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Research article

Impact of economic policy uncertainty on Chinese airline stocks: Evidence from recent crisis periods using TVP-VAR connectedness and quantile-on-quantile analysis

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Abstract: In this paper, we investigate the dynamic relationship between economic uncertainty in China and share prices in the Chinese airline industry, focusing on periods of market crisis. Using daily data from January 2015 to June 2022 and covering major crisis events, including the China stock market crash, US-China trade war, COVID-19 pandemic, and Russia-Ukraine war coinciding with Shanghai's lockdown, we employed Time-Varying Parameter Vector Autoregression (TVP-VAR) connectedness and Quantile-on-Quantile regression methodologies to examine dynamic spillover effects between Chinese economic policy uncertainty (EPU) and individual airline stocks across market conditions. We found that policy uncertainty transforms from a passive recipient to the dominant spillover transmitter only during the most severe crisis (2022 Russia-Ukraine war/Shanghai lockdown), with total connectedness reaching 82.82% compared to 60% in normal periods, and that state-owned airlines exhibit systematically higher sensitivity to policy uncertainty during stable market conditions, while private airlines show greater resilience. These findings challenge the conventional view that policy uncertainty uniformly affects all firms within a sector, revealing that crisis severity and firm characteristics jointly determine vulnerability patterns, with critical implications for portfolio diversification strategies and policy coordination mechanisms in emerging market economies where government intervention plays a central role in economic stability.

Keywords: Chinese economic policy uncertainty; Chinese airline industry; market crisis period; TVP-VAR connectedness; Quantile-on-Quantile Regression

JEL Codes: G12, G18, C32, L93

1. Introduction

Research has highlighted how Economic Policy Uncertainty (EPU), defined as uncertainty about government policy actions and their economic consequences, can affect economic outcomes. Fernández-Villaverde et al. (2015) demonstrated that unexpected changes in uncertainty surrounding fiscal policies can significantly impact economic activity through various channels, including investment and hiring decisions. When policymakers try to influence the business environment of economic sectors directly or indirectly through the fiscal, monetary, exchange rate, and regulatory policies, uncertainty arises from two sources: External factors, which mainly force majeure events such as geopolitical crises, natural disasters, and global economic crises; and internal factors, specifically the controversy and conflict between political factions over economic policies (Azzimonti, 2018; Abedin et al., 2024). Since the Global Financial Crisis (GFC) in 2008, increased uncertainty has become an essential impediment to economic recovery, and imperfections in financial markets have harmed economic growth, especially in times of market stress (Zeng et al., 2025; Wu et al., 2025a).

In the case of the Chinese economy, the government can intervene in economic operations and resource allocation (Gao and Hafsi, 2015; Wang et al., 2025). The introduction of economic policies not only helps iron out economic cycle fluctuations and reduce the negative influence of external shocks on the Chinese economy but also guides the direction of industrial development and optimizes and upgrades the industrial structure. However, in reality, Chinese economic growth has slowed significantly, and conflicts such as overcapacity and irrational industrial structure have become increasingly prominent (Jian and Yu, 2019; Hu et al., 2025), making it urgent to promote high-quality economic development by shifting development momentum (Liu, 2023). Concurrently, uncertainties such as rising international trade protectionism and geopolitical crises have hampered global economic recovery significantly (Ciravegna and Michailova, 2022). Under this background, Chinese governments at all levels have adopted proactive economic policies to make counter-cyclical adjustments, mitigating the impact of internal and external uncertainties on the economy. These policies lack a systemic, holistic, and continuous nature, leading to increased EPU (Wu et al., 2025b; He and Hamori, 2021). In addition, in periods of crisis, such as COVID-19, the sudden and unknown nature of the crisis makes it difficult to adjust economic policies to meet market demand promptly, leading to shocks of EPU.

The Chinese airline industry exhibits several unique characteristics that make it particularly susceptible to EPU compared to other sectors. First, the industry's high fixed costs and long-term investment horizons make it especially vulnerable to policy uncertainty, as policy changes can significantly impact investment returns and operational planning. Second, the industry's heavy regulation and dependence on government policies for routes, pricing, and infrastructure development create direct exposure to policy shifts. Third, empirical evidence suggests that the airline industry's stock returns show higher sensitivity to EPU compared to the overall market average. This global and strategic importance makes the Chinese airline industry an ideal subject for studying the impact of EPU. It is worth noting that the airline industry is one of the most severely affected by external uncertainties, especially EPU among many industries. This high sensitivity makes the airline industry an ideal "laboratory" for studying the impact of EPU. By examining the effects of EPU on the airline industry, we can more clearly observe and understand the mechanisms by which EPU affects the economy. For listed air transport companies, return on equity is an essential indicator of a firm's value and a focus of attention for all parties, including the firm's shareholders, investors, analysts, and the market. Changes in stock returns can have an impact on the following aspects of a company's operations: (1) Ability to raise capital: If the share price keeps rising, the company will have a higher market capitalization and thus be more likely to obtain financing (Chauvin and Hirschey, 1993; Yang et al., 2025). (2) Employee motivation: A higher share price will enable employees to earn higher returns through stock options, thus increasing employee motivation. (3) Reputation: A higher share price enhances the company's reputation, attracting more customers and investors (Fombrun, 2004). (4) Cost of capital: If the share price falls, then investors will demand higher returns, and the company may face a higher cost of capital (Easley and O'hara, 2004; Zhang et al., 2025).

In the context of the Chinese system, economic policy is one of the essential instruments for developing the civil aviation industry (Liu et al., 2020). In particular, when the stock market is highly volatile, the government will adjust or introduce policies to intervene in the stock market, which is why the Chinese stock market is often referred to as a "policy-driven market" (Brunnermeier et al., 2022; Lu et al., 2023). As a result, changes in economic policy can impact the stock returns of firms listed in the Chinese air transport sector, and the resulting uncertainty of economic policy, which is not directly or expectedly observable, is making EPU an increasing focus for investors. This unique institutional background makes the Chinese airline industry an ideal case for studying the impact of EPU. Moreover, due to the special nature of the airline industry and China's unique institutional background, the impact of EPU on the Chinese airline industry may exhibit patterns different from other industries or countries. By studying these unique patterns in depth, we may discover new mechanisms by which EPU affects the economy, thereby providing new insights for economic policy making. Despite extensive research on EPU effects across sectors, we address a critical gap by examining the time-varying spillover mechanisms between Chinese (CNEPU) and individual airline stocks during crisis periods, focusing on the unprecedented 2022 Shanghai lockdown. We seek to answer the following questions: (1) What are the pattern and emotional impacts of CNEPU shocks in the Chinese airline industry? (2) What are the behaviors of return spillover between them across crisis periods? (3) What patterns emerged in the impact of CNEPU on the Chinese aviation industry across different market conditions?

As one of the most popular econometric techniques in recent years, Diebold and Ylmaz's (2012) seminal work can be seen as a landmark in studying dynamic network spillover and the adverse effects of periods of potential contagion. It is essential for market participants to study the propagation mechanisms of economic and financial shocks, which can help establish early warning systems to stimulate the economy and stabilize the financial system. To investigate system-specific connectedness between markets, we use the extended TVP-VAR connectedness approach of Diebold and Ylmaz (2012). It is hard to evaluate the optimal window size using the traditional DY method because experimental results vary across window sizes. The second limitation of the rolling window approach is that it cannot obtain results within the initial window cycle, especially when the window setting is significant, since more observations are lost during the initial window size. Additionally, the rolling window size is susceptible to outliers. Experimental results will be inaccurate if the window contains outliers. Based on this, Antonakakis et al. (2020) developed a TVP-VAR-based network spillover model that overcomes the disadvantages of the above models. This was done by combining the analytical method of Diebold and Yilmaz (2012, 2014) with the time-varying parameter vector autoregressive (TVP-VAR) function introduced by Koop and Korobilis (2014). As the regression elements can be dynamically adjusted, there is no rolling window, observation loss is not encountered, and it is not sensitive to anomalous data. On the other hand, we employ the Quantile-on-Quantile Regression (QQR) approach. This method independently estimates the complexity that exists between CNEPU and the Chinese aviation industry, as well as among distinct segments of Chinese airlines under various market conditions. Compared to the conventional Quantile Regression (QR) estimation techniques, QQR provides more comprehensive information on the interdependencies between variables. Specifically, traditional QR methods often fail to capture the complete dependency relationships between variables, particularly under heterogeneous quantiles (market conditions) (Han et al., 2016). Overall, TVP-VAR connectedness methodology is particularly suitable for capturing the evolving nature of policy uncertainty spillovers without imposing arbitrary structural breaks, while QQR enables examination of cross-quantile dependencies that reveal how extreme market conditions interact.

Our significant findings of this paper are as follows: First, we contribute new evidence on the dynamic spillover transmission mechanism between the CNEPU index and the Chinese airline industry by adopting the dynamic connectedness approach of TVP-VAR. The findings show that the total static system connectedness after the 2022 Russia-Ukraine war (Shanghai city lockdown) is the highest of all periods. Second, the network analysis results show that China Eastern Airlines (CEA) is a net transmitter of returns, and Spring Airlines (CQ) is a net recipient of return spillover in all periods. In addition, CQ is the net receiver of pairwise connectedness in the system in all periods. Before the 2022 Russia-Ukraine War (Shanghai City lockdown), the Airline transportation sector (ATR) consistently sent the strongest trans-pairwise spillover in the system to CQ. Moreover, after the 2022 Russia-Ukraine War (Shanghai city lockdown), there was a significant shift in the spillover pattern in the network, with CNEPU becoming the dominant spillover sender in the system. In contrast, CEA is not sensitive to crisis shocks. These results suggest that the 2022 Russia-Ukraine War (Shanghai city lockdown) was a sudden major crisis. These black swan events significantly increased CNEPU and enhanced CNEPU's cyclical shocks to the Chinese airline industry. Third, the dynamic total connectedness results show a high point in early 2020 following the outbreak of COVID-19. This is closely related to the global pause in economic activity, and it is worth noting that the COVID-19 outbreak did not cause much of a shock to Chinese airline share prices, which appears to be due to multiple reasons, possibly related to the Chinese government bailout at the beginning of COVID-19. Fourth, for large state-owned airlines, their operations are likely more dependent on the macroeconomic environment and the stability of policies. When the CNEPU is positioned around the median, indicating relative stability in economic policy, the stock prices of these companies are at extremely low percentiles and may face greater exposure to risk, with the negative impacts of CNEPU being more pronounced. Additionally, the business of large state-owned airlines is possibly more susceptible to fluctuations in the macroeconomic environment and policy changes. In contrast, CQ, as a smaller private company, may have more flexible risk management strategies, and its sensitivity to national economic policy uncertainties is likely relatively lower.

The incremental contributions of this article to the literature are as follows: First, CNEPU can have a significant influence on Chinese airline stock returns during sudden outbreaks of uncertainty, and we provide an empirical basis for exploring the causes of abnormal stock market return volatility and for predicting stock market return volatility. As we focus on China, we add an event that has yet to receive much attention in the literature: The Shanghai city lockdown, which began in early March and ended in early May, around the time of the outbreak of the Russo-Ukrainian War in 2022. This is a landmark event in implementing China's epidemic prevention and control evaluates for the COVID-19 virus in 2022. Moreover, while the epidemic prevention and control measures have profound long-term implications for the Chinese economy and the global supply chain system (Huang et al., 2022), China's economic growth in 2022 also shows the second lowest level in almost half a century (AP News, 2023) at only 3%.

Furthermore, the rapid growth of China's air transport sector, which is the second largest in the world (IATA, 2022), has attracted many investors, and the findings of this article offer fresh perspectives for investors and policymakers. Additionally, the results can assist practitioners in the Chinese airline industry in developing targeted marketing, investment, and financing strategies, thereby enhancing the Chinese airline sector's crisis response capabilities and market competitiveness while promoting its sustainable growth.

Finally, the influence of CNEPU on the share prices of airlines is inconsistent. In times of stable market conditions, major airlines (such as AC, CSA, and HN) tend to experience greater fluctuations in their stock prices due to CNEPU influences. In contrast, CQ, as a small private airline, is likely more reliant on the demand specific to certain regions and possesses a more independent management system. Consequently, its sensitivity to national economic policy uncertainties is relatively lower.

Our results could provide more generalized results and offer investors in the Chinese airline industry more opportunities to diversify and transfer risk. In particular, our empirical results show that CNEPU significantly impacted the Chinese airline industry after the 2022 Russia-Ukraine War (Shanghai city lockdown), thus providing direction for investors to create persuasive time-varying portfolios for different risk periods. CEA demonstrates relative stability during crisis periods, though further robustness analysis would be needed to confirm its safe-haven properties.

2. Literature review

Over the past twenty years, a series of unforeseen events, colloquially termed "black swan" occurrences, shaped economic landscapes. The airline industry, characterized by high capital intensity, regulatory dependence, and operational sensitivity to external shocks, represents a particularly vulnerable sector to policy uncertainty (Sobieralski, 2020). Researchers have documented the aviation sector's heightened sensitivity to macroeconomic volatility compared to other industries, with airline stock returns exhibiting amplified responses to policy changes due to the sector's unique operational constraints and regulatory environment (Merkert and Swidan, 2019). Notable instances include the 2015–2016 stock market crash in China, the 2018 trade tensions between the US and China, and the 2020 COVID-19 pandemic. Such events prompted heightened scrutiny regarding the impact of uncertainty on financial markets, drawing attention from stakeholders, including individual investors, institutions, scholars, and regulators. While unconventional stimulus measures effectively countered economic downturns, they also amplified inherent tensions within the economic framework, consequently intensifying economic policy uncertainties. Researchers have delved into exploring the ramifications of EPU on diverse facets such as economic growth (Balcilar et al., 2016; Liu et al., 2025; Ma et al., 2025), monetary policy dynamics (Aastveit et al., 2013; Du et al., 2023), and business cycles (Bloom, 2014). Studies have further advanced our understanding of EPU's multifaceted impacts. Liu et al. (2025) demonstrated that external trade policy uncertainty significantly amplifies corporate risk exposure and stock market volatility, while Zeng et al. (2025) revealed important spillover dynamics between sustainability indices and stock markets during transition periods. Additionally, Wu et al.

(2025) provided compelling evidence on how extreme climate events, another source of uncertainty, affect tourism sector stock markets through quantile and time-frequency perspectives, suggesting broader applications of uncertainty transmission mechanisms.

A seminal contribution in this domain is the research conducted by Zhang et al. (2025), whose theoretical framework posits that policy adjustments precipitate stock price declines. Specifically, heightened uncertainty surrounding governmental economic policies, particularly against the backdrop of a mild economic downturn preceding policy shifts, correlates with more pronounced stock price declines. Subsequent studies, leveraging the EPU index formulated by Baker et al. (2016), have increasingly focused on delineating the impact of EPU on stock markets. Li and Peng (2017) examined the repercussions of EPU on stock market interlinkages in the United States and China, concluding that EPU dampens interlinkages within the US market. Yang and Jiang (2016) adopted a dynamic approach to dissect the relationship between EPU and Chinese stock returns, affirming a robust correlation between EPU levels and stock market performance. Moreover, employing a rolling window causality test, Li et al. (2016) discerned a bidirectional causal relationship between EPU and stock returns in China and India, underscoring nuanced temporal dynamics. Xu et al. (2021) probed the predictive prowess of EPU in the Chinese stock market, unveiling significant negative impacts of monthly EPU indices on subsequent month's stock returns. Arouri et al. (2016) scrutinized the impact of EPU on the US stock market spanning from 1900 to 2014, unearthing a stark reduction in stock returns amid escalating EPU levels, particularly during periods of heightened market volatility. Chen et al. (2017) explored the influence of EPU on anticipated stock market returns in China, revealing a significant dampening effect of EPU on expected returns, a relationship robust even after accounting for an array of economic and uncertainty covariates. Within the transportation sector, empirical evidence suggests that airlines demonstrate disproportionate sensitivity to policy uncertainty compared to other transportation modes, primarily due to their dependence on government policies for route allocation, pricing mechanisms, and infrastructure development (Vickerman, 2024).

After thoroughly reviewing the literature, researchers have primarily centered on assessing the influence of EPU on fluctuations in stock market activity. Conversely, scant attention has been given to exploring the effects of EPU on the stock performance of Chinese aviation firms amidst abrupt episodes of uncertainty. Given the substantial magnitude of China's aviation sector, ranking as the world's second-largest, and the sector's rapid expansion attracting considerable investor interest, investigating their interaction amid sudden uncertainty surges could aid investors and managers in recognizing the contagious nature of uncertainty and risk. Such analysis could also serve as an early warning mechanism, prompting a reevaluation of investment strategies. Moreover, diverging from conventional research methodologies in the literature, we adopt Diebold and Yilmaz's (2012) expanded model-TVP-VAR connectedness framework. This approach mitigates the limitations of prevailing models, such as the absence of a rolling window, overlooking losses, insensitivity to anomalous data, and static regression parameters. Consequently, this model offers enhanced precision in delineating the interplay between EPU and stock returns within China's aviation sector amidst sudden uncertainty upheavals. In addition, we employ the QQR method to investigate the cross-quantile dependency patterns between EPU and stock returns in the Chinese aviation industry, further reinforcing our principal findings. We address the research gap by providing the first comprehensive analysis of dynamic connectedness patterns between CNEPU and individual Chinese airlines across crisis periods.

3. Methodology and data

3.1. The TVP-VAR connectedness approach

These advanced econometric approaches are chosen to address the dynamic and non-linear characteristics of policy uncertainty transmission in financial markets. We apply the time-varying parametric vector autoregressive (TVP-VAR) model introduced by Koop and Korobilis (2014) to study the transmission of returns between Chinese airline segments and airlines. The TVP-VAR dynamic connectedness method has been used in a wide range of market, financial, and economic variables to analyze connectedness and spillover dynamics (Adekoya and Oliyide, 2021). The TVP-VAR approach offers distinct advantages over alternative methods such as Markov-Switching VAR or regime-dependent models in capturing gradual structural changes and avoiding arbitrary regime classifications (Antonakakis et al., 2020). While Markov-Switching models assume discrete regime changes, TVP-VAR enables continuous parameter evolution, which is particularly suitable for analyzing policy uncertainty that evolves gradually rather than through sudden regime shifts.

According to the Bayesian information criterion (BIC), we use the time variable:

$$Y_t = \Phi_t Y_{t-1} + u_t; u_t \setminus \Omega_{t-1} \backsim N(0, S_t)$$
$$\Phi_t = \Phi_{t-1} + v_t; v_t \setminus \Omega_{t-1} \backsim N(0, R_t) \tag{1}$$

where Y_t is a vector of (N× 1) and Ω_{t-1} is an array of data accessible to $t-1$. Y_{t-1}denotes (Np × 1)-lagged array of relevant parameters. Φ_t is the ($N \times Np$)-matrix of time-varying coefficients. u_t and v_t are dimensional arrays of (N × 1)-error terms. S_t and R_t are ($N \times N$) and ($Np \times Np$) variance covariance matrices for u_t and v_t, respectively.

Following the estimation of the TVP-VAR model, our subsequent procedure involves transitioning to the TVP-VAR framework. As outlined by Diebold and Yilmaz (2012), the TVP within the vector moving average component serve as foundational elements of the connectedness index. It is noteworthy that Koop et al. (1996) introduced relevant concepts such as the Generalized Impulse Response Function (GIRF) and Generalized Forecasting Error Variance Decomposition (GFEVD).

Therefore, we transform equation $Y_t = \Phi_t Y_{t-1} + u_t; u_t \setminus \Omega_{t-1} \backsim N(0, S_t)$ as follows:

$$Y_t = \Phi_t Y_{t-1} + u_t = A_t u_t \tag{2}$$

where $A_t = (A_{1,t} \quad A_{2,t}, \quad \dots \quad A_{p,t})'$ is an (N×N)-dimensional matrix like $A_{i,t} = \sum_{k=1}^{p} \Phi_{1,t} A_{i-k,t}$ if $i \neq 0$; otherwise, I_N. Thus, GIRF means the response of all elements to a perturbation in element i. j to i directional spillover is indicated by GFEVD,$\Psi_{j,t}^{g}(J)$, which shows the effect of element j on element i. The prediction error variance can be shown as:

$$\Pi_{j,t}^{g}(J) = \frac{\sum_{t=1}^{J-1} \Psi_{ij,t}^{2,g}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \Psi_{ij,t}^{2,g}} \tag{3}$$

where $\Pi^{g}_{j,t}(J)$ denotes the fraction of variance of a parameter relative to the other parameters,$\Psi^{g}_{j,t}(J) = S^{-\frac{1}{2}}_{jj,t} A_{J,t} S_t u_{j,t}$, $\sum_{j=1}^{N} \Pi^{N}_{j,t}(J) = 1$, and $\sum_{i,j=1}^{N} \Pi^{N}_{j,t}(J) = N$.

Using the GFEVD, we set a Total connectedness Index (TCI), which indicates the total connectedness in the model. More specifically, the method enables us to demonstrate how a perturbation on one element spills over to other elements and is represented by the following equation:

$$H^{g}_{t}(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \Pi^{g}_{ij,t}(J)}{N} \times 100 \tag{4}$$

Next, we calculate the directional connectedness received by each variable from all other variables in the system. This measures the proportion of forecast error variance in variable *i* that is attributable to shocks from all other variables *j* (where *j≠i*), expressed as:

$$H^{g}_{i\leftarrow j,t}(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \Pi^{g}_{ij,t}(J)}{\sum_{j=1}^{N} \Pi^{N}_{ij,t}(J)} \times 100 \tag{5}$$

Similarly, we estimate the directional connectedness that parameter i passes to the other parameters after the perturbation. To summarize, we can calculate the total connectedness with the other parameters, expressed as:

$$H^{g}_{i\to j,t}(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \Pi^{g}_{ji,t}(J)}{\sum_{j=1}^{N} \Pi^{N}_{ji,t}(J)} \times 100 \tag{6}$$

At last, we can calculate network connectedness, which is the effect of the element i on the variable frame.

$$H^{g}_{i,t}(J) = H^{g}_{i\to j,t}(J) - H^{g}_{i\leftarrow j,t}(J) \tag{7}$$

If $H^{g}_{i,t}(J) > 0$, it means that the parameter has more influence on the frame than it is influenced by it. If $H^{g}_{i,t}(J) < 0$, it means that the parameter i is driven by the frame.

3.2. Quantile-on-quantile (QQ)

The choice of QQR methodology complements the TVP-VAR framework by providing cross-quantile dependency analysis that traditional linear models cannot capture. Unlike conventional quantile regression that examines only univariate quantile effects, QQR reveals how market conditions (quantiles) of both variables interact, offering a more comprehensive understanding of tail dependencies during extreme market events (Tao et al., 2025). We apply a non-parametric quantile regression approach described as follows:

$$\mathrm{AT_t} = \beta^{\theta}(CNEPU_t) + \mu^{\theta}_{\mathrm{t}} \tag{8}$$

Here, $\mathrm{AT_t}$ represents the returns of Chinese airline industries during period *t*, and $CNEPU_t$ stands for the EPU of China at time *t*. *θ* indicates the quantiles of the conditional distribution of ATs, with $\mu^{\theta}_{\mathrm{t}}$ as the quantile error term, whose conditional θ_{th} quantile is expected to be zero. $\beta\theta(.)$ is treated as an unknown parameter.

To analyze Equation (8), local linear regression is utilized around the vicinity of $CNEPU^{\tau}$, as shown:

$$\beta^{\theta}(\mathrm{CNEPU_t}) \approx \beta^{\theta}(\mathrm{CNEPU}^{\tau}) + \beta^{\theta'}(\mathrm{CNEPU}^{\tau})(\mathrm{CNEPU_t} - \mathrm{CNEPU}^{\tau}) \tag{9}$$

In the above equation, $\beta^{\theta'}$ signifies the rate of change of $\beta^{\theta}(\mathrm{CNEPU}_t)$ with respect to $CNEPU_t$, termed as the partial impact. With $\beta^{\theta}(\mathrm{CNEPU}^{\tau})$ defined as $\beta_0(\theta,\tau)$ and $\beta^{\theta'}(\mathrm{CNEPU}^{\tau})$ as $\beta_1(\theta,\tau)$. Consequently, the reformulated version of Equation (9) is expressed as:

$$\beta^{\theta}(\mathrm{CNEPU}_t) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(\mathrm{CNEPU}_t - \mathrm{CNEPU}^{\tau}) \tag{10}$$

Substituting equation (10) back into Equation (8) yields equation (11) for the QQR method,

$$\mathrm{AT}_t = \underbrace{\beta_0(\theta,\tau)+\beta_1(\theta,\tau)(\mathrm{CNEPU}_t-\mathrm{CNEPU}^{\tau})}_{(*)} + u_t^{\theta} \tag{11}$$

Equation (11) defines the framework of the QQ method, with (*) indicating the θ_{th} conditional quantile of AT. This equation illustrates the direct effect of the θ_{th} quantile of CNEPU on the τ_{th} quantile of AT. β_0 and β_1, factors doubly indexed by θ and τ, delineate the quantile interaction between CNEPU and *AT*. Their values shift based on the quantiles of dependent and independent variables, thus defining a comprehensive model of interdependence.

The QQR model, as outlined in equation (11), strictly incorporates the dependent variable, ATs, and an independent variable, CNEPU, as it operates within a bivariate regression framework.

The selection of the bandwidth parameter (h) is pivotal in nonparametric QQ evaluation, as demonstrated in equation (12):

$$\mathrm{Min}_{\hat{\omega}_b\delta_1} \sum_{t=1}^{n} \sigma_{\varphi}\left[\mathrm{AT}_t - \hat{\delta}_0 - \delta_1(\mathrm{CNEPU}_t - \mathrm{CNEPU}^{\tau})\right]\left[\frac{M_n(\mathrm{CNEPU}_t)-\tau}{h}\right] \tag{12}$$

σ_{φ} represents the quantile loss framework, and *L(.)* denotes the Gaussian kernel framework, which serves as a minimal weighting criterion to augment estimation precision. This function has much significance to observations close to $CNEPU^{\tau}$, with h specifying the bandwidth of the kernel of Gaussian. This kernel distributes weights more heavily to nearby observations and is symmetric around zero. Notably, in our analysis, the Gaussian kernel's weights are inversely related to the distance from the empirical distribution framework of *CNEPUt*, shown by $\mathrm{M}_n\,(\mathrm{CNEPU}_t) = \frac{1}{n}\sum_{k=1}^{n} I(\mathrm{CNEPU}_k < \mathrm{CNEPU}_t)$, to the quantile value at $CNEPU_t$, indicated by τ, where I is the standard indicator framework.

3.3. Data

In this paper, we aim to analyze the static and time-varying correlation between economic uncertainty in China and the Chinese airline industry, with a particular focus on periods of crisis. We utilize daily data spanning from 21 January 2015 to 17 June 2022, contingent on the availability of the CNEPU. Moreover, we account for the most recent periods of systematic market stress experienced by the Chinese economy, dividing the sample into four sub-periods. Table 1 presents the chronological categorization of major events, including the Russia-Ukraine War, which coincided with the Shanghai city lockdown in early 2022. The fact that the Daily China EPU Index is updated only through 2022, our data coverage extends to 2022. Since CQ stock price data commences from 2015, our sample period begins from 2015.

Table 1. Chronology of crisis events affecting connectedness between CNEPU and the Chinese airline industry.

No.1	2015–2016 China Stock Market Crash
No.2	2018 China-US Trade War
No.3	2020 COVID-19 outbreak
No.4	2022 Russo-Ukrainian War (Shanghai city lockdown)

Note: In chronological order.

To examine the performance of the Chinese airline industry, we collect daily stock price data, which effectively reflect companies' operational status and market expectations (Cornell and Shapiro, 1987). We include the following major Chinese airlines: Air China (AC), CEA, CQ, China Southern Airlines (CSA), and Hainan Airlines (HN). We also incorporate the Shanghai Stock Exchange ATR index to capture the industry-wide exposure to EPU, as it serves as an investable asset and a comprehensive indicator of China's aviation sector performance. All stock market data are obtained from the Wind database (www.wind.cn). The CNEPU data are sourced from the Daily China EPU Index (https://economicpolicyuncertaintyinchina.weebly.com/). This index, constructed from 114 mainland Chinese newspapers provided by Wisers Information, offers a comprehensive measurement of economic uncertainty in China (Huang and Luk, 2020). Figure 1 illustrates the evolution of airline stock prices alongside the original, unadjusted values of China's economic uncertainty index.

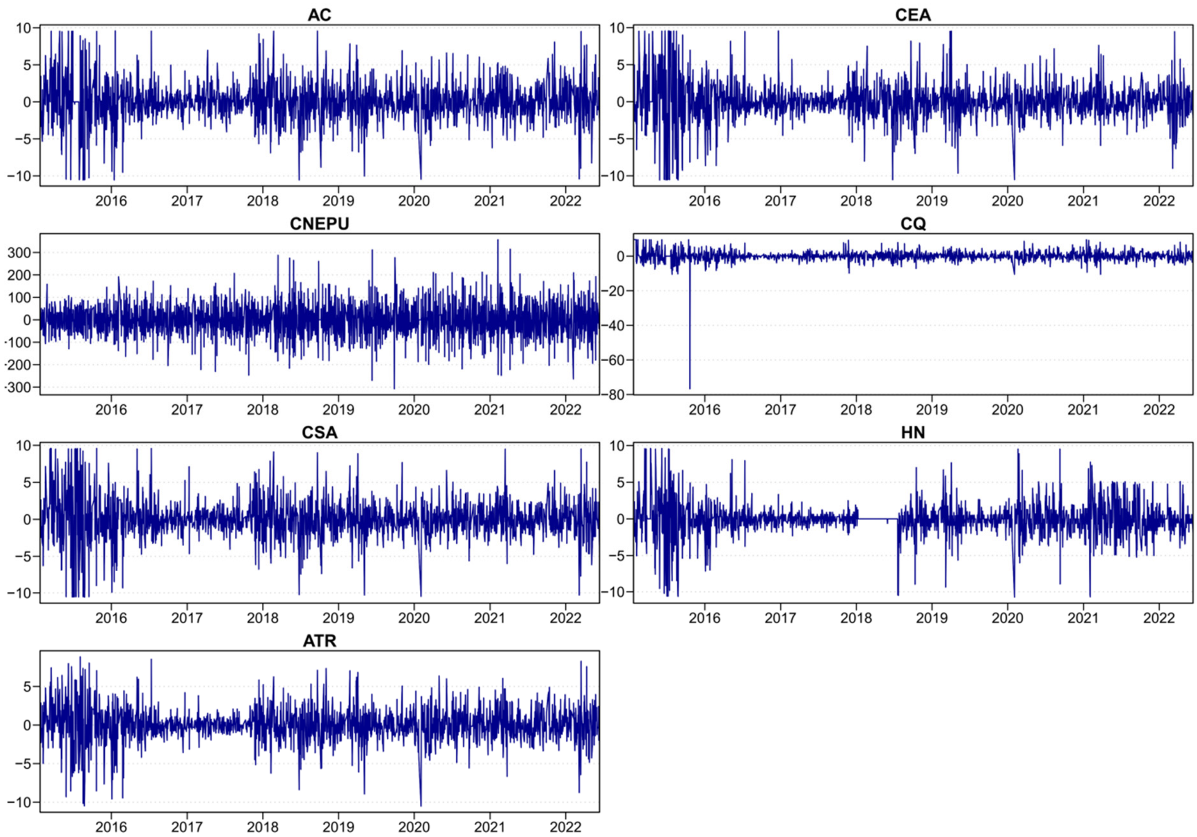

Figure 1. Dynamic of time series.

4. Empirical results analysis

Table 2 represents the summary statistics for all series of returns for logarithms. All data series have positive means except for CEA and HN, which are undesirable. The AC, CEA, CQ, CSA, and HN medians are all close to 0. All series have negative skewness except for CNEPU, for which the series is right skewed, and all series exhibit hyperkeratosis (kurtosis＞3) in the kurtosis coefficient. The high kurtosis values across all series indicate frequent extreme movements, which are characteristic of financial markets during periods of heightened uncertainty and crisis events.

Table 2. Descriptive statistics.

	AC	CEA	CNEPU	CQ	CSA	HN	ATR
Mean	0.007	−0.008	0.003	0.031	0.009	−0.041	0.017
Median	0.000	0.000	−1.865	0.000	0.000	0.000	−0.052
Skewness	−0.034	−0.070	0.113	−7.775	−0.059	−0.174	−0.186
Kurtosis	5.784	6.883	4.308	197.756	6.374	8.844	5.819
J−B	580.384***	1129.509***	131.748***	2856523***	852.942***	2564.569***	604.913***
ADF	−12.318***	−13.023***	−17.89***	−13.306***	−12.57***	−12.734***	−12.783***

Note：The J-B statistic (Jarque-Bera Statistics) is applied to test whether the return series can be considered to be from a normal aggregate. The ADF test is to determine whether there is a unit root in the series. *** means significant at 1% level.

In addition, the Jarque-Bera test for normality is significant for all series, implying that the return series are not normally distributed. Finally, we perform an ADF unit root test to confirm that the log series of the variables we use are smooth. Thus, subsequent analyses can be performed. The negative mean returns for CEA and HN suggest these airlines faced operational challenges or market headwinds during the sample period, possibly reflecting their exposure to policy uncertainty and operational inefficiencies.

The dynamic connectedness table of the return series is illustrated in Tables 3–8. Within the table, the entries at row *i* and column *j* depict the pairwise directional connectedness, signifying the transmission of spillover effects from variable *j* to variable *i* and vice versa. The "FROM" category denotes the spillover effects received by a market from all other markets, while the "TO" category represents the spillovers from one market to others, calculated as the sum of values in column *j*. Additionally, the "NET" column delineates the disparity between the amounts of spillovers "TO" and "FROM". The "NPDC" field denotes the net-paired directional connectedness, indicating instances where variable i transmits more spillover than it receives. Last, the TCI entry signifies the total connectedness index.

Table 3 for the overall sample range shows a total connectedness of 59.45%, indicating a high degree of connection between our variables. The average results in Table 2 also show that CNEPU receives a more significant impact than it does on other markets. This illustrates the role of CNEPU as a net spillover receiver within the connectedness network over the sample period.

Table 3. Total Period connectedness index.

	AC	CEA	CNEPU	CQ	CSA	HN	ATR	FROM
AC	26.66	18.06	0.23	6.61	19.76	8.24	20.44	73.34
CEA	17.68	26.00	0.24	6.45	19.55	9.55	20.55	74.00
CNEPU	1.40	1.09	93.30	1.25	0.99	0.77	1.20	6.70
CQ	10.15	10.14	0.36	43.35	11.02	5.37	19.61	56.65
CSA	18.91	18.96	0.14	6.71	25.43	9.33	20.53	74.57
HN	10.53	12.73	0.30	4.37	12.83	45.63	13.60	54.37
ATR	18.10	18.59	0.15	11.10	19.14	9.41	23.51	76.49
TO	76.77	79.58	1.41	36.48	83.29	42.67	95.92	416.12
NET	3.43	5.58	−5.29	−20.17	8.71	−11.70	19.43	TCI=59.45%
NPDC	3.00	4.00	0.00	1.00	5.00	2.00	6.00	

Note: This table is estimated by the TVP-VAR connectedness model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

The average results are mainly used to summarize potential interconnections. These findings cannot be used to examine a crisis event or significant shock. Therefore, it is crucial to use the dynamics of total connectedness or time variation to analyze the development of the market and the changing role of the sector. Figure 2 depicts the total connectedness between CNEPU and the Chinese airline industry while estimating the total sample cycle. We observe that the TCI has been changing and fluctuating between 45% and 70%, indicating that the connectedness between CNEPU and the Chinese airline industry is highly correlated and changing over time. Specifically, after a sharp increase in mid-2018, TCT increased significantly during the COVID-19 and the 2022 Russia-Ukraine war. The peak in TCI occurred in March 2020 when the World Health Organization (WHO) declared COVID-19 a pandemic. This was due to the rise of market uncertainty and the spread of investor panic during the abovementioned period (Jiang and Chen, 2022; Zeng et al., 2022). Our finding of peak connectedness in March 2020 aligns with Xia et al. (2020) who documented heightened spillovers between EPU and financial markets during COVID-19, and extends Guo et al. (2022) by demonstrating that cross-category spillovers between China and the US were particularly pronounced during this period. However, our results reveal an important distinction: While researchers found uniformly elevated spillovers during COVID-19, we observe that the most severe spillover intensity (82.82%) occurred during the 2022 Russia-Ukraine war concurrent with Shanghai's lockdown, suggesting that the combination of geopolitical crisis and domestic zero-COVID policy created unprecedented uncertainty transmission mechanisms.

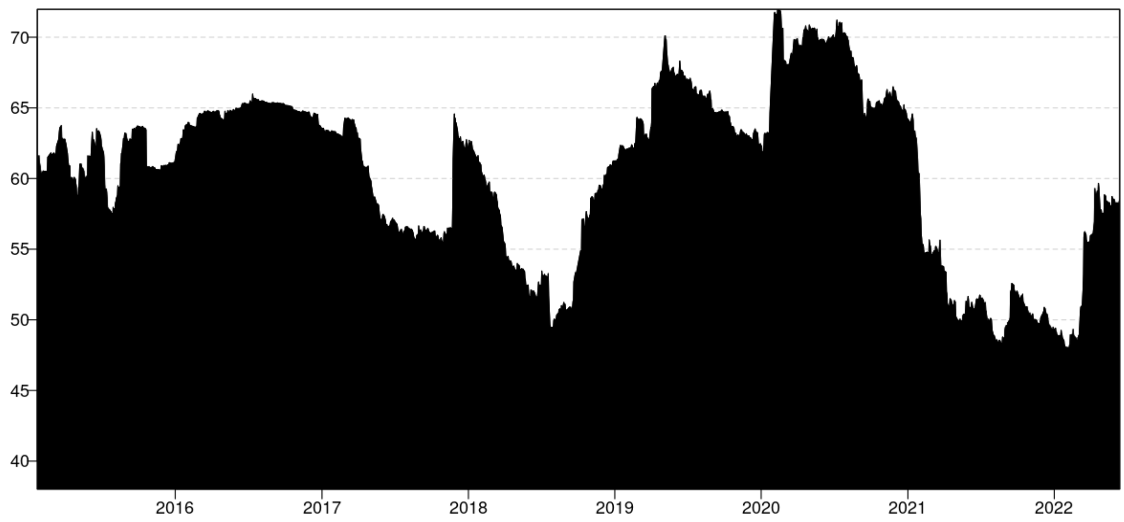

Figure 2. Dynamic return connectedness between CNEPU and major Chinese airline stocks.
Notes: This figure is estimated by the TVP-VAR connectedness model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

Moreover, major economic or political events throughout the research period may have exerted positive or negative effects on the variables under study. As dynamic connectedness tables and networks cannot show the impact of specific events on connectedness, we divide the sample into several periods for separate analysis based on the results in Table 1 to see the long-term or cyclical influence of certain crisis events on return connectedness. The connectedness tables for the periods in which these crisis events occurred are also collated chronologically in Tables 4–8. Across all crisis periods, a consistent pattern emerges where policy uncertainty's role transforms from passive recipient to active transmitter as crisis severity intensifies, with the 2022 period representing the most dramatic structural shift in spillover dynamics.

We observe in Table 4 that CNEPU is highly integrated with the Chinese airline industry (TCI = 60.86%). ATR dominates the system, contributing the largest net spillover (21.18%). In addition, CQ absorbs the largest net spillover from the system (−23.18%). Moreover, CNEPU is the second largest net recipient of connectedness from the system (−10.57%).

Table 5 shows the total spillover matrix's valuation following the China stock market crash outbreak. In addition, shocks originating from certain variables appear to bring more change to the system than the variables. Moreover, ATR makes the largest contribution to the system, at 19.14%. Conversely, CQ receives the largest shocks from other variables (−25.86%). In contrast, CNEPU absorbs a small shock from the system (−0.88%). This was mainly during the 2015–2016 China stock market crash, when increased market volatility led to a sharp increase in uncertainty and investor panic flooding the trading system (Chen et al., 2022)

Table 4. Period 1 connectedness index (2015/01/21–2015/06/28).

	AC	CEA	CNEPU	CQ	CSA	HN	ATR	FROM
AC	25.61	17.89	0.88	2.53	18.95	14.16	19.99	74.39
CEA	17.93	25.71	1.41	2.22	18.72	14.48	19.53	74.29
CNEPU	2.54	4.28	83.56	1.18	0.76	5.68	2.00	16.44
CQ	6.10	4.93	0.82	59.43	7.42	3.56	17.75	40.57
CSA	18.87	18.29	0.27	3.06	26.83	12.80	19.89	73.17
HN	16.41	16.56	1.85	1.42	15.06	29.77	18.94	70.23
ATR	18.26	17.65	0.64	6.98	18.59	14.79	23.09	76.91
TO	80.11	79.59	5.87	17.39	79.50	65.46	98.09	426.01
NET	5.72	5.30	−10.57	−23.18	6.33	−4.77	21.18	TCI=60.86%
NPDC	4.00	3.00	0.00	1.00	5.00	2.00	6.00	

Note: This table is estimated by the TVP-VAR connectedness model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

Table 5. Period 2 (2015/06/29–2018/02/28).

	AC	CEA	CNEPU	CQ	CSA	HN	ATR	FROM
AC	28.97	16.21	0.22	4.59	17.89	12.57	19.55	71.03
CEA	14.50	26.03	0.22	4.31	18.87	15.78	20.29	73.97
CNEPU	0.53	0.30	97.71	0.43	0.30	0.35	0.38	2.29
CQ	8.43	8.54	0.27	47.95	10.14	8.18	16.49	52.05
CSA	15.52	18.16	0.25	4.77	24.70	16.32	20.28	75.30
HN	12.34	17.22	0.27	4.48	18.66	28.13	18.90	71.87
ATR	15.81	18.30	0.17	7.61	19.06	15.79	23.26	76.74
TO	67.14	78.74	1.41	26.19	84.91	69.00	95.88	423.26
NET	−3.89	4.77	−0.88	−25.86	9.61	−2.87	19.14	TCI=60.47%
NPDC	2.00	4.00	0.00	1.00	5.00	3.00	6.00	

Note: This table is estimated by the TVP-VAR connectedness model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

Table 6. Period 3 (2018/03/01–2020/01/22).

	AC	CEA	CNEPU	CQ	CSA	HN	ATR	FROM
AC	24.97	19.33	0.31	7.72	21.77	4.36	21.53	75.03
CEA	19.28	25.03	0.50	8.36	20.36	4.87	21.60	74.97
CNEPU	3.40	3.37	84.60	0.41	3.03	2.37	2.81	15.40
CQ	11.44	13.03	0.30	39.37	11.93	3.35	20.58	60.63
CSA	21.29	19.91	0.34	7.76	24.48	4.73	21.49	75.52
HN	6.98	8.88	0.78	4.27	8.33	62.02	8.73	37.98
ATR	19.69	19.82	0.21	12.50	20.17	4.66	22.96	77.04
TO	82.08	84.33	2.45	41.03	85.60	24.33	96.74	416.56
NET	7.06	9.36	−12.95	−19.60	10.08	−13.65	19.70	TCI=59.51%
NPDC	3.00	4.00	0.00	2.00	5.00	1.00	6.00	

Note: This table is estimated by the TVP-VAR connectedness model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

Table 7. Period 4 (2020/01/23–2022/02/23).

	AC	CEA	CNEPU	CQ	CSA	HN	ATR	FROM
AC	25.94	19.38	0.21	9.74	20.04	4.46	20.24	74.06
CEA	19.66	25.89	0.28	8.99	20.78	4.52	19.87	74.11
CNEPU	2.35	2.16	83.46	2.78	4.36	1.24	3.65	16.54
CQ	12.89	11.75	0.27	36.45	13.06	3.35	22.23	63.55
CSA	19.85	20.19	0.21	9.70	25.31	4.50	20.25	74.69
HN	8.16	8.66	0.46	4.46	8.75	61.31	8.20	38.69
ATR	18.84	18.22	0.21	15.14	19.02	4.26	24.32	75.68
TO	81.75	80.35	1.63	50.81	86.01	22.32	94.44	417.32
NET	7.69	6.24	−14.91	−12.74	11.32	−16.36	18.77	TCI=59.62%
NPDC	4.00	3.00	0.00	2.00	5.00	1.00	6.00	

Note: This table is estimated by the TVP-VAR connectedness model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

We then look at the transmission mechanism in Table 6 in the aftermath of the US-China trade war. We note that the value of the TCI, according to Table 5, is 59.51%, which implies an extreme interdependence in the network for this variable. Focusing on the average net senders and net receivers, it is clear that ATR is the dominant net sender in the network, followed by CSA and CEA. In contrast, CQ and HN show to be the dominant net receivers in the network. On the other hand, CNEPU acts as a net recipient of return spillover but receives significantly more return spillover from the system than in previous periods. This illustrates how the US-China trade war in 2018 has not had much impact on China's economic policy and that the crisis appears to be manageable. It is worth noting that the value received by HN from the system has also increased more than in previous periods due to HN's operational mismanagement, which was struggling with debt repayment at the time (Yide, 2018).

Based on the findings in Table 7 for COVID-19, we note that the TCI is not significantly different from the previous period (59.62%). In addition, we observe that close to 83.5% of CNEPU returns are attributable to self-drive, while 16.5% are network-driven from the system, indicating that CNEPU was mainly self-influenced during COVID-19. Furthermore, we discover that HN is the largest recipient of spillover (−16.36%), followed by CNEPU (−14.91%). This reflects a shift in spillover patterns during the COVID-19 period. In contrast, ATR (18.77%) and CSA (11.32%) are the most significant net transmitters of system impact. Our results also confirm that during the COVID-19 period, EPU came from shocks subject to more spillover from other financial markets in the system (Xia et al., 2020; Guo et al., 2022). The reduced sensitivity of Chinese airlines to EPU during COVID-19, despite global aviation sector distress, could be attributed to the Chinese government's targeted bailout measures and controlled reopening strategy that provided operational certainty. This contrasts sharply with the 2022 Shanghai lockdown period, where the unpredictability of zero-COVID policy implementation created unprecedented uncertainty that traditional government support mechanisms could not offset, thereby amplifying CNEPU's influence on airline stock performance. This pattern contrasts markedly with Liu et al. (2020), who found that Chinese airlines implemented effective cost containment strategies during early COVID-19, and Zhang et al. (2021), who documented rapid recovery in domestic flights after mid-February 2020. Our results suggest that the 2022 lockdown represented a qualitatively different shock; while the 2020 pandemic response provided operational certainty through coordinated government support, the 2022 zero-COVID policy's unpredictability fundamentally altered the policy uncertainty transmission mechanism, transforming CNEPU from a passive receiver to the dominant spillover transmitter.

As the early COVID-19 period ushered in a widespread global embargo and brought with it soaring oil prices and higher operating costs globally (Asadi et al., 2023), uncertainty, and additional economic and financial consequences (Zeng and Lu, 2022), these were transmitted to the airline industry through various channels. Interestingly, however, we find that China's significant airlines were unaffected by the EPU following the post-COVID-19 outbreak. On the one hand, Liu et al. (2020) suggested that this was due to some cost containment policies and management strategies adopted by Chinese airlines to offset the decline in demand and revenue. On the other hand, Zhang et al. (2021) pointed out that after mid-February 2020, as the impact of the epidemic in China was effectively contained, flight controls were gradually liberalized within the country, and a subsequent increase in flight and passenger numbers was achieved. The latter distinguishes the strict lockdown measures from the strict dynamic clearance policy in China after 2022, which resulted in a significant reduction or disruption of public passenger traffic dispatches and flows in most parts of the country (Zeng et al., 2024).

Table 8. Period 5 (2022/02/24–2022/06/13).

	AC	CEA	CNEPU	CQ	CSA	HN	ATR	FROM
AC	15.76	16.88	19.18	10.96	10.22	14.29	12.71	84.24
CEA	13.63	19.18	16.92	10.35	11.27	15.40	13.26	80.82
CNEPU	12.60	15.80	28.63	10.48	7.46	15.03	10.00	71.37
CQ	14.82	16.04	14.84	11.70	9.59	20.48	12.54	88.30
CSA	14.89	17.57	19.98	10.66	10.60	13.71	12.60	89.40
HN	12.34	16.39	21.06	10.53	8.37	20.88	10.42	79.12
ATR	14.70	18.35	15.70	11.40	10.80	15.53	13.52	86.48
TO	82.98	101.03	107.67	64.38	57.71	94.44	71.53	579.74
NET	−1.26	20.21	36.30	−23.93	−31.70	15.33	−14.95	TCI=82.82%
NPDC	3.00	5.00	6.00	1.00	0.00	4.00	2.00	

Note: This table is estimated by the TVP-VAR connectedness model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

Table 8 presents the results for the 2022 Russia - Ukraine War and the Shanghai lockdown period, which differ notably from the previous periods, with a significant shift observed in the spillover pattern. We record the highest TCI (82.82%) of all periods. This dramatic shift in spillover patterns reflects the fundamental change in market dynamics when policy uncertainty becomes the dominant driver rather than industry-specific factors. The transformation of CNEPU from a net receiver to the primary transmitter suggests that during severe crises, policy responses become the focal point of investor attention, overriding traditional sectoral interdependencies. Uncertainty arising from war and political action have a more significant impact on the connectedness system, reflecting the sensitivity of the airline industry to financial instability and geopolitical risk. It is clear that direct or indirect shocks from the propagation of these channels affect the airline industry's operating costs and operable route traffic and could have potential long-term impacts.

Next, we observe that CSA, CQ, and ATR respond to spillover indices of around −31.70%, −23.93%, and −14.95%, respectively. CSA shows a higher negative connectedness, indicating vulnerability and the impact of financial and geopolitical instability (Zaremba et al., 2022). Moreover, while CNEPU has the most significant net spillover, strict dynamic clearing policies and market turbulence resulting from financial and political uncertainty crises (Hu and Liu, 2021) explain CNEPU's highly correlated impact on the Chinese airline industry. To further visualize the dynamic connectedness table of the return series for more intuitive access to information, we refer to Diebold and Yilmaz (2014) and Demirer et al. (2018) to network tables 3–8, as shown in Figure 3. The problematic threshold is 0.5. The node's color represents the role played by the system: Green is the spillover sender, and red nodes are spillover receivers. The direction of the arrow indicates the direction of transmission of the pairwise directional connectedness between two variables.

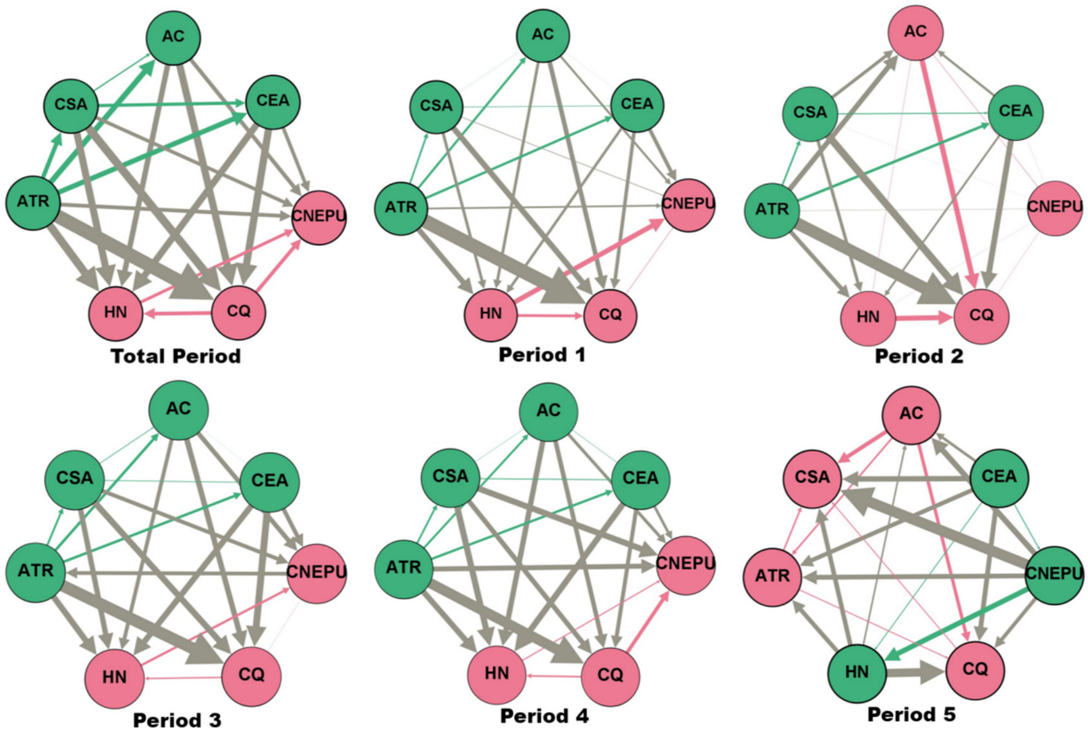

Figure 3. Paired net directional spillover across sample periods.

Notes: Figure 3 depicts the net pairwise connectedness network plots under different sub-sample periods. The connectedness (red) nodes indicate the net transmitters (receivers) of shocks. The direction of the arrow of the line points to the direction of the net spillover between the two variables.

We first observe that CNEPU receives paired net spillover from the China airline industry variable during the total sample period, indicating that CNEPU is the net spillover recipient in the system. In contrast, ATR is the net spillover transmitter, sending net spillover to all other variables. Strikingly, HN and CQ are net spillover receivers in the system, receiving the strongest return spillover from the other variables, especially CQ as the most potent net receiver of return spillover in the sample. However, they maintain sending return spillover to CNEPU. In Period 1, the spillover pattern mostly stays the same from the overall sample period. The CQ remains the most robust net receiver of return spillover in the system, while the ATR is the strongest net spillover sender and continues to send the strongest paired net spillover to the CQ. For CNEPU, the level of net spillover from other variables it receives is significantly lower compared to the overall sample period. Further, we find that the level of pairwise connectedness in Period 1 decreases compared to the overall period. We observe that the role of CQ and ATR as the largest receivers and senders in the system remains unchanged. The effect of CNEPU acceptance on other variables is almost negligible compared to those before. Strikingly, AC becomes a receiver of spillover during this period, with ATR contributing significant net spillover to AC. However, AC provides a significant net return spillover to CQ.

We then look at Periods 3 and 4. The spillover mechanism in these two periods is almost identical, returning to the spillover pattern of the total sample period and Period 1. CNEPU resumes receiving significant net spillover from other variables in the system. While CQ remains the most potent net receiver in the system, followed by HN and CNEPU, ATR remains the dominant player in sending return overflows. In both periods, AC also reverts to the return overflow sender role of Period 1. Period 5 sees a significant shift in the network connectedness spillover pattern. This is mainly due to the 2022 Russo-Ukrainian war (Shanghai city lockdown). To our surprise, we note that CNEPU and HN become net senders of spillover, with HN and CNEPU sending net spillover to other variables in the system, and CNEPU passing net spillover to CSA in the most substantial direction in the system. In contrast, ATR, CSA, and AC become simultaneously static receivers of spillover, receiving net directional spillover from most of the variables sent. For ATR and CSA, this is the first time this is the case. Finally, CQ has maintained its role as the net receiver of overflow in the system.

To briefly summarize the above findings, CQ is a net spillover receiver in all periods; HN and CNEPU act as net spillover senders in Period 5 and are net spillover receivers in all other periods. Conversely, ATR and CSA are net spillover receivers in Period 5 and senders in all other periods. Most notably, the CEA is a net spillover sender in all periods. CEA's consistent role as a spillover transmitter across all periods can be attributed to its status as China's flagship carrier and its systematic importance in the aviation sector, making it a bellwether for industry-wide sentiment. The stability of this role during crisis periods suggests that large state-owned airlines serve as information aggregators, with their stock movements reflecting broader market expectations about policy directions. In contrast, CQ's persistent role as a net receiver reflects its smaller market capitalization and limited institutional investor base, making it more susceptible to sentiment-driven capital flows rather than fundamental policy assessments.

We examine the structural impact of CNEPU under cross-market conditions (quantiles) on the Chinese aviation sector and its segmented airlines. Figure 4 displays the cross-quantile associations between the CNEPU and the Chinese aviation sector, obtained using the QQR method. In the case of CEA, a predominantly negative correlation is observed between CNEPU and CEA across most quantile ranges. Notably, the few positive correlations are primarily concentrated within the non-extreme quantiles of CNEPU (0.2–0.8) and the extreme quantiles of CEA (above 0.9 or below 0.1). Specifically, the strongest positive correlation occurs within the highest quantile ranges of CEA, corresponding to CNEPU quantiles of 0.3 and 0.7. However, when CNEPU is at median levels, this positive correlation shifts to a significant negative correlation.

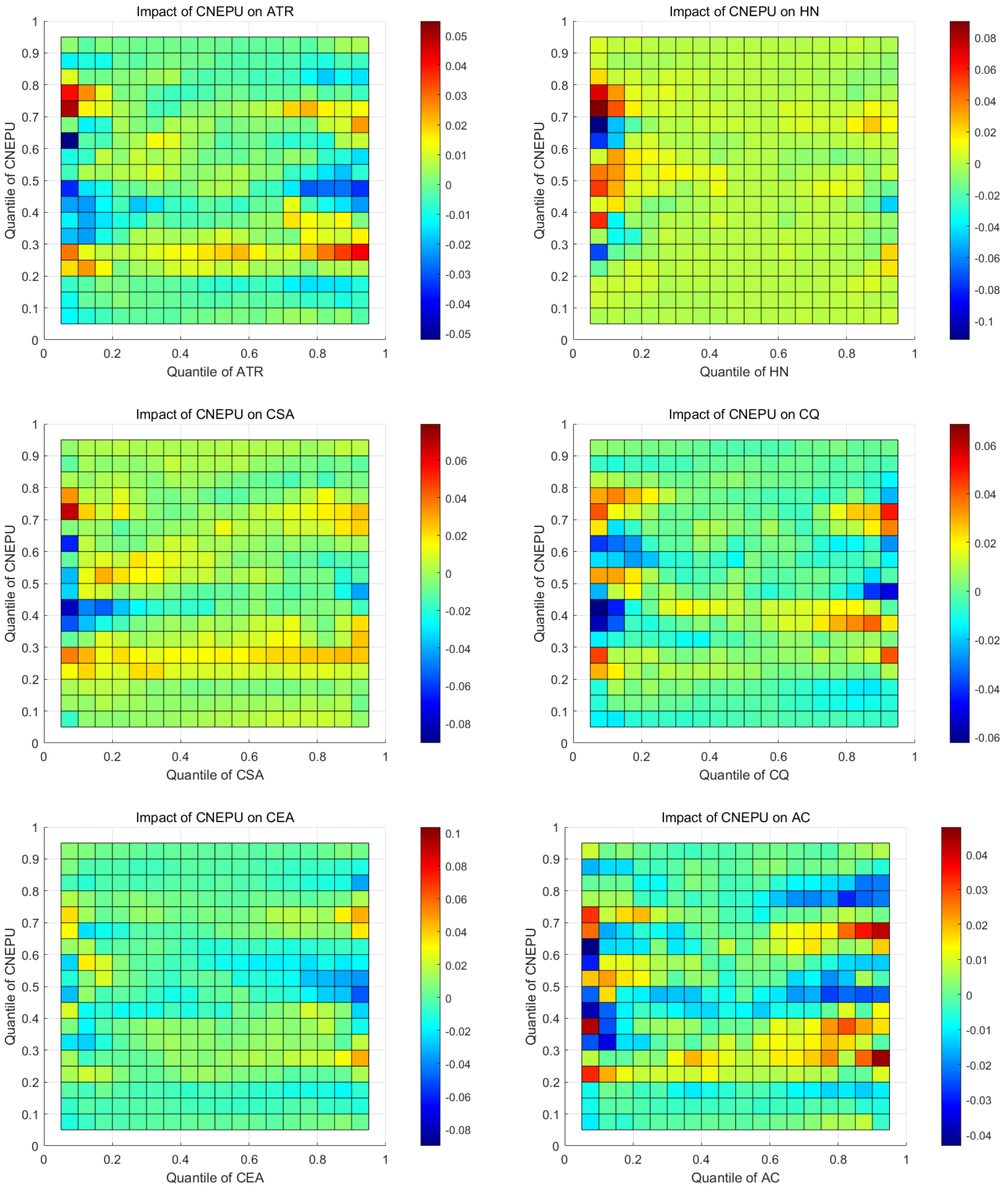

Figure 4. The QQR findings between CNEPU and Chinese Airline stocks.

Notes: The investigation into the cross-quantile effects of the CNEPU on segmented Chinese airline stocks utilizes the QQR method, and the outcomes are illustrated in Figure 4. The association between the CNEPU and stocks of Chinese airlines is depicted by the color bars on the right side of the diagram, demonstrating the influence of the CNEPU across percentile ranges. It is essential to acknowledge that these color bars feature a gradient, where darker tones of blue and red denote the lowest and highest coefficient values, respectively.

For CQ, a strong correlation with CNEPU is noted within specific quantile ranges. However, this pronounced correlation alternates as quantile levels change, indicating that significant correlations appear intermittently as market conditions fluctuate. This alternating correlation pattern suggests that when CNEPU is between 0.65–0.75 and 0.2–0.3 quantiles, corresponding to extreme quantiles of CQ, fluctuations in CNEPU lead to sharp price movements in CQ stock. In contrast, within other quantile ranges depicted in Figure 4, a predominance of negative or insignificantly positive correlations is observed. This alternating correlation pattern for CQ reflects the distinct operational model of low-cost carriers, which rely heavily on a price-sensitive leisure travel demand that responds differently to policy uncertainty compared to business travel. The intermittent correlations suggest that CQ's private ownership structure and flexible cost management enable it to decouple from policy uncertainty during moderate market conditions, but extreme policy changes trigger significant price adjustments through investor risk perception channels.

Furthermore, the quantile correlation patterns between CNEPU and CSA as well as HN depicted in Figure 4 share similarities with the CNEPU-CQ pattern. However, the correlations between CNEPU and CSA and HN are relatively stronger (with an overall yellow hue) compared to those with CQ. Interestingly, when CSA and HN are at extreme quantiles, corresponding to median or near-median quantiles of CNEPU, the negative impacts are particularly pronounced. This suggests that during stable market periods, the extreme impacts of CNEPU on airline stock prices are relatively weaker, especially during periods of significant stock price volatility (sharp increases or decreases).

Further analysis of the relationship between CNEPU and the Chinese stock market's aviation sector (ATR) and AC reveals that EPU has a weaker correlation with ATR and AC when CNEPU is at median quantiles combined with extreme quantiles of ATR and AC. Conversely, when CNEPU is at higher or lower quantiles, this insignificantly positive correlation transforms into a significant positive impact. As China's largest state-controlled airline, AC's operational decisions and stock performance are more influenced by national economic policies. When EPU is at a moderate level, the market expectation of policy is relatively stable, thus showing a weaker correlation with AC. However, higher or lower levels of CNEPU could imply significant expected changes in policy, impacting AC's stock price more profoundly. Additionally, the aviation industry is highly sensitive to economic cycles and policy changes. When CNEPU it at extreme levels, this likely indicates greater economic uncertainty, impacting the overall performance of the aviation sector. In such scenarios, ATR, as an indicator reflecting the overall trend of the aviation industry, might show a stronger correlation with CNEPU. This outcome suggests that combining higher and lower quantiles of CNEPU with extreme quantiles of ATR and AC could have significant impacts.

5. Conclusions and policy remarks

The results of the complete data set show that the sample of markets analyzed is highly correlated over the sample period. Our findings emphasize the impact of the interconnectedness of the crisis markets. These markets became more volatile after the COVID-19 crisis and the outbreak of the Russo-Ukrainian war. TCI values range from approximately 60.86% to 82.82%, depending on the sub-sample period. Time-varying net connectedness and pairwise directional connectedness studies represent how participation in each market varies over time in our proposed system. However, CQ is a recipient of net spillover in all periods, while CEA acts as a sender of net spillover in all periods. Further, CNEPU acted as a net sender of return spillovers only during the 2022 Russia-Ukraine War (Shanghai city lockdown). Based on this research, the performance of the Chinese airline sector in the face of EPU is now more transparent. The impact of EPU on the Chinese airline industry during the 2022 Russia-Ukraine War (Shanghai city lockdown) has become increasingly evident and unpredictable. Based on these results, we can determine that the market risk to which our plotted network is exposed after a Black Swan event is high, especially for sudden, major multiple crises that lack reaction time (e.g., the 2022 Russia-Ukraine War and the Shanghai city lockdown). Finally, the results of the QQR provide us with further insights, demonstrating that the impact of CNEPU on the stock prices of different airlines vary. Specifically, during periods of market stability, the stock prices of large state-owned airlines are more susceptible to the effects of CNEPU factors. In contrast, CQ is relatively less sensitive to CNEPU compared to large state-owned airlines. These findings hold significant implications for investors and policymakers, indicating that an assessment of the impact of EPU on the aviation industry should consider the characteristics of companies and the market environment.

Based on our empirical findings, we propose several recommendations for different stakeholders. For policymakers, we recommend establishing a three-tier policy framework to enhance the stability of the airline industry. First, at the macro level, they should develop an EPU Early Warning System (EPU-EWS) for the aviation sector. This system should incorporate quantitative indicators (such as our empirical findings on spillover effects) and qualitative assessments from industry experts to predict potential policy-induced market disruptions. The EPU-EWS would require integration of real-time policy announcement feeds, market volatility indices, and airline operational metrics, with automated alert mechanisms triggered when spillover intensity exceeds predetermined thresholds. Implementation would involve collaboration between regulatory bodies, airlines, and financial market authorities to ensure data accessibility and response coordination. Second, at the institutional level, we suggest implementing a “Policy Impact Assessment Mechanism” that requires all major economic policies affecting the aviation sector to undergo a comprehensive evaluation of their potential market impact before implementation. This mechanism should particularly focus on assessing the differential impacts on state-owned versus private airlines, as our results show varying sensitivities to policy uncertainty. Third, at the operational level, policymakers should establish a regular communication channel with airline industry stakeholders, including quarterly policy briefings and feedback sessions.

For investors, our findings suggest several practical investment strategies. First, given our empirical evidence that CEA consistently acts as a net sender of spillover effects while maintaining stability during crises, investors should consider CEA as a potential hedge in their aviation portfolio, particularly during periods of high EPU. Second, we recommend a dynamic portfolio allocation strategy based on our quantile regression results; increasing exposure to private airlines like CQ during periods of high policy uncertainty, as they show lower sensitivity to CNEPU fluctuations. Third, investors should develop a crisis-responsive reallocation strategy triggered by our identified threshold levels of EPU.

The implementation framework would require establishing quantitative triggers based on our empirical thresholds, with portfolio rebalancing protocols activated when CNEPU levels exceed the 75th percentile or when cross-airline spillover intensity surpasses 80%. These strategies should be supported by real-time monitoring systems that track the connectedness indices developed in this study. These strategies should be tailored to individual risk tolerance levels and investment horizons, as the effectiveness of these approaches may vary significantly across investor profiles and market conditions.

Several limitations should be acknowledged in our study. First, our findings are specific to the Chinese market and may have limited generalizability to other emerging economies with different institutional frameworks. Second, our analysis relies primarily on historical stock price data, which may not fully capture all relevant operational and strategic factors affecting airline performance during policy uncertainty periods.

Author contributions

Ran Wu: Conceptualization, Methodology, Data curation, Writing-original draft; Shenglin Ma: Formal analysis, Investigation, Writing-original draft; Hongjun Zeng: Supervision, Writing-review & editing, Validation. All authors have read and approved the final version of the manuscript.

Use of AI tools declaration

This paper uses ChatGPT for text proofreading and grammar polishing.

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No.

Conflict of interest

The author declares no conflicts of interest in this paper.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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