

Analyzing Dairy Market Price Co-movement and Risk Transmission Using a Copula-GARCH Model

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ABSTRACT To characterize time-varying dependence and abrupt structural changes in commodity-market linkages, this paper develops a segmented modeling framework combining the Bai-Perron breakpoint test with a dynamic Copula-GARCH model. The proposed framework overcomes the limitations of conventional models in identifying risk “jumps” by explicitly detecting structural breakpoints in market dependence. Empirical results demonstrate high sensitivity to structural mutations, with an average correlation-coefficient shift of $\Delta\rho = 0.2$. Raw milk and international whole milk powder are identified as major risk sources, showing significant asymmetric tail dependence in which negative shocks transmit more strongly than positive shocks. Incorporating carbon-emission intensity further indicates that low-carbon production can weaken extreme risk linkages, reducing lower-tail dependence by 0.10 to 0.18 compared with high-emission groups. The study provides a quantitative basis for collaborative stabilization strategies and green riskmanagement frameworks in dairy value chains, supporting operational resilience and sustainable development under nonlinear and asymmetric market-risk transmission.

INDEX TERMS dairy industry chain, risk transmission, bai-perron breakpoint test, copula-garch, asymmetric tail dependence

I. INTRODUCTION

AS the global dairy industry supply chain rapidly adjusts to structural changes caused by changes in international trade, shifts in consumption structures, and mounting pressures for green transformation, the nature of price linkages between dairy markets has become increasingly complex, leading to more frequent occurrences of extreme risk transmissions across dairy markets. Correspondingly, the industry is also adjusting to a profound change; its highly globalized production networks continue to experience significant disruption from geopolitical tensions, while the industry’s rapid transition toward sustainable sourcing is changing internal price signal complexity and expanding extreme risk transmission derived from its raw materials and finished goods markets [1-3]. Conventional static correlation analysis struggles to capture the nonlinear and asymmetric dependency structure between markets. Markets and sectors may even experience structural mutations in their correlations due to exogenous shocks such as epidemics or policy changes, that is, discontinuous transitions within dependency relationships due to major shifts in institutions, supply and demand, or interruptions in the global supply chain [4]. For instance, if environmental production restrictions lead to a large drop in the supply of raw milk, and/or interruptions in the world supply chain causes the

cost of imported milk powder to plummet, the existing price transmission chain may not only be disrupted but also establish new coupling patterns of risk. To capture the nonlinear dependence and asymmetric risk spillover within this dynamic environment, the Copula-GARCH model has become a pivotal tool for studying price fluctuations and risk dependencies in commodity markets, including agriculture and animal husbandry [5-7]. However, existing applications often assume a smooth evolution of market dependencies, ignoring the potential for abrupt structural breakpoints triggered by major events. This modeling bias makes it difficult to accurately capture the true “jump”-like dynamics of price linkage during industrial chain restructuring, potentially leading to an underestimation of systemic risk [8,9]. Consequently, the dairy market risk management process needs a new analytical framework that allows for identifying structural changes over time and accurately measures risk transmission pathways. As a component of the agricultural product pricing system, the dairy product market price transmission mechanism will have an impact on dairy farm income, processing company costs, and consumer welfare. Wang Q [10]’s research shows that there is a two-way volatility spillover effect between the global dairy trade of whole milk powder and the Chinese raw milk market, and a

one-way volatility spillover effect between the global dairy trade of skimmed milk powder and the Chinese raw milk market; Xue H [11] found that New Zealand's skimmed milk powder export price maintains a leading position in China, while Ireland's skimmed milk powder export price is more consistent with the international market price; these two studies jointly reveal the significant volatility spillover effect of international dairy trade on the Chinese raw milk market. Hillen J [12] studied the vertical price transmission in the Swiss dairy and cheese supply chain and found that there was almost no long-term price relationship between different links and products, and no significant asymmetry. Tuncay B [13] found that the transmission between the prices of liquid milk and raw milk was asymmetric in both the long and short term. From the perspective of carbon emission limitations, Liu C [14] noted that digital technology can reduce short-term production inputs and increase long-term inputs in dairy farming. Findings from this research have shown that the dairy pricing system had a multi-dimensional structure, dynamic (motion) in nature, and firmly couched within the pressures to be greener (green transformation). In fact, there is an important space for further study that investigates all risk linkages in the ongoing dairy market system. The parallels are apparent in the complexities of competing tensions and changes in the global industry: raw material price pressures, globally complex sourcing and supply chains, and urgent intentions / pressures to be greener (sustainability, green transformation) have maintained price mechanisms of multi-dimensional complexity and volatility in the market. Therefore, a deeper exploration of price dynamics through the lens of risk linkage is critically and immediately necessary. To capture the nonlinear dependence and risk spillover between markets, Zhang P [15] used the copula-DCC (Dynamic Conditional Correlation)-GARCH model to study the systemic risk spillover effects between some financial industries and the stock market in China from 2009 to 2021, providing important risk warning and management insights for regulators, investors, and portfolio managers. Sadraoui T [16] used a multivariate GARCH model based on copula, and the results supported the existence of a significant risk spillover effect between the crude oil market (natural gas market) and the stock markets of the BRICS countries. The dynamic generalized Pareto-GARCH-Copula model proposed by K lekci B Y [17] can better capture the behavior of real data and reduce the bankruptcy probability of fat-tailed and non-traditional related insurance data. Zou Y [18] used the GARCH-Copula-CoVaR model to analyze the dynamic behavior of the dry bulk shipping secondary market freight rate index. The results showed that route distance and geographical location may be the key factors affecting the intensity of risk spillover. Ahmed Z A [19] utilized the GARCH model with key economic indicators (including GDP growth rate, livestock production, and crop production) to analyze the volatility trend of the agricultural economy in Somalia. The forecast results demonstrated the unpredictable nature of

the economy that suggests the presence of external shocks, including climate change and geopolitical instability.

This type of model generally assumes that the correlation coefficient evolves smoothly, or only enhances flexibility through latent variables. In essence, it is still limited by the continuity and stationary assumptions of the parameters. It cannot explicitly identify and deal with structural breakpoints, and is prone to misjudging the real "jump" risk transmission as a gradual process, leading to underestimation of risks. This paper introduces a segmented modeling framework that combines the Bai-Perron breakpoint test with a dynamic Copula-GARCH model to systematically analyze the price linkage and risk transmission mechanisms in the dairy product market. First, the GJR (Glosten-Jagannathan-Runkle)-GARCH (1,1) model is used to model the marginal distribution of the price returns of raw milk, liquid milk, infant formula, and international whole milk powder, and to extract standardized residuals. Second, the Bai-Perron multiple breakpoint test is introduced to identify structural breakpoints in the inter-market dependence structure, dividing the entire sample into multiple stable sub-intervals. Within each subinterval, it can fit time-varying t-Copula, Clayton, and Gumbel copulas using a rolling window method. The best model is dynamically selected based on the Akaike Information Criterion (AIC) criterion to capture the evolution of symmetric and asymmetric tail dependencies. The paper then builds a downside/upside risk spillover index and ΔCoVaR to measure asymmetrical extreme risk transmission paths. It then brings in carbon emission intensity as a proxy variable for green transition, compares lower-tail dependencies by splitting into groups by median, and evaluates the moderation of low-carbon production on risk interlinkages. This approach creatively and directly incorporates detection of structural mutation directly into the model found in the Copula-GARCH framework, allowing for exact identification of breakpoint-transition relationships between trust and response structures of prices. Importantly, because it brings in the dimension of green development – especially considering sustainable and low-carbon production alternatives within the sector – this approach can not only showcase the adjustment effect of such a transition on extreme risk transmission, but substantially increase the dynamic utility and policy explanatory power in understanding complex external shocks in the global apparel supply chain.

II. ALGORITHM DESIGN

A. MARGINAL FLUCTUATION MODELING AND RESIDUAL EXTRACTION

To accurately characterize the volatility clustering, fat-tailedness, and asymmetric volatility response characteristics of dairy product price returns, this paper constructs a GJR-GARCH(1,1) model for each market series to model marginal distributions. Assuming the price series of the first dairy product is $\{P_{i,t}\}_{t=1}^T$, the generation process of its logarithmic return $r_{i,t}$ is characterized by the following

model [20,21]:

$$r_{i,t} = \mu_i + \epsilon_{i,t}, \quad \epsilon_{i,t} = \sigma_{i,t} z_{i,t}, \quad z_{i,t} \sim t_\nu \quad (1)$$

$$\sigma_{i,t}^2 = \omega_i + \alpha_i \epsilon_{i,t-1}^2 + \gamma_i I_{t-1}^- \epsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 \quad (2)$$

In formula (1), μ_i is the mean return term, and $\epsilon_{i,t}$ is the residual term; in formula (2), $\sigma_{i,t}^2$ is the conditional variance. ω_i is the long-term benchmark level of the conditional variance, α_i represents the symmetric volatility coefficient, and γ_i is the leverage effect coefficient. β_i is the GARCH term coefficient, and I_{t-1}^- is the asymmetric shock indicator function, which is defined as:

$$I_{t-1}^- = \begin{cases} 1, & \epsilon_{i,t-1} < 0, \\ 0, & \epsilon_{i,t-1} \geq 0. \end{cases} \quad (3)$$

The model parameter vector $\theta_i = (\mu_i, \omega_i, \alpha_i, \gamma_i, \beta_i, \nu)$ is jointly estimated using the quasi-maximum likelihood estimation method, and the optimization objective is the log-likelihood function [22,23]:

$$L_i(\theta_i) = \sum_{t=1}^T \left[-\frac{1}{2} \ln(2\pi) - \frac{1}{2} \ln(\sigma_{i,t}^2) - \frac{1}{2} \frac{\epsilon_{i,t}^2}{\sigma_{i,t}^2} + \ln f_\nu(z_{i,t}) \right] \quad (4)$$

In formula (4), $f_\nu(z_{i,t})$ is the probability density function of the standardized t distribution:

$$f_\nu(z_{i,t}) = \frac{\Gamma(\frac{\nu+1}{2})}{\sqrt{(\nu-2)\pi} \Gamma(\frac{\nu}{2})} \left(1 + \frac{z^2}{\nu-2} \right)^{-\frac{\nu+1}{2}} \quad (5)$$

After parameter estimation is complete, extract the standardized residual series:

$$\hat{z}_{i,t} = \frac{\hat{\epsilon}_{i,t}}{\hat{\sigma}_{i,t}}, \quad t = 1, 2, \dots, T \quad (6)$$

This sequence has removed the conditional mean and conditional heteroskedasticity in the original yield, forming input variables that are approximately independent and identically distributed, meeting the basic requirements of Sklar's theorem for Copula modeling. It serves as input data for constructing a multivariate dependency structure in the next stage. The overall framework is shown in Figure 1.

Figure 1 illustrates the overall algorithmic framework of this method: First, based on the GJR-GARCH(1,1) model, marginal fluctuations are modeled for the price-return ratios of raw milk, liquid milk, infant formula, and international whole milk powder (WMP), extracting standardized residuals. Next, the Bai-Perron breakpoint test is introduced to identify structural breakpoints in the dependency structure and, accordingly, to divide the dynamic analysis window. Within each stable subinterval, a rolling window fit of the time-varying t-Copula, Clayton Copula, and Gumbel

Copula was used to characterize the asymmetric evolution of symmetric correlations and upper and lower tail dependencies, respectively. Downward/upward risk spillover indices and CoVaR were then constructed to quantify the intensity of bidirectional risk transmission. Finally, the carbon emission intensity of animal husbandry was used as a proxy variable for green transition, and the animals were divided into low-carbon and high-carbon groups based on the median. This systematically evaluated the moderating effect of low-carbon production models on the linkage of extreme risks, achieving synergistic modeling of market risk and green development.

B. IDENTIFICATION OF STRUCTURAL BREAKPOINTS AND TIME WINDOW DIVISION

To overcome the modeling bias of the traditional Copula-GARCH model in scenarios where structural breakpoints are required, this paper introduces the Bai-Perron breakpoint test method to systematically identify structural changes in the price linkage relationship between dairy product markets [24,25]. The Bai-Perron test was applied to the Spearman rank correlation coefficient series calculated using a rolling window, which served as a proxy variable for time-varying dependency parameters. This application focuses on the dependency structure between markets itself, measuring dependency through a direct and robust nonparametric method. Furthermore, before constructing the series, the original returns were preprocessed using a GJR-GARCH model to extract standardized residuals, ensuring that the detected structural discontinuities reflect genuine changes in dependency relationships, rather than spurious signals caused by volatility clustering in individual markets. A piecewise regression model is constructed with the sliding window correlation coefficient as the explained variable:

$$r_t = \delta_k + u_t, \quad t \in (\tau_{k-1}, \tau_k], \quad k = 1, 2, \dots, m+1 \quad (7)$$

In formula (7), r_t is the rolling Spearman rank correlation coefficient, δ_k is the mean parameter of the kth interval, τ_k is the kth breakpoint location, u_t is the error term, and m is the number of breakpoints. The model parameters are estimated using the generalized least squares method, minimizing the weighted residual sum of squares while considering the autocorrelation and heteroskedasticity of the error term [26,27]. To determine the optimal number of breakpoints, the modified Bayesian information criterion [28,29] is used:

$$BIC^*(m) = \ln \left(\frac{1}{T} \sum_{t=1}^T \hat{u}_t^2 \right) + C_T \frac{(m+1) \ln T}{T} \quad (8)$$

In formula (8), C_T is the penalty adjustment constant used to control the overfitting risk caused by multiple breakpoints. A statistical significance test is performed using the supercritical search method to determine whether at least

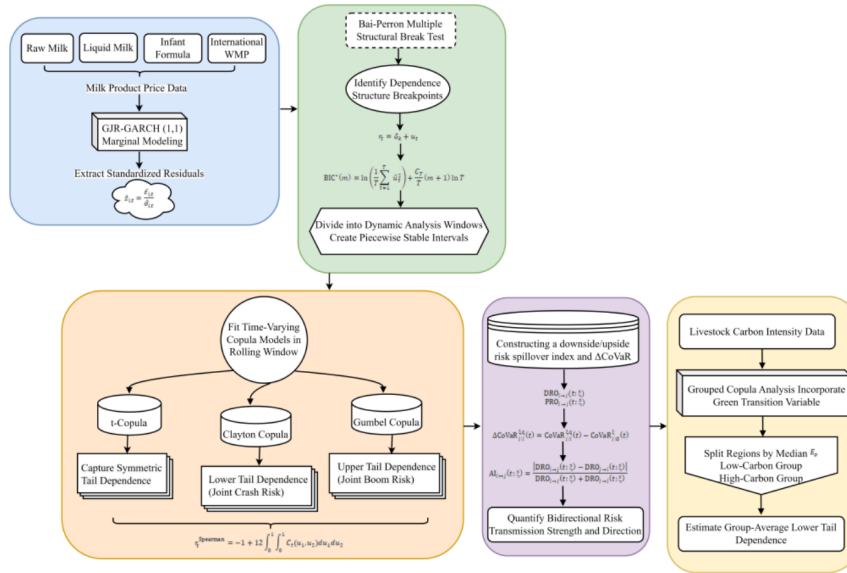


FIGURE 1. Overall Framework

one breakpoint exists, and the globally optimal breakpoint configuration is selected in combination with BIC (Bayesian Information Criterion). Finally, the entire sample interval is divided into $m+1$ subintervals. Within each subinterval, the inter-market dependency structure is assumed to be stable, providing a time window division basis for the subsequent independent fitting of the time-varying Copula model within each segment.

C. DYNAMIC DEPENDENCY STRUCTURE MODELING

To accurately characterize the time-varying characteristics of the nonlinear dependency structure between dairy product markets, this paper uses a rolling window method to construct a time-varying Copula model within each structurally stable subinterval [30,31]. Let the k th structurally stable interval be $T_k = (\hat{\tau}_{k-1}, \hat{\tau}_k]$.

Within this interval, standardized residual pairs are sequentially extracted using a rolling window $W = [t - W + 1, t]$ to dynamically estimate the Copula parameters. Three types of time-varying Copula functions are constructed to comprehensively capture the dependency structure characteristics: Time-varying t-Copula: Characterizes symmetrical tail risk linkage, and its form is:

$$C_t^t(u_1, u_2 | \rho_t, \nu_t) = \frac{\int_{-\infty}^{t_{\nu_t}^{-1}(u_1)} \int_{-\infty}^{t_{\nu_t}^{-1}(u_2)} \frac{\Gamma(\frac{\nu_t+2}{2})}{\Gamma(\frac{\nu_t}{2}) \sqrt{\nu_t \pi (1 - \rho_t^2)}} \times \left(1 + \frac{s_1^2 - 2\rho_t s_1 s_2 + s_2^2}{\nu_t (1 - \rho_t^2)}\right)^{-\frac{\nu_t+2}{2}} ds_1 ds_2 \quad (9)$$

In formula (9), ρ_t is a dynamic correlation parameter. The time-varying Clayton-Copula specifically captures the lower

tail dependence to reflect the market's co-fall risk, and its expression is [32]:

$$C_t^{Clayton}(u_1, u_2 | \theta_t) = \left(u_1^{-\theta_t} + u_2^{-\theta_t} - 1\right)^{-1/\theta_t}, \quad \theta_t > 0 \quad (10)$$

The time-varying Gumbel-Copula method focuses on the upper tail dependence to identify the common surge scenario, and fully reveals the dynamic evolution characteristics of asymmetric risk transmission between dairy product markets. Its form is [33]:

$$C_t^{Gumbel}(u_1, u_2 | \theta_t) = \exp\left\{-\left[(-\ln u_1)^{\theta_t} + (-\ln u_2)^{\theta_t}\right]^{1/\theta_t}\right\}, \quad \theta_t \geq 1 \quad (11)$$

All copula parameters are estimated using maximum quasi-likelihood estimation. To avoid model misspecification, the Akaike Information Criterion is used to dynamically select the optimal copula type within each window:

$$AIC_t = -2 \ln L_t(\hat{\psi}_t) + 2k_t \quad (12)$$

In formula (12), L_t is the log-likelihood value and k_t is the number of parameters.

To avoid model specification errors and ensure optimal fitting of the observed dependency structure, this paper adopts the Akaike Information Criterion (AIC) as the primary criterion for dynamic model selection within each rolling window. Among the time-varying t-Copula, Clayton-Copula, and Gumbel-Copula models fitted within a given window, the model with the lowest AIC value is selected as the optimal model for that specific time period. The

final output is the time-varying dynamic Spearman rank correlation coefficient:

$$r_t^{Spearman} = -1 + 12 \int_0^1 \int_0^1 C_t(u_1, u_2) du_1 du_2 \quad (13)$$

D. ASYMMETRIC RISK TRANSMISSION MEASUREMENT

To quantify the intensity and directionality of cross-market transmission of extreme risks in dairy product markets, this paper constructs an asymmetric risk spillover index and conditional value at risk based on the optimal time-varying Copula model selected in the previous step, achieving a refined measurement of the downside and upside risk transmission paths[34]. The downside risk spillover index is defined as the conditional probability that when market i is in an extreme downturn, market j can plummet at the same time:

$$DRO_{i \rightarrow j}(t; \xi) = P(r_{j,t} \leq VaR_{j,t}(\xi) \mid r_{i,t} \leq VaR_{i,t}(\xi)) \quad (14)$$

In formula (14), ξ is the quantile level and $VaR_{i,t}(\xi) = F_i^{-1}(\xi)$ is the marginal VaR of market i . Using the Copula expression, the conditional probability can be converted into:

$$DRO_{i \rightarrow j}(t; \xi) = \frac{C_t(\xi, \xi \mid \psi_t)}{\xi} \quad (15)$$

The upside risk spillover index is defined as the probability that a sharp rise in market i can drive up market j :

$$\begin{aligned} PRO_{i \rightarrow j}(t; \xi) &= P(r_{j,t} > VaR_{j,t}(1 - \xi) \mid r_{i,t} > VaR_{i,t}(1 - \xi)) \\ &= \frac{\bar{C}_t(\xi, \xi \mid \psi_t)}{\xi} \end{aligned} \quad (16)$$

The conditional value at risk (CoVaR) is further introduced to measure the systemic risk level of market j when market i is under stress [35]:

$$P(r_{j,t} \leq CoVaR_{j|i}^{\xi,q}(t) \mid r_{i,t} \leq VaR_{i,t}(q)) = \xi \quad (17)$$

To eliminate the impact of individual risks, the incremental conditional value at risk ($\Delta CoVaR$) is defined as:

$$\Delta CoVaR_{j|i}^{\xi,q}(t) = CoVaR_{j|i}^{\xi,q}(t) - CoVaR_{j|\emptyset}^{\xi}(t) \quad (18)$$

In formula (18), $CoVaR_{j|\emptyset}^{\xi}(t) = F_j^{-1}(\xi)$ is the unconditional VaR, which reflects the additional risk contribution of the i market to the j market when the i market is in an extreme state. By comparing the two-way transmission strength, an asymmetric risk spillover index is constructed:

$$AI_{i \leftrightarrow j}(t; \xi) = \frac{|DRO_{i \rightarrow j}(t; \xi) - DRO_{j \rightarrow i}(t; \xi)|}{DRO_{i \rightarrow j}(t; \xi) + DRO_{j \rightarrow i}(t; \xi)} \quad (19)$$

The indicator takes values in the range [0,1]. The larger the value, the more asymmetric the risk transmission direction is. The risk spillover is shown in Figure 2.

Figure 2 uses a heat map to visually demonstrate the intensity of downside risk spillovers across dairy product markets. Based on the downside risk spillover index, it depicts the transmission relationship between different markets under extreme downturn scenarios. Raw milk presents the highest risk exposure to infant formula and liquid milk, with internationally sourced whole milk powder reflecting the highest risk exposure to infant formula, suggesting international import price as the major external risk of high-end products. Infant formula reflects weak risk exposure to raw milk and liquid milk, indicating that it is on the receiving end of risk. The overall risk transmission model is characterized as, “upstream dominates, internationally imported, and terminal resiliency,” demonstrating the asymmetric dependency structure of the industry chain.

E. EMBEDDING A GREEN DEVELOPMENT REGULATORY MECHANISM

In order to fill the gap regarding the regulatory impact of the green transformation of animal husbandry on the risk transmission of the dairy product market, this paper utilizes carbon emission intensity per unit of milk

production as a proxy variable for green production levels, and builds a grouped Copula analysis framework to test whether low-carbon production models significantly weaken the extreme risk linkages in market prices. Carbon emission intensity reflects to a broad extent the various elements of resource use efficiency and the efficiency of ecological energy allocation in optimizing productivity through environmental management across the farming process. It is a core indicator in measuring the extent of sustainability of development across the industry. Low-carbon production models are often accompanied by more advanced feeding technologies, manure treatment systems, and energy alternatives. This not only reduces negative environmental externalities but also enhances the stability and resilience of the production system. Assume that the carbon emission intensity per unit of milk production in the dairy farming system of the p th province (or region) is:

$$E_p = \frac{\sum_{k=1}^K \gamma_k \cdot Q_k}{M_p}, \quad p = 1, 2, \dots, P \quad (20)$$

In formula (20), Q_k is the activity data of greenhouse gas sources of category k , γ_k is the corresponding k emission factor, and M_p is the average annual milk production of the region. All regions are divided into two groups according to the median of E_p : low-carbon group and high-carbon group. Within each group, the standardized residual series of raw milk prices and terminal dairy product prices in the corresponding region are collected to estimate the dynamic lower-tail dependence coefficient of each region. The average lower-tail dependence intensity within the group is defined as:

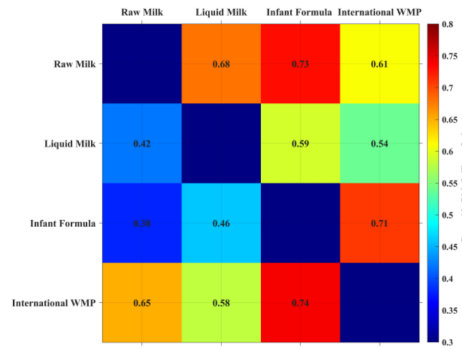


FIGURE 2. Risk Spillover Heat Map

$$\bar{\lambda}_L^G = \frac{1}{|G|} \sum_{p \in G} \left(\frac{1}{T_p} \sum_{t=1}^{T_p} \lambda_L^{(p)}(t) \right) \quad (21)$$

In formula (21), T_p is the effective sample length of region p , and $|G|$ is the number of regions in the group. To test the moderating effect of green production level on extreme risk transmission, a tail-dependent difference test is proposed. Under a large sample, the Z statistic is constructed:

$$Z = \frac{\bar{\lambda}_L^H - \bar{\lambda}_L^L}{\sqrt{\text{Var}(\bar{\lambda}_L^H) + \text{Var}(\bar{\lambda}_L^L)}} \quad (22)$$

The variance is estimated by the nonparametric bootstrap method:

$$\text{Var}(\bar{\lambda}_L^G) = \frac{1}{B-1} \sum_{b=1}^B \left(\bar{\lambda}_L^{G,(b)} - \bar{\lambda}_L^G \right)^2 \quad (23)$$

By repeatedly sampling B times and calculating the empirical distribution, it can further construct the green regulation effect index:

$$GMI = 1 - \frac{\bar{\lambda}_L^L}{\bar{\lambda}_L^H}, \quad GMI \in [0, 1] \quad (24)$$

Formula (24) represents the reduction ratio of the low-carb group to the high-carb group in extreme risk linkage. E_p is introduced as a continuous moderator variable into the panel copula regression model:

$$\lambda_L^{(p)}(t) = \beta_0 + \beta_1 E_p + \beta_2 X_p(t) + \eta_p + \epsilon_{p,t} \quad (25)$$

In formula (25), $X_p(t)$ is a control variable, and η_p is a regional fixed effect, identifying the marginal impact of p carbon emission intensity on tail dependence. This framework links the level of green development in animal husbandry with market risk structure, providing a quantifiable modeling path for the coordinated governance of the “ecological-economic” system.

III. EXPERIMENTATION AND VERIFICATION

A. EXPERIMENTAL DESIGN

Raw milk, liquid milk, infant formula, and international whole milk powder were selected as core variables. All price-return series were subjected to the ADF (Augmented Dickey-Fuller) unit root test to confirm stationarity. Missing months were filled using linear interpolation to ensure time alignment. The experimental setup is shown in Table 1. The rolling window size was set to 24 months. This choice was the result of a trade-off between statistical reliability and dynamic responsiveness. A sufficiently long window is necessary to ensure the stability of parameter estimates, while the window must be short enough to capture the time-varying characteristics of market dependence and to respond promptly to structural changes identified by the Bai-Perron test.

TABLE 1. Experimental Setup

Category	Specification
Processor	Intel® Core™ i7-12700K CPU (Central Processing Unit) @ 3.60GHz (12 cores, 20 threads)
Memory (Random Access Memory, RAM)	64 GB DDR5 4800 MHz
Storage	1 TB NVMe SSD
Computing Platform	MATLAB R2023a
Rolling window size	24 months
Step	1 month
Bootstrap replications	1,000
Monte Carlo simulations	10,000

B. EVALUATION OF STRUCTURAL MUTATION RESPONSE SENSITIVITY

The mean change in the dynamic correlation coefficient of the model within 12 months before and after the breakpoint detected by Bai-Perron was calculated:

$$\Delta \rho_k = |\bar{\rho}_{\text{post},k} - \bar{\rho}_{\text{pre},k}|, \quad k = 1, \dots, m \quad (26)$$

In formula (26), $\bar{\rho}_{\text{post},k}$ and $\bar{\rho}_{\text{pre},k}$ are the average correlation coefficients of the windows before and after the k th breakpoint, respectively.

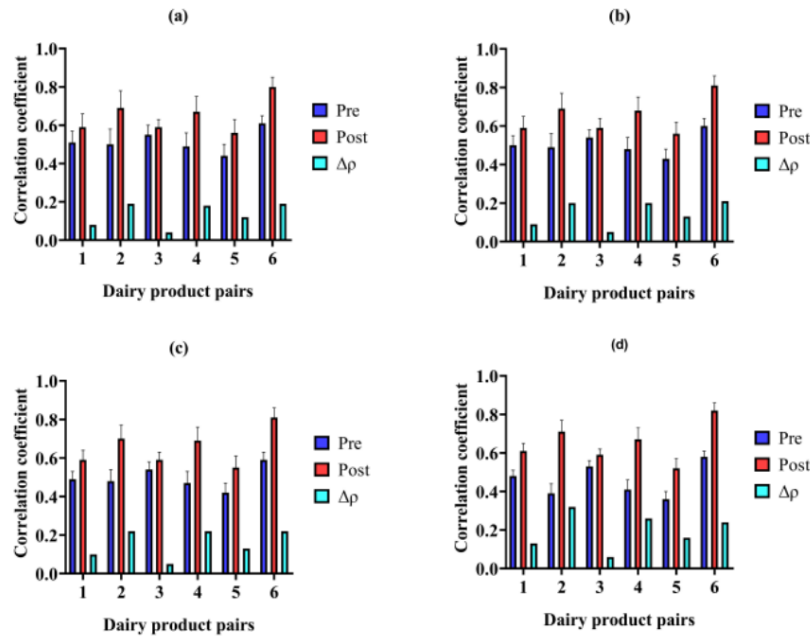


FIGURE 3. Evaluation of Structural Mutation Response Sensitivity: (a) DCC-GARCH; (b) Time-Varying t-Copula-GARCH; (c) D-Vine Copula-GARCH; (d) Proposed Method

Figure 3 shows the structural mutation response capabilities of proposed method, DCC-GARCH, time-varying t-Copula-GARCH, and D-Vine Copula-GARCH on six dairy product combinations. The horizontal axes (1–6) represent the six dairy product combinations: raw milk-liquid milk, raw milk-infant formula, liquid milk-infant formula, raw milk-international whole milk powder, liquid milk-international whole milk powder, and infant formula-international whole milk powder. The vertical axis shows the average correlation coefficient and the magnitude of change ($\Delta\rho$) before and after the breakpoint. Proposed method exhibits the highest $\Delta\rho$ value among all combinations, reaching 0.32 for the raw milk-infant formula pair, significantly exceeding the 0.19 for DCC-GARCH, the 0.2 for time-varying t-Copula-GARCH, and the 0.22 for D-Vine Copula-GARCH. Proposed method also leads the other methods in the infant formula-international whole milk powder pair, achieving a $\Delta\rho$ of 0.24. Furthermore, proposed method exhibits generally smaller standard deviations, indicating more stable correlation estimates within the breakpoint interval.

This advantage is due to the mechanism design of the proposed method: Traditional models like DCC-GARCH models assume a smooth evolution of correlations. D-Vine Copula-GARCH offers the opportunity to incorporate a flexible specifications and capture complex dependency structures, but it relies on the assumption of parameter stationarity, resulting in challenges in understanding jump-like coupling at sudden transitions. In this paper, we incorporate the Bai-Perron breakpoint test to distinguish explicit structural breakpoints due to external shocks (such as an

epidemic and policies initiated in response), and we fit a dynamic copula method in a segmented moving window to accommodate modeling of the dependency structure's "breakpoint-jump" mechanism. Furthermore, the restructuring of the supply chain that exists between upstream raw materials (like raw milk and infant formula) and high-valued added finish products has not just impacted prices, but also caused a qualitative shift in the price transmission mechanism. The proposed approach is capable of capturing this discontinuous transition through segmented modeling. Models based on rolling or stationary assumptions tend to smooth the process and underestimate the true intensity of risk transmission. Therefore, this framework demonstrates greater adaptability and explanatory power in the face of frequent external disturbances in the dairy market.

C. EVALUATING THE TAIL DEPENDENCE ASYMMETRY RATIO

Constructing the LUTR to quantify risk transmission asymmetry:

Figure 4 compares the tail dependence asymmetry of proposed method, DCC-GARCH, time-varying t-Copula-GARCH, and D-Vine Copula-GARCH for six dairy product portfolios, as described in Section 3.2. The horizontal axis shows the dependency coefficient and ratio, while the vertical axis shows the six dairy product portfolios. All models show a LUTR greater than 1, indicating a widespread risk asymmetry in the dairy product market, with falling prices outperforming rising prices. For the raw milk-infant formula portfolio, the proposed method achieves a LUTR of 2.26, significantly higher than the DCC-GARCH (1.60), the time-varying t-Copula-GARCH (1.81), and the

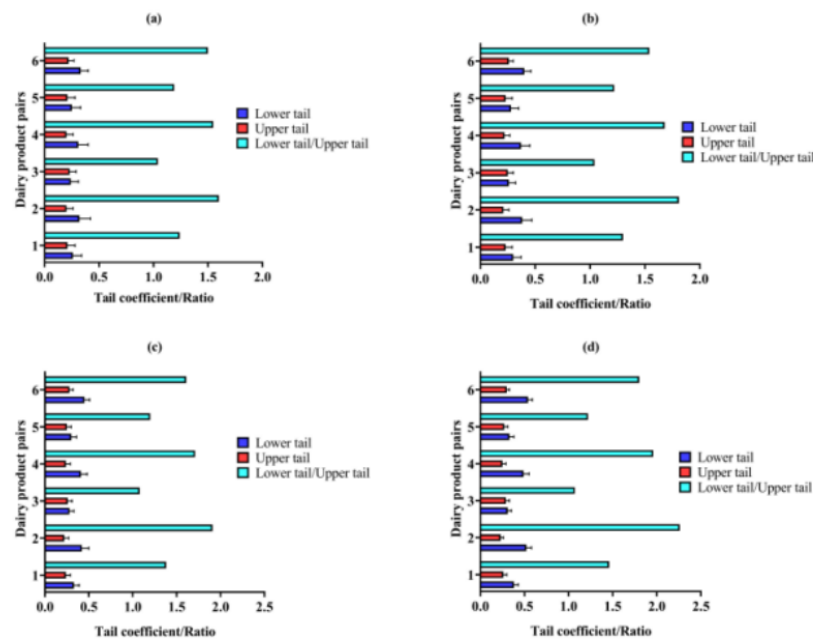


FIGURE 4. Evaluation of Tail Dependence Asymmetry Ratio: (a) DCC-GARCH; (b) Time-Varying t-Copula-GARCH; (c) D-Vine Copula-GARCH; (d) Proposed Method

D-Vine Copula-GARCH (1.91). For the infant formula-international whole milk powder portfolio, proposed method achieves a LUTR of 1.80, also outperforming other methods, which averaged 1.63. Proposed method's smaller standard deviation indicates that its estimate of downside risk is not only stronger but also more stable, highlighting its advantage in identifying extreme risks.

This advantage comes from the proposed method's joint prediction of asymmetrical dependence and structural breaks. The DCC-GARCH model assumes symmetric tails which makes it challenging to differentiate between upper and lower tails. Although the time-varying t-Copula-GARCH model can reflect dynamic comovements, it still operates under the same symmetric tail assumption which restricts its ability to model co-decline risk. The D-Vine Copula-GARCH model provides flexibility in high-dimensional modeling, but it is also reliant on symmetric copula units and does not have a breakpoint approach, which may result in smoothed responses to external shocks. In this paper, we use Bai-Perron tests to detect parameter structural breakpoints and fit both Clayton and Gumbel copulas in each interval so we can effectively model asymmetric tail dependence in segments. Chains such as fresh milk and infant formula experience dependency both from cost transmission and dependence on imports. This method can effectively capture the jump-like response of combined price plunges under policy or epidemic shocks, significantly improving the authenticity and sensitivity of lower tail/upper tail dependency ratio (LUTR) estimates.

D. MEASURING RISK TRANSMISSION LAG AND INTENSITY

Based on the rolling DRO series $DRO_{i \rightarrow j}(t)$ and $DRO_{j \rightarrow i}(t)$, the maximum value of their cross-correlation function and its corresponding lag order are calculated. The maximum value is used as the peak cross-correlation coefficient to measure the strength of risk linkage, and the corresponding lag order is used as the optimal lag to identify the time delay of risk transmission.

Figure 5 demonstrates how this method, based on cross-correlation analysis of the rolling downside risk spillover index, systematically identifies the lag and intensity characteristics of risk transmission across dairy product markets. The horizontal axis is the dairy product combination and its transmission path, 1 to 12 are raw milk $\rightarrow$ liquid milk, liquid milk $\rightarrow$ raw milk, raw milk $\rightarrow$ infant formula, infant formula $\rightarrow$ raw milk, liquid milk $\rightarrow$ infant formula, infant formula $\rightarrow$ liquid milk, raw milk $\rightarrow$ international whole milk powder, international whole milk powder $\rightarrow$ raw milk, liquid milk $\rightarrow$ international whole milk powder, international whole milk powder $\rightarrow$ liquid milk, infant formula $\rightarrow$ international whole milk powder and international whole milk powder $\rightarrow$ infant formula. The transmission of raw milk price fluctuations to end markets generally exhibits a time lead and is accompanied by high correlation strength. The optimal lag for the raw milk to infant formula path is 1.5 ± 0.4 months, with a cross-correlation of 0.73 ± 0.08 , indicating that the risk of extreme price declines on the raw material side is significantly transmitted to high-end products with a delay of approximately one and a half cycles. The lag for the raw milk to liquid milk path is 1.0 ± 0.3 months, with a cross-correlation of 0.68 ± 0.09 , indicating that the

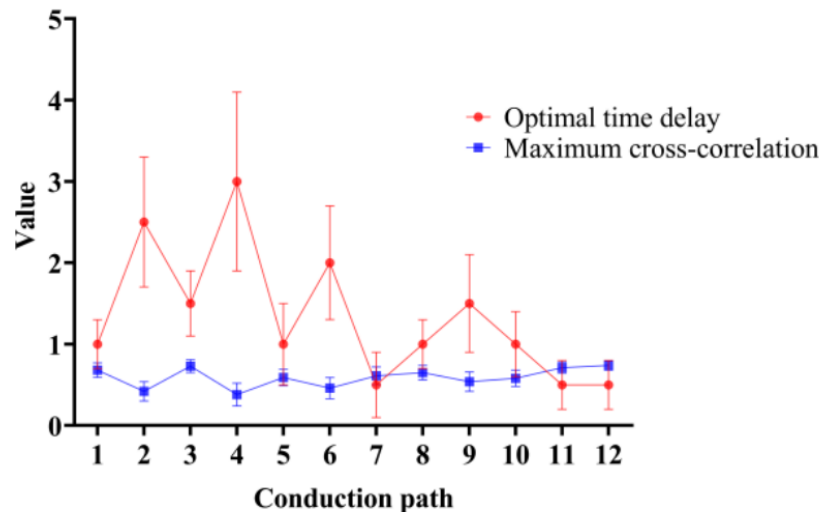


FIGURE 5. Measuring the Lag of Risk Transmission

mid- and low-end end markets respond more quickly but with slightly lower intensity. In contrast, the reverse path, from infant formula to fresh milk, not only exhibits a long lag of 3.0 ± 1.1 months, but also exhibits a cross-correlation of only 0.38 ± 0.14 , demonstrating high volatility and weak strength, making it difficult to establish an effective feedback mechanism. International whole milk powder exhibits strong transmission across all links: its cross-correlation with infant formula is as high as 0.74 ± 0.06 , with a lag of 0.5 ± 0.3 months, indicating near-real-time synchronized fluctuations in the import-dependent market. This “high correlation + short lag” transmission behavior is indicative of the structural asymmetry of the dairy industry chain and market openness differentials. Prices for raw milk, as a primary product, are ultimately driven by supply-and-demand fundamentals. Once a cost shock or oversupply occurs, however, processing companies (that utilize inventory buffers) are still compelled to alleviate the pressure through adjusting terminal sell prices within one to two months. This creates a stable positive transmission path, characterized by a medium lag and high correlation. Infant formula, due to its high reliance on imported raw materials, faces a tight global supply chain, where international price fluctuations directly reshape production cost expectations. This results in a transmission pattern from international whole milk powder to infant formula with a low (0.5 ± 0.3 month) lag and a very strong correlation (0.74). This method, through dynamic DRO (Downside Risk Spillover) sequence modeling, breaks through the traditional linear causal assumption and accurately captures the nonlinear, asymmetric, and time-varying risk transmission network, providing a quantitative basis for early warning of key transmission channels.

E. NET RISK SPILLOVER ASSESSMENT

A risk spillover network is constructed, and the out-degree centrality of a market is defined to measure its systemic importance as a risk exporter:

$$C_{out}(i) = \frac{1}{N-1} \sum_{j \neq i} DRO_{i \rightarrow j} \quad (27)$$

And similarly define the in-degree centrality $C_{in}(j)$ to identify the risk receiving end.

Figure 6 shows the results of net systemic risk spillovers in the dairy market using proposed method, DCC-GARCH, time-varying t-Copula-GARCH, and D-Vine Copula-GARCH. As the model evolves from DCC-GARCH to the breakpoint test-dynamic Copula framework proposed in this paper, net risk spillovers in key markets show a sustained upward trend. For example, the net risk spillover for raw milk increased from 0.13 using DCC-GARCH to 0.34 using proposed method, while that for international whole milk powder increased from 0.24 to 0.46, indicating that its systemic importance as an upstream source and transmission hub for external shocks is significantly underestimated by traditional models. For infant formula and liquid milk, proposed method consistently shows negative net risk spillovers of -0.04 and -0.06, respectively, indicating that both are net receivers in the price risk network.

This evolutionary trend stems from the varying ability of different models to capture the dynamics of dependency structures. The traditional DCC-GARCH model assumes smooth evolution of correlations, making it difficult to capture the jump-type risk transmission caused by external shocks such as epidemics and policies, resulting in a serious underestimation of the risk spillovers to raw milk and international milk powder. Although the time-varying t-Copula introduces latent variables to enhance flexibility, it is

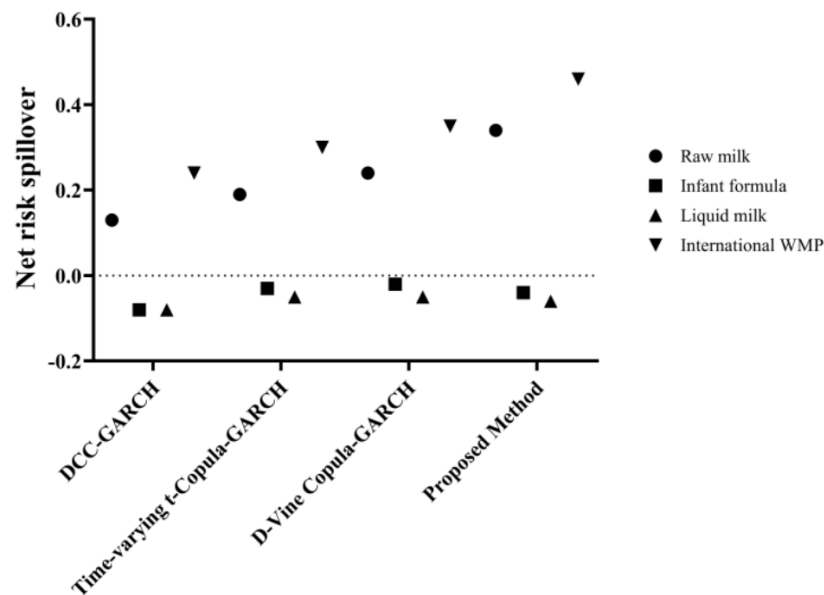


FIGURE 6. Net Risk Spillover Assessment

still limited to the symmetric Copula form. Although the D-Vine model can construct high-dimensional dependencies, it usually ignores structural breakpoints, resulting in a lag in the risk network estimation. The method in this paper accurately identifies the mutation time point through the Bai-Perron test and fits an asymmetric Copula within the segmented window, significantly improving the sensitivity and stability of identifying extreme risk spillovers. This method reflects the immediate impacts of abrupt shifts in import prices throughout the supply chain. This method also provides a better indication of the international price for milk powder and upstream raw materials, that indicate the most systemically important nodes in the network, than other methods. These offer a basis to inform differentiated regulatory and mitigation strategies.

F. MODEL STRUCTURE SUITABILITY TEST

The paper used rolling window model selection frequency statistics to calculate the percentage of t-Copula, Clayton, and Gumbel models selected as optimal by the AIC within each subinterval. If the optimal copula type switches frequently, it indicates that the dependency structure is highly time-varying, verifying the necessity of introducing breakpoint testing.

Figure 7 shows the frequency distribution of the optimal copula model for six dairy product groups across four structural stages. The vertical axes (1-4) represent the stable period, shock period, recovery and regulation period, and turbulent period, respectively. During the stable period, the t-Copula dominated, with the liquid milk-infant formula combination accounting for 75% and the raw milk-liquid milk combination accounting for 68%, indicating that the linkage between markets is mainly symmetrical. During

the shock period, the Clayton Copula's share increased significantly, and structural shifts occurred in multiple key chains: The ratio of raw milk to infant formula jumped from 30% to 60%, and infant formula to international whole milk powder reached 65%, reflecting a significant increase in the risk of extreme declines. During the turbulent period, this asymmetry further solidified, with the Clayton ratio of infant formula to international whole milk powder reaching 70%, while the ratios of raw milk to infant formula and raw milk to international whole milk powder reached 55% and 52%, respectively, indicating that the transmission of downside risks has become a norm. This pattern of evolution illustrates the structural change in the dairy marketplace's risk landscape due to exogenous shocks. Existing models accept there is some dependency structure moving through time, therefore the challenge of the models is explaining why the Clayton Copula suddenly becomes the dominant structure at certain points. This paper brings in a Bai-Perron breakpoint test in order to break up structural stages to show that at these breaking points there is a meaningful relationship with events that shaped the market. When the previously noted shocks occurred, market participants panic, experience declining prices, and lose tail dependence from symmetric to significantly downward tail dependence. In fact, if structural change is occurring, and if tails are downward skewed, using symmetric models (e.g., t-Copula, Gumbel, etc.) or upper-tails models in such instances will grossly under-estimate systemic risk. The segmented Copula modeling strategy employed in this paper allows for flexible selection of the optimal dependency structure at different stages. This not only improves model adaptability but also reveals, from a mechanistic perspective, that "event-driven structural mutations" are the fundamental source of non-

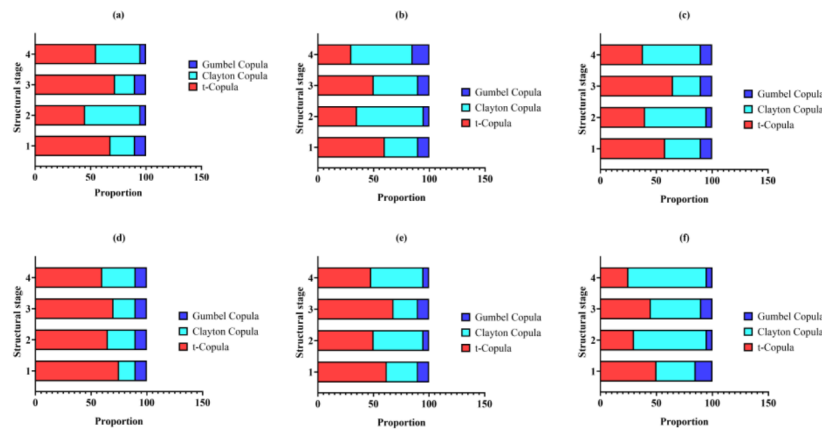


FIGURE 7. Model Structural Suitability Test: (a) Raw Milk vs. Liquid Milk; (b) Raw Milk vs. Infant Formula; (c) Raw Milk vs. International Whole Milk Powder; (d) Liquid Milk vs. Infant Formula; (e) Liquid Milk vs. International Whole Milk Powder; (f) Infant Formula vs. International Whole Milk Powder

linear risk transmission in the dairy market, providing a modeling paradigm supporting dynamic risk management.

G. LOWER TAIL DEPENDENCY DIFFERENCES

This paper uses the lower-tail dependency difference between low-carbon and high-carbon groups as a core indicator to measure the moderating effect of green production on extreme risk linkage. This reflects that under the same external shock, high-carbon farming areas face a higher risk of coordinated plunges than lowcarbon areas.

TABLE 2. Lower-tail dependency difference table

Dairy Product Pair	Low-Carbon Group	High-Carbon Group	Difference in Lower Tail Dependence	p-value
Raw Milk – Liquid Milk	0.34 ± 0.05	0.48 ± 0.07	0.14	0.003
Raw Milk – Infant Formula	0.45 ± 0.06	0.62 ± 0.08	0.17	0.001
Liquid Milk – Infant Formula	0.28 ± 0.04	0.38 ± 0.06	0.10	0.012
Raw Milk – International WMP	0.42 ± 0.06	0.59 ± 0.07	0.17	0.002
Liquid Milk – International WMP	0.30 ± 0.05	0.44 ± 0.06	0.14	0.006
Infant Formula – International WMP	0.50 ± 0.05	0.68 ± 0.07	0.18	0.001

Table 2 systematically assesses the differences in extreme risk transmission between dairy product markets under low-carbon and high-carbon production models, quantifying the regulatory effect of green development on price linkage using the difference in lower-tail dependence. The lower-tail dependence coefficients of all dairy product groups in the high-carbon group were significantly higher than those in the low-carbon group. The difference in lower-tail dependence between the low-carbon group and the high-carbon group was 0.10 to 0.18: The infant formula-international whole milk powder combination had a value of 0.68 ± 0.07 in the highcarbon group and only 0.50 ± 0.05 in the low-carbon group, with a lower-tail dependency difference of 0.18. The lower-tail dependency differences for both raw milk-infant formula and raw milk-international whole milk powder were 0.17, indicating that the risk linkage between upstream raw materials and high-end terminals is particularly fragile under a high-carbon model. Even within the relatively stable liquid milk-infant formula chain, the high-carbon group had a value of 0.38 ± 0.06 , significantly higher than the low-carbon group’s 0.28 ± 0.04 , with a lower-tail dependency difference

of 0.10. All comparisons were confirmed significant via Ztests, demonstrating that green production can effectively reduce the risk of a common market crash. The buffering function is rooted in the structural enhancements that green transformation can offer in industrial chain stability and cost resiliency. Low-carbon pastures tend to demonstrate improved resource use efficiencies, more stable forage supply systems, and greater resiliency to environmental changes. They also have less price fluctuation from external shocks, which limits risk spillover to downstream markets. Greencertification and production supply chain integration and possible policy can additionally assist productivity in low-carbon production to build financially viable production and market access, and supporting greater overall risk resiliency. As this study demonstrates by creating a carbon emission intensity variable as a grouping variable into a copula analysis, evidencing ecological investment, is not simply an environmental question, but also a risk governance approach. Low-carbon production achieves synergies between ecological benefits and economic stability by mitigating endogenous system vulnerabilities and diluting tail coupling strength of market prices. This provides empirical evidence for promoting green subsidies and the development of a lowcarbon benchmarking system for the dairy industry.

H. EXTERNAL SHOCK SCENARIO SIMULATION ANALYSIS

A counterfactual scenario was established: a 10% single-day plunge in international whole milk powder prices was simulated. Monte Carlo simulations were conducted to calculate the probability of raw milk and infant formula prices falling below VaR95 (Value at Risk at a 95% confidence level) and assess the transmission strength of the external shock.

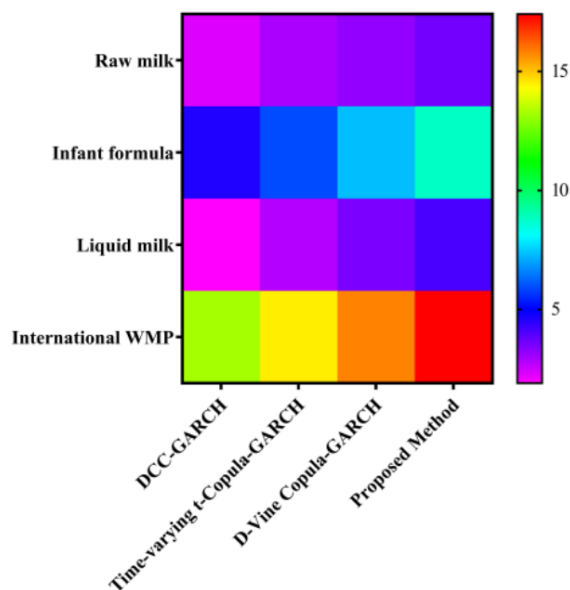


FIGURE 8. External Shock Scenario Simulation Analysis

Figure 8 shows the simulation results of risk transmission across various markets using proposed method, DCC-GARCH, time-varying t-Copula-GARCH, and D-Vine Copula-GARCH, under the scenario of a 10% plunge in international whole milk powder prices. Proposed method yields the highest risk probability increase in all markets. In the infant formula market, proposed method achieves an 8.8% probability increase, significantly exceeding the 4.6% of DCC-GARCH, the 5.9% of time-varying t-Copula-GARCH, and the 7.3% of D-Vine Copula-GARCH. For raw milk, proposed method achieves a 3.6% probability increase, also significantly exceeding the 2.3% of DCC-GARCH and the 3.2% of D-Vine Copula-GARCH. The inherent risk amplification effect of international whole milk powder is most pronounced in proposed method (17.4%), while the other methods generally exhibit lower values, indicating that these methods struggle to fully capture the tail resonance characteristics of the global market.

The essence of this forecast discrepancy lies in the differing depth of their depiction of the behavioral response mechanisms of market players. Traditional models implicitly assume that market participants rationally adjust based on stable expectations, failing to capture the nonlinear price transmission triggered by inventory panic, delayed cost transfers, and sudden shifts in consumer expectations during major external shocks. When the price of global whole milk powder declines sharply, processors do not immediately adjust infant formula prices downward. Instead, they release price pressure slowly after they have exhausted the existing raw material or completed contracts, and in some cases exhibit channel competition that imposes a lagged and seasonal risk release window. This constitutes steps that drive the structural breakpoints that also link the dependency tran-

sitions and hangovers from these institutional and behavioral frictions. It is then coupled with the Clayton Copula model to capture the tail-amplification effect during co-decline situations in order to reconstruct the true dynamic path of the supply chain: passive pressure in the upstream, delayed shipment in the midstream, and delayed end response. The data-driven, segmented modeling approach is not only used to increase the realism of these extreme passive pressure scenarios, but also reveal a uniquely fragile and constraining transmission chain of the dairy supply chain in an open environment, and provide a behavioral baseline to establish proactive systems-based intervention mechanism.

IV. CONCLUSION

This paper presents a piecewise modeling framework that integrates the Bai-Perron breakpoint test and a dynamic Copula-GARCH model to more systematically examine the price interdependencies and risk spillover mechanisms in the dairy market. This rich methodology can also be readily applied in the industry for rigorous breakpoints identification of the structural shifts that occur due to significant trade policy changes or temporary or long-term supply chain disruptions in cotton or apparel. Using this combined technique allows the research to divide the data at the identified breakpoints and evaluate how they respectively changed in price interdependence and spillover across the multi-levels of the supply chain segments. A GJR-GARCH model is utilized to extract residuals from yields, the Bai-Perron methodology to identify the breakpoints in dependence structures, and within each stable subinterval, the best dynamically selected time-varying copula models would be fitted. Asymmetric risk transmission is measured by combining ΔCoVaR with a risk spillover index. In conclusion, the regulatory effect of the green transition was evaluated by embedding carbon emission intensity. Empirical results from different markets reveal that the mean structural mutation response sensitivity change of the estimated effects is 0.2 and the average Lower Tail Dependence (LUTR) estimate is 1.63. Further, using the same data in a relevant context provides evidence that a low-carbon production commitment within the industry significantly reduces the risk of extreme co-declines across markets and contributes evidential support for the constructive regulatory effect that preemptive green development policies have on the overall stability of the market.

AUTHOR CONTRIBUTIONS

Conceptualization – Jiao Wang and Yongren Ma; methodology – Jiao Wang and Yongren Ma; investigation – Jiao Wang and Yongren Ma; writing-original draft preparation – Jiao Wang and Yongren Ma. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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