ESTIMATING FINANCIAL RISK TRANSMISSION EFFECT IN NEW ENERGY VEHICLE SUPPLY CHAINS BASED ON GARCH–TIME-VARYING COPULA–COVAR MODEL UNDER THE DUAL CARBON TARGET IN CHINA

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Abstract. The development of new energy vehicles is an important path to promote the realization of the dual carbon target. However, the complex and changeable external macro environment, large capital investment required in the early stage of new energy vehicle projects, and unstable returns results in high financial risks for new energy vehicle enterprises. Furthermore, factors such as information asymmetry, moral hazard and the uncertainty of the external macro environment make the dynamic characteristics of financial risk transmission between enterprises in the new energy vehicle supply chain more prominent. Existing studies on risk transmission have mainly focuses on theoretical exploration and qualitative research, while the quantitative research is limited. This study empirically analyzed the financial risk transmission effect between the new energy vehicles chain enterprises using the GARCH–time-varying copula–CoVaR model in China. It selected 8 upstream enterprises, 2 midstream enterprises and 8 downstream enterprises; constructed 36 financial risk transmission chains and used the stock returns of sample companies from 2017 to 2022 as research data. The results indicated that: (1) the financial risk between upstream and downstream enterprises in the supply chain of new energy vehicles had a bidirectional and heterogeneous transmission effect; (2) compared with midstream and downstream enterprises, financial risk was more transmissible between upstream and midstream enterprises; and (3) the financial risk transmission effect between enterprises had time-varying characteristics, which affected by the external macro environment and the degree of cooperation between enterprises.
Keywords: *strategic emerging industries, COVID-19 pandemic, financial crisis, risk spillover*

Introduction

The promotion of new energy vehicles involves elements such as the green transformation of energy consumption, intelligent travel and new carriers of mobile Internet, and brings together new technologies, materials, and energy types, as well as other industrial integrations and innovations. Therefore, in the context of promoting the realization of the global "dual carbon" goal, the development of new energy vehicles has become an important means of global "carbon unlocking" (Wu and Wang, 2023). However, the complex and changeable external macro environment, as well as the large capital investment required in the early stage of new energy vehicle projects, unstable income and other problems, sharply increase the financial risks of new energy vehicle enterprises. Rapid economic development has made the connection between enterprises in the supply chain of new energy vehicles closer and the level of cooperation more complex. Factors like asymmetrical information, ethical concerns, external financing and the ecological environment can lead to a capital break in a node enterprise, which can affect other supply chain partners in financial trouble. Therefore, the dynamic

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transmission of financial risk between enterprises in the new energy vehicle supply chain is more prominent. When the financial risk of nodal enterprises exceeds the risk threshold they can bear, the financial risk will overflow and will be transmitted to the associated upstream and downstream enterprises through risk carriers such as information flow, logistics and capital flow in the supply chain, resulting in the bullwhip and domino effects of risk transmission (Xie and Zhou, 2021).

The domestic battery giant Waterma declared bankruptcy in 2018. Waterma defaulted on the debts of 559 suppliers, totaling about CNY 5.4 billion (Xiao, 2019). This affected the production and operation of vehicle manufacturers such as China FAW Group Corp. and Dongfeng Motor Corp., as they were unable to receive the necessary supplies. More than 20 upstream and downstream listed enterprises in the supply chain were affected by the collapse of Waterma. The "huddling for heating" of new energy automobile enterprises has become a "burning joint operation". Any financial crisis is transmitted along the supply chain between upstream and downstream enterprises. Upstream enterprises fall into financial difficulties, which affects production and operation activities, in turn affecting the normal delivery of products to downstream cooperative enterprises. For upstream enterprises, once there is a problem with downstream payment, the capital chain is easily broken. Based on this, in order to measure the spillover effect of financial risk between upstream and downstream enterprises, it conducted an empirical study of the financial risk transmission effect between enterprises in the supply chain of new energy vehicles, so as to provide an objective empirical basis for controlling the financial risk transmission of related enterprises at the root, reduce the financial risk of new energy vehicle enterprises, and promote the realization of the “double carbon” goal.

This study aims to (1) propose a method for measuring the risk transmission effect that combines copula theory with GARCH and CoVaR models; (2) measure the financial risk transmission effect among new energy automobile enterprises from the perspective of the supply chain based on the GARCH–time-varying copula–CoVaR model; and (3) provide a reference for preventing financial risk and controlling new energy automobile enterprises based on risk transmission.

The main contributions of this article are shown in two aspects. First, it puts forward a new perspective to discuss the financial risk transmission effect among enterprises in the supply chain, the tail dependency perspective, which enriches the existing research on enterprise risk transmission. It also offers an effective approach for measuring the transmission effect of financial risk. The GARCH model, skewed-t distribution and descriptive copula function are introduced into the CoVaR model, which amends the defects of the CoVaR model, thus guaranteeing scientific and accurate measurement results.

This paper consists of five sections. Section 2 begins with a literature review, followed by an explanation of the theories of GARCH, copula, and CoVaR models, leading to the proposal of a GARCH–time-varying copula–CoVaR model. Finally, it outlines the selection of sample firms and provides descriptive statistics of the research data. Section 4 discusses the contagion effect of financial risk among enterprises in the new energy vehicle supply chain. The final section presents the research conclusions and the prevention and control strategies for financial risk transmission.

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Materials and methods

Study area overview

Financial risk transmission of enterprises

There is scarce research specifically on enterprise financial risk transmission. Enterprise risk transmission originates from financial risk transmission, and foreign research focuses on financial risk transmission. Kindleberger et al. (1996) defined financial risk transmission as the transmission and diffusion of financial risk between countries. Subsequently, the influencing factors of financial risk transmission have been extensively studied. Cook and Spellman (1996) proposed that an increase in guaranteed risk will increase the possibility of financial risk transmission. Kodres and Pritsker (2002) noted that the application of dynamic derivatives is also an important factor leading to financial risk transmission. Baig and Goldfajni (1999) and Kaminsky and Reinhart (2000) noted that the transmission of financial risk varies among countries and regions.

In recent years, few scholars have conducted research on financial risk transmission in China. Shen and Deng (2006) defined the concept of enterprise risk transmission based on the physical heat conduction principle. The earliest domestic research focused on the process of financial risk transmission. The financial risk transmission path was proposed by Shen and Deng (2007), which is conducted in various financial management links within enterprises and between enterprises and their external interest subjects. By studying the financial risk transmission process of small and micro enterprises in science and technology based on the small-world network approach, Liu et al. (2015) concluded that the complexity of social and economic processes is mainly reflected in the complex relationships among behavioral participants. In addition, Zhang (2018) proposed that the financial risk transmission process of enterprise groups' related-party transactions manifests through financial risk conduction in associated purchases and sales, asset transactions, and capital mutual financing. From a financial chain perspective. Jin (2018) suggested that risks are transmitted through financial networks among internal departments within an enterprise and between enterprises on the same financial chain, utilizing appropriate channels for effective conduction.

Some experts and scholars have studied the transmission mechanism of financial risk. Xia (2009) elucidated the process of financial risk generation and its conduction within enterprises by examining key elements such as risk sources, risk manifestations, risk carriers, risk flows, and risk thresholds. Wang (2013) categorized the financial risk conduction mechanisms in supply chain-oriented enterprises into aggregated conduction, amplified conduction, boosted conduction, intensified conduction, and altered conduction. Gao (2016) systematically analyzed the impact of risk sources, risk conduction paths, and risk thresholds on cash budget formulation based on the mechanism of financial risk conduction. The research demonstrated that financial risk sources in coal enterprises are transmitted according to a specific sequential logic inherent to the cash budget compilation methodology. Zhang and Liu (2016) proposed that industry-finance integration exhibits bidirectional risk transmission effects, necessitating the establishment of fund, business, and personnel "firewall" mechanisms for risk isolation and control to achieve synergistic benefits. Gu and Hu (2021) constructed a transmission model from a supply chain perspective to analyze the impact mechanism of financial distress in small and medium-sized enterprises (SMEs) on the credit risk of upstream suppliers. The study revealed that financial distress in SMEs significantly exacerbates the credit risk of upstream suppliers, creating a lose-lose contagion effect. The risk is primarily transmitted

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through accounts receivable defaults, with a higher dependency of suppliers on distressed enterprises leading to greater credit risk impact.

In summary, the existing research is basically at the stage of theoretical discussion and qualitative research; that is, the mechanism, characteristics and path of enterprise risk transmission are directly determined through empirical analysis. However, there is a lack of quantitative research on the enterprise risk transmission effect. Accordingly, in this paper we measure the effect of financial risk transmission of new energy vehicle enterprises based on the supply chain through an empirical analysis from a quantitative perspective, so as to accurately measure the spillover effect of financial risk between upstream and downstream enterprises in the supply chain of new energy vehicles and provide an objective empirical basis for controlling the financial risk transmission of related enterprises in the supply chain at the root.

Research methods of risk conduction effect

There is a lack of research on the risk transmission effect at home and abroad. Some experts and scholars have studied the risk contagion effect among enterprises based on an empirical model. There are three methods to measure the risk contagion effect: The first is to use a traditional statistical measurement model, such as the default probability model (Schonbucher, 2003; Giesecke and Weber, 2004; Collin-Dufresne et al., 2010), vector auto regressive model (Ma et al., 2019; Liu et al., 2022), and VaR model (Cao and Cai, 2013; Xu and Yu, 2016). The traditional statistical econometric model can reflect the fluctuating changes of related entities in the market through index data. Its advantages are low requirements for model structure and wide applicability, but it has a poor fitting effect for nonlinear factors. Second is the network model method (Yuan et al., 2020). The core of this method lies in utilizing common data shared among multiple sectors under study to construct a reasonable network structure, thereby achieving an accurate simulation of risk contagion pathways. However, network models require large amounts of data, and it is difficult to model nonlinear relationships and interactions between variables. The third method is tail analysis, which mainly includes the marginal expected shortfall (MES) method (Guo, 2013; Bo and Li, 2015), Systemic Risk Index (SRISK) method (Liang et al., 2013; Ren et al., 2021) and CoVaR method (Wang and Gao, 2019; Wang and Li, 2019; Bian et al., 2023). The idea is to study the contagion effect of inter-sector risk by analyzing the tail correlations of different financial sequences. The MES method and the SRISK method are suitable for measuring the contagion effect of systemic risk. The Conditional Value at Risk (CoVaR) method was proposed by Adrian and Brunnermeier (2016) based on the method Value at Risk (VaR). This method has been widely used in the measurement of systemic risk contagion spillover in banking (Li et al., 2019; Liu and Liu, 2020; Wu et al., 2020; Zhao and Chen, 2021; Lin et al., 2022; Huang et al., 2023). However, the limitations of the CoVaR research methodology lie in two main aspects: firstly, the model itself fails to account for the widespread presence of Autoregressive Conditional Heteroskedasticity (ARCH) effect in time series; secondly, the method is unable to fully capture the nonlinear dependencies among the various time series. By integrating the GARCH model with CoVaR theory and introducing the copula function, which captures strong correlations between economic entities, we can measure and analyze the financial risk spillover intensity among enterprises in the new energy vehicle supply chain more accurately. Therefore, drawing on existing methods for assessing risk contagion effects, this paper establishes a GARCH–copula–CoVaR model to analyze the transmission of financial risk within the supply chain. Constructed from a supply chain

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perspective, this model aims to more accurately measure the spillover effects of financial risk from enterprises within the new energy vehicle supply chain to their upstream and downstream partners when the financial risk is at extreme levels.

Applicability of GARCH–time-varying Copula–CoVaR model

The CoVaR model has been widely applied to measure the risk spillover effect, such as inter-financial institutions (Liu and Liu, 2020), inter-financial institutions and entities (Cao and Lei, 2019), inter-industry (Chen et al., 2019), inter-stock market (Lin and Zhao, 2020) and systemic risk spillover (Zhou, 2021). This study constructs a GARCH-Time-Varying Copula-CoVaR model, which is suitable for measuring the financial risk contagion effect between upstream and downstream enterprises in supply chains. (1) The Copula-CoVaR model is appropriate for investigating tail risk, i.e., the impact of extreme events. The occurrence of extreme events, such as the COVID-19 pandemic, tends to facilitate the transmission of financial risks along the supply chain among new energy vehicle enterprises. (2) The Copula model can effectively capture nonlinear relationships and dependencies among multiple variables. Due to factors such as information asymmetry, moral hazard, and adverse selection, nonlinear risk dependence among enterprises within the new energy vehicle supply chain is particularly prominent. (3) The selected time series data in this study do not exhibit standard normal distribution characteristics, leading to potential parameter estimation issues in the model. Therefore, it is necessary to employ the GARCH model to optimize the time series, thereby enhancing the scientific rigor of the measurement results.

Methodology

GARCH model

Through the study of the historical data of time series, it is proved that the mean and variance of time series all have time-varying characteristics. The autoregressive conditional heteroscedasticity (ARCH) time series model proposed by Engel (1982), the main idea of which is the conditional variance of the disturbance term u_t, depends on the magnitude of its previous value u_{t-p}. Taking ARCH (1) as an example, the conditional variance of time *t* depends on the magnitude of the perturbation term σ_t^2 at time $t-1$. The equation is expressed as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \xi_t \qquad \text{(Eq.1)}$$

where α_0 and α_1 are parameters of the variance equation, ξ_t is a white noise process, and the conditional distribution of the disturbance term u_t satisfies $N\left[0,\left(\alpha_0 + \alpha_1 u_{t-1}^2\right)\right]$.

ARCH（*q*）is an extension of the model, and the equation is expressed as follows:

$$Var(u_t) = \sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + ... + \alpha_p u_{t-p}^2 \qquad \text{(Eq.2)}$$

In order to ensure the stability of u_t^2, this model requires $\alpha_0 + \alpha_1 + \alpha_2 + \cdots + \alpha_p < 1$.

The ARCH model has been widely used in the financial field because of its advantages in capturing market fluctuations. However, the shortcoming of the ARCH model is that

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an unrestricted estimation may violate the restriction that a_i is non-negative when the lag order p is too large. However, in fact, the condition variance ${\sigma_t}^2$ is constant and positive, which is required to provide assurance. Considering the distributed lag model of ${\sigma_t}^2$ in *Equation (2)*, Bollerslev (1986) further extended the ARCH model, replacing multiple lag values ${u_t}^2$ with one or two lag values ${u_t}^2$ to effectively reduce the lag order. This extension made the model estimation more effective and was named the generalized auto-regressive conditional heteroscedastic (GARCH) model. The GARCH (1,1) model is mainly used in time series research, and its form is as follows:

$$y_t = x_t\gamma + u_t, t = 1,2,...T \tag{Eq.3}$$

$${\sigma_t}^2 = \omega + \alpha {u_{t-1}}^2 + \beta {\sigma_{t-1}}^2 \tag{Eq.4}$$

where $x_t = (x_{1t}, x_{2t},...x_{kt})'$ is the explanatory variable, $\gamma = (\gamma_1, \gamma_2,...\gamma_k)'$ is the coefficient variable, and the mean value equation shown in *Equation (3)* is a function of an exogenous variable with a perturbation term. ${\sigma_t}^2$ is the conditional variance, so *Equation (4)* is called the conditional variance equation, which usually covers the constant term ω and uses the square of the time disturbance term $t-1$ of the mean value equation to measure the information ${u_{t-1}}^2$ of the volatility obtained from the previous period (ARCH term) and the prediction variance ${\sigma_{t-1}}^2$ of the previous period (GARCH term). Time series are generally characterized by spikes and thick tails, which usually violate the hypothesis of "residual follows normal distribution" in the GARCH model. Therefore, the hypothesis of normal distribution is often replaced by t distribution or skewed t distribution in empirical studies so as to improve the model's fitting degree to financial time series. Therefore, the GARCH–partial-t model is used in this empirical study.

Copula function theory

The copula function theory was first proposed by Sklar (1959). The copula function is an analytical function that describes the correlation of multiple variables. Because it can effectively connect the joint distribution with the respective edge distribution, it is also called the connection function or dependency function. The copula method has been widely used in academia and industry since it was proposed. The copula function was first used in finance by Embrechts et al. (1999). Subsequently, the copula function was applied by Rodriguez (2007) and other scholars for the study of credit risk contagion. Copula functions with more complex structures, such as vine copula, were proposed by Patton (2009), Kurowicha and Joe (2011) and others. Although research on the copula method started late in China, it developed rapidly. With the help of the development of computer technology and the continuous improvement of modeling technology, the copula method has been widely used in the financial field. The advantages of the copula method are as follows: First, the multivariate distribution can be decomposed into the edge distribution of a single variable and a copula function describing the correlation structure between variables by using copula theory. This split not only effectively reduces the complexity of modeling, but also improves the practicality of the model. Second,

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copula theory is good at describing the nonlinear structure among variables and dealing with the correlation of distribution tails, and the description of risks usually corresponds to the distribution of tails, so the copula function meets the needs of enterprise financial risk management.

CoVaR model

The basic idea of the $CoVaR$ method is to measure the impact of a financial institution's level of risk stress on the risk level of the financial industry or other financial institutions. The formula is as follows:

$$\Pr = (X^i \le CoVaR_q^{ij} \mid X^j = VaR_q^{\,j}) = q \qquad \text{(Eq.5)}$$

where $CoVaR_q^{ij}$ represents the risk level of financial institution i when financial institution j is at a certain risk level with a significance level of q. In essence, CoVaR is a kind of conditional value of risk, or the conditional value of the risk of financial institution i relative to financial institution j. It measures the total risk of financial institution i, including the unconditional value at risk (VaR) at a significance level of q, and the risk spillover value of extreme risk events of institution j. The risk spillover value of the risk event of institution j to institution i is represented by $\Delta CoVaR_q^{ij}$, and its expression is shown in *Equation (6)*:

$$\Delta CoVaR_q^{ij} = CoVaR_q^{ij} - VaR_q^i \qquad \text{(Eq.6)}$$

where $\Delta CoVaR_q^{ij}$ reflects the size of the risk spillover effect of institution j on institution i. Since the value of VaR_q^i differs greatly for different financial institutions i, in order to facilitate the comparison of risk spillover effects, we obtained the risk spillover effect of j on i, $\%CoVaR_q^{ij}$, after standardized treatment of $\Delta CoVaR_q^{ij}$, and the calculation formula is shown in *Equation (7)*:

$$\%CoVaR_q^{ij} = \frac{\Delta CoVaR_q^{ij}}{VaR_q^i} \times 100\% \qquad \text{(Eq.7)}$$

Construction of GARCH-time varying Copula-CoVaR model

It is necessary to solve the univariate edge fitting distribution and select a suitable copula function to describe the joint edge distribution to estimate the financial risk transmission effect. In order to better fit the existing characteristics of peak, thick tail and heteroscedasticity in the return rate time series, the ARMA (p, q), GARCH (r, m), SKST (partial t) model was selected to fit the edge distribution of upstream and downstream enterprises in the supply chain of new energy vehicles. First, the time series ARMA model is a mixture of the AR and MA models. Compared with AR and MA models, the ARMA model can better reflect the statistical characteristics of variables in time series changes (that is, it has greater elasticity) and is widely used in the financial field. Therefore, in this paper we chose the ARMA model as the time series model. Second, because an ARCH effect exists in the stock return series of most listed companies, the GARCH model can fit and analyze the random disturbance terms with ARCH effect well. Third, since the stock return series of sample companies basically have the feature of "peak and thick tail", and the skewed t distribution has higher kurtosis and a thicker tail than the normal distribution, it is closer to reality to describe the return series by using the skew t distribution hypothesis than the normal distribution hypothesis. Therefore, the ARMA (p, q), GARCH (r, m), partial t model can better fit the edge distribution of upstream and downstream enterprises in the supply chain of new energy vehicles. Since some time series do not have self-correlation, the model in this paper was set as follows: The ARMA (0,0), GARCH (1, 1), and partial t model was first used to estimate the univariate edge distribution. According to the estimated edge distribution, the original time series was subjected to probability integral transform to obtain the time series conforming to [0, 1] uniform distribution, and then the appropriate copula function was selected to estimate the joint distribution.

(1) Sequence edge distribution fitting

In this paper, the ARMA (0, 0), GARCH (1, 1), and partial t model is established to fit the edge distribution of the stock return series of each sample company. The mathematical expression of the model is as follows:

$$r_{i,t} = \delta_0 + \delta \sum_{i=1}^{n} r_{i,t-1} + \varepsilon_{i,t}{}^2 \qquad \text{(Eq.8)}$$

$$\sigma_{i,t}{}^2 = \beta_0 + \beta_1 \sum_{i=1}^{p} \varepsilon_{i,t-1} + \beta_2 \sum_{i=1}^{q} \sigma^2{}_{i,t-1} + u^2{}_{i,t} \qquad \text{(Eq.9)}$$

$$e_{i,t} = \sigma_{i,t} \times \varepsilon_{i,t} \qquad \text{(Eq.10)}$$

where $r_{i,t}$ is the stock return rate of new energy automobile supply chain enterprise i at time t. The stock return rate is the difference after taking the logarithm of the asset value in two periods, and represents the fluctuation of the financial risk of supply chain enterprises. Its calculation formula is as follows:

$$r_{i,t} = \ln \frac{p_{i,t}}{p_{i,t_{-1}}} \qquad \text{(Eq.11)}$$

where $\varepsilon_{i,t-1}^2$ and $\sigma_{i,t-1}^2$ represent the ARCH term and GARCH term, respectively, and the perturbation term $e_{i,t}$ follows a partial t distribution with kurtosis parameter η_i and asymmetric parameter λ_i, and its probability density function is:

$$Skewed-t(e_{i,t}|\eta_i,\lambda_i)=\begin{cases} bc\left[1+\dfrac{1}{\eta_i-2}\left(\dfrac{be_{i,t}+a}{1-\lambda_i}\right)^2\right]^{-(\eta_i+1)/2}, e_{i,t}<-\dfrac{a}{b} \\ bc\left[1+\dfrac{1}{\eta_i-2}\left(\dfrac{be_{i,t}+a}{1+\lambda_i}\right)^2\right]^{-(\eta_i+1)/2}, e_{i,t}\geq-\dfrac{a}{b} \end{cases} \quad \text{(Eq.12)}$$

Here, the coefficient satisfies *Formula (13)*:

$$a=4\lambda_i c\frac{\eta_i-2}{\eta_i-1},\ b=1+3\lambda_i^2-a^2,\ c=\frac{\Gamma(\eta_i+1/2)}{\sqrt{\pi(\eta_i-2)}\Gamma(\eta_i/2)} \quad \text{(Eq.13)}$$

The parameters satisfy the boundary conditions: $3<\eta_i<\infty,-1<\lambda_i<1$.

(2) Estimation of time-varying Copula-dependent structures

In order to obtain a dynamic CoVaR, referring to Engle (2012) and Patton (2006), seven time-varying copula models were used to estimate dynamically correlated structures in this paper. Then, the optimal time-varying T-DCC-Copula model was selected by the AIC criterion, BIC criterion and log-likelihood function value to estimate the dynamic correlation structure between logarithmic return series (Li and Yan, 2015). The T-DCC-Copula model assumes that conditional correlation matrix $R_t=\begin{bmatrix}1,\rho_t\\ \rho_t,1\end{bmatrix}$ follows the dynamic DCC (1, 1) process:

$$Q_t=(1-\alpha-\beta)\bar{Q}+\alpha e_{t-1}e_{t-1}^{'},R_t=\tilde{Q}_t^{-1}Q_t\tilde{Q}_{t-1}^{-1} \quad \text{(Eq.14)}$$

where u_t and v_t are subsequences of U (0,1) distributions obtained by the probability integral conversion of residual $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ after edge distribution fitting of $r_{i,t}$ and $r_{j,t}$, respectively:

$$e_{t-1}=(t_v^{-1}(u_{t-1}),t_v^{-1}(v_{t-1})) \quad \text{(Eq.15)}$$

where t represents the inverse distribution of the standard t-distribution, which freedom is constant v. $\bar{Q}$ is the sample covariance matrix of e_t and $\tilde{Q}$ is the square root of the main original diagonal Q_t, in a matrix with non-diagonal elements of 0. The model parameter constraints meet the conditions: $\alpha+\beta<1,\alpha,\beta\in(0,1)$.

(3) Calculation of time-varying risk overflow degree (%CoVaR)

After performing $ARMA(0,0),GARCH(1,1)$, partial t model edge distribution estimation and optimal time-varying T-DCC-Copula model nonlinear structure estimation on the return series, $CoVaR$ is then calculated. First, the time-varying $VaR_q^{i,t}$ of stock return series i of the sample company at significance level q is calculated by the following formula:

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$$VaR_q^{i,t} = \mu_i + \sigma_{i,t} \times Q_{skwet(\eta_i,\lambda_i)}(q) \quad \text{(Eq.16)}$$

where $Q_{Skwet(\eta_i,\lambda_i)}$ represents the q quartile of a partial t-distribution with a kurtosis parameter of η_i and an asymmetric skewness coefficient of λ_i. According to Sklar's theorem, when F is a two-dimensional joint distribution function with edge distribution F_1 and F_2, there must be a copula function C, $[0,1]^2 \to [0,1]$, that makes $F(x_1, x_2) = C(F_1(x_1), F_2(x_2))$, and the density function corresponding to F can be further deduced as follows:

$$f(x_1, x_2) = C(F_1(x_1), F_2(x_2)) f_1(x_1) f_2(x_2) \quad \text{(Eq.17)}$$

where $c(u,v) = \dfrac{\partial^2 C(u,v)}{\partial u \partial v}$ is the density function of the copula function, $f_1(x)$ and $f_2(x)$ are the density functions of random variables X_1 and X_2, respectively; then, the conditional density function of random variables X_1 and X_2 is as follows:

$$f(x_1|x_2) = \frac{f(x_1,x_2)}{f_2(x_2)} = \frac{c(F_1(x_1), F_2(x_2)) f_1(x_1) f_2(x_2)}{f_2(x_2)} = c(F_1(x_1), F_2(x_2)) f_1(x_1) \quad \text{(Eq.18)}$$

According to the properties of the copula function, it can be seen that it remains unchanged under monotonic increase and change. Since $r_{i,t}$ and $r_{j,t}$ are monotonic increase functions of $e_{i,t}$ and $e_{j,t}$, respectively, the study of the correlation structure between stock return series of each sample company can be converted to a study of the correlation structure between residual series. Thus, the time-varying conditional density function of yield $e_{i,t}$ with respect to $e_{j,t}$ is:

$$f_t(e_{i,t}|e_{j,t}) = c_t(F_{kewt(\eta_i,\lambda_i)}(e_{i,t}), F_{kewt(\eta_i,\lambda_i)}(e_{j,t})|\rho_t, df) f_{Skewt(\eta_i,\lambda_i)}(e_{i,t}) \quad \text{(Eq.19)}$$

where $c_t(...,...|\rho_t,\eta)$ represents the density function of a time-varying T-DCC-Copula with time-varying correlation structure parameter ρ_t and degree of freedom parameter η, so the time-varying distribution function of $e_{i,t}$ and $e_{j,t}$ is as follows:

$$F(e_{i,t}|e_{j,t}) = \int_{-\infty}^{e_{i,t}} c_t(F_{Skewt(\eta_i,\lambda_i)}(e_{i,t}), F_{Skewt(\eta_i,\lambda_i)}(e_{i,t})|\rho_t,\eta) f_{Skewt(\eta_i,\lambda_i)}(e_{i,t}) de_{i,t} \quad \text{(Eq.20)}$$

When $r_{j,t}$ is at the financial risk level, $e_{j,t}$ is also at the financial risk level. Therefore, according to the definition of $CoVaR$, the following integral equation should be calculated before calculating the value at risk under time-varying conditions:

$$\int_{-\infty}^{e_{i,t}} c_t(F_{Skewt(\eta_i,\lambda_i)}(e_{i,t}), q|\rho_t,\eta) f_{Skewt(\eta_i,\lambda_i)}, (e_{i,t}) de_{i,t} = q \quad \text{(Eq.21)}$$

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Supposing the solution to this equation is $e_{i,t}^{q}$, then:

$$CoVaR^{ij,t} = u_i + \sigma_i \times e_{i,t}^{q} \quad \text{(Eq.22)}$$

Finally, according to *Formulas (6) and (7)*, the time-varying risk transmission value ($\Delta CoVaR^{ij,t}$) and time-varying risk transmission contribution degree ($\%CoVaR_q^{ij,t}$) of the financial risk event of enterprise j to enterprise i with a cooperative relationship can be calculated.

The contagion effect of financial risk refers to the negative impact on the financial risk levels of upstream and downstream enterprises in the supply chain when a company's financial risk reaches extreme levels. This paper introduces a $CoVaR$ model to study the financial risk contagion effect in new energy enterprises within the supply chain context. Here, VaR is used to measure the financial risk level of a node enterprise in the new energy vehicle supply chain without considering risk contagion. $CoVaR$ is used to measure the financial risk level of an upstream or downstream enterprise when one company in the new energy vehicle supply chain experiences extreme financial risk. Time-varying risk transmission value $\Delta CoVaR$ and time-varying risk transmission contribution $\%CoVaR$ are used to measure and analyze the impact of node enterprises on the financial risks of upstream or downstream enterprises, that is, the spillover effects of financial risks among supply chain enterprises.

Sample selection and data description

In this paper, raw material suppliers were classified as upstream enterprises; "three power" parts enterprises that produce batteries, motors and electronic controls were classified as midstream enterprises; and vehicle enterprises, charging facilities and battery recycling enterprises were classified as downstream enterprises of the new energy vehicle supply chain (Wu, 2013; Ji and Wu, 2017; Li et al., 2020). In terms of domestic production, the number of manufacturers that have developed electric controls for new energy vehicles supporting the OEMs is not large. Many electronic control systems comprise the internal support of new energy vehicles, and there is also a case that the electronic control system is jointly completed by new energy vehicle enterprises and parts manufacturers (Hua, 2022). Therefore, we selected two enterprises that produce new energy vehicle batteries—Gotion High-tech Co., Ltd., and EVE Energy Co., Ltd. The cooperative relationship between supply chain and downstream enterprises and the strategic alliance formed by supply chain enterprises can be obtained from web news content. The selection of sample companies is shown in *Table 1*.

The abbreviations in *Table 1* are formed by the first letters of the Chinese company names. For example, Ningbo Shanshan Co., Ltd. is abbreviated as SSGF. The sample company names in the following text are abbreviated according to *Table 1*.

This article selects a total of 18 sample companies in the new energy vehicle supply chain, including eight upstream enterprises, two midstream enterprises, and eight downstream enterprises in China. The financial data and the stock market data of listed companies came from the China Stock Market & Accounting Research Database (CSMAR) database. MATLAB 2021a was used for data processing. The original data processing method was as follows: The index daily rate of return series was obtained after the first-order logarithmic difference of the daily closing price. In order to facilitate

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subsequent calculation, the logarithmic rate of return was amplified by 100 times, and the stock return expression of each sample company was finally obtained as follows:

$$r_i = 100 \times \ln \frac{p_i}{p_{i-1}} \quad \text{(Eq.23)}$$

where P_i and P_{i-1} represent the closing price and the return rate of the sample company's stock, respectively.

Table 1. *Selection of sample companies*

Upstream enterprises	Ningbo Shanshan Co., Ltd. (SSGF), Hua You Cobalt (HYGY), Shenzhen Capchem Technology Co., Ltd (XZB), Green Eco-Manufacture (GLM), Hunan Zhongke Electric Co., Ltd. (ZKDQ), Nuode New Materials Co., Ltd. (NDGF), Yinghe Technology (YHKJ), Shenzhen Senior Technology Material Co.,Ltd. (XYCZ)
Midstream enterprises	Gotion High-tech Co., Ltd. (GXGK), EVE Energy Co., Ltd. (YWLN)
Downstream enterprises	Jiangling Motors Corporation (JLQC), China Changan Automobile Group (CAQC), Great Wall Motor (CCQC), Anhui Jianghuai Automobile Co., Ltd., (JHQC), Dongfeng automobile (DFQC), Anhui Ankai Automobile Co.,Ltd.(AKKC), Guangzhou Automobile Group Co., Ltd.(GQJT), King Long Motor (JLQC)

In view of the heterogeneity of the relationship between midstream enterprises and upstream and downstream enterprises, this paper first explored the financial risk transmission of new energy automobile enterprises in the supply chain from the perspective of the transmission between the two enterprises. Considering that the financial risk transmission model among new energy vehicle supply chain enterprises follows an interactive pattern, this paper identifies 18 financial risk transmission paths between upstream and midstream enterprises, 18 paths between midstream and downstream enterprises, and thus a total of 36 financial risk transmission paths along the upstream–midstream–downstream chain. The transmission paths between sample companies are shown in *Figure 1*.

Data analysis and preliminary test

This study selects the daily closing prices of 18 sample companies from 2017 to 2022 as the fundamental research data. The stock returns of these 18 sample companies for the 2017-2022 period are calculated based on Formula 23. The mean and standard deviation of the stock returns for each sample company can be obtained through statistical analysis. As shown in *Table 2*, the mean stock returns for both upstream and midstream companies in the new energy vehicle supply chain are greater than 0, indicating that these sample companies were profitable. However, among downstream companies, except for CAQC with a stock return of 0.0189 and CCQC with a stock return of 0.1044, the returns of other companies are all below 0, indicating that most downstream firms operated at a loss. The standard deviation ranges from a minimum of 2.4111 to a maximum of 3.8902, indicating significant volatility in the stock returns of the sample companies. Therefore, new energy vehicle companies face relatively high financial risk.

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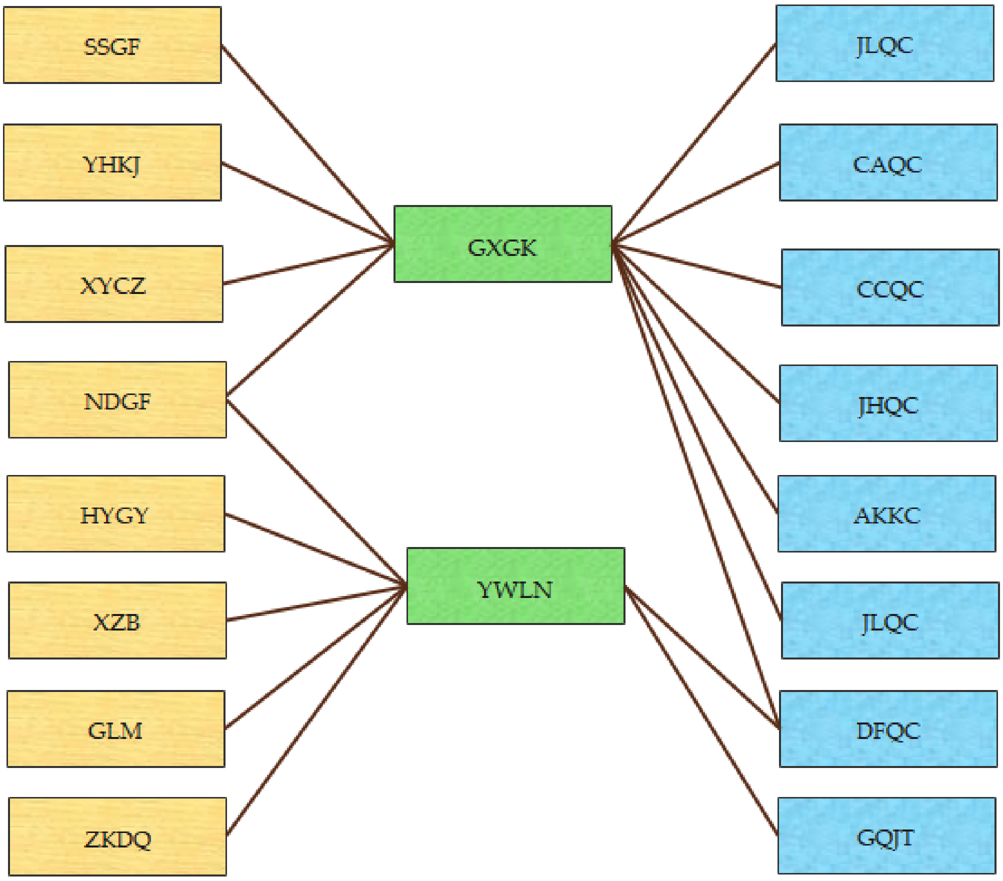

Figure 1. *New energy qutomobile enterprise financing risk transmission path research based on supply chain view*

As described from *Table 2*, the skewness coefficient of the return series was not equal to 0, which corresponded to normal distribution, and the kurtosis coefficient of each series in the sample was higher than 3 (corresponding to normal distribution), indicating that the concentration of each return series was higher than the normal distribution, and it was characterized by sharp peaks and thick (or heavy) tails. In addition, the P-value of JB statistics of all return series approaches 0, so the stock daily return series of each sample company does not comply with normal distribution. In this paper, the ADF unit root test was carried out on the stock return series of each sample new energy vehicle company. Since the P-value of the ADF test results of each series was close to 0, the null hypothesis was rejected; that is, the above return series were stable, so the GARCH model can be built to calculate VaR and CoVaR. Considering the P-value of the Ling-Box test of each return series when the lag order is 10, we can see that only the return time series of JHQC, AKKC and JLQC have auto-correlation, while the time series of the other 15 sample companies had no auto correlation. In Table 2, the results of the ARCH effect test showed that the P-value for the 18 sample companies was basically less than 0.05 under different hysteresis orders, which indicated that the null hypothesis was rejected at a significance level of 5% and each return series was considered to have ARCH effect.

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Table 2. *Sample companies descriptive statistics and pre-testing*

Sequence	Mean	Standard	Skewness	Kurtosis	JB test	ADF	Q（10）	ARCH
SSGF	0.1195	3.2810	0.1183	4.2456	76.2193 (0.001)	-32.9157 (0.0010)	5.1803 (0.8788)	12.4022 (0.0004)
HYGY	0.1356	3.8902	-0.1130	3.5278	15.6316 (0.0019)	-32.3914 (0.0010)	6.2511 (0.794)	20.4498 (0.0010)
XZB	0.1482	3.3343	0.3210	4.9828	205.9689 (0.0010)	-35.1251 (0.0010)	11.794 (0.2990)	33.6945 (0.0283)
GLM	0.0499	2.8745	0.2065	4.8232	165.6957 (0.0010)	-34.9042 (0.0010)	11.5336 (0.3175)	6.4075 (0.0114)
ZKDQ	0.1307	3.5522	0.2953	5.1749	240.8410 (0.0010)	-32.5308 (0.0010)	8.1882 (0.6100)	17.4302 (0.0000)
NDGF	0.0334	3.3688	0.1944	4.3085	88.3569 (0.0010)	-32.3905 (0.0010)	11.164 (0.3450)	10.5036 (0.0012)
YHKJ	0.0759	2.8828	-0.1275	8.5626	1470.2776 (0.0010)	-30.9322 (0.0010)	9.7037 (0.4670)	9.1496 (0.0025)
XYCZ	0.0739	3.7262	0.0467	4.5215	110.1806 (0.0012)	-32.2415 (0.0010)	9.8938 (0.4500)	22.0861 (0.0050)
GXGK	0.0563	3.2467	0.0297	4.6017	121.8103 (0.0010)	-32.8087 (0.0010)	9.6651 (0.4701)	35.7641 (0.0000)
YWLN	0.2444	3.6053	0.0402	4.7096	138.9005 (0.0010)	-33.7873 (0.0010)	9.7697 (0.4610)	33.1669 (0.0045)
JLQC	-0.0309	3.5968	0.3909	5.3178	283.7057 (0.0010)	-31.8668 (0.001)	9.6833 (0.4690)	73.8114 (0.0000)
CAQC	0.0189	2.9749	0.1739	5.4781	296.9193 (0.0010)	-33.472 (0.0010)	16.183 (0.0950)	26.5688 (0.00)
CCQC	0.1044	3.1004	0.4007	4.9960	219.3616 (0.0010)	-31.6975 (0.0010)	14.149 (0.1660)	24.8129 (0.0000)
JHQC	-0.0225	3.0183	0.2627	5.5537	322.3096 (0.0010)	-33.717 (0.0010)	31.338 (0.0010)	86.1014 (0.0000)
DFQC	-0.0210	2.6189	0.2034	6.4597	575.4003 (0.0010)	-34.1554 (0.001)	12.029 (0.2830)	23.6633 (0.0000)
AKKC	-0.0773	2.8634	0.0026	5.0189	193.2711 (0.0010)	-30.1142 (0.0010)	35.608 (0.0000)	100.585 (0.0000)
GQJT	-0.0027	2.4111	0.3432	6.0215	455.2116 (0.0010)	-32.6482 (0.0010)	5.6942 (0.8400)	19.4849 (0.0000)
JLQC	-0.0902	2.5568	-0.118	5.9548	416.6296 (0.0010)	-29.5778 (0.0010)	32.354 (0.0000)	120.0801 (0.0000)

(Data source: CSMAR,https://data.csmar.com)

Results

Edge distribution fitting

Based on the descriptive statistics of the sample companies' time series presented in *Table 2*, several companies, including XZB, CCQC, and JLQC, show significant skewness. Therefore, this paper assumes that the residual term of the GARCH model follows a skewed t-distribution, and the marginal distribution is fitted accordingly. Given that the return series exhibits an ARCH effect, and considering that the GARCH(1, 1) model is commonly used and fits most time series well, it adopt the ARMA(0,0)-GARCH(1,1) model with a skewed t-distribution to model the stock return series of the sample companies, especially since some series show no significant autocorrelation.

As shown in *Table 3*, δ_0 and δ_1 represent the constant and autoregressive terms of the mean value equation, respectively; β_0 represents the constant term of the variance equation; β_1 and β_2 represent the ARCH and GARCH terms, respectively; and η and λ

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represent degrees of freedom and skewness, respectively. After ARMA (0,0), GARCH (1,1), partial t model fitting, the K-S probability values are all greater than 0.1, and the ARCH term β_1, GARCH term β_2, degrees of freedom η and skewness λ all pass the 10% significance test, which indicates that at the 10% significance level, there is no good reason for each time series to reject the null hypothesis, suggesting that the new series follows the (0,1) distribution. At the same time, according to the K-S statistic, it can be seen that the value for each sample company is less than 0.05, which indicates that the deviation between the fitting result of the edge distribution of each sample company and the empirical distribution is not obvious. If the K-S probability is greater than 0.1, it means the fitted new series passes the test. Therefore, the residual sequence of the edge distribution estimated by the ARMA (0, 0), GARCH (1, 1), partial t model after probability integral transform is independent and follows U (0,1) uniform distribution, which indicates that this model is ideal to fit the return rate series of sample companies.

Table 3. *Parameter estimation for marginal distribution models*

Sequences	δ_0	δ_1	β_0	β_1	β_2	η	λ	**K-S statistics**	**K-S Probability values**
SSGF	0.1472	0.0123	0.1589	0.0610*** (0.0130)	0.9329*** (0.0140)	4.5607*** (0.6670)	0.1302*** (0.0370)	0.0210	0.6901
HYGY	0.1214	0.0435	0.3842	0.0503*** (0.0120)	0.9265*** (0.0170)	7.6420*** (1.5820)	-0.0520* (0.0300)	0.0252	0.4591
XZB	0.1464	-0.0636	0.1793	0.0393*** (0.0100)	0.9486*** (0.0120)	4.6224*** (0.7180)	0.0317** (0.0155)	0.0257	0.4344
GLM	-0.0001	-0.0457	0.1105	0.0707*** (0.0150)	0.9240*** (0.0160)	4.3715*** (0.5570)	0.0942** (0.0420)	0.0266	0.3905
ZKDQ	0.0465	0.0007	0.1307	0.0703*** (0.0170)	0.9267*** (0.0180）	4.7675*** (0.6210)	0.0230* (0.0130)	0.0312	0.2126
NDGF	-0.0870	0.0337	0.1076	0.0792*** (0.0190)	0.9174*** (0.0190)	5.4327*** (0.8940)	0.0824** (0.0390)	0.0241	0.5139
YHKJ	0.0981	0.0158	0.1361	0.0899*** (0.0190)	0.9100*** (0.0210)	3.2729*** (0.2670)	0.1187*** (0.0420)	0.0205	0.7154
XYCZ	0.0277	0.0238	0.2124	0.0427** (0.0190)	0.9433*** (0.0190)	6.2039*** (0.8940)	-0.0390*(0.0210)	0.0123	0.9947
GXGK	-0.0037	0.0149	0.1571	0.0819*** (0.0260)	0.9126*** (0.0310)	4.5851*** (0.6230)	0.0468* (0.0250)	0.0177	0.8615
YWLN	0.2360	-0.0223	0.1197	0.0198* (0.0110)	0.9737*** (0.0180)	4.3167*** (0.5970)	0.0580* (0.0320)	0.0391	0.9410
JLQC	-0.0757	-0.0147	0.6571	0.1405*** (0.0430)	0.8268*** (0.0550)	4.1806*** (0.5220)	0.0937** (0.0390)	0.0180	0.8493
CAQC	-0.0911	-0.0043	0.0186	0.0444*** (0.0100)	0.9555*** (0.0130)	4.1600*** (0.4570)	-0.0029*** (0.0010)	0.0204	0.7246
CCQC	-0.0374	0.0325	0.0666	0.0695*** (0.0190)	0.9303*** (0.0230)	3.9842*** (0.4410)	0.1125** (0.0550)	0.0347	0.1252
JHQC	-0.0750	-0.0527	0.1426	0.1120*** (0.0300)	0.8860*** (0.0330)	4.0191*** (0.4720)	0.0344** (0.0160)	0.0171	0.8884
DFQC	-0.0360	-0.0990	0.0854	0.0812*** (0.0200)	0.9187*** (0.0190)	3.5518*** (0.4190)	0.0596** (0.0300)	0.0176	0.8677
AKKC	-0.1043	0.0244	0.2539	0.1573*** (0.0390)	0.8336*** (0.0440)	4.9030*** (0.8310)	-0.0195** (0.0098)	0.0204	0.7225
GQJT	0.0179	-0.0002	0.0654	0.0832*** (0.0180)	0.9166*** (0.0250)	3.6696*** (0.4120)	0.0974*** (0.0330)	0.0350	0.1191
JLQC	-0.0644	0.0468	0.4881	0.1494*** (0.0500)	0.7811*** (0.0900)	5.3524*** (0.7950)	0.0280** (0.0120)	0.0158	0.9353

Note: The values in brackets are the standard errors corresponding to the parameters. ***, ** and * indicate that the parameters are significant at 1%, 5% and 10% levels, respectively

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Model parameter estimation for time-varying Copula

After estimating the edge distribution of the return rate series of each sample company, the time-varying T-DCC-Copula model was used to estimate the probability integral sequence corresponding to the transformed standardized residual sequence. It can be seen from *Table 4* that parameters α and β meet the constraints of model $\alpha + \beta < 1$, and all estimated parameters pass the test at a significance level of 10%. Therefore, the T-DCC-Copula model was applied to measure the financial risk transmission effect between enterprises in the supply chain.

Table 4. *Parameter estimation results of the T-DCC-Copula model*

Financial risk transmission chain	ω	α	β	AIC criterion	BIC criterion	Logarithmic likelihood value
SSGF--GXGK	9.0182*** (2.8600)	0.0288* (0.0170)	0.8491*** (0.0820)	-397.9055	-382.7944	201.9530
NDGF--GXGK	7.6864*** (2.2310)	0.0170* (0.0100)	0.8064*** (0.0850)	-320.3571	-305.2460	163.1790
YHKJ--GXGK	8.8470*** (2.4720)	0.0189** (0.0090)	0.9569*** (0.0190)	-223.4204	-208.3093	114.7100
XYCZ--GXGK	9.9639*** (3.2050)	0.0451** (0.0230)	0.5426** (0.2380)	-375.1931	-360.0820	190.5970
HYGY--YWLN	8.7397*** (2.6330)	0.0311*** (0.0110)	0.9416*** (0.0250)	-361.2384	-346.1273	183.6190
XZB--YWLN	7.7405*** (2.4930)	0.0280*** (0.0100)	0.9643*** (0.0130)	-562.3630	-547.2519	284.1810
GLM--YWLN	6.4318*** (1.3680)	0.0213*** (0.0060)	0.9750*** (0.0090)	-350.4949	-335.3838	178.2470
ZKDQ--YWLN	8.6626*** (2.7820)	0.0741** (0.0280)	0.7041*** (0.1760)	-303.5140	-288.4029	154.7570
NDGF--YWLN	11.3103** (4.4250)	0.0435* (0.0230)	0.8720*** (0.2080)	-307.7085	-292.5974	156.8540
GXGK--JLQC	9.1725*** (2.4420)	0.0345** (0.0170)	0.0032** (0.0013)	-128.9722	-113.8611	67.4860
GXGK--CAQC	16.4186** (7.4130)	0.0125** (0.0060)	0.9755*** (0.0090)	-155.0727	-139.9616	80.5360
GXGK--CCQC	14.1122** (5.7910)	0.0174** (0.0070)	0.9751*** (0.0090)	-136.2015	-121.0904	71.1010
GXGK--JHQC	11.5632** (4.3000)	0.0680** (0.0280)	0.7122*** (0.1830)	-292.8700	-277.7589	149.4350
GXGK--DFQC	10.6175*** (3.6630)	0.0088* (0.0050)	0.9885*** (0.0070)	-229.0104	-213.8993	117.5050
GXGK--AKKC	16.7268** (7.4070)	0.0320** (0.0140)	0.9325*** (0.0370)	-147.1118	-132.0007	76.5560
GXGK--JLQC	10.2422*** (3.2010)	0.0136* (0.0080)	0.9783*** (0.0220)	-178.4424	-163.3313	92.2210
YWLN--DFQC	8.6395*** (2.3280)	0.0287*** (0.0100)	0.9509*** (0.0180)	-212.8018	-197.6907	109.4010
YWLN--GQJT	11.0753** (4.1800)	0.0162** (0.0080)	0.9562*** (0.0240)	-124.3108	-109.1997	65.1550

Note: The values in brackets are the standard errors corresponding to the parameters. ***, ** and * indicate that the parameters are significant at 1%, 5% and 10% levels, respectively

In order to describe the degree of interdependence between supply chain enterprise, the time-varying copula model was used to describe the dynamic interdependence

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between upstream and downstream enterprises of new energy vehicles. *Tables 5 and 6* show the mean values of nonlinear dynamic time-varying correlation coefficients of upstream and midstream enterprises and midstream and downstream enterprises in the supply chain of new energy vehicles, respectively. *Table 5* shown that the average correlation coefficient between upstream and midstream enterprises was above 0.4, the average nonlinear time-varying correlation coefficient of financial risk transmission of enterprises from upstream to midstream was 0.4958, and the average nonlinear time-varying correlation coefficient of financial risk transmission of enterprises from midstream to downstream was 0.3581. This indicated that there was a greater degree of risk dependence between upstream and midstream enterprises than that between midstream and downstream enterprises in the new energy vehicle supply chain. Compared with midstream and downstream enterprises, financial risk was more conductive between upstream and midstream enterprises.

Table 5. *Table of nonlinear time-variant relationship of financial risk transmission between upstream and midstream enterprises in supply chain*

Financial risk transmission chain	SSGF--GXGK	NDGF--GXGK	YHKJ--GXGK
Mean of dynamic time-varying correlation coefficients	0.5338	0.4810	0.4072
Financial risk transmission chain	XYCZ--GXGK	HYGY--YWLN	XZB--YWLN
Mean of dynamic time-varying correlation coefficients	0.5167	0.4960	0.6046
Financial risk transmission chain	GLM--YWLN	ZKDQ--YWLN	NDGF--YWLN
Mean of dynamic time-varying correlation coefficients	0.4819	0.4661	0.4750

Table 6. *Table of nonlinear time-variant relationship of financial risk transmission between midstream and downstream enterprises in supply chain*

Financial risk transmission chain	GXGK--JLQC	GXGK--CAQC	GXGK--CCQC
Mean of dynamic time-varying correlation coefficients	0.3043	0.3473	0.3070
Financial risk transmission chain	GXGK--JHQC	GXGK--DFQC	GXGK--AKKC
Mean of dynamic time-varying correlation coefficients	0.4584	0.4103	0.3306
Financial risk transmission chain	GXGK--JLQC	YWLN--DFQC	YWLN--GQJT
Mean of dynamic time-varying correlation coefficients	0.3667	0.3910	0.3077

Figure 2 shows the time-varying dynamic dependence coefficients between upstream raw material enterprises and midstream new energy vehicle battery enterprises, and *Figure 3* shows those between midstream new energy vehicle battery enterprises and downstream vehicle enterprises. It can be seen from *Figures 1 and 2* that the transmission of financial risk between upstream and midstream enterprises and between midstream enterprises and downstream enterprises has time-varying characteristics.

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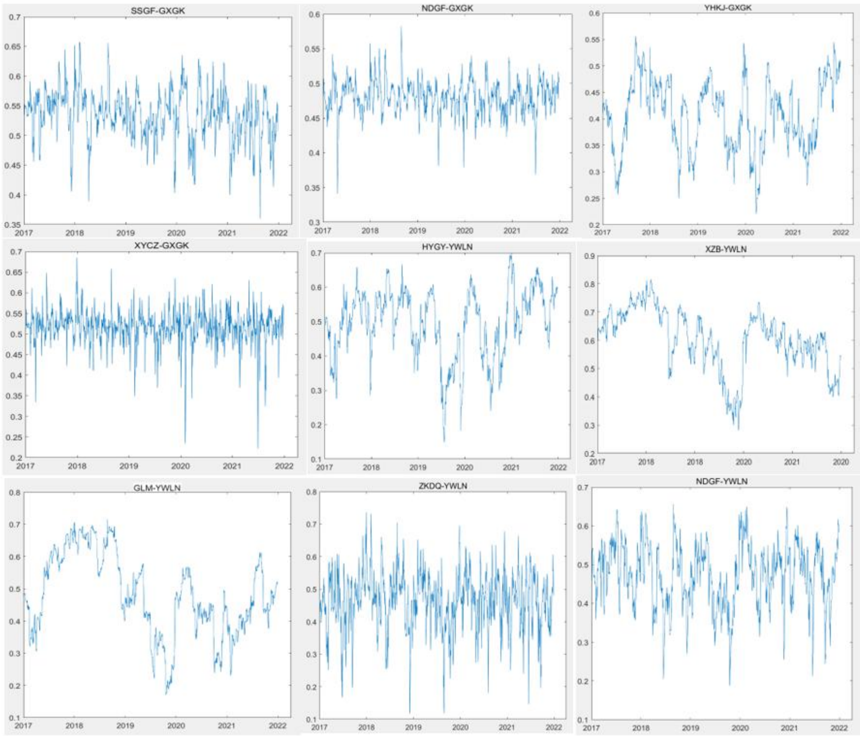

Figure 2. *The figure of nonlinear time-varying correlation coefficient of financial risk transmission between upstream and midstream enterprises*

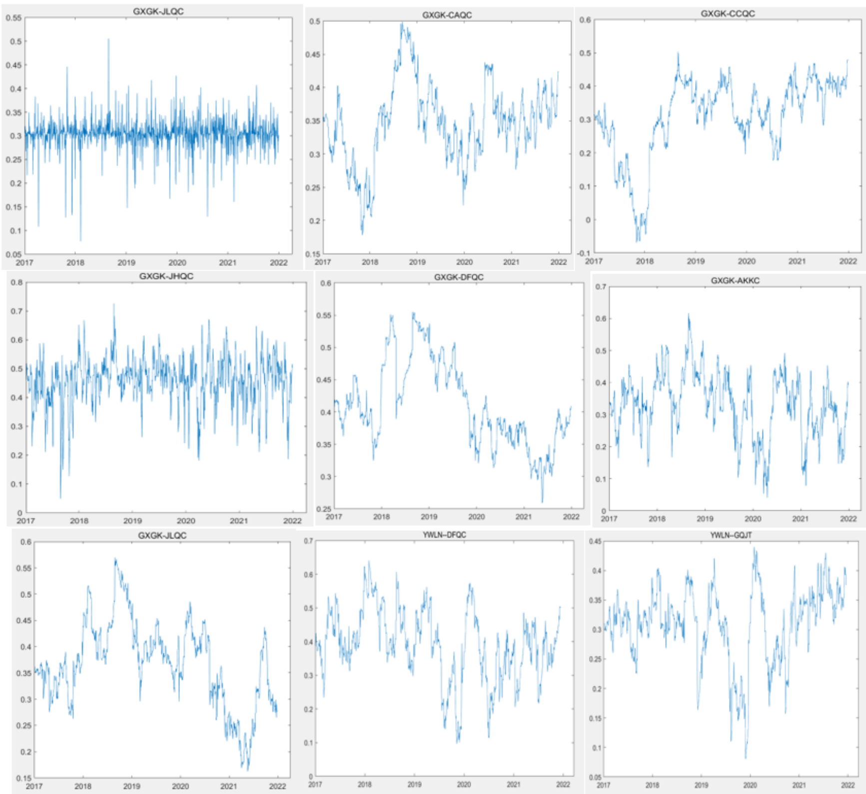

Figure 3. *The figure of nonlinear time-varying correlation coefficient of financial risk transmission between midstream and downstream enterprises*

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Analysis of financial risk transmission effect measurement results

Table 7 shows the financial risk of upstream and midstream enterprises in the supply chain of new energy vehicles and the financial risk transmission effect between them within a 95% confidence interval. As described from *Table 7*, on average, the conditional value at risk (CoVaR) of upstream and midstream enterprises was greater than the unconditional value at risk (VaR), indicating that there was a financial risk transmission effect between upstream and midstream enterprises of the supply chain of new energy vehicles. For example, the mean VaR of GXGK, a midstream enterprise, was -5.3708. After considering the financial risk transmission effect of SSGF, an upstream enterprise, the mean CoVaR of GXGK was -7.4560.

Table 7. *Analysis of financing risks and transmission effects of upstream and midstream enterprises in the new energy vehicle supply chain*

Conduction path	VaR		CoVaR		△CoVaR		%CoVaR	
	Mean value	Mean	Mean value	Mean	Mean value	Mean	Mean value	Mean
Upstream→ Midstream								
SSGF→GXGK	-5.3708	-5.3708	-7.4560	-7.0624	-2.9219	-2.8789	0.5696	0.5625
NDGF→GXGK	-5.3708	-4.9258	-7.3800	-6.7715	-2.6761	-2.5124	0.5126	0.5024
YHKJ→GXGK	-5.3708	-4.9258	-6.8676	-6.5318	-1.9853	-1.8403	0.3778	0.3567
XYCZ→GXGK	-5.3708	-4.9258	-7.7318	-7.3275	-3.1410	-3.0560	0.6175	0.6210
HYGY→YWLN	-5.9510	-5.7882	-8.2891	-8.0033	-3.1764	-3.1812	0.5336	0.5455
XZB→YWLN	-5.9510	-5.7882	-8.0121	-7.8194	-3.3233	-3.4106	0.5652	0.5751
GLM→YWLN	-5.9510	-5.7882	-7.4762	-7.2383	-2.3189	-2.2389	0.3915	0.3756
ZKDQ→YWLN	-5.9510	-5.7882	-7.9588	-7.8773	-2.7283	-2.5744	0.4570	0.4451
NDGF→YWLN	-5.9510	-5.7882	-7.8776	-7.5565	-2.6757	-2.5510	0.4439	0.4403
Midstream→ Upstream								
GXGK→SSGF	-5.4636	-5.3571	-7.2906	-2.8653	-2.9219	-2.6595	0.5284	0.5011
GXGK→NDGF	-5.5577	-5.1744	-7.4561	-6.9576	-2.5876	-2.3564	0.4825	0.4676
GXGK→YHKJ	-4.8034	-4.5886	-6.5616	-6.3380	-2.2022	-2.1046	0.4723	0.4674
GXGK→XYCZ	-6.0796	-5.8994	-7.9705	-7.7087	-2.7739	-2.5448	0.4564	0.4334
YWLN→HYGY	-5.4789	-5.4789	-8.3739	-8.1924	-2.9691	-2.8937	0.4701	0.4676
YWLN→XZB	-5.7882	-5.3291	-7.8808	-7.7954	-3.5811	-3.6842	0.6640	0.6778
YWLN→GLM	-4.8240	-4.6418	-7.0181	-6.8608	-2.8445	-2.8368	0.6164	0.6144
YWLN→ZKDQ	-5.8283	-5.6094	-7.8941	-7.7323	-2.7772	-2.7450	0.5078	0.4912
YWLN→NDGF	-5.5577	-5.1744	-7.6854	-7.3748	-2.8399	-2.7705	0.5400	0.5407

This indicated that the existence of the financial risk of the upstream enterprise SSGF could increase the financial risk of the downstream enterprise GXGK; that is, there was a transmission effect between upstream and downstream enterprises in the supply chain. The VaR of the upstream company SSGF was -5.4636, and after considering the risk transmission effect of the midstream company GXGK, the average CoVaR of SSGF was -7.2906, which indicated that the financial risk of the midstream enterprise could increase the financial risk of the upstream enterprise; that is, midstream enterprises in the supply chain also had a financial risk transmission effect on upstream enterprises. Therefore, the financial risk between upstream and midstream enterprises in the new energy vehicle supply chain has a two-way transmission effect. According to the analysis results

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of %CoVaR in *Table 7*, the financial risk transmission effect of upstream and midstream enterprises is heterogeneous, that is, the risk transmission effect of upstream to midstream enterprises is different from that of midstream to upstream enterprises. For example, the %CoVaR of SSGF → GXGK was 0.5625, and the %CoVaR of GXGK → SSGF → SSGF was 0.5011; the %CoVaR of NDGF → GXGK was 0.5024, while the %CoVaR of GXGK → NDGF was 0.4676. This is related to the degree of cooperation between supply chain enterprises.

Table 8 shows the financial risk of midstream and downstream enterprises themselves and the financial risk transmission effect between them in the new energy vehicle supply chain within a 95% confidence interval. As shown from *Table 8* that the CoVaR of midstream and downstream enterprise was greater than the VaR of midstream and downstream enterprises themselves, which indicated that there was a financial risk transmission effect between midstream and downstream enterprises of the supply chain of new energy vehicles. For example, the mean VaR of GXGK, a midstream enterprise, was -5.3708. After considering the financial risk transmission effect of JLQC, a downstream enterprise, the mean CoVaR of GXGK was -6.9495. This indicated that the financial risk of the downstream enterprise SSGF could increase the financial risk of the midstream enterprise GXGK. It is meaning the financial risk of downstream enterprises in the supply chain has a transmission effect on midstream enterprises. Similarly, the financial risk of midstream enterprises has a transmission effect on downstream enterprises. Therefore, the financial risk between midstream and downstream enterprises in the new energy vehicle supply chain has a two-way transmission effect.

Table 8. *Analysis of financing risk and transmission effect of midstream and downstream enterprises in the new energy vehicle supply chain*

Conduction path	VaR		CoVaR		△CoVaR		%CoVaR	
	Mean value	**Median**	**Mean value**	**Median**	**Mean value**	**Median**	**Mean value**	**Median**
Midstream→ Downstream								
GXGK→JLQC	-6.0354	-5.5357	-7.3807	-6.8849	-1.6360	-1.4938	0.2845	0.2768
GXGK→CAQC	-4.7761	-4.7961	-6.3223	-6.1440	-1.8619	-1.7676	0.4140	0.4103
GXGK→CCQC	-5.1309	-5.1018	-6.5052	-6.4791	-1.6871	-1.6122	0.3249	0.3254
GXGK→JHQC	-4.9763	-4.3688	-6.8497	-6.1501	-2.4669	-2.1929	0.5225	0.5082
GXGK→DFQC	-4.4029	-3.8846	-6.1716	-5.8586	-2.1579	-2.0424	0.5279	0.5095
GXGK→AKKC	-4.8359	-4.6010	-6.2637	-6.1600	-1.7286	-1.6079	0.3879	0.3662
GXGK→JLQC	-4.1138	-3.7149	-5.7636	-5.4381	-1.9516	-1.7315	0.5021	0.4578
YWLN→DFQC	-4.4029	-3.8846	-6.3368	-5.8739	-2.3159	-2.2683	0.5746	0.5582
YWLN→GQJT	-4.0004	-3.8486	-5.6389	-5.3641	-1.8500	-1.7622	0.4928	0.4804
Downstream→Midstream								
JLQC→GXGK	-5.3708	-4.9258	-6.9495	-6.4795	-1.8374	-1.6690	0.3620	0.3382
CAQC→GXGK	-5.3708	-4.9258	-6.7109	-6.3548	-1.6849	-1.7324	0.3210	0.3197
CCQC→GXGK	-5.3708	-4.9258	-6.7342	-6.2409	-1.6748	-1.6943	0.3184	0.3384
JKQC→GXGK	-5.3708	-4.9258	-7.0531	-6.3862	-2.3097	-1.9861	0.4320	0.4125
DFQC→GXGK	-5.3708	-4.9258	-6.6826	-6.3416	-1.7799	-1.6586	0.3483	0.3211
AKKC→GXGK	-5.3708	-4.9258	-6.6476	-6.4544	-1.5978	-1.4761	0.3257	0.2923
JLQC→GXGK	-5.3708	-4.9258	-6.4838	-6.1617	-1.5029	-1.3991	0.3018	0.2901
DFQC→YWLN	-5.9510	-5.7882	-7.1631	-6.8156	-1.7241	-1.6093	0.2886	0.2647
GQJT→YWLN	-5.9510	-5.7882	-6.9209	-6.6640	-1.2552	-1.1576	0.2076	0.2023

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Discussion

Financial risk transmission between upstream and midstream enterprises

Based on the analysis of financial risk transmission paths between upstream and midstream enterprises in the new energy vehicle supply chain, as illustrated in *Figure 1*, there are a total of nine pairs of cooperative relationships between upstream and midstream sample companies. To illustrate the overall trend of financial risk spillover effects between upstream and midstream enterprises, the time-varying risk transmission contributions (%CoVaR) of these nine pairs of cooperating enterprises are collectively presented in *Figure 4*. As shown in *Figure 4*, the %CoVaR values from upstream to midstream enterprises and from midstream to upstream enterprises consistently exceed zero, indicating the presence of bidirectional financial risk spillover effects between upstream and midstream enterprises in the new energy vehicle industry.

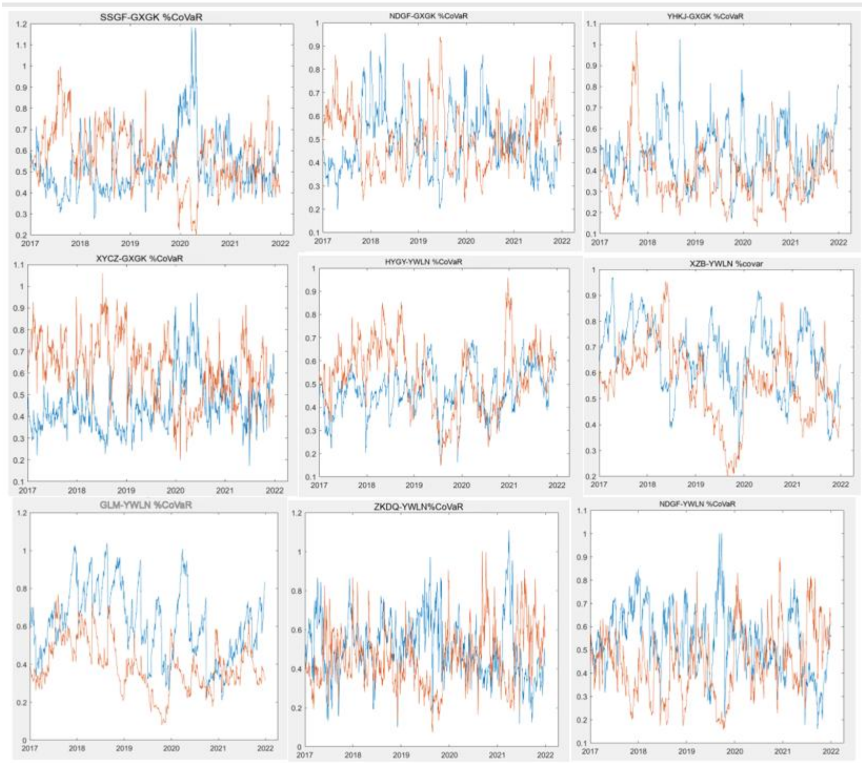

Figure 4. *Financing risk spillover from upstream companies to midstream companies in the new energy vehicle supply chain %CoVaR. Note: The blue curve represents the financial risk transmission effect of midstream enterprises to upstream enterprises, and the orange curve represents the financial risk transmission effect of upstream enterprises to midstream enterprises*

Figure 4 shows the dynamic change process of the financial risk transmission effect between upstream and midstream enterprises in the supply chain of new energy vehicles. In general, the financial risk transmission fluctuation was relatively unstable. Notably, in 2020, the financial risk transmission of several supply chains fluctuated greatly: for example, SSGF to GXGK, NDGF to GXGK, and NDGF to YWLN. This was due to the impact of the new corona virus pandemic in 2020 and the dual impact of government subsidies.

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On one hand, as a global crisis, the COVID-19 pandemic significantly exacerbated the transmission of financial risks between upstream raw material suppliers and midstream enterprises in the new energy vehicle industry chain by disrupting both supply stability and market demand. Firstly, the pandemic triggered a surge in raw material prices. Mining operations and port logistics were halted in multiple regions worldwide, causing a physical shortage of critical materials such as lithium, cobalt, and nickel, thereby driving up raw material costs. The rising procurement expenses sharply increased production costs for midstream three-electric manufacturers. Secondly, midstream enterprises faced a dual-squeeze financial dilemma, which severely weakened the risk absorption capacity. While upstream raw material prices fluctuated freely with market conditions, supply contracts between midstream manufacturers and downstream vehicle producers were largely long-term agreements with price adjustments lagging by several months. As a result, midstream firms were forced to absorb the full burden of cost increases over an extended period, leading to a sharp compression of profit margins. Finally, in order to ensure supply continuity, midstream enterprises were compelled to shift their inventory strategies, further straining their cash flow. In response to supply chain disruptions, these firms abandoned efficient Just-In-Time practices in favor of a Just-In-Case approach, stockpiling large quantities of raw materials at high prices. This shift tied up substantial working capital, impairing liquidity, reducing financial resilience, and significantly elevating financial risks. In summary, the COVID-19 pandemic amplified inherent structural vulnerabilities within the industry chain. Upstream supply and price risks were effectively transmitted and accumulated in the midstream segment through three major channels including spiraling costs, ineffective price transmission mechanisms, and increased capital immobilization in inventory, thereby heightening systemic financial risks across the entire industrial chain.

On the other hand, the phase-out of government subsidies has altered the demand dynamics and cost-sharing mechanisms within the new energy vehicle market, thereby intensifying the transmission of financial risks between upstream raw material suppliers and midstream three-electric enterprises. The core issue lies in the fact that the subsidy withdrawal amplifies the vulnerability of midstream firms, undermining their role as a "buffer" in cost transmission. Firstly, the reduction in subsidies leads to higher vehicle purchase costs for consumers, resulting in a slowdown in market growth. Secondly, influenced by the subsidy phase-out policy, raw material prices rising significantly compress the profit margins of midstream enterprises, severely weakening their cash flow generation capacity and accelerating the accumulation of financial risks. Lastly, the reduction of subsidies has exacerbated the inventory and capital risks of midstream enterprises. The subsidy phase-out signals a transition from policy-driven to market-driven industry development, intensifying competition and accelerating technological iteration. Preemptive investments made by midstream firms to capture market share may face diminished returns due to lower-than-expected demand. In summary, the subsidy phase-out has disrupted the prior mechanism of risk dispersion and absorption within the industrial chain. Instead, financial risks are now transmitted more directly and rapidly between upstream and midstream enterprises, ultimately amplifying systemic financial risks across the entire. Therefore, the financial risk transmission effect among upstream and midstream enterprises of new energy vehicles is influenced by the external macro environment.

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Financial risk transmission between midstream and downstream enterprises

There are nine pairs of cooperative relationships between midstream and downstream enterprises in the new energy vehicle supply chain as shown in *Figure 1*. The time-varying risk transmission contributions (%CoVaR) of these nine pairs of cooperating midstream and downstream enterprises are collectively presented in *Figure 5*, which illustrates the overall trend and dynamic process of financial risk spillover effects between these enterprises. As observed in *Figure 5*, the %CoVaR values from midstream to downstream enterprises and from downstream to midstream enterprises are consistently greater than zero, indicating the presence of bidirectional financial risk spillover effects between midstream and downstream enterprises in the new energy vehicle industry. A comparative analysis of *Figures 4 and 5* reveals that, compared to midstream and downstream enterprises, financial risk exhibited a higher degree of transmission between upstream and midstream enterprises. *Figure 5* shows the dynamic change process of the financial risk transmission effect between midstream and downstream enterprises in the supply chain of new energy vehicles. In general, the financial risk transmission fluctuation between midstream and downstream enterprises was unstable, similar to the transmission between upstream and midstream enterprises, and the financial risk transmission in multiple supply chains fluctuated greatly in 2020, such as GXGK to JHQC and GXGK to JLQC. This is also because enterprises were affected by the impact of the new corona virus pandemic in 2020 and the dual impact of the government subsidy reduction policy.

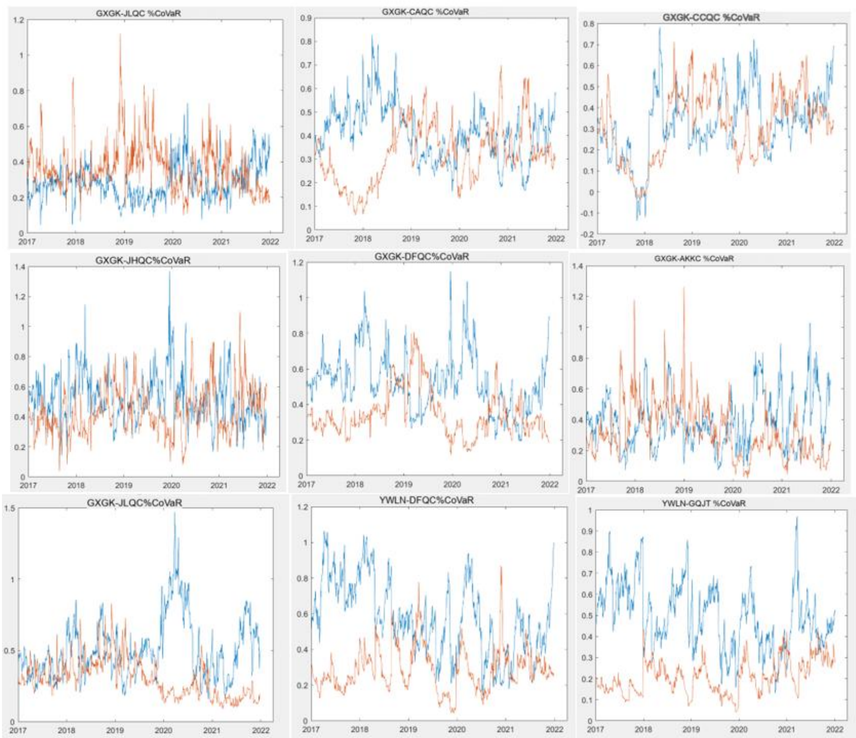

Figure 5. *Financing risk spillover from midstream enterprises to downstream enterprises in the new energy vehicle supply chain %CoVaR. (Note: The blue curve represents the financial risk transmission effect of midstream enterprises to downstream enterprises, and the orange curve represents the financial risk transmission effect of downstream enterprises to midstream enterprises*

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The COVID-19 pandemic and the phase-out of government subsidies have jointly exacerbated the transmission of financial risks between midstream enterprises and downstream vehicle manufacturers in the new energy vehicle supply chain. The core mechanism lies in their synergistic effect of reducing terminal market demand elasticity and altering the bargaining power dynamics within the industry, which obstructs cost pass-through and amplifies financial risk propagation between midstream and downstream segments. Firstly, the pandemic caused production halts and weakened consumer confidence, leading to a decline in the new energy vehicle sales. Meanwhile, the reduction in subsidies increased the actual purchase cost for consumers, further dampening market demand. Midstream vehicle manufacturers faced dual pressures of slowing sales growth and intensified competition, significantly squeezing their profitability and cash flow. To maintain financial stability, downstream enterprises leveraged their dominant position to exert stronger price reduction pressures and extend payment terms on midstream suppliers, thereby transmitting financial risks backward along the chain. Secondly, the pandemic triggered a surge in raw material prices, leading upstream enterprises transmit cost pressures to midstream manufacturers. Concurrently, the phase-out of subsidies increased vehicle purchase costs for end consumers, potentially dampening market growth. In response, downstream vehicle manufacturers, aiming to maintain market share, further exerted countervailing cost pressures on midstream suppliers. Consequently, midstream firms experienced severe compression of profit margins, deteriorating cash flow conditions, and elevated financial risks. Lastly, the combined impact of pandemic volatility and policy withdrawal created substantial market uncertainty, prompting downstream enterprises to adopt conservative production and procurement strategies. This made it difficult for midstream firms to conduct stable long-term production planning, leading to underutilized capacity, reduced operational efficiency, and increased fixed costs. Moreover, redundant inventory maintained to mitigate supply chain disruption risks tied up significant working capital. In summary, the dual effects of the COVID-19 pandemic and subsidy phase-out facilitated the transfer of financial pressures from downstream vehicle manufacturers to midstream suppliers, exacerbating systemic risk propagation across the the new energy vehicle industrial chain.

It can be seen from the analysis in *Figure 5* that the financial risk transmission effect was stronger from midstream to downstream enterprises than downstream to midstream enterprises. This is because the "three power" parts enterprises are the core enterprises in the new energy vehicle supply chain, and as parts suppliers, they have a huge impact on the development of downstream vehicle enterprises and even the entire supply chain.

Differences in financial risk transmission effect of different enterprise risk hosts with the same risk source

In the process of financial risk transmission from upstream to midstream enterprises, upstream enterprises represent the risk source. *Figure 1* shows that NNDG, as a source of financial risk, can transmit its risk to midstream companies GXGK and YWLN. It can be seen from the analysis in *Table 7* that the average △CoVaR of the financial risk transmission effect from NNDG to GXGK and YWLN was -2.6761 and -2.6757, respectively. This shows that for the same enterprise risk sources, the financial risk transmission effect differs in different supply chains. This is because different risk-hosting enterprises have different abilities to resist risk, which leads to varying financial risk transmission effects.

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Differences in financial risk transmission effect of different transmission paths of the same enterprise risk hosts

Because of the bidirectional effect of financial risk transmission in the supply chain of new energy vehicles, midstream enterprises can be both risk sources and risk recipients. When the financial risk of upstream enterprises is transmitted to midstream enterprises, for example, midstream enterprises GXGK and YWLN accept the financial risks transmitted by upstream enterprise risk sources as risk recipients. *Figure 5* shown that four upstream financial risk transmission enterprises were risk recipients of GXGK: SSGF, NDGF, YHKJ, and XYCZ, which constitute financial risk transmission chains. As a risk recipient, YWLN has five upstream financial transmission risk enterprises: HYGY, XZB, GLM, ZKDQ, and NDGF, which constitute financial risk transmission chains. From *Table 5*, it can be seen that the average CoVaR of the financial risk transmission from SSGF to GXGK, NDGF to GXGK, YHKJ to GXGK, and XYCZ to GXGK was -2.9219, -2.6761, -1.9853, and -3.1410, respectively. The average financial risk transmission effect of HYGY to YWLN, NZB to YWLN, GLM to YWLN, ZKDQ to YWLN, and NDGF to YWLN was -3.1764, -3.3233, -2.3189, -2.7283, and -2.6757, respectively. This shows that the financial risk transmission effect is different with different transmission paths and the same risk-hosting enterprise.

Conclusion

Although research on enterprise risk transmission has emerged recently, however, studies focusing on financial risk transmission effect remain limited. The existing literature remains largely confined to theoretical discussions and qualitative analyses. While these studies often identify the mechanisms, characteristics, and pathways of enterprise risk transmission through empirical observation, they offer limited quantitative assessment of the transmission effect itself. To address this gap, this study proposes a GARCH–time-varying copula–CoVaR model to quantitatively measure the financial risk transmission effect among new energy vehicle enterprises from a supply chain perspective, thereby contributing to the research on corporate financial risk transmission. Based on the empirical findings, the main conclusions of this study are as follows.

Firstly, financial risk within the new energy vehicle supply chain exhibits a bidirectional transmission effect between upstream and downstream enterprises, with significant heterogeneity in its manifestation. On the one hand, the strength and nature of risk transmission vary along the same financial linkage path. As shown in *Table 7*, which presents the risk transmission effects between upstream–midstream and midstream–upstream enterprises. *Table 8* shows the results of measuring the financial risk transmission effect between midstream and downstream enterprises. The research showed that the financial risk transmission between upstream and downstream enterprises in the supply chain of new energy vehicles was different. Furthermore, the interdependence among enterprises exhibits significant variation. When the risk-originating enterprise remains the same, the financial risk transmission effect differs depending on the risk-receiving enterprise. As shown in *Table 7*, the mean ΔCoVaR values measuring the financial risk transmission effect from Nuode Shares to Guoxuan High-Tech and Eve Energy were -2.6761 and -2.6757, respectively. Conversely, even for the same risk-receiving enterprise, the transmission effect varies with different risk-originating enterprises and transmission paths. For instance, the mean ΔCoVaR values for the financial risk transmission from HYGY, XZB, GLM, ZKDQ, and NNGF to YWLN were

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-3.1764, -3.3233, -2.3189, -2.7283, and -2.6757, respectively. This clearly demonstrates that the financial risk transmission effect for an identical risk-receiving enterprise differs across various transmission paths.

Secondly, financial risk exhibits greater conduciveness between upstream and midstream enterprises than between midstream and downstream enterprises in the new energy vehicle supply chains. As shown in *Tables 5 and 6*, the average correlation coefficient between upstream and midstream enterprises exceeds 0.4, with a mean nonlinear time-varying correlation coefficient of 0.4958. In contrast, the average nonlinear time-varying correlation coefficient for financial risk transmission from midstream to downstream enterprises is 0.3581. This indicates that the overall degree of risk dependence between upstream and midstream enterprises is stronger than that between midstream and downstream enterprises. Consequently, the financial risk transmission effect is more pronounced between upstream and midstream enterprises in the new energy vehicle supply chain.

Thirdly, the financial risk transmission effect among enterprises in the new energy vehicle supply chain exhibits time-varying characteristics, influenced by factors such as the external macro-environment and the closeness of inter-firm cooperative relationships. *Figure 4* illustrates the dynamic evolution of this effect between upstream and midstream enterprises. Significant fluctuations were observed in 2020 across several supply chain pairs (e.g., SSGF→GXGK, NDGF→YWLN), attributable to the combined impact of the COVID-19 pandemic and the phase-out of government subsidies during that period.

Based on the above conclusions, in order to foster the high-quality development of the new energy vehicle, it is imperative to implement effective measures to prevent and control the transmission of financial risk in supply chain, thereby supporting the realization of the dual carbon objectives.

Firstly, maintaining a stable external macro-environment is essential. To keep the external macro environment stable, first of all, we should give play to the overall coordinating role of the government as well as national coordinating agencies in the prevention and control of financial risk transmission of new energy automobile enterprises (Zhang et al., 2013; Zhang and Fang, 2017; Zhang and Liu, 2021). It is then necessary to establish a dynamic enterprise financial risk warning and monitoring system at the national level. In addition, a national risk information-sharing platform should also be established. Second, it is important to reduce the policy risk of new energy automobile enterprises. The policy orientation of the new energy automobile industry must be clarified, while market-led, policy-guided development ideas should be fully implemented. It is essential to respond to the decline in financial subsidies with technological innovation (Liao and Shuang, 2017; Zhou and Pan, 2019). Third, a reasonable risk- and benefit-sharing mechanism should be established. Finally, new energy vehicle enterprises should adapt to the external macroeconomic environment and flexibly adjust their financial policies.

Second, enhancing the capacity of the new energy vehicle enterprises to resolve financial risks is crucial. On one hand, the financing level of new energy vehicle enterprises should be continually improved, such as through optimizing financing structures, reducing financing costs, expanding financing channels, and increasing the scale of financing. On the other hand, it is essential to strengthen fund application management for new energy vehicle enterprises, such as through improving innovation ability, strengthening inventory management, and improving profitability.

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Third, blocking the pathways of financial risk transmission is necessary. Blocking the financial risk transmission path is an important measure to prevent and control financial risk transmission in new energy automobile enterprises. On the one hand, we should strengthen the management of financial risk carriers. The transmission of financial risk among enterprises needs to pass through various tangible or intangible carriers. Controlling and managing financial risk carriers such as control logistics, capital flow, information flow, etc., can effectively reduce the probability of financial risk transmission among enterprises in the supply chain. On the other hand, we should effectively transfer the financial risks within the supply chain to other entities outside the supply chain, such as through purchasing property insurance from insurance companies. In addition, it is transferred to professional institutions or departments through guarantees, outsourcing, contracts, etc. (Chen et al., 2020; He et al., 2021).

Finally, strengthening supply chain coordination and management is vital. Coordinated development among supply chain enterprises can enhance the overall system's resilience. First, new energy vehicle enterprises should reinforce specialization and collaboration across R&D, production, assembly, and sales. Accelerating transformation and upgrading through supply chain integration will help ensure that all segments keep pace with economic development, thereby sustaining value creation and competitiveness. Improved communication and cooperation are also needed to reduce information asymmetry and gaming behavior among stakeholders. Ensuring smooth information flow and collaborative relations will help enterprises better withstand financial shocks (Liu et al., 2019; Gao, 2021; Guo et al., 2023).

In this study, a methodological framework was proposed to measure the financial risk transmission effect among new energy vehicle enterprises from a tail dependence perspective. By constructing a dynamic time-varying copula model, we captured the time-varying nature of financial risk spillovers between upstream and downstream firms in the supply chain. Furthermore, a GARCH–time-varying copula–CoVaR model was constructed to quantify the transmission effect, thereby enriching the existing literature on risk contagion. The primary limitation of this study lies in its relatively narrow sample selection. Due to constraints in data availability, the empirical analysis was confined to listed companies within the new energy vehicle supply chain, meaning data from non-listed enterprises could not be included. Furthermore, as many midstream battery companies in the supply chain became listed relatively late, the number of available sample firms is limited, resulting in insufficient data. This shortfall may introduce a certain degree of bias into the empirical findings. Future research will aim to incorporate a larger sample of firms to address this limitation.

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Conflicts of interest. The authors declare no conflict of interest.

Data availability statement. The data used to support the findings of this study are available from the corresponding author upon request.

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