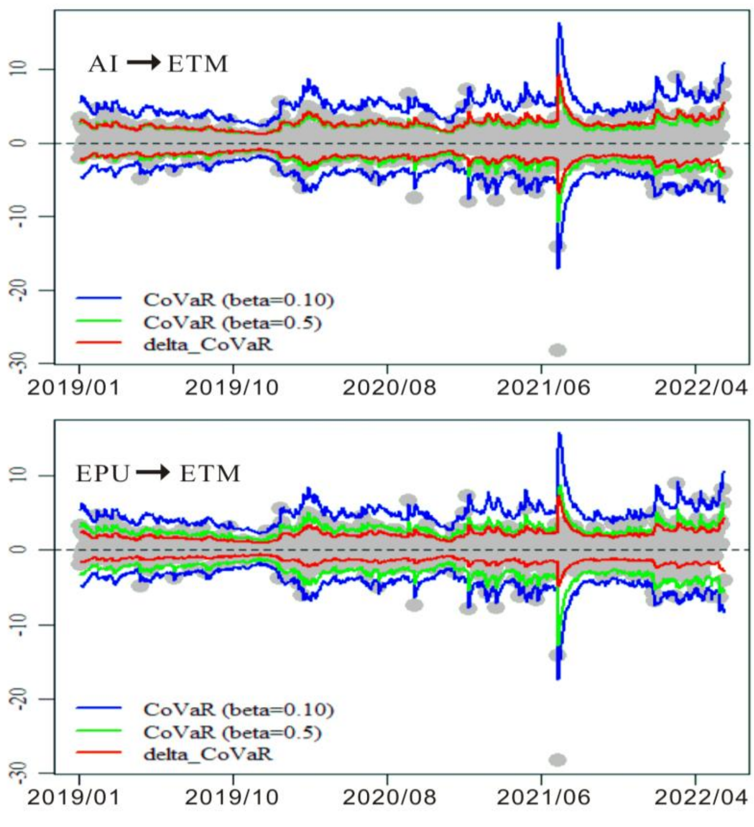

Figure 10. Dynamic CoVaR and Risk Spillover

Note. In each subplot, the gray dots represent ETM. The green line and blue line represent the CoVaR under the benchmark state and distress state, respectively. The red line represents the downside or upside risk spillover.

Figure 10 shows that at a 95% confidence level, the dynamic risk spillovers (CoVaR and $\Delta CoVa$R) from AI industry and EPU to ETM exhibit significant heterogeneity. The trajectories of CoVaR and $\Delta CoVa$R for AI and EPU display differentiated characteristics over the time dimension: the upside risk spillover of AI has a relatively wide fluctuation range, reflecting the nonlinear driving effect of capital inflows on the education market during the technological innovation cycle; in contrast, the upside and downside risk spillovers of EPU are relatively stable, indicating that the impact of policy adjustments on the education market is more steady.

From the perspective of event shocks, the sudden change nodes of CoVaR and $\Delta CoVa$R are highly associated with key policy and technological events. For instance, both experienced sharp fluctuations around the release of the "Double Reduction" policy. In addition, the extreme upside risk of AI and the extreme downside risk of EPU both occurred during periods of severe market sentiment volatility, verifying the "crisis resonance" effect of tail dependence. This graphical evidence also indicates that the upside risk spillover effects of AI and EPU on ETM are significantly greater than their downside risk spillover effects, which is consistent with the risk spillover test results in Table 7.

4.4.5 Asymmetric Characteristics and Police Implications

The risk spillovers from AI and EPU to ETM exhibit significant asymmetry, with the intensity of upside risk spillovers far exceeding that of downside ones. This phenomenon may stem from the unique attributes of the edtech market: the implementation of AI technological innovations (such as adaptive learning systems and intelligent educational hardware) is often accompanied by the expansion of market demand and capital inflows. While policy uncertainty (e.g., tightened regulation) triggers short-term fluctuations, long-term market trends remain dominated by technology-driven growth expectations. In this regard, policymakers need to focus on the dual impacts of technological iteration and policy coordination: on the one hand, they should amplify the positive spillover effects of AI through industrial support policies; on the other hand, they ought to establish a dynamic monitoring mechanism to prevent market overheating caused by extreme upside risks. For investors, when allocating ETM assets, they need to balance the dividends of technological innovation against the risks of policy adjustments, and adopt dynamic hedging strategies to enhance portfolio stability.

5. Conclusion

This study employs the nonparametric quantile causality test, cross-quantilogram method, and GARCH-CQR-CoVaR model to investigate the nonlinear relationships between AI/EPU and ETM, as well as between AI and EPU. First, based on the causality-in-quantiles test, we found unidirectional causality in AI-ETM, EPU-ETM and AI-EPU. Secondly, by the cross-quantilogram method we verified the proposed hypotheses and draw the following conclusions: firstly, the AI industry exhibits a significant positive correlation to the ETM under the high quantiles condition. This suggests that when AI technology and industry are in a rapid development stage, the education and training industry can also benefit from it, showing a trend of simultaneous growth. Second, EPU has a dual role. EPU has a significant positive impact on ETM at high quantiles, reflecting the fact that the ETM may become an option for investors seeking stability and risk aversion during periods of economic policy turbulence. However, this effect exhibits a negative correlation across lags and market conditions, suggesting that long-term policy uncertainty can also lead to investor anxiety, which affects investment and consumption decisions, and in turn, ETM's volatility and instability. At the same time, education is self-adaptive in uncertain economic environments, and it has a stabilizing and adaptive effect in the context of EPU, enhancing the ability of individuals to cope with uncertain economic environments and contributing to the stability and growth of the overall economy by fostering more rational and well-informed decision makers. Finally, the risk spillovers from AI to ETM exhibit the characteristics of "high volatility and strong extremeness," while the impact of EPU is relatively moderate but more persistent.

In summary, there are significant differences in the impacts of AI and EPU on ETM under different lag and quantile conditions. Policymakers and education and training organizations should take factors related to AI and EPU into account and develop more forward-looking and adaptive strategies to cope with market uncertainty and ensure the stable and sustainable development of ETM.

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Appendix A

Table A. Copula model

Model	Copula function	Parameter
Clayton	$C^{C}(u,v;\delta)=(u^{-\delta}+v^{-\delta}-1)^{-1/\delta}$	$\delta\in[0,\infty)$
Joe	$C^{J}(u,v;\delta)=1-((1-u)^{\delta}+(1-v)^{\delta}-(1-u)^{\delta}(1-v)^{\delta})^{1/\delta}$	$\delta\in[1,\infty)$
Gumbel	$C^{G}(u,v;\delta)=\exp(-((-\log u)^{\delta}+(-\log v)^{\delta})^{1/\delta})$	$\delta\in[1,\infty)$
Galambos	$C^{Ga}(u,v;\delta)=uv\exp(-((-\log u)^{\delta}+(-\log v)^{\delta})^{1/\delta})$	$\delta\in[0,\infty)$
Hüsler-Reiss	$C^{HR}(u,v;\delta)=\exp(\Phi(\delta^{-1}+0.5\delta\log(\log u/\log v))\log u$ $+\Phi(\delta^{-1}+0.5\delta\log(\log u/\log v))\log v)$	$\delta\in[0,\infty)$
Rotated Clayton	$C^{RC}(u,v;\delta)=u+v-1+C^{C}(1-u,1-v;\delta)$	$\delta\in[0,\infty)$
Rotated Joe	$C^{RJ}(u,v;\delta)=u+v-1+C^{J}(1-u,1-v;\delta)$	$\delta\in[1,\infty)$
Rotated Gumbel	$C^{RG}(u,v;\delta)=u+v-1+C^{G}(1-u,1-v;\delta)$	$\delta\in[1,\infty)$
Rotated Galambos	$C^{RGa}(u,v;\delta)=u+v-1+C^{Ga}(1-u,1-v;\delta)$	$\delta\in[0,\infty)$
Rotated Hüsler-Reiss	$C^{RHR}(u,v;\delta)=u+v-1+C^{HR}(1-u,1-v;\delta)$	$\delta\in[0,\infty)$

Note. Φ is the marginal distribution function of the standard normal distribution.

Appendix B

Table B. Conditional copula model

Model	Conditional distribution functions
Clayton	$C_1^{C}(v\mid u;\delta)=(1+u^{\delta}(v^{-\delta}-1))^{-(1+\delta)/\delta}$
Joe	$C_1^{J}(v\mid u;\delta)=(1+(1-u)^{-\delta}(1-v)^{\delta}-(1-v)^{\delta})^{(1-\delta)/\delta}(1-(1-v)^{\delta})$
Gumbel	$C_1^{G}(v\mid u;\delta)=u^{-1}C^{G}(u,v;\delta)(1+(\log v/\log u)^{\delta})^{(1-\delta)/\delta}$
Galambos	$C_1^{Ga}(v\mid u;\delta)=u^{-1}C^{Ga}(u,v;\delta)(1-(1+(\log u/\log v)^{\delta})^{-(1+\delta)/\delta})$
Hüsler-Reiss	$C_1^{HR}(v\mid u;\delta)=C^{HR}(u,v;\delta)u^{-1}\Phi(\delta^{-1}+0.5\delta\log(\log u/\log v))$
Rotated Clayton	$C_1^{RC}(v\mid u;\delta)=1-(1+(1-u)^{\delta}((1-v)^{-\delta}-1))^{-(1+\delta)/\delta}$
Rotated Joe	$C_1^{RJ}(v\mid u;\delta)=1-(1+u^{-\delta}v^{\delta}-v^{\delta})^{(1-\delta)/\delta}(1-v^{\delta})$
Rotated Gumbel	$C_1^{RG}(v\mid u;\delta)=1-(1-u)^{-1}C^{G}(1-u,1-v;\delta)$ $\times(1+(\log(1-v)/\log(1-u))^{\delta})^{(1-\delta)/\delta}$
Rotated Galambos	$C_1^{RGa}(v\mid u;\delta)=1-(1-u)^{-1}C^{Ga}(1-u,1-v;\delta)$ $\times(1-(1+(\log(1-u)/\log(1-v))^{\delta})^{-(1+\delta)/\delta})$
Rotated Hüsler-Reiss	$C_1^{RHR}(v\mid u;\delta)=1-C^{HR}(1-u,1-v;\delta)(1-u)^{-1}$ $\times\Phi(\delta^{-1}+0.5\delta\log(\log(1-u)/\log(1-v)))$

Note. Φ is the marginal distribution function of the standard normal distribution.