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Dynamic relationship between global economic policy uncertainty, food prices and maritime transport: Evidence from the TVP-VAR-SV model

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Abstract

This paper investigates the dynamic interactions among global economic policy uncertainty, food prices, and maritime freight rates, focusing on changes in the global food landscape since China's WTO official accession. Using a time-varying parameter vector autoregressive model with stochastic volatility (TVP-VAR-SV), it analyzes the impacts of economic policy changes, environmental policy, geopolitical risks, and global public health events on food and transportation markets. Additionally, it explores how fluctuations in maritime freight rates may affect food prices and, consequently, global economic development. Finally, the paper offers recommendations for food import and export countries to enhance food security and promote sustainable development in food transport firms.

Keywords: global economic policy uncertainty; food market; food maritime transport; TVP-VAR-SV; food security

JEL: O13; Q18; R41; L92

Résumé

Cet article étudie les interactions dynamiques entre l'incertitude des politiques économiques mondiales, les prix des denrées alimentaires et les taux de fret maritime, en se concentrant sur les changements intervenus dans le paysage alimentaire mondial depuis l'adhésion officielle de la Chine à l'OMC. À l'aide d'un modèle vectoriel autorégressif à paramètres variables dans le temps et à volatilité stochastique (TVP-VAR-SV), nous analysons l'impact des changements de politique économique, de la politique environnementale, des risques géopolitiques et des événements de santé publique mondiaux sur les marchés de l'alimentation et du transport. En outre, nous explorons la manière dont les fluctuations des taux de fret maritime peuvent affecter les prix des denrées alimentaires et, par conséquent, le développement économique mondial. Enfin, nous proposons des recommandations aux pays importateurs et exportateurs de denrées alimentaires afin de renforcer la sécurité alimentaire et de promouvoir la soutenabilité au sein des entreprises de transport de denrées alimentaires.

1. Introduction

The Russia-Ukraine conflict compounds existing global economic challenges alongside COVID-19 and climate change, particularly affecting developing countries. Predictions by the United Nations Conference on Trade and Development anticipate a 1% decrease in global GDP growth due to the war, with increased volatility observed in agricultural, metal, and energy markets (Fang and Shao, 2022; OECD FAO, 2021). This volatility poses a significant threat to vulnerable populations, especially in developing countries, which heavily rely on food and energy imports and are susceptible to price fluctuations (Green et al., 2014). Developing countries' dependence on food imports exacerbates imbalances in the international food transport market, where developed nations hold pricing advantages (UNCTAD, 2020, 2020). Economic policy uncertainty, coupled with transport imbalances, further complicates the global economic policy environment.

This study aims to promote sustainable development in the food and maritime transport markets by investigating their dynamic relationships with economic policies. Global Economic Policy Uncertainty (GEPU) serves as a key indicator of uncertainty stemming from political, climate, and environmental factors (Davis, 2016; Davis, 2019; Baker et al., 2016). Research suggests that geopolitical risks, environmental policies, and global health events affect food markets through economic policies, resulting in varied reactions in the spot market (Nong, 2021). While some studies highlight the negative impact of economic policy uncertainty (EPU) on food security (Su et al., 2023) and agricultural imports stability (Zhang et al., 2022), there has been limited direct analysis of its relationship with food maritime transport. Leonov and Nikolov (2012) investigated fluctuations in the Baltic Panamax Index (BPI), which represents food transportation, using wavelet and neural network models or Rescaled Range Analysis. Gu et al. (2022) also focused on specific events such as COVID-19 and their impact on Panamax shipping. Exploring the evolving connection between food transport and global economic policy uncertainty is therefore valuable for deeper insights.

Numerous studies have explored the nexus between food and financial markets, employing models like the time-varying parameter VAR (TVP-VAR) model to investigate shock transmission across international food, energy, and financial sectors. For instance, Helmi et al. (2023) examined the impact of news reports on financial markets, contrasting their findings with GARCH models used for commodity price volatility analysis. Structural vector autoregression (SVAR) models were also employed to capture the volatility among variables. However, these studies often lacked a clear unified approach to volatility dynamics and structural change identification. To address these shortcomings, Primiceri (2005) introduced the TVP-VAR model with stochastic volatility, allowing for both temporary and permanent shifts in parameters. This flexible model structure allows us to capture potential regime shifts caused by large-scale economic disruptions (e.g., trade wars or pandemics), which may drive the time variation observed in economic relationships. Yang et al. (2022) analyzed trade policy uncertainty and geopolitical risks' impact on commodity market prices using a time-varying parameter vector autoregressive model with stochastic volatility (TVP-VAR-SV) model, revealing widespread price reactions across various commodity markets. Other studies, such as Jebabli et al. (2014) and Cross and Nguyen (2017), considered stochastic time-varying volatility, finding it provided a better fit than TVP-VAR with constant volatility. In the Chinese economy context, Zhong et al. (2023) extensively investigated commodity price responses to joint shocks from economic policy uncertainty and global risk premium using the TVP-SV-VAR model, with a focus on diverse impacts across energy, agricultural products, and non-ferrous metals. Compared with standard VAR, SVAR, or

GARCH models, the TVP-VAR-SV framework is more suitable for analyzing the evolving and uncertain nature of economic relationships. The time-varying parameters allow the model to reflect structural changes in transmission mechanisms, such as those induced by trade frictions, financial shocks, or pandemic disruptions—changes that static models may not capture adequately. Moreover, incorporating stochastic volatility enables the model to treat uncertainty itself as dynamic and endogenous rather than fixed or exogenous, which is crucial in settings where the magnitude and persistence of shocks fluctuate over time. In the context of our research, which focuses on how economic policy uncertainty affects food and transportation markets in a temporally heterogeneous way, this modeling approach provides both theoretical consistency and empirical flexibility.

Existing research on food transportation markets, particularly maritime transportation, is limited. However, as a critical route for food import and export trade, the impact of maritime freight fluctuations on the food market is significant. Melas et al. (2025) showed that economic policy uncertainty can have a lasting impact on shipping costs, underlining the importance of uncertainty in maritime markets. Building on these insights, our study addresses this gap by examining the bidirectional causal relationship between economic policy changes, food markets, and food maritime transport markets from 2000 to 2022. We also investigate the effects of environmental policy, geopolitical risks, and other potential factors on economic policy uncertainty, food markets, and food transportation markets across six key time points. By considering short- and long-term changes amid current global economic uncertainty, we recognize the reverse effect of the transport market on the economic environment. While food systems are not the only sectors affected by economic uncertainty, they represent a uniquely vulnerable domain. Their reliance on global trade routes, sensitivity to environmental and policy shocks, and direct connection to basic welfare outcomes justify sector-specific focus. Although previous studies have examined uncertainty transmission in energy or industrial sectors (Yang et al., 2022), the food transport system has received less attention. Our study builds on these findings by applying a time-varying framework to this underexplored area. Employing the TVP-VAR-SV model, we assess how these variables mutually influence each other over time, particularly during crisis periods, enabling better preparation for future volatility in food and food transport markets.

The study is organized as follows: Section 2 reviews literature and outlines research methods on the interdependence between GEPU, food prices, and food maritime transport freight rates. Section 3 covers data and the TVP-VAR-SV model. Section 4 presents empirical results. Finally, Section 5 concludes with policy implications and suggestions for future research.

2. Literature review

Global economic policy uncertainty's impact on food security and price fluctuations is a pressing concern for regulatory authorities (Ben Hassen and El Bilali, 2022). Recent rise in global economic policy uncertainty, alongside past financial crises, has disrupted global food trade and supply, leading to increased price volatility (Li and Li, 2021). The GEPU index also reflects economic policy changes in response to political changes, especially during periods of geopolitical risk. Higher geopolitical risk is also associated with higher probability of economic disasters and with larger downside risks to the global economy (Caldara et al., 2022). Meanwhile, geopolitical risks stemming from political changes further compound long-term food inflation by causing regional economic turmoil and changes in trade policies (such as tariffs and trade disputes) (Sohag et al., 2022; Charoenwong et al, 2023). Events like the Sino-US trade war in 2018 and the Russia-Ukraine war in 2022 disrupted food exports, altering food prices (Hua et al, 2022; Mbah and Wasum, 2022; Zhang et al, 2024). Grossman et al. (2024) also indicated that sudden changes in tariff policies can disrupt existing trade flows and logistics arrangements, imposing additional uncertainty in commodity markets, including agriculture. Additionally, climate-related disasters and global health crises have impacted agricultural development and food security through supply chain disruptions (Atanga and Tankpa, 2021; Breisinger et al., 2016; Alabi and Ngwenyama, 2023). These impacts extend to food maritime transport, affecting the economies of food-exporting nations (Ben Hassen and El Bilali, 2022). Hence, there is a call to improve sustainable food transport (Maiyar and Thakkar, 2022).

Previous studies have highlighted the impact of uncertainty on investment and commodity markets. The real options theory elucidates how firms navigate investment decisions under uncertainty (Dixit and Pindyck, 1994), while analyses of commodity markets reveal how storage behaviors influence price volatility (Wright & Williams, 1991). These theoretical frameworks inform our approach to examining the effects of economic policy uncertainty on food prices and shipping costs. The relationship between global economic policy uncertainty and food freight rates is less clear than the relationship between food prices and food maritime freight rates. The research on dry bulk cargo shipping freight price is more extensive. Some studies have analyzed macroscopic cyclical fluctuations in dry bulk freight prices. However, it remains uncertain whether this relationship is equally applicable for specific food shipments and whether there is a lead-lag connection (Leonov and Nikolov, 2012; Ozili, 2022). Based on the VAR model and the least absolute shrinkage and selection operation (LASSO) regression to explore the impact of China's EPU on dry bulk freight rates, Gu and Liu (2022) obtained that Chinese PMI mainly affects freight rates of Panamax and Capsize sub-segments of the global shipping market. Under different economic policies, the length and the sign of the impact on prices still need further analysis.

The correlation between food prices and food shipments is more evident. Food prices play a crucial role in facilitating the functioning of these markets and are closely linked to food transportation. Gu and Liu (2022) emphasized the importance of food prices in shaping the freight rates volatility for food maritime transportation. The interdependent relationship between food prices and transportation is determined by supply and demand factors. As such, analyzing food price data over time and space can provide insights into the temporal and spatial dimensions of food transportation demand (USDA, 2020). Research has shown that the impact of maritime freight rates on food prices lags behind the effect of food prices on freight rates. For example, Bessler and Lee (2022) used Error Correction Models to investigate the relationship among money, income, nominal prices, and wheat prices in the US, while Haigh and Bessler (2004) extended this analysis to the relationship between commodity market and transport market, finding that these two markets are interrelated. Sun et al. (2024) employed a wavelet-based approach and found significant dynamic linkages between global economic policy uncertainty, food prices, and ocean freight rates. Goodwin and Schroeder (1991) employed a VAR model and impulse response analysis to examine wheat price dynamics in six different international markets while accounting for the influence of both freight rates and exchange rates.

Recent studies have begun to emphasize the dynamic, asymmetric, and geopolitical dimensions of policy uncertainty, suggesting a need for more flexible empirical frameworks (Su et al., 2023; Wen et al., 2021; Sohag et al., 2022). While recent work has increasingly examined policy uncertainty in energy, metals, and financial sectors (Yang et al., 2022; Zhong et al., 2023), the food transport sector remains comparatively understudied. These sectors often show volatility spillovers and regime sensitivity, but the structural exposure and behavioral mechanisms in food systems differ in important ways. Our study builds on these broader findings by focusing on the food market, where supply-chain fragility, environmental risks, and policy interventions play distinct roles. Our research aims to fills the gap in the study of the relationship between global economic policy, food prices and freight rates. We analyze the potential influencing factors behind global economic policy uncertainty and their impacts on food maritime transport and food markets through economic policy. The reverse effect of food maritime transport on economic policy and food price is included. Additionally, we seek to understand the short, medium, and long-term differences in food freight rates and analyze the complex associative structures between economic policy uncertainty, food prices, and freight rates. Our study will contribute to this emerging literature by employing a TVP-VAR-SV model to jointly examine food prices and freight rates under economic uncertainty.

3. Method and data

We employ a TVP-VAR-SV model to investigate the random volatility and potential dynamic time varying relationships between GEPU, food prices, and food maritime transport. The empirical results demonstrate significant changes in the relationship between these macroeconomic variables over time, as evidenced by time-varying impulse responses.

3.1. Time varying parameter-vector autoregression model

Relying on recent works, we adopt a time-varying parameter vector autoregression model with stochastic volatility (TVP-VAR-SV) to capture the dynamic interactions between variables. In contrast to a standard VAR with fixed coefficients or a GARCH model that focuses only on single-series volatility, the TVP-VAR-SV allows both the cross-variable relationships and shock variances to evolve over time. This flexibility is crucial for capturing structural changes and the time-varying impact of uncertainty shocks (e.g., differences before and after major crises) that a constant-parameter model might miss. Following Nakajima et al. (2009) and Primiceri (2005), the model can be specified as follows:

$$y_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t, \quad t = s+1, \dots, n \tag{1}$$

where $y_t = (GEPU_t, CRB_t, BPI_t)'$ denotes the vector of the three endogenous variables at time t, representing global economic policy uncertainty, the food price index, and the food maritime transport freight rate, respectively. Note that X_t corresponds to a matrix of lagged variables and constant term, β_t is the associated time-varying regression coefficients, A_t a lower triangular matrix capturing contemporaneous (simultaneous) structural relationships, Σ_t a diagonal matrix of stochastic volatility ($\sigma_{1,t}$, $\sigma_{2,t}$, $\sigma_{3,t}$), ε_t a vector of structural shocks (standard normal). Finally, all the parameters β_t, A_t and Σ_t are time-varying. Note also that

$$A_t \equiv \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{2,1,t} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k,1,t} & \cdots & a_{k,k-1,t} & 1 \end{pmatrix} \text{ and } \Sigma_t \equiv \begin{pmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{k,t} \end{pmatrix}.$$

Let a_t be a vector containing all the elements in A_t and $h_t = (h_{1,t}, \dots, h_{k,t})$ where $h_{j,t} \equiv \ln \sigma_{j,t}^2$, $j = 1,2, \dots, k$. It represents the log variance of shock j at time t. Assume that these parameters follow a random walk, for $t = s+1, \dots, n$:

$$\begin{aligned} \beta_{t+1} &= \beta_t + u_{\beta,t} \\ a_{t+1} &= a_t + u_{a,t} \\ h_{t+1} &= h_t + u_{h,t} \end{aligned} \tag{2}$$

and that

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta,t} \\ u_{a,t} \\ u_{h,t} \end{pmatrix} \sim N \left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_{\beta,t} & 0 & 0 \\ 0 & 0 & \Sigma_{a,t} & 0 \\ 0 & 0 & 0 & \Sigma_{h,t} \end{pmatrix} \right) \tag{3}$$

where Σ_β, Σ_a, and Σ_h are diagonal matrices, and $\beta_0 \sim N(\mu_{\beta,0}, \Sigma_{\beta,0}), a_0 \sim N(\mu_{a,0}, \Sigma_{a,0})$, $h_0 \sim N(\mu_{h,0}, \Sigma_{h,0})$. Shocks to the parameters β_t, a_t, and h_t are then independent of each other.

Since the stochastic volatility term in the TVP-VAR model is an unstable factor, using the maximum likelihood method is not advisable. Therefore, we use the Markov Chain Monte Carlo algorithm (MCMC) to estimate the parameters as in Nakajima et al. (2011). The initial values are $\mu_{\beta,0} = \mu_{a,0} = \mu_{h,0} = 0$, $\Sigma_{\beta,0} = \Sigma_{a,0} = 10 \times I$, and $\Sigma_{h,0} = 100 \times I$. The priors for the jth diagonal values of the covariance matrix are $(\Sigma_\beta)_j^{-2} \sim \Gamma(20, 10^{-4})$, $(\Sigma_a)_j^{-2} \sim \Gamma(4, 10^{-4})$, and $(\Sigma_h)_j^{-2} \sim \Gamma(4, 10^{-4})$. According to the marginal likelihood function, the lag order is selected as lag 1 period, and the intercept term is time-invariant.

3.2. Data

Focusing on changes in the global food landscape since China's WTO accession in December 2001, we analyze monthly data from January 2000 to December 2022 (data on 2000 allowing to cover any anticipation effect with respect to the official accession). Our analysis centers on economic and food market data from that year. Prior to 2000, major food reserves declined steadily, and staple food prices (e.g., wheat, rice, and urea) reached a low point (Wright, 2012). To assess the impact of economic policy uncertainty on markets, we employ the widely-used GEPU index, which represents the instability of the overall economic environment. This index is a GDP-weighted average of national EPU indices for 21 countries, each reflecting the tone of newspaper articles discussing economic policy uncertainty in that country.[1]

We utilize the Commodity Research Bureau Index (CRBI) to study global commodity markets, as it aggregates prices across various sectors to reveal overall price movements (Hayes, 2022). We found that the CRB Foodstuffs Spot Price Index (CRB) in CRBI reflects the movements in the food market, covering agriculture and livestock commodities. For maritime transport of foodstuffs, we examine Panamax vessels (Gu and Liu, 2022), with their freight rates commonly represented by the Baltic Panamax Index (BPI). This index, published by the Baltic Exchange (data are drawn from Clarkson Research), comprises five main international routes (P1A_82, P2A_82, P3A_82, P4_82, P6_82) and serves as a key indicator in the dry bulk shipping market.

[1] Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States. GEPU is available at http://www.policyuncertainty.com/about.html

Since data on the CRB, BPI and GEPU may have nonstationary and seasonal effects, in order to address heteroscedasticity and nonstationary, we take the log-difference of GEPU, BPI, and CRB to obtain smooth time series. Table 1 shows the main statistics.

Table 1. Basic statistical characteristics of all variables.

	Mean	Median	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF
CRB	0.004011	0.005993	0.034125	-0.489688	4.862068	50.72002***	-10.67918
GEPU	0.005279	-0.014736	0.179309	0.568963	4.117650	29.15017***	-14.69679
BPI	0.000562	0.008416	0.215082	-0.578121	7.411643	238.3275***	-13.56513

Notes. Significance level: *** 1%. Source: Authors computation using EViews.

GEPU, CRB, and BPI are right-skewed distributed (positive skewness). Both GEPU and BPI exhibit leptokurtic distributions, as indicated by their kurtosis values exceeding 3. In contrast, CRB demonstrates a flatter distribution relative to the normal distribution (kurtosis < 3). The Jarque-Bera index shows that GEPU and BPI are not normal at the 1% level, while CRB has a normal distribution. These findings highlight the significance of studying co-movements across time and frequencies.

4. Empirical analysis

4.1. Markov Chain Monte Carlo algorithm validity test

We employ MCMC with 10,000 iterations, discarding the initial 1000 to establish the posterior distribution of Markov Chain convergence. Mean estimations of parameters are calculated, and the effectiveness of MCMC is assessed through Geweke test and invalid factors. Results from Table 2 show small standard deviations for all parameters, with 95% confidence intervals confirming their significance. Geweke test rejects the null hypothesis of parameter convergence to a posterior distribution in only 2 out of 6 cases at the 5% level. With less than 100 invalid factors, MCMC generated samples are deemed reliable. Additionally, the model aligns with the Bayesian deviation information criterion, further affirming the reliability of MCMC. These findings validate the convergence and efficiency of the Markov Chain, confirming the robustness of the Bayesian inference results.

Table 2. Estimation results of selected parameters in the TVP-VAR model with stochastic volatility.

Parameter	Mean	St.Dev.	95% Upper bound	95% Lower bound	Geweke	Invalid factor
$(\Sigma_\beta)_1$	0.0023	0.0003	0.0018	0.0029	0.042	17.94
$(\Sigma_\beta)_2$	0.0023	0.0003	0.0018	0.0028	0.359	18.11

$(\Sigma_a)_1$	0.0049	0.0012	0.0031	0.0078	0.001	53.93
$(\Sigma_a)_2$	0.0056	0.0015	0.0033	0.0092	0.370	90.70
$(\Sigma_h)_1$	0.0056	0.0015	0.0034	0.0093	0.517	95.27
$(\Sigma_h)_2$	0.2368	0.0317	0.1812	0.3057	0.210	27.01

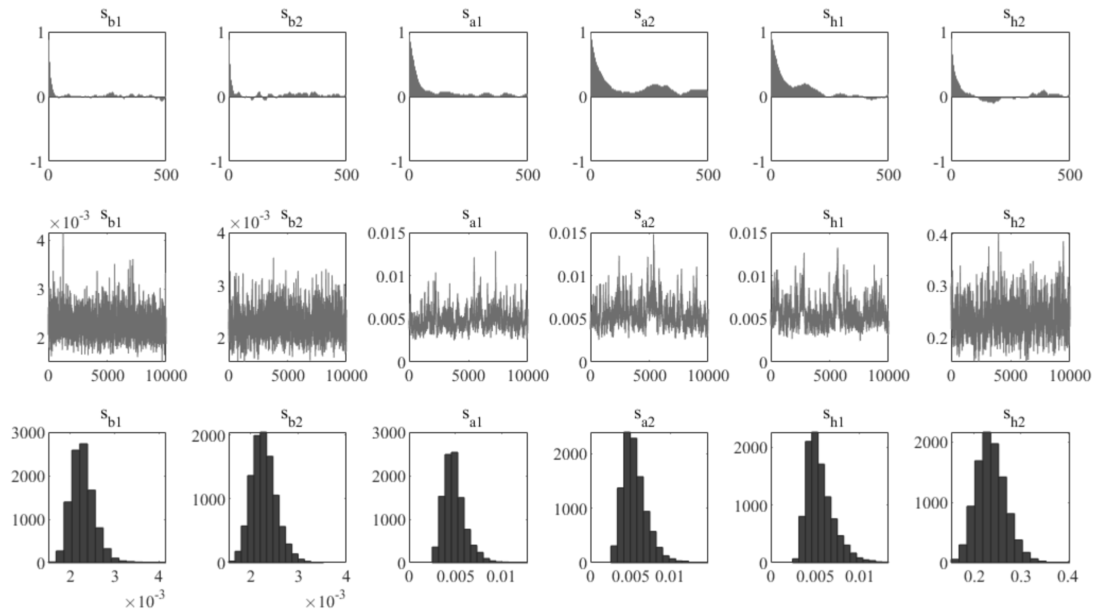

Figure 1. MCMC parameter simulation results (b corresponds to β in the model). The top row shows sample autocorrelation functions; the middle row shows trace plots; and the bottom row displays posterior densities. These diagnostic plots demonstrate convergence and effective sampling.

Figure 1 reports MCMC simulations for our parameters. The sample autocorrelation diagram in the top row shows a rapid decrease in the sample coefficient with each simulation until it finally converges to 0. The path diagram in the middle row shows fluctuation clustering around the mean value. The posterior density distribution diagram in the bottom row shows that parameters obey the posterior distribution and convergence criterion. These findings further confirm the robustness and reliability of our MCMC estimates.

4.2. Impulse response analysis

Figure 2 displays the posterior estimates of stochastic volatility (SV) and the simultaneous relation. Plots depict posterior draws on each date, focusing on free elements in the simultaneous relation specified by the lower triangular matrix. This indicates the size of the simultaneous effect of other variables on one unit of the structural shock, determined by recursive identification.

The stochastic volatility of GEPU demonstrates a relatively stable trend, diverging from traditional financial market frameworks by acknowledging volatility as a dynamic parameter. Despite economic changes over time, GEPU's volatility remains consistent from 2000 to the present. While the COVID 19 outbreak in 2020 initially spiked CRB's volatility due to production resource shortages and transportation issues (Alabi and Ngwenyama, 2023), subsequent stabilization led to a downward trend in food prices. Conversely, the Russia-Ukraine conflict in 2022 caused food prices to rise again due to supply chain interruptions and supply-demand dynamics (Jens-Uwe, 2013). Compared to the 2008 financial crisis, this impact is more pronounced for food-importing countries. However, the longer-term random volatility of CRB during food crises is less evident than that caused by the pandemic. Fluctuations in food transportation prices, as represented by BPI, surged notably following the 2006 food crisis and peaked in 2008. Various factors, including extreme weather events, trade policies, and geopolitical conflicts, contributed to fluctuations in BPI since the financial crisis, with significant decreases in 2010 and 2011 (Yeni and Alpas, 2017; Dupraz and Postolle, 2011). The COVID-19 pandemic further exacerbated fluctuations in BPI post-epidemic. Therefore, it is necessary to further examine the impulse response functions to analyze the magnitude of food price changes under economic policy uncertainty at different time horizons.

Our TVP-VAR-SV model shows time-varying simultaneous relationships where the (GEPU → BPI) relations are positive while the (CRB → BPI) relation is almost constant over the period of study. Conversely, the (GEPU → CRB) relation varies over time (Figure 2, second row).

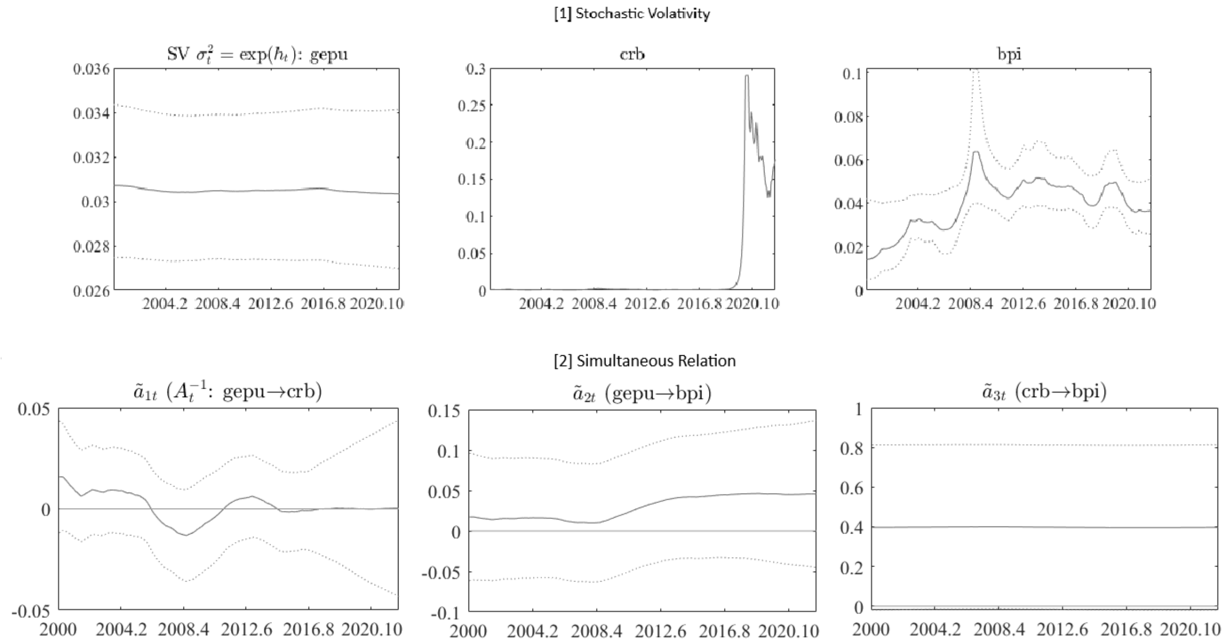

Figure 2. Posterior estimates for [1] Stochastic volatility of the structural shock, $\sigma_t^2 = \exp(h_t)$, and [2] Simultaneous relation, $\tilde{a}_{it}$, for the variable set of (GEPU, CRB, BPI). Posterior means (solid line) and 95% confidence intervals (dotted line).

It is important to clarify that the impulse response functions (IRFs) in our study are derived from the posterior distribution of the estimated parameters using Bayesian techniques, following the methodology of Primiceri (2005) and Nakajima et al. (2011). Unlike traditional VAR models which rely on frequentist confidence intervals and p-values to assess statistical significance, our Bayesian estimation assesses inference through the entire posterior distribution.

In this context, the dotted, dashed, and solid lines in the IRF graphs (Figure 3) correspond to different forecast horizons (1-month, 3-month, and 6-month ahead, respectively). Statistical inference is based on the distributional characteristics of the posterior samples obtained via MCMC, including the shape and persistence of response trajectories over time. This approach captures both parameter uncertainty and time-varying structural dynamics, consistent with Bayesian econometric best practices.

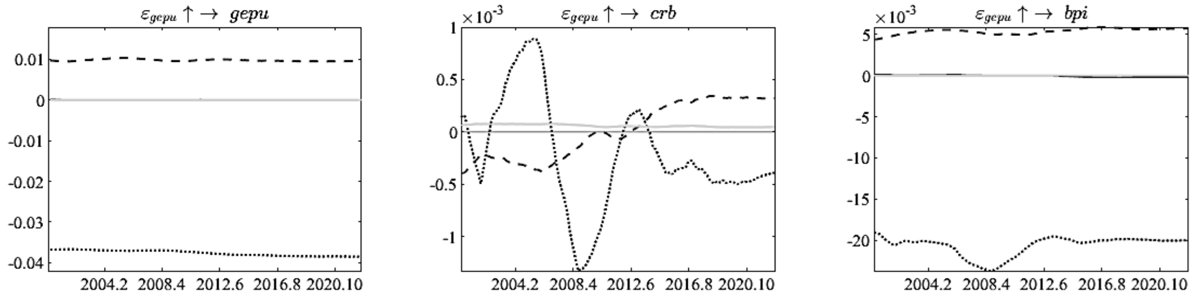

Figure 3. Impulse responses of global economic policy uncertainty (GEBU) on food prices (CRB), food maritime transport freight rate (BPI) and itself. The dotted, dashed, and solid lines correspond to 1-month, 3-month, and 6-month ahead forecasts, respectively.

We analyze the impulse response graph of global economic policy uncertainty, food prices, and food maritime transport freight rates. These time-varying patterns likely reflect structural changes in the global economic environment. A one-standard-deviation shock to GEPU initially causes a rise in the food price index (CRB) within the first month, but this effect becomes negative by the medium term and largely dissipates over longer horizons. By contrast, the freight rate (BPI) responds negatively to a GEPU shock at all horizons, with the largest decline occurring in the short term. These patterns suggest that policy uncertainty shocks have the most pronounced effects on food and transport markets in the immediate aftermath, while longer-term impacts are more muted. In Figure 3, the positive shock of short-term GEPU is followed by exert a negative response in BPI in all future periods. As food is a vital necessity, during times of economic policy uncertainty, food exporters typically prioritize domestic consumption. For instance, during the first food crisis, countries such as Russia and India restricted the export of wheat and rice to secure their domestic supply (Akter, 2022). Such actions led to a decline in export market demand, which subsequently caused a decrease in BPI. After China joined the WTO in 2002, international trade with the international community became closer (Han and He, 2012). Frequent economic policy announcements have triggered market turmoil, causing instability in the form of short-term food prices. The GEPU increases were associated with rising CRB in the early 2000s, between September 2001 and 2007, and from around 2010 until 2013, coinciding with two food crises. Notably, the growth of industrial manufacturing in emerging economies and the massive demand for energy increased international crude oil prices, leading to higher agricultural production costs and food prices (Keil et al., 2009). However, this effect diminished in the second half of 2005 and was reversed around 2007.

Global trade liberalization contributed to the impact of lower import prices outweighing the effect of higher world food prices (Hertel et al., 2009). In response to the financial crisis in 2008, about 45% of developing countries reduced tariffs and/or imposed taxes on food, while nearly 30% of them restricted food exports by levying export taxes or otherwise (Wodon and Hassan, 2008). Although short-term policy actions and exchange rate changes can reduce the impact of price increases on vulnerable consumers, policies that shield domestic food market from changes in world food prices do not maintain low food prices. As a result, CRB rebounded after the 2018 financial crisis (Anderson, 2012). The second food crisis occurred for similar reasons following the 2018 crisis as instability of the U.S. fiscal policy and fluctuations in investor sentiment reduced capital liquidity. In the same year, the U.S. enacted the Renewable Energy Act to promote biofuels, leading to an increase in demand for food such as corn, thereby pushing up CRB (Kaufman et al., 2010). The transient surge in food prices after uncertainty shocks can be attributed to precautionary buying and speculative storage behavior, akin to the concept of "precautionary demand" in commodity markets (Wright & Williams, 1991). The impact of GEPU on CRB gradually waned from the reverse effect. A second food crisis erupted in 2012, but after the lessons learned from the first crisis, governments quickly adjusted to increase food production while controlling food exports and increasing imports, mitigating the positive impact of the economy on CRB. Thus, GEPU may prompt changes in the transportation and consumption strategies of food import and export agents, and the demand for biofuels as an alternative to energy transition may also contribute to this increased volatility, ultimately affecting CRB (Bahel et al., 2013). The observed decline in shipping activity following uncertainty shocks aligns with the real options theory, which posits that firms delay irreversible investments under uncertainty to preserve flexibility. These behaviors underscore the role of risk aversion in amplifying market volatility during periods of heightened uncertainty.

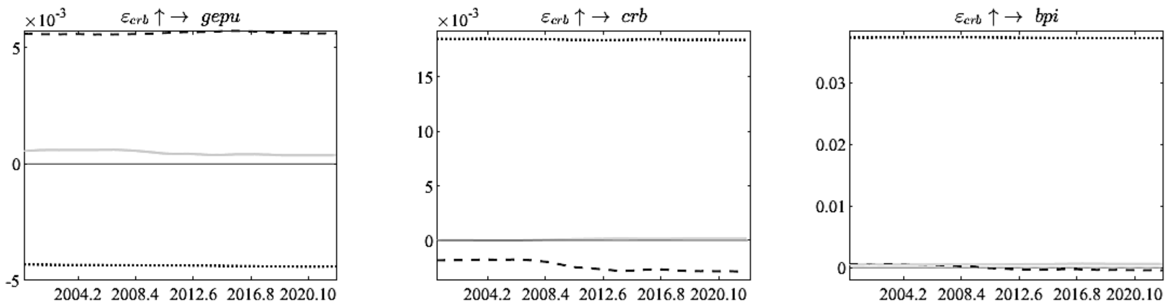

Figure 4. Impulse responses of food prices (CRB) to global economic policies (GEBU), food transportation prices (BPI), and itself. The dotted, dashed, and solid lines correspond to 1-month, 3-month, and 6-month ahead forecasts, respectively.

Figure 4 displays how CRB respond to GEPU and BPI. In all periods, the short-term increase in food prices is affected by future food transportation prices. However, under medium-term shocks such as after 2008, there is a slight negative trend. To increase the supply of food, many countries boosted their food production during the 2018 financial crisis, leading to intensified competition in the food transportation market and prolonged reduction in BPI (Anderson and Nelgen, 2012). During the same period, various countries implemented multiple monetary policies to stimulate economic growth following the financial crisis. Nevertheless, they resulted in currency depreciation, which not only increased CRB but also raised BPI, exceeding the impact on CRB (Aliyev and Kocenda, 2022). While a short-term uptick in CRB is observed, higher economic policy uncertainty corresponds to a sustained decline in CRB over the entire period. This impact is however reversed in the medium to long term. The response of CRB to GEPU is lagged, and changes in economic policy do not quickly vary with short-term market conditions. The relationship between the two variables is not significant. Due to the influence of food market relationships on national development and stability, a prolonged increase in food prices could have a significant economic impact on many developing countries. Further research is necessary to investigate the medium to long-term effects of GEPU on CRB and its impact on the stability and development of countries.

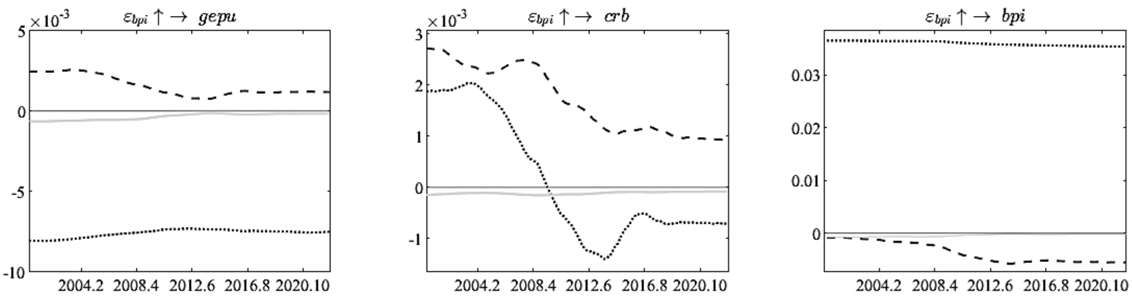

Figure 5. Impulse responses of food transport prices (BPI) to global economic policy uncertainty (GEBU), food prices (CRB), and itself. The dotted, dashed, and solid lines correspond to 1-month, 3-month, and 6-month ahead forecasts, respectively.

Figure 5 presents the impulse response of a one-standard-deviation positive shock to the BPI index on GEPU, CRB, and BPI itself across short-, medium-, and long-term forecast horizons. The results indicate that GEPU shows negligible response to BPI shocks at all horizons, suggesting limited backward transmission from shipping costs to policy uncertainty. The maritime freight sector, while highly sensitive to macroeconomic shocks, does not play a central signaling role in policy formulation. Due to the impact of the subprime and financial crisis in 2007, food demand decreased, and the massive construction of food transport vessels prior to the financial crisis resulted in excess capacity of food carriers and lower transport prices (Fan et al., 2018). Some countries implemented protectionist measures, such as limiting exports, to stabilize domestic food markets and reduce global economic policy uncertainty. Government interventions are intended to prevent volatility in global economic policy uncertainty by stabilizing individual countries' own economic environment. However, the poor coordination on a regional and global scale can result in problems (Jones and Hiller, 2017), given that International Maritime Organization rules help improve transport safety and reduce risks and insurance costs, thereby alleviating the positive impact of BPI on GEPU (Schröder-Hinrichs et al., 2013).

The impact of transportation prices on food prices is equally noteworthy, and the transmission mechanism is clearly time-varying. As shown in Figure 5, a positive BPI shock had a short-term positive effect on CRB during the early 2000s. This likely reflected a period of global trade expansion and balanced food-supply chains (Kaar, 2004; Luckstead, 2022), alongside improved shipping efficiency and new international agreements promoting agricultural trade. Several countries also implemented food reserve policies (Qian et al., 2013; Cummings et al., 2006), helping stabilize food prices despite higher transport costs. However, after the 2008 global financial crisis, the medium-term impact of BPI shocks on CRB turned negative, which aligns with the post-crisis contraction in global demand, rising credit costs, and trade protectionism (Fan et al., 2018; Wang et al., 2021). Transport costs increased, but sellers found it more difficult to pass them to consumers, thus weakening the price transmission. By the time of the Paris Agreement (2016), renewable energy promotion further pushed up freight costs (Wu et al., 2019), but climate adaptation and food reserve mechanisms (Isakson, 2014) helped buffer the impact, resulting in a decline in the magnitude of the inverse effect. These observations highlight that the direction and strength of price transmission from freight to food markets depend on both macroeconomic conditions and policy responses, and are especially sensitive in the medium term. As expected, the BPI exhibits stable and persistent positive self-response across all horizons, indicating sustained effects of freight market shocks on future shipping costs.

Our analysis reveals that GEPU plays a structurally exogenous role in the system, exerting stronger and more immediate effects on CRB than on BPI. In particular, CRB exhibits pronounced short- and medium-term responses to policy uncertainty shocks, suggesting that food prices are highly sensitive to changes in global macroeconomic sentiment. In contrast, BPI shows a more muted and short-lived response, highlighting the relative insulation of freight markets from such shocks in the short run. When BPI is the impulse variable, its shocks generate noticeable effects on CRB, especially at the medium horizon, reflecting cost transmission and market expectation effects. However, the reverse—CRB's influence on BPI—is limited to a minor short-term response with no sustained impact. Despite this asymmetry in dynamic strength, the broader structure of global commodity and transport markets suggests the presence of a bidirectional yet uneven interaction between CRB and BPI. While GEPU appears largely unaffected by shocks from either CRB or BPI, it remains a key upstream driver shaping the behavior of both markets.

To obtain variables' responses to a shock on one variable, we calculate impulse response functions for GEPU, CRB, and BPI at various time points as outlined in Table 3.

Table 3. Time points with corresponding economic events.

Time point	Economic event	Representation
2005.9	The first food crisis broke out.	t=69
2009.1	The lowest point of economic growth during the financial crisis	t=109
2012.9	A second food crisis broke out	t=153
2016.1	One month after the signing of the Paris agreement	t=193
2020.2	The COVID-19 Pandemic	t=242
2022.4	Russia-Ukraine conflict broke out	t=268

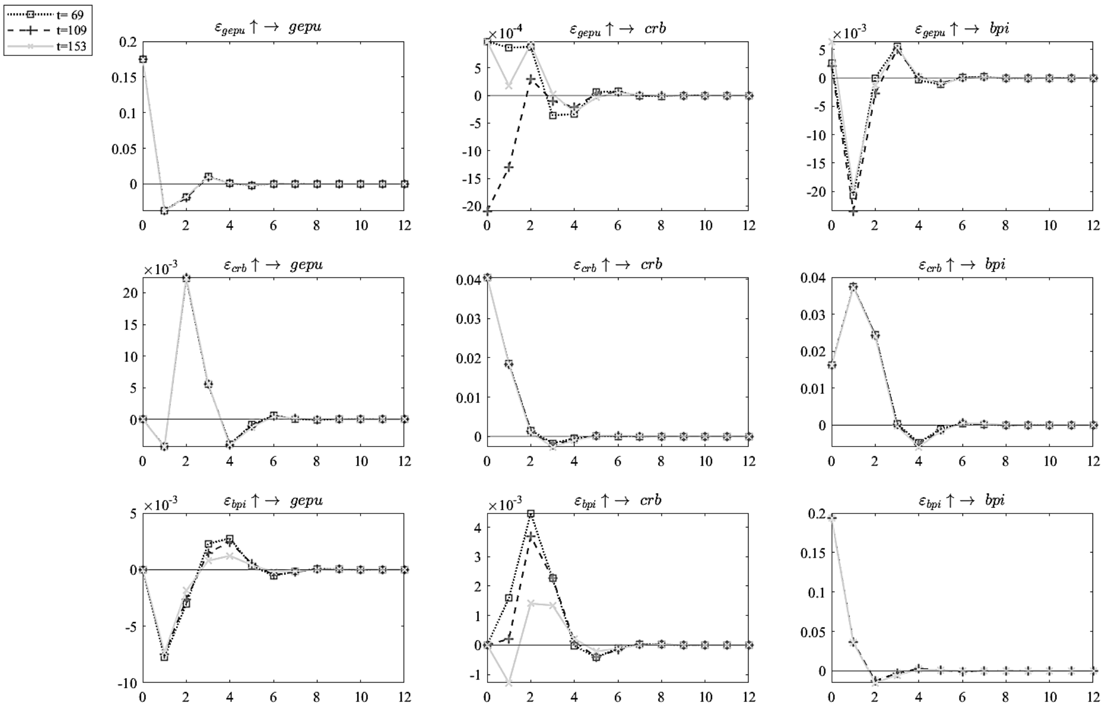

Figure 6. Impulse responses under the influence of variables at different time points (first group).

Based on Figure 6, the food crisis outbreak in 2005 had a positive effect of one unit on global economic policy uncertainty, leading to a decrease from 0.17 to close to zero. In contrast, the impact on food prices significantly decreases to -4 in periods 2 to 3 and then rises sharply to almost zero in period 5, signifying the high volatility of GEPU effect on CRB. However, for BPI, the impact of one-unit shock on GEPU is short and sharp, which is similar to the negative correlation shown by the impulse response function in Figure 3. When CRB is subjected to a 1-unit shock, the effect on BPI initially rises from 0.016 to nearly 0.04, and then falls to around -0.005 in period 4 before recovering to zero and remaining constant thereafter. The effect of CRB drops sharply, recovers to zero, and remains stable, suggesting that CRB and BPI exhibit similar trend changes, albeit at a relatively slower pace concerning BPI. Upon subjecting BPI to a 1-unit effect, the impact on CRB is sharp, while the impact on GEBU falls to -8 in the previous period, gradually rebounding to 3, then falling to zero, and remaining unchanged.

Our impulse response results highlight that the dynamic changes in the impact of GEPU are not random but plausibly linked to structural shifts in the global economy. For instance, the sharp increase in responsiveness of food prices post-2008 corresponds to the global financial crisis, which led to a wave of commodity market financialization and speculation (Isakson, 2014), thereby intensifying the sensitivity of food prices to macro-level uncertainties. The resurgence of volatility in the post-2020 period coincides with the COVID-19 pandemic and the Russia-Ukraine conflict, both of which disrupted food supply chains, triggered export bans, and increased political uncertainty. These disruptions likely altered the dynamics of price formation, reinforcing the impact of policy uncertainty on commodity prices during these periods. Similarly, changes in global trade patterns and regulatory frameworks after 2012, such as food stockpiling policies and carbon regulation, may also contribute to regime-dependent responses observed in the model.

During the economic recovery period following the 2009 financial crisis, the trend in the impact of CRB on itself, GEPU and BPI is almost identical to the trend observed in 2005. At the same time, the trend in the impact of BPI on CRB is comparable to the trend in 2005, but less volatile in terms of volatility. This also reflects that the export restriction strategy has contributed to the decline in BPI. To a certain extent, this can mitigate the upward price trend. When GEPU is affected by a single unit, its impact (due to the financial crisis) on CRB is greater than in 2005. The volatility on CRB dramatically fluctuates from -20 to 3 in 2 periods. This effect is in a different direction than the one brought by the 2005 food crisis, which was positive in 2005 and negative in 2009. The financial crisis broke the global trade liberalization and the short-lived food price decline brought about by export restrictions. Although food is a necessity, the food market is gradually starting to become financialized (Isakson, 2014). The market saw a lot of financial speculation in food-based derivatives, and the movement of capital in and out of the market had a large impact on the related spot market. It also affects the decisions made by farmers, agricultural traders and processors (Tadesse et al., 2013). This also means that the relationship between food markets and financial markets has become closer after the financial crisis.

The impact of BPI on CRB under the second food crisis in 2012 is somewhat similar to the direction of change in the impact of GEPU on CRB in 2009. Only the negative impact of food transportation on CRB since the outbreak of the food crisis in 2012 is short-lived. After the 2009 crisis, countries stockpiling food can safeguard CRB from market fluctuations. Yet, the food market must also navigate supply, demand, environmental policies, and rising transportation costs impacting CRB.

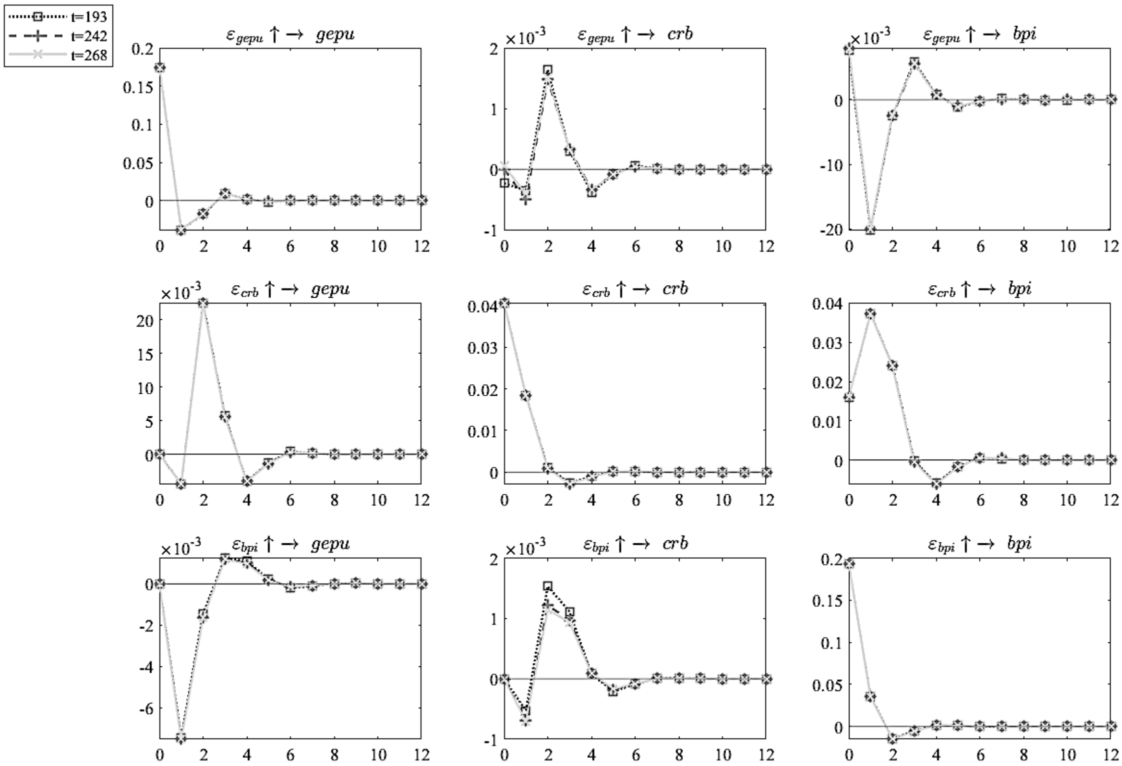

Figure 7. Impulse responses under the influence of variables at different time points (second group).

Figure 7 (second group) covers different time points: the signing of the Paris Agreement in 2016, the outbreak of COVID-19 in 2020, and the Russia-Ukraine conflict in 2022. These events, while heterogeneous in nature—ranging from environmental regulation to public health and geopolitical crisis—share the common feature of affecting global economic policy through trade constraints, supply chain disruptions, and regulatory shifts. Notably, all three shocks further impacted food market volatility, and the relationships among GEPU, CRB, and BPI exhibit nearly synchronized responses across these periods.

The impulse response functions in Figure 7 suggest that these structural disruptions coincide with changes in the effect of GEPU on BPI. In 2020, the GEPU–BPI relationship becomes notably stronger, likely reflecting severe supply chain breakdowns, port closures, and maritime freight insurance volatility during the peak of the COVID-19 crisis. A similar strengthening is observed in 2022, corresponding to the outbreak of the Russia-Ukraine conflict, which disrupted grain corridors and exposed vulnerabilities in Black Sea shipping routes (Jagtap et al., 2022). In contrast, the relatively stable but moderate influence post-2016 may reflect slow adjustments to environmental regulations and carbon compliance mechanisms after the Paris Agreement (Wong et al., 2022; Meng et al., 2022; Schwartz et al., 2020). Taken together, these results imply that the transmission of global policy uncertainty into freight markets is regime-dependent, influenced by structural shifts in the global economy such as climate governance, global health disruptions, and war-induced supply realignments.

Compared to the first group, it is observed that GEPU has a more pronounced impact on CRB under the influence of financial and food crises. Additionally, the effect of BPI on CRB is more evident during the three periods of the first group. This highlights that countries have placed on the stability of the food market since the second food crisis in 2012. Cross-border cooperation has been established to develop regional strategic reserves (Kalkuhl et al., 2016), and governments have constructed reserve facilities to maintain normal food supply. Relevant organizations have also responded quickly to these crises, such as the joint release of news by the IMF and the WTO after the epidemic, reaffirming the importance of maintaining open trade policies in dealing with food insecurity (IMF, 2020), which to some extent has smoothed the fluctuations.

Analyzing the six time periods reveals variable relationships. Comparing shocks between 2009 and 2005, the financial crisis had a greater impact on food prices in 2009, disrupting the gradual financialization of food markets. GEPU shows a closer relationship with food markets. After 2012, short-term import/export restrictions and medium-to-long-term food storage policies stabilized food prices but also posed rebound risks. After 2016, environmental policies, global health crises, and geopolitical shifts indirectly influenced food transportation prices through economic policy changes, exhibiting negative correlations. These underlying factors persisted longer than direct economic market changes.

4.3. Robustness test

We use Qi et al.'s (2022) Granger causality method to analyze relationships between GEPU, CRB, and BPI. Granger tests were done on two and three variable interactions (Tables 4 and 5). Rejection of the null hypothesis ($p < 0.05$) indicates Granger causality. We examine bidirectional relationships and direction of information transmission using Granger tests on all of three variables simultaneously and on each pair of variables. Results for CRB-BPI remain consistent between the simultaneous and pairwise tests due to identical lag orders. We observe a bidirectional time-varying relationship between CRB and BPI, while GEPU has only a unidirectional time-varying relationship with both of them. This also proves the validity and robustness of using MCMC in the establishment of TVP-VAR-SV model. We additionally tested alternative lag structures (e.g., using 1- and 3-lag specifications) and found that the impulse response patterns remained stable, further confirming the model's robustness to specification changes.

Table 4. Full-sample Granger causality tests between any two variables.

Null hypothesis	F-statistic	P-value
CRB does not Granger cause BPI	5.29397***	0.0056
BPI does not Granger cause CRB	3.03098**	0.0499
GEPU does not Granger cause BPI	4.04017**	0.0454
BPI does not Granger cause GEPU	0.02300	0.8796
GEPU does not Granger cause CRB	3.52363**	0.0156
CRB does not Granger cause GEPU	0.63282	0.5944

Notes. Significance level: ** 5%, *** 1%.

Table 5. Full-sample Granger causality tests among the three variables.

Null Hypothesis	F-Statistic	P value
CRB does not Ganger cause BPI	5.29397***	0.0056
BPI does not Ganger cause CRB	3.03098**	0.0499
GEPU does not Ganger cause BPI	2.47751	0.0859
BPI does not Ganger cause GEPU	0.09071	0.9133
GEPU does not Ganger cause CRB	2.48714	0.0851
CRB does not Ganger cause GEPU	1.33993	0.2636

Notes. Significance level: ** 5%, *** 1%.

To assess the robustness of our findings, we conducted additional analyses using an alternative uncertainty measure and a key control variable. Replacing GEPU with the Global Geopolitical Risk (GPR) index (Caldara & Iacoviello, 2022) produced similar time-varying effects on food prices and freight rates, indicating that our results are not sensitive to the choice of uncertainty proxy. We also included global oil prices (Brent crude) as an exogenous control, given their relevance to food production and transport costs. The addition of oil prices did not materially affect the direction or significance of the estimated relationships. While the magnitude of the freight rate responses was slightly reduced—reflecting fuel-related variation—the key patterns remained consistent. These exercises reinforce confidence in the stability of our main results. The model is kept intentionally parsimonious to ensure clarity, with scope for future research to explore broader extensions.

4.4 Extended Discussion

Our empirical results show that the effects of global economic policy uncertainty (GEPU) on food prices and freight rates are not constant, but vary over time and across events. This observation is consistent with a growing body of research that highlights the time-varying and event-specific nature of uncertainty shocks on food systems and commodity markets. Wen et al. (2021) documented that food prices in China respond more strongly to negative shocks in economic policy uncertainty than to positive ones, suggesting asymmetric dynamics. While our model does not explicitly separate positive and negative shocks, the time-varying structure of the TVP-VAR-SV framework allows it to capture such nonlinearities implicitly. Other recent studies echo our findings in different contexts. Sohag et al. (2022) emphasized the role of geopolitical risks in driving food inflation, while Su et al. (2023) found that policy uncertainty poses evolving challenges to food security. These studies, like ours, highlight that uncertainty has differential effects over time and across supply chain nodes. Grossman et al. (2024) further illustrated how abrupt changes in trade policy can disrupt logistics infrastructure and freight flow, reinforcing the idea that food price volatility is tightly linked to transport dynamics. From a methodological perspective, our use of a time-varying and volatility-sensitive framework supports the broader literature that advocates flexible empirical models to capture evolving interdependencies. For example, Melas et al. (2025) suggested that stable freight pricing systems can buffer the effects of uncertainty shocks, a recommendation supported by our findings that uncertainty influences freight rates in both the short and medium term.

Overall, the results presented here situate our study within the contemporary debate on how uncertainty shapes food and transport markets. By identifying time-specific dynamics, we contribute to the understanding of how policy instability transmits through the agri-logistics chain, with implications for price volatility, trade efficiency, and supply chain resilience.

5. Conclusion

Combining the econometric methods of Nakajima (2011), Nakajima et al. (2011), and Qi et al. (2022), this paper uses the TVP-VAR-SV model to discuss and analyze the time-varying response between the food market, food maritime transportation market, and global economic policy uncertainty. By applying the impulse response function, we study the impact of a unit shock on these variables at six important economic events from January 2000 to December 2022, and obtain a dynamic relationship and time-lag effect of information transmission between them. These observed fluctuations likely reflect underlying structural shifts in the global economy during the sample period, such as financial crises, global pandemics, and geopolitical conflicts. Incorporating these events into our interpretation helps explain why the relationships between variables vary over time.

Firstly, global economic policy uncertainty shows both positive and negative associations with food prices, with effects manifesting after short-term delays. In the long run, food price changes significantly shape economic policies, especially in developing countries. Additionally, uncertainty in global economic policy influences food transportation primarily through food prices, impacting food-exporting nations. To ensure food security, these countries often implement food reserve policies or restrict international transportation and trade. Conversely, food transportation prices are mainly influenced by trade agreements and international factor flow, altering food market dynamics and affecting consumption and economic policies. The relationship between food transportation prices and food prices is bidirectional, with transportation price volatility affecting food prices over time, while changes in food prices have a more significant impact on transportation prices.

Finally, the analysis on causality and information transmission among the variables reveals key insights: (i) After the financial crisis, the food and financial markets intertwined, with speculation in food derivatives notably influencing spot market dynamics and decisions of stakeholders. (ii) Short-term food trade restrictions and long-term reserve policies emerged as significant measures for controlling food prices, though they may lead to price rebounds. (iii) Since 2016, food maritime transport prices were notably influenced by environmental decarbonization policies, global health security events, and geopolitical risks. Policies targeting carbon emission reduction in shipping particularly impacted transportation costs, indirectly affecting the transportation market through lasting economic policy changes. This enhances our understanding of how environmental policies and geopolitical risks impact transport markets and broader economic activity.

While our results reveal meaningful lead-lag dynamics among global economic policy uncertainty, food prices, and transport costs, it is important to note that the empirical approach does not identify structural causality. The TVP-VAR-SV model captures time-varying associations and Granger-type predictive relationships, but unobserved factors—such as macroeconomic conditions or climate events—may influence the patterns we observe. These findings should therefore be interpreted as conditional correlations, not as definitive evidence of one variable causing another. This distinction is important for framing the scope and limitations of our policy implications.

5.1. Policy implications and suggestions

The results of this study highlight the need for more adaptive and risk-aware strategies in managing food price volatility and transport disruptions under global policy uncertainty. For food-exporting countries, reducing exposure to sudden policy shocks can be achieved through more diversified trade destinations and alternative transport corridors. Strategic grain reserves remain an effective buffer against volatility and can complement trade flexibility during crisis periods.

At the operational level, risk mitigation tools—such as commodity futures, freight rate derivatives, and cargo insurance—are increasingly relevant in smoothing the short-term impact of uncertainty. While such instruments are common in energy or industrial commodities, they are still underutilized in food systems and merit wider adoption. Environmental and climate-related policy shifts, particularly around carbon taxation and emissions regulation in shipping, pose a distinct challenge. As our findings suggest, these policy areas influence food logistics indirectly but significantly. Policymakers should avoid abrupt changes in regulatory regimes that could distort transport costs and trade flows. Instead, gradual implementation and sector-specific transition strategies are advisable, especially for perishable and bulk agricultural trade. In parallel, firms involved in food transport and trade are encouraged to enhance their internal resilience—through investment in low-emission technology, emissions tracking, and flexible routing—and to anticipate policy developments through scenario-based planning. Finally, the role of international cooperation cannot be overstated. Many recent disruptions have been magnified by fragmented responses and a lack of timely information. Better coordination on trade rules, environmental policies, and port protocols can reduce uncertainty spillovers across borders and support more stable market expectations.

These recommendations do not offer a one-size-fits-all solution but point to a set of priorities where targeted action by governments, firms, and multilateral institutions can meaningfully reduce the exposure of food systems to external shocks.

5.2. Limitations and directions for future work

This study focuses on the dynamic interactions among GEPU, CRB, and BPI using a TVP-VAR-SV framework. While this triadic structure allows for a clear investigation of key uncertainty-price transmission channels, we did not include additional exogenous variables—such as global oil prices or trade indices—to maintain model parsimony. We now acknowledge that incorporating these factors could capture additional macroeconomic or supply chain dynamics, and we recommend this as a direction for future extensions. Nonetheless, future research could benefit from incorporating such exogenous variables as standalone controls. Doing so may help to disentangle the effects of specific external drivers—such as oil price shocks or trade regime shifts—from general economic policy uncertainty. This would improve interpretability and enhance structural robustness testing.

We also suggest expanding the model to include environmental policy factors such as carbon pricing, given their growing impact on food transport costs. Mechanisms like the EU ETS and carbon border adjustments are likely to influence freight dynamics across regions and product types. Beyond adding variables, the framework could be applied to other sectors. Although we focus on food transport, similar models could be used to examine uncertainty effects in energy, manufacturing, or service-related logistics. Cross-sector comparisons would provide insights into how supply chains with different institutional settings respond to global shocks.

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Data Availability Statement

The BPI is published by the Baltic Exchange, and its data are from Clarkson Research. CRB Foodstuffs Spot Price Index is available at https://macrovar.com/commodities/crb-foodstuffs-index/ , GEPU is available at http://www.policyuncertainty.com/global_monthly.html

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Conflicts of Interest
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