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How have global pandemics destabilised the food market?

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Abstract: The paper explores the influence of global pandemic uncertainty (*GPU*) on food prices (*FP*) by using the mixed-frequency vector autoregression (MF-VAR) model. Empirical findings indicate that the influence of *GPU* on *FP* varies across different scenarios, exhibiting either positive, negative, or insignificant effects. A positive influence implies that *GPU* fuels panic-buying and stockpiling behaviours, thereby boosting food demand. Concurrently, disruptions in agricultural production and food export restrictions tighten the market supply, potentially pushing *FP* upwards. Conversely, a negative effect suggests that the global economic downturn and food safety anxieties stemming from pandemic-related uncertainty may dampen food demand, causing *FP* to decline. In some instances, *FP* remains unaffected mainly by *GPU* due to the competing pressures from adverse climate change risks on the food market. Notably, *FP*'s predictive error variance decomposition underscores that the net impact of *GPU* on *FP* is stimulatory. This overall effect aligns with the inter-temporal capital asset pricing model (ICAPM), which posits a positive influence of *GPU* on *FP*. The findings recommend that consumers and investors diversify their food sources, while policymakers should bolster food supply chain resilience, promote sustainable agriculture, establish emergency reserves and coordinate aid.

Keywords: COVID-19; food prices; world pandemic uncertainty; low-frequency model; mixed-frequency model

This paper aims to identify the influence of global pandemic uncertainty (GPU) on food prices (FP). Infectious diseases affecting humans have increased dramatically since 1980 across the globe (Smith et al. 2019), and newly discovered virus species average more than three per year (Woolhouse et al. 2012). Zoonotic types (non-human hosts) account for at least 60% of emerging infectious diseases (Otte and Pica-Ciamarra 2021). More notably, infectious diseases are a leading cause of death worldwide, accounting for approximately one-third of all mortality (Verikios 2020). The globe has experienced several pandemics of infectious diseases, such as the 1918 Spanish flu, the 1957 Asian flu, severe acute respiratory syndromes (SARS) in 2003, swine influenza (H1N1) in 2009, Middle East respiratory syndrome (MERS) in 2012, Ebola virus outbreaks in 2014, and most recently the Coronavirus disease 2019 (COVID-19) (Qin et al. 2024a). Infectious disease pandemics significantly burden human health and have a considerable socioeconomic impact across the globe (Naguib et al. 2021), such as the destruction of the food market (Pu and Zhong 2020). To be specific, the impact of infectious diseases on the food market is not only manifested in the potential direct contamination of food raw materials and processing processes, thereby triggering severe food safety issues but also profoundly affects the stability of the entire food supply chain (Gong et al. 2021).

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These issues result in an imbalance in food supply and demand in the market, triggering price fluctuations and consumer panic (Alam et al. 2024).

Significant pandemics may occur unexpectedly and exhibit considerable uncertainty (Mishra et al. 2021), substantially impacting the food market; the most obvious example is COVID-19. The outbreak of COVID-19 has caused global uncertainty to spike dramatically (Chowdhury et al. 2021), which has not only significantly affected the real economy but severely shocked commodity markets (Zhou et al. 2023). Global food markets have been severely disrupted, leading to price fluctuations (Laborde et al. 2020; Udmale et al. 2020; Yao et al. 2020). Due to export restrictions by some major food-producing countries, the reduction in agricultural commodity supplies has resulted in a rise in FP (Saboori et al. 2022). These export restrictions may stabilise domestic markets in the short term, but they reduce the global supply of food commodities, thereby contributing to a rise in *FP* (Sun et al. 2021). Besides, the COVID-19 shock has caused some consumers to stockpile storable staple foods due to concerns that the pandemic would lead to shortages later. Panic-buying and national measures to prevent the pandemic, particularly trade restrictions on food exports, could cause prices to surge and destabilise the global food market. Therefore, we observe that the uncertainty caused by the infectious disease epidemic could significantly destabilise the food market. Understanding this impact can help policymakers formulate specific policy responses to the pandemic uncertainty shock on the food market and effectively assist countries in preventing large fluctuations in *FP*. Besides, it may offer revelations for the Food and Agriculture Organization of the United Nations (FAO) to consider the pandemic uncertainty shock in their food security risk management strategies.

The existing studies analyse the unpredictable pandemic events that impact the food market, suggesting that such occurrences may have severe and far-reaching consequences. Sufficient evidence indicates that pandemic events have increased food commodity prices. Laborde et al. (2020) point out that a key problem with food export restrictions during the COVID-19 pandemic is that they can create an upward spiral in global prices. Nicola et al. (2020) found that panic buying and stockpiling have increased food demand during the pandemic. Vercammen (2020) indicates that as COVID-19 has caused global food shortages, consumers have hoarded wheat in the short run, pushing its price. Yao et al. (2020) assert that the COVID-19 outbreak, which escalated into a global pandemic in early 2020, has disrupted agricultural supply chains, resulting in a swift surge in *FP*. Adewopo et al. (2021) reveal that due to COVID-19, rice and corn prices have risen by 44and 26%, respectively. Falkendal et al. (2021) argue that trade restrictions on food exports have led to a surge in *FP* in some low- and middle-income countries in the early period of COVID-19 (Alam et al. 2024). Cariappa et al. (2022) found that during COVID-19 induced lockdown, prices soared for chickpeas (4.8%), mung beans (5.2%), and tomatoes (78.2%), reflecting significant losses due to high perishability and price spike. Roubík et al. (2022) underline that the latest impacts of the ongoing coronavirus crisis have resulted in disruptions to the movement of agricultural workers and inefficient farming practices, posing a threat to food security. AL-Rousan et al. (2024) indicate that the Russo-Ukrainian conflict, Brent oil prices, and COVID-19 favourably impact food price indices. Urak et al. (2024) discover that the pandemic and war have caused disruptions in the supply of grain, oilseeds, and fertilisers from Russia and Ukraine to Türkiye, as well as several Middle Eastern and African countries, posing a threat to food security.

By contrast, several studies support the idea that being affected by pandemic events and weak global aggregate demand will exert intense downward pressure on *FP*. Udmale et al. (2020) demonstrate that related trade limitations triggered by COVID-19 have dramatic adverse effects on the agricultural sector as global trade and prices have plummeted. Beckman et al. (2021) denote that the COVID-19 lockdowns led to a decrease in global GDP of 7.2% and grain prices of 9%. Chowdhury et al. (2021) indicate that the continued spread of COVID-19 has significantly reduced *FP*. Erten and Ocampo (2021) state that the pandemic-driven global recession has rapidly declined global commodity prices. Saboori et al. (2022) document that COVID-19 negatively influences the global food market and reduces levels of food security.

Although existing research has either constructed theoretical models or focused on specific pandemic events (primarily COVID-19) to discuss their impact on the food market, there remains a gap in the literature regarding a global-level specific time-series analysis considering the effect of pandemic-induced uncertainty on *FP*. In this regard, we contribute to the literature by exploring the impact of uncertainty shocks related to global pandemics, encompassing all major outbreaks since 1996, on the price of food commodities. In addition, the traditional method mainly uses

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variables with a single frequency, which fails to capture the influence of high-frequency data on low-frequency series. The study explores the impact of quarterly *GPU* on annual *FP* by applying the MF-VAR model, which can obtain more reliable results.

This paper makes the following contributions. First, the global epidemic of infectious diseases has increased market uncertainty, which could disrupt the supply and demand of food commodities and lead to price fluctuations. Motivated by these studies, this paper expands the literature by exploring how global pandemics, encompassing all major outbreaks since 1996 and not just COVID-19, destabilise the food market by specific time-series analysis. Second, these studies use the *GPU* index that Ahir et al. (2022) developed to measure the uncertainty shocks related to global pandemics, distinguishing our analysis from prior studies. Also, we innovatively choose the annual Southern oscillation index (*SOI*) as the control variable to mirror climate change risks. Then, this study selects quarterly *GPU* from 1996Q1 to 2023Q4 and annual *FP* and *SOI* from 1996 to 2023 and shows that there are positive influences, negative effects, or no significant impacts of *GPU* on *FP* under various circumstances. Based on the predictive error variance decomposition of *FP*, it is evident that the overall impact of *GPU* on *FP* is stimulation. The findings can provide implications for consumers and investors to diversify food sources to mitigate the pandemic. Policymakers should strengthen food supply chain resilience, promote sustainable agriculture, establish emergency reserves, and coordinate aid. The FAO should monitor trends, facilitate knowledge sharing, and advocate for policy coordination to ensure food security. Third, previous studies have generally aggregated high-frequency data to achieve a single frequency for all sequences required by traditional methods, which can lead to an incorrect statistical estimate. The mixed-frequency vector autoregressive (MF-VAR) approach can effectively capture the influence of high-frequency variables on low-frequency data. Accordingly, the study can be considered a pioneering effort to examine the effect of quarterly *GPU* on yearly *FP* based on the MF-VAR model.

The paper's order is as follows: Section 2 illustrates the intertemporal capital asset pricing model. Section 3 discusses the methodology adopted. Section 4 presents the data sources and the descriptive analysis, while sections 5 and 6 provide the empirical results and discussions. The last section concludes and then gives the policy implications.

The inter-temporal capital asset pricing model

Cifarelli and Paladino (2010) explore the impact of systemic risks on asset values through the development of the Inter-temporal Capital Asset Pricing Model (ICAPM). This study uses the *GPU* and the global *FP* index as proxy indicators. Initially, we postulate the existence of two distinct investor categories in the food market: informed traders, who typically engage in trading activities by assessing systemic risks and returns, and feedback traders, who base their investment decisions on the *FP* from the previous period. Furthermore, we presume that diversification in the food market cannot mitigate systemic risks, which are reflected by the *GPU* index, a measure of global pandemic uncertainty. Informed traders are inclined to make well-informed predictions about *FP* using the *GPU* and determine the quantity of food commodities to invest in. Consequently, the demand for food commodities from this group is formulated as follows:

$$FD_t^i = \frac{E_{t-1}(FP_t) - FP^f}{\mu(GPU_t)} \tag{1}$$

where: FD_t^i – percentage of food commodities held by all informed traders during the time period t; $\mu(GPU_t) > 0$ – positive value; $\mu'(GPU_t) > 0$ implies that an increase in *GPU* results in an increase in $\mu(GPU_t)$; FP^f – price of food commodities in the absence of a pandemic; the conditional expected value of *FP* in the previous time period $t-1$ – $E_{t-1}(FP_t)$; FP_t – ex-post *FP* in the t period; if $FD_t^i = 1$ it suggests that the food market comprises informed traders.

By transforming Equation (1) into Equation (2), we discover that an increase in *GPU* indicates a rising trend in *FP*, suggesting that uncertainty related to pandemics has an effect on the food market.

$$E_{t-1}(FP_t) = FP^f + \mu(GPU_t) \tag{2}$$

Furthermore, another category of investors in this market bases their current investment decisions on past *FP* values. The proportion of these feedback traders' demand (FD_t^i) for food commodities is formulated by Equation (3).

$$FD_t^f = \gamma FP_{t-1} \tag{3}$$

where: $\gamma > 0$ indicates that if the previous change in *FP* were positive (or negative), these traders would likely boost (or reduce) their investment in food commodi-

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ties. Recognising that the market comprises mainly two types of investors: informed traders and feedback traders, then:

$FD_t^i + FD_t^f = 1.$

Consequently, Equation (1) is ultimately transformed into Equation (4).

$$E_{t-1}(FP_t) = FP^f + \mu(GPU_t) - \gamma\mu(GPU_t)FP_{t-1} \quad (4)$$

Compared to Equation (2), $-\gamma\mu(GPU_t)FP_{t-1}$ is a new term, this shows that the food market is influenced by feedback traders' investment behaviour. $1-\gamma FP_{t-1}$ is the total coefficient of $\mu(GPU_t)$, and it is a positive value due to $\gamma FP_{t-1} = FD_t^f$. Therefore, the ICAPM has demonstrated that the *GPU* positively impacts the *FP*. When the *GPU* increases, indicating heightened pandemic uncertainty, the *FP* tends to rise to mitigate the associated systemic risks. Additionally, we observe that pandemic uncertainty notably influences the food market, leading to an elevation in *FP*.

MATERIAL AND METHODS

Low-frequency VAR model

In the first stage, we construct a standard low-frequency vector autoregressive (LF-VAR) model shown in Equation (5).

$$\begin{bmatrix} GPU_{At} \\ FP_t \\ SOI_t \end{bmatrix} = \sum_{l=1}^{2} \begin{bmatrix} a_{11,l} & a_{12,l} & a_{13,l} \\ a_{21,l} & a_{22,l} & a_{23,l} \\ a_{31,l} & a_{32,l} & a_{33,l} \end{bmatrix} \begin{bmatrix} GPU_{At-l} \\ FP_{t-l} \\ SOI_{t-l} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix} \quad (5)$$

where: GPU_{At}, FP_t and SOI_t – annual global pandemic uncertainty, food prices and climate change risks, respectively; the causal link between *GPU* and *FP* may be affected by climate change risks; *SOI* – control variable for the study; *At* – annual time; then, we assume that each series is sufficiently differenced to satisfy the covariance stationarity (Motegi and Sahahiro 2018). We set the lag length *l* from 1 to 2, which obtains potential seasonality. Besides, under the constraints of m, n = 1, 2, 3 and l = 1, 2; $a_{mn,l}$ – correspondent constants.

Accordingly, FP_t is converted to Equation (6) as follows:

$$FP_t = \sum_{l=1}^{2} \left[a_{21,l} GPU_{At-l} + a_{22,l} FP_{t-1} + a_{23,l} SOI_{t-1} \right] + \varepsilon_{2t} \quad (6)$$

where: $GPU_{At} = (GPU_{1t} + GPU_{2t} + GPU_{3t} + GPU_{4t}) / 4$ – average *GPU* of the quarter; GPU_{it} – GPU in the *i* quarter of year *t*, with the restriction that $i = 1, \ldots, 4$; among them, GPU_1, GPU_2, GPU_3 and GPU_4 – global pandemic uncertainty during the first, second, third, and fourth quarters. Therefore, we obtain the following Equation (7), and the homogeneous influence of $GPU_{i,\,t-1}$ on FP_t is $a_{21,l}$ / 4.

$$FP_t = \sum_{l=1}^{2} \left[a_{21,l} \left(\frac{1}{4} \sum_{i=1}^{4} GPU_{i,t-1} \right) + a_{22,l} FP_{t-l} + a_{23,l} SOI_{t-l} \right] + \varepsilon_{2t} \quad (7)$$

Mixed-frequency VAR model

The LF-VAR model necessitates aggregating all series to the lowest sampling frequency, converting mixed-frequency data to a uniform format through averaging, substitution, or interpolation methods. However, this approach may lead to information loss or distortion, ultimately yielding inaccurate analyses and estimation results. To overcome the shortcomings of the LF-VAR model, Ghysels and Valkanov (2004) suggest that sampling regression estimation with mixed data is more effective than the traditional method of low-frequency sampling regression. Then, the mixed-frequency vector auto-regression (MF-VAR) approach is introduced, which allows for modelling directly with mixed-frequency data without altering the original data (Ghysels et al. 2016), offering superior estimation capabilities. Notably, the MF-VAR method is primarily intended for use with smaller proportions of sampling frequencies (Ghysels et al. 2016). Accordingly, we construct the MF-VAR model, including quarterly *GPU*, annual *FP* and *SOI* as Equation (8).

$$\begin{bmatrix} GPU_{1t} \\ GPU_{2t} \\ GPU_{3t} \\ GPU_{4t} \\ FP_t \\ SOI_t \end{bmatrix} = \sum_{l=1}^{2} \begin{bmatrix} a_{11,l} & a_{12,l} & a_{13,l} & a_{14,l} & a_{15,l} & a_{16,l} \\ a_{21,l} & a_{22,l} & a_{23,l} & a_{24,l} & a_{25,l} & a_{26,l} \\ a_{31,l} & a_{32,l} & a_{33,l} & a_{34,l} & a_{35,l} & a_{36,l} \\ a_{41,l} & a_{42,l} & a_{43,l} & a_{44,l} & a_{45,l} & a_{46,l} \\ a_{51,l} & a_{52,l} & a_{53,l} & a_{54,l} & a_{55,l} & a_{56,l} \\ a_{61,l} & a_{62,l} & a_{63,l} & a_{64,l} & a_{65,l} & a_{66,l} \end{bmatrix} \begin{bmatrix} GPU_{1,t-l} \\ GPU_{2,t-l} \\ GPU_{3,t-l} \\ GPU_{4,t-l} \\ FP_{t-l} \\ SOI_{t-l} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \end{bmatrix} \quad (8)$$

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where: $a_{mn,\,l}$ – coefficient matrix and ε_{it} – interference term, under the restriction of m, n = 1, ..., 6 and l = 1, 2. For the fitting of parametric functions of high-frequency variables, the number of coefficients is reduced by mixed regression estimation (Motegi and Sahahiro 2018). It can be seen that GPU_{1t}, GPU_{2t}, GPU_{3t}, and GPU_{4t} all stack up as one vector, these notations are employed to incorporate data of varying frequencies into the MF-VAR model, see Qin et al. (2024a). Therefore, we present the effect of *GPU* on *FP* more clearly and further transform Equation (8) in the following way:

$$FP_t = \sum_{l=1}^{2}\left[\sum_{q=1}^{4}\alpha_{5g,l}GPU_{q,t-1} + \alpha_{55,l}FP_{t-l} + \alpha_{56,l}SOI_{t-l}\right] + \varepsilon_{5t} \quad (9)$$

Since $\alpha_{5q,k}$ is a different value when q = 1, ..., 4, we argue that the influence of $GPU_{i,\,t-1}$ (i = 1, ..., 4) on FP_t is heterogeneous. In this way, the MF-VAR model could directly accommodate mixed data sets encompassing various frequencies, thereby circumventing potential information loss associated with preprocessing and facilitating a more precise capture of data-embedded information. Subsequently, we conduct prediction error variance decomposition and impulse response analysis. The Cholesky order is set as:

$GPU_t \rightarrow FP_t \rightarrow COP_t$ (the LF-VAR model), and $GPU_{1t} \rightarrow GPU_{2t} \rightarrow GPU_{3t} \rightarrow GPU_{4t} \rightarrow FP_t \rightarrow COP_t$ (the MF -VAR model).

In general, temporal aggregation is the conventional method for processing data of different frequencies. Nevertheless, Silvestrini and Veredas (2008) show that statistical estimates are inaccurate when roughly aggregating high-frequency data. The advantage of the MF-VAR model is that it can effectively determine the relationship between different frequency variables (Motegi and Sahahiro 2018). Thus, using the MF-VAR approach, this paper explores the effect of the high-frequency quarterly variable *GPU* on the low-frequency yearly variable *FP*.

Data

The study investigates the influence of pandemic uncertainty shocks on the food market, covering 112 quarters (28 years) from 1996Q1 to 2023Q4. During this period, there have been several pandemics of infectious diseases across the globe, such as SARS, bird flu (avian influenza H5N1) (Highly pathogenic, severe viral infection primarily affecting birds but with zoonotic potential to humans, characterised by high mortality rates and significant pandemic risks., H1N1, MERS, Ebola virus, and COVID-19. Throughout several pandemics of contagious diseases, fear and quarantine measures have severely affected human health and economic development around the globe. For instance, the global COVID-19 epidemic and associated trade restrictions have contributed to an imbalance between supply and demand in the food system, leading to increases in *FP* (Adewopo et al. 2021; Su et al. 2025). We conclude that there may be a close relationship between pandemic uncertainty shocks and the food market. Then, the study selects the *GPU* index established by Ahir et al. (2022) to measure the uncertainty related to global pandemic diseases. The *GPU* index is calculated by searching and counting the frequency of keywords about infectious diseases (e.g. coronavirus, Ebola virus, and influenza) in the Economist Intelligence Unit country reports (Hammoudeh et al. 2022). A higher *GPU* index signifies a relatively greater severity of global pandemic diseases, and conversely, a lower *GPU* index implies less severity. Further, we set GPU_1, GPU_2, GPU_3 and GPU_4 as *GPU* in the first, second, third and fourth quarter of each year, respectively, and GPU_A is the average of GPU_1, GPU_2, GPU_3 and GPU_4. The *FP* index, developed by the FAO (2025), is a weighted average of 5 significant sub-categories price indices (meat, dairy, cereals, vegetable oil, and sugar), and the weights are assigned based on the proportion of exports during

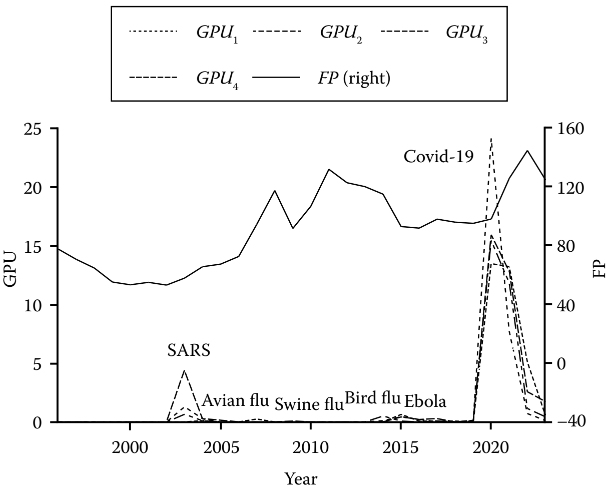

Figure 1. The trends of GPU_1, GPU_2, GPU_3, GPU_4 and *FP*

Presenting a graph with mixed-frequency data is challenging; thus, we plot it with same-frequency data, which could roughly observe the underlying trends; FP - food prices

Source: Own calculations based on Ahir et al. (2022), and FAO (2025)

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the period from 2014 to 2016. This index tracks annual price changes for a basket of traded food to reflect global agricultural commodity market developments. Choosing annual data over monthly data offers comprehensive and stable information, avoiding short-term fluctuations, seasonal effects, and noise, mainly since the impact of infectious disease outbreaks, often persistent and complex, can gradually manifest over a more extended period on food supply chains and price movements. More importantly, the explanatory variable (*GPU*) contains many zero values, and utilising annual data for the explained variable helps to address model instability arising from data sparsity.

Figure 1 displays the trends of GPU_1, GPU_2, GPU_3, GPU_4 and *FP*. We can observe that *GPU* does not always move in the same direction as *FP*. The outbreak of SARS in 2003 has spread throughout the globe and kept *GPU* at a relatively high level. This global infectious disease devastates agricultural production by reducing the labour supply and impeding other inputs, which may lead to reduced supply and higher prices of food commodities. The pandemic of H5N1 caused *GPU* to increase sharply in 2006, and *FP* is also on the rise. However, the global financial crisis led to a sharp decline in *FP* due to decreased demand and restricted capital flows despite the swine flu. Between 2014 and 2016, global food prices experienced a steep decline, influenced mainly by abundant supplies, sluggish global demand, and a strengthening US dollar exchange rate, while the Ebola virus outbreak played a negligible role. COVID-19 is an easily transmissible disease, which was identified in December 2019 and declared a pandemic by the World Health Organization (WHO) on March 11, 2020, making *GPU* soar. Panic-buying and export restrictions on food commodities in certain countries and regions ultimately lead to a surge in *FP*. Consequently, uncertainty related to global pandemics might influence the food market. Besides, climate change risks profoundly influence the global food market through various avenues, such as extreme weather events, shifts in agricultural production patterns, and supply chain disruptions, leading to intensified price fluctuations. This paper chooses the annual Southern oscillation index (*SOI*) as the control variable to mirror these risks (Qin et al. 2024b), where the negative values represent an El Nino phenomenon (Bureau of Meteorology Australia 2025). Based on the analyses above, it is evident that the data frequencies of *GPU*, *FP* and *SOI* vary, suggesting that the interplay between pandemic uncertainty and the food market is non-linear, intricate, and influenced by climate change risks. The traditional LF-VAR method is unable to capture this complex relationship; therefore, the study employs the MF-VAR technique to conduct a more thorough analysis of the influence of *GPU* on *FP*.

Table 1 reports the descriptive statistics for all variables. The *GPU*, *FP* and *SOI* mean values are 1.229, 91.432 and 0.969, respectively. Their positive skewness reflects that all variables are right-skewed distributions, underlying that the data deviates more from the median or mean on the right than the left. The kurtosis of GPU_1, GPU_2, GPU_3, GPU_4, GPU_A and *GPU* is greater than 3, thereby satisfying the leptokurtic distributions. However, *FP* and *SOI* satisfy the identification criteria of platykurtic distributions since the kurtosis is less than 3. Moreover, GPU_1, GPU_2, GPU_3, GPU_4, GPU_A and *GPU* are non-normally distributed at a 1% level, which has been proved by the Jarque-Bera test, but *FP* and *SOI* cannot reject the null hypothesis.

Table 1. Descriptive statistics for GPU_1, GPU_2, GPU_3, GPU_4, GPU_A, *GPU*, *FP* and *SOI*

Variables	GPU_1	GPU_2	GPU_3	GPU_4	GPU_A	*GPU*	*FP*	*SOI*
Mean	1.196	1.390	1.249	1.081	1.229	1.229	91.432	0.969
Median	0.000	0.000	0.000	0.000	0.017	0.000	93.650	0.079
Max.	13.460	15.920	24.110	15.430	17.229	24.110	144.700	13.783
Min.	0.000	0.000	0.000	0.000	0.000	0.000	53.100	–11.667
SD	3.560	3.814	4.710	3.586	3.815	3.893	27.082	6.759
Skewness	3.005	3.081	4.393	3.406	3.468	3.757	0.133	0.156
Kurtosis	10.436	11.208	21.456	12.940	13.820	17.291	1.892	2.364
Jarque-Bera	106.667***	122.894***	487.449***	169.417***	192.727***	1 216.611***	1.514	0.585

***significance at 1% level; global pandemic uncertainty (*GPU*) is quarterly data, while others are annual ones; *FP* – food prices; *SOI* – Southern oscillation index; SD – standart deviation

Source: Own calculations based on Ahir et al. (2022), Bureau of Meteorology Australia (2025), and FAO (2025)

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RESULTS

By estimating the LF-VAR model (estimated parameters are presented in Table 2), Figure 2 reports the result of low-frequency impulse response functions, with 95% confidence intervals constructed by bootstrapping 1 000 iterations of the parameters for h = 0, 1, ..., 12. Among them, h refers to the time horizon for predictions using the existing sample data. Specifically, a single period (h = 1) indicates a prediction for the immediate next year, while h = 4 multiple periods (e.g. period = 4) signify predictions made for a more distant future time point, such as the 4th period ahead.

Table 2. Estimated parameters of the LF-VAR model

Variables	GPU_A	FP	SOI
GPU_A (−1)	0.612***	1.844**	0.443
GPU_A (−2)	0.062*	1.029	−0.086
FP (−1)	−0.198	−0.212***	0.351
FP (−2)	−0.281	−0.430	0.154
SOI (−1)	−0.038	−0.179	0.071*
SOI (−2)	0.047	−0.094	−0.185

*, **, ***significance level at 10, 5, and 1% respectively; *GPU* – global pandemic uncertainty; *FP* – food prices; *SOI* – Southern oscillation index

Source: Own calculations based on Ahir et al. (2022), Bureau of Meteorology Australia (2025), and FAO (2025)

As can be seen, the response of FP to one-standard-deviation uncertainty shock from GPU_A (expressed as '$GPU_A \rightarrow FP$') is significantly positive. We can explain it from two respective sides. First, the positive response of FP to GPU can be attributed to the rapid increase in food demand caused by panic at the beginning of the epidemic. Pandemics of infectious diseases are emerging globally at an unprecedented rate, usually triggering panic among the public. An increase in demand for food commodities may result in an elevation of FP. Second, global food supply chains are increasingly susceptible to systemic risks, with pandemic uncertainty shocks potentially leading to provision changes and price spikes. A severe pandemic results in deaths and a reduced available labour force, which affects timely planting and harvesting activities and may cause severe global food shortages.

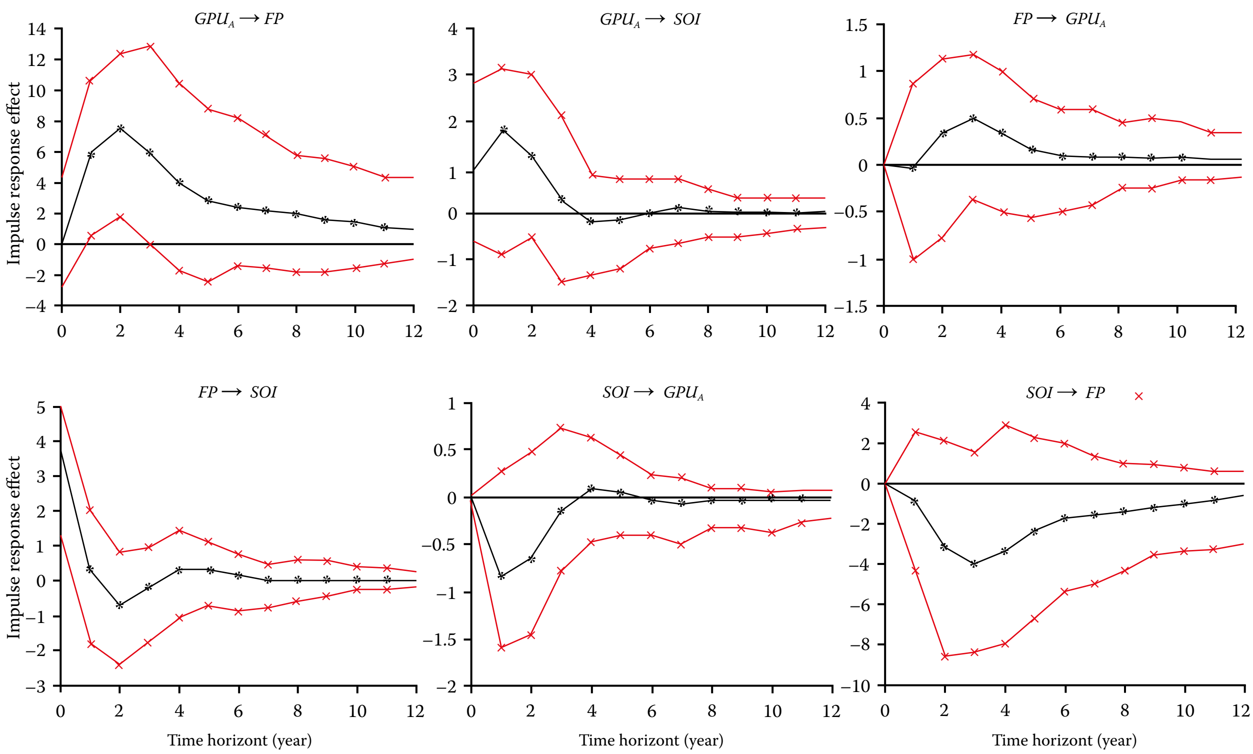

Figure 2. Impulse responses for the low frequency vector autoregressive model

The x-axis is h, which is the time horizon (year); *GPU* – global pandemic uncertainty; *FP* – food prices; *SOI* – Southern oscillation index

Source: Own calculations based on Ahir et al. (2022); Bureau of Meteorology Australia (2025); and FAO (2025)

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For example, the outbreak of COVID-19 and associated trade restrictions have severely disrupted food systems, such as interrupted transport and limited labour supplies (Gong et al. 2021), which has translated into unanticipated increases in *FP*. Additionally, some major food-producing countries have taken export restrictions to ensure adequate supplies to the domestic food market during the pandemic (Yao et al. 2020). For instance, India, Myanmar, and Vietnam have reduced rice exports, Sudan has banned sorghum and corn exports, and the Russian Federation has imposed export quotas on wheat and other grains. These export restrictions may stabilise domestic markets, but they reduce the global supply of food commodities, contributing to a rise in *FP* (Sun et al. 2021). Overall, panic-buying, stockpiling, agricultural production disruptions and export restrictions on food during the pandemic period may result in a rapid increase in *FP*. Accordingly, the positive impact of *GPU* on *FP* can be evidenced, and this conclusion is consistent with the ICAPM.

Besides, *SOI* exerts a negative influence on *FP*, indicating that the El Nino phenomenon (negative values) would cause an increase in food prices, which could be explained as follows: First, the El Nino phenomenon brings about extreme weather conditions such as high temperatures, droughts, or heavy rainfall. These conditions impact crops' growth cycles, yields, and quality, pushing up *FP*. Second, El Nino-induced natural disasters, such as floods and hurricanes, can damage transportation and logistics infrastructure, disrupting the food supply chain and elevating *FP*. Third, El Nino events may experience panic buying due to food shortages, further driving up *FP*.

Table 3 reports the variance decomposition of prediction error in the LF-VAR model. We can observe that the prediction error variance of *FP* is similar for h = 4, 8, 12, and the variance of *FP* prediction error can be explained by *GPU*, *SOI*, and itself by 35.9% to 36.1%, 13.3% to 13.4%, and 50.8% to 50.5%, respectively. However, *GPU* is the aggregated high-frequency data, leading to incorrect statistical estimates. Given this, to accurately explore the influence of *GPU* on *FP*, this paper utilises the MF-VAR model.

By estimating the MF-VAR model (estimated parameters are presented in Table 4), Table 5 presents the forecast error variance decomposition of the MF-VAR model. It can be noted that *GPU* (consisting of GPU_1, GPU_2, GPU_3 and GPU_4) accounts for roughly 45% of the variation in prediction errors for *FP*, specifically 44% in the short term, 45.6% in the medium term, and 45.8% in the long term. This finding suggests that the MF-VAR system provides greater explanatory power than the LF-VAR one due to its ability to leverage mixed-frequency data fully. Therefore, it is trustworthy to employ the MF-VAR method to discern the intricate influence of *GPU* (quarterly frequency) and *FP* (annual frequency) while considering *SOI* (annual frequency).

Table 3. Variance decomposition of prediction error in LF-VAR model

Forecast ranges	GPU_A	*FP*	*SOI*
	decomposition of GPU_A		
h = 4	0.902	0.023	0.075
h = 8	0.892	0.033	0.065
h = 12	0.890	0.035	0.075
	decomposition of *FP*		
h = 4	0.359	0.508	0.133
h = 8	0.361	0.505	0.134
h = 12	0.361	0.505	0.134
	decomposition of *SOI*		
h = 4	0.048	0.225	0.727
h = 8	0.065	0.209	0.726
h = 12	0.067	0.207	0.726

This is a LF-VAR (4) model with annual global pandemic uncertainty (GPU_A), food prices (*FP*), and Southern oscillation index (*SOI*), with h = 4, 8, 12 representing different forecast ranges; LF-VAR – low frequency vector autoregressive
Source: Own calculations based on Ahir et al. (2022), Bureau

The mixed-frequency impulse response functions have confirmed that GPU_1 and GPU_4 can significantly and positively affect *FP*, GPU_3 exerts a negative impact on *FP*, while *FP* is unaffected by GPU_2. The reasons for the positive effects have been analysed in the LF-VAR model, which includes panic-buying, stockpiling, agricultural production disruptions, and export restrictions. Then, there are two angles to explain the negative influence of *GPU* on *FP*. On the one hand, a global pandemic of infectious influenza could easily lead to poor economic performance (Verikios et al. 2020). Uncertainty shocks can weaken agents' confidence and delay investment decisions (Ilut and Schneider 2014), reducing macroeconomic activity. The actual negative reaction of the global economy might lead to reduced demand and lower prices for food commodities. On the other hand, infectious diseases,

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Table 4. Estimated parameters of the MF-VAR model

Variables	GPU_1	GPU_2	GPU_3	GPU_4	FP	SOI
GPU_1 (–1)	–4.685	–6.291	–8.208	–5.338	42.354*	19.302
GPU_1 (–2)	–1.200	–1.723	–1.945	–1.384	7.559	1.714
GPU_2 (–1)	2.342	3.639	4.057	3.200	–8.318*	–3.404
GPU_2 (–2)	2.504	2.397	3.299	1.833	–29.803	–12.889
GPU_3 (–1)	0.058	0.073	0.103	0.065	1.001	–0.096
GPU_3 (–2)	–0.191	–0.268	–0.352	–0.218	–0.019	0.414
GPU_4 (–1)	0.764	1.207	1.352	0.975	–0.91	2.186
GPU_4 (–2)	–0.796	–1.218	–1.486	–0.966	1.768*	0.280
FP (–1)	0.403	0.694	0.900	0.677	3.962**	3.186
FP (–2)	1.710	2.375	2.968	1.804	–21.454	–12.711
SOI (–1)	–0.045	–0.071	–0.084	–0.052	–0.119*	0.085*
SOI (–2)	0.024	0.048	0.052	0.032	0.051	–

*, **significance level at 10 and 5%; *GPU* – global pandemic uncertainty; *FP* – food prices; *SOI* – Southern oscillation index
Source: Own calculations based on Ahir et al. (2022), Bureau of Meteorology Australia (2025), and FAO (2025)

such as bird flu and anthrax, would cause panic and anxiety among consumers after the outbreak (Gong et al. 2021). Consumers may be concerned about food safety and thus reduce the consumption of certain foods (such as poultry and meat). For instance, following outbreaks of Rift Valley fever in Saudi Arabia and Yemen in 2000, Arab countries banned livestock imports from Africa, leading to the complete collapse of the livestock market in Somalia. In the context of the COVID-19 pandemic, prices of all meat types have fallen globally. Specifically, ovine meat prices have registered the steepest drop, affected by the seasonally increased supply and weak import demand. Thus, affected by the global economy deterioration and food safety concerns during the pandemic, the decline in global food demand ultimately leads to a decrease in *FP*. Overall, we have evidence that the higher *GPU* is associated with lower *FP* during specific periods. Besides, under certain circumstances, *FP* is unaffected by *GPU*, mainly because the weather may more influence *FP*. The negative effect of *SOI* on *FP* provides further evidence of the detrimental shocks to the food market that are occasioned by climate change risks.

By examining the predictive error variance decomposition of *FP*, we find that in the short term, GPU_1 and GPU_4 collectively contribute 31.7% to *FP*, rising to 33.1% in the medium term and 33.2% in the long term. These contributions are notably higher than those of GPU_2 and GPU_3, which stand at 12.3, 12.5, and 12.6%, respectively, in the short, medium, and long-term periods. Based on these findings, we can deduce that the impact of *GPU* on *FP* can vary across different scenarios, manifesting as positive influence, negative effect, or no significant impact, but the overall effect leans towards stimulation. This overall effect

Table 5. Decomposition of prediction error in MF-VAR model

	Decomposition of FP						
forecast ranges	GPU_1	GPU_2	GPU_3	GPU_4	Sum (GPU_i)	FP	SOI
h = 4	0.251	0.079	0.044	0.066	0.440	0.390	0.170
h = 8	0.266	0.079	0.046	0.065	0.456	0.374	0.170
h = 12	0.267	0.079	0.047	0.065	0.458	0.372	0.170

This is a MF-VAR (4) model with quarterly global pandemic uncertainty (GPU_i), yearly food prices (*FP*) and Southern oscillation index (*SOI*), with h = 4, 8, 12 representing different forecast ranges; due to limited space, only the decomposition of *FP* directly pertinent to the topic is plotted in this table
Source: Own calculations based on Ahir et al. (2022), Bureau of Meteorology Australia (2025), and FAO (2025)

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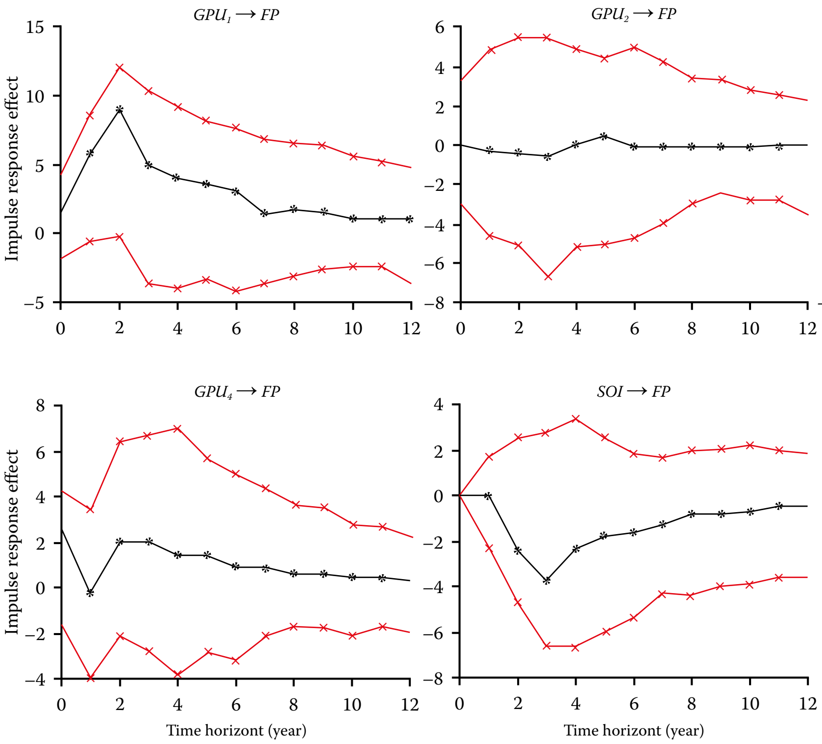

Figure 3. Impulse responses for the MF-VAR model

Due to limited space, only the impulse responses to *FP* directly pertinent to the topic are plotted in this table; the x-axis is *h*, which is the time horizon (year)

Source: Own calculations based on Ahir et al. (2022); Bureau of Meteorology Australia (2025); and FAO (2025)

aligns with the theoretical analysis, which suggests that *GPU* exerts a favourable influence on *FP*.

DISCUSSION

This article delves into a detailed comparison of the predictive error variance decomposition between the LF-VAR technique and the MF-VAR methodology. The findings unveiled in this comparison are particularly illuminating, revealing that the MF-VAR methodology offers a significantly superior explanatory power when capturing the dynamics of mixed-frequency variables. This advantage makes the MF-VAR methodology a more trustworthy tool for unravelling the intricate and often nonlinear relationships between such variables, exemplified in this study by *GPU* and *FP*.

The MF-VAR approach provides a robust framework for understanding these relationships and furnishes quantitative evidence for assessing how global pandemics, such as the recent COVID-19 crisis, can destabilise the food market. Furthermore, to bolster the precision and robustness of their quantitative analyses, the study incorporates *SOI* as a control series.

The impulse responses derived from the MF-VAR methodology offer a nuanced view of the relationships between *GPU* and *FP*. These responses indicate that the influence of GPU on FP can vary widely under different circumstances, manifesting as a positive effect, a negative effect, or no significant impact at all. The positive effect of *GPU* on *FP*, for instance, suggests that during pandemics, panic-buying and stockpiling behaviours can lead to a surge in food demand. Simultaneously, disruptions in agricultural production and food export restrictions would further tighten market supply, potentially causing a sharp rise in food prices.

Conversely, the negative impact of *GPU* on *FP* highlights the potential for global economic recession and food safety concerns triggered by pandemic-induced uncertainty to reduce the demand for food. This demand reduction can lead to a downward trend in food prices as consumers cut back on spending. In some situations, however, the influence of *GPU* on *FP* may be negligible. This can occur when other factors, such as detrimental climate change risks to the food market, overshadow the impact of *GPU*. These climate change risks would disrupt agricultural production and affect food supply chains, making food prices less sensitive to changes in *GPU*.

More importantly, the predictive error variance decomposition of *FP*, as analysed using the MF-VAR methodology, reveals a clear overall impact of *GPU* on *FP*, that is, stimulation. This finding is further sup-

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ported by the ICAPM, which posits that *GPU* positively affects *FP*. Together, these insights offer a comprehensive understanding of the complex influences from *GPU* to *FP* and provide valuable guidance for policymakers and stakeholders seeking to stabilise food markets in the face of global challenges.

CONCLUSION

Policy implications

This paper employs an MF-VAR model to investigate the influence of uncertainties associated with the global pandemic on the food market. The empirical results suggest positive influences, negative effects, or no significant impact of *GPU* on *FP* under various circumstances. The positive effect of *GPU* on *FP* indicates that panic-buying and stockpiling increase the food demand, while agricultural production disruptions and food export restrictions reduce market supply, potentially causing a sharp rise in *FP*. However, the negative impact suggests that global economic recession and food safety concerns caused by the pandemic-induced uncertainty could reduce the demand for food, resulting in a downward trend in *FP*. Furthermore, *FP* might be primarily unaffected by *GPU* in several situations due to the detrimental climate change risks to the food market. More importantly, based on the predictive error variance decomposition of *FP*, it is evident that the overall impact of *GPU* on *FP* is stimulation. This overall impact is supported by the ICAPM, stating that *GPU* positively affects *FP*.

Understanding the impact of pandemic uncertainty on the food market in different periods can provide valuable implications for the public (consumers and investors), policymakers and FAO. Consumers and investors should diversify their food sources and store essential food items to mitigate potential shortages and price fluctuations. This can be achieved through community-supported agriculture (CSA) programs, local farmers' markets, and home gardening. Secondly, investors should consider supporting innovative technologies that enhance food security, such as precision agriculture, vertical farming, and food traceability systems. These technologies would help ensure food quality, safety, and availability during crises. Thirdly, consumers and investors should stay informed about global food market trends and pandemic-related disruptions. Planning, such as setting budgets and emergency food plans, could help manage risks and expenses.

Policymakers should first implement policies that support the resilience of the food supply chain, including investments in infrastructure, logistics, and technology. This could ensure smoother and more efficient food distribution, even during crises. Second, they should encourage sustainable agricultural practices to increase food production and reduce environmental impacts. Policies could include incentives for organic farming, water conservation, and soil health improvement. Third, they should develop and maintain emergency food reserve systems to provide immediate relief during pandemics. These systems should be strategically located to ensure rapid distribution to affected areas. Fourth, they should enhance coordination among international organisations and governments to provide timely and effective food aid during crises. This includes facilitating the flow of food and essential supplies across borders and supporting vulnerable populations.

For the FAO, it is crucial to continuously monitor and analyse global food market trends, including the impact of pandemics, to provide early warnings and recommendations to governments and stakeholders. Additionally, the organisation should facilitate knowledge sharing and capacity building among member countries through training programs, technical assistance, and best practice exchanges, enhancing their ability to respond to food security challenges. Furthermore, the FAO should advocate for policy coordination among international organisations and governments, promoting regional and global cooperation and facilitating dialogue among stakeholders to ensure a cohesive and effective response to food security crises.

REFERENCES

Adewopo J.B., Solano-Hermosilla G., Colen L., Micale F. (2021): Using crowd-sourced data for real-time monitoring of food prices during the COVID-19 pandemic: Insights from a pilot project in northern Nigeria. Global Food Security, 29: 100523.

Ahir H., Bloom N., Furceri D. (2022): World Uncertainty Index Database [Dataset]. Available at https://worlduncertaintyindex.com/ (accessed Feb 15, 2025).

Alam S.A., Liu S.X., Pörtner C.C. (2024): Navigating food price shocks in a pandemic: Food insecurity and coping mechanisms in Burkina Faso. World Development, 182: 106714.

Al-Rousan N., Al-Najjar H., Al-Najjar D. (2024): The impact of Russo-Ukrainian war, COVID-19, and oil prices on global food security. Heliyon, 10: e29279.

https://doi.org/10.17221/323/2023-AGRICECON

Beckman J., Baquedano F., Countryman A. (2021): The impacts of COVID-19 on GDP, food prices, and food security. Q Open, 1: 1–17.

Bureau of Meteorology Australia (2025): Southern Oscillation Index Database [Dataset]. Available at http://www.bom.gov.au/climate/enso/soi/ (accessed Feb 15, 2025).

Cariappa A.G.A., Acharya K.K., Adhav C.A., Ramasundaram R.S.P. (2022): COVID-19 induced lockdown effects on agricultural commodity prices and consumer behaviour in India – Implications for food loss and waste management. Socio-Economic Planning Sciences, 82: 101160.

Chowdhury M.A.H., Meo M.S., Aloui C. (2021): How world uncertainties and global pandemics destabilized food, energy and stock markets? Fresh evidence from quantile on quantile regressions. International Review of Financial Analysis, 76: 101759.

Cifarelli G., Paladino G. (2010): Oil price dynamics and speculation: A multivariate financial approach. Energy Economics, 32: 363–372.

Erten B., Ocampo J.A. (2021): The future of commodity prices and the pandemic-driven global recession: Evidence from 150 years of data. World Development, 137: 105164.

Falkendal T., Otto C., Schewe J., Jägermeyr J., Konar M., Kummu M., Puma M.J. (2021): Grain export restrictions during COVID-19 risk food insecurity in many low-and middle-income countries. Nature Food, 2: 11–14.

FAO (2025): FAOSTAT Database [Dataset]. Available at https://www.fao.org/faostat/en/#home (accessed Feb 15, 2025).

Ghysels E., Hill J.B., Motegi K. (2016): Testing for Granger causality with mixed frequency data. Journal of Econometrics, 192: 207–230.

Ghysels E., Valkanov R. (2004): The MIDAS touch: Mixed data sampling regression models. UCLA, Finance. Available at https://escholarship.org/uc/item/9mf223rs (accessed Feb 3, 2024).

Gong B., Zhang S., Liu X., Chen K.Z. (2021): The zoonotic diseases, agricultural production, and impact channels: Evidence from China. Global Food Security, 28: 100463.

Hammoudeh S., Uddin G.S., Sousa R.M., Wadstrom C., Sharmi R.Z. (2022): Do pandemic, trade policy and world uncertainties affect oil price returns? Resources Policy, 77: 102705.

Ilut C.L., Schneider M. (2014): Ambiguous business cycles. American Economic Review, 104: 2368–2399.

Laborde D., Martin W., Swinnen J., Vos R. (2020): COVID-19 risks to global food security. Science, 369: 500–502.

Mishra A., Bruno E., Zilberman D. (2021): Compound natural and human disasters: Managing drought and COVID-19 to sustain global agriculture and food sectors. Science of the Total Environment, 754: 142210.

Motegi K., Sadahiro A. (2018): Sluggishprivate investment in Japan's lost decade: Mixed frequency vector autoregression approach. North American Journal of Economics and Finance, 43: 118–128.

Naguib M.M., Li R., Ling J., Grace D., Nguyen-Viet H., Lindahl J.F. (2021): Live and wet markets: Food access versus the risk of disease emergence. Trends in Microbiology, 29: 573–581.

Nicole M., Alsafi Z., Sohrabi C., Kerwan A., Al-Jabir A., Losifidis C., Agha R. (2020): The socio-economic implications of the coronavirus and covid-19 pandemic: A review. International Journal of Surgery, 78: 185–193.

Otte J., Pica-Ciamarra U. (2021): Emerging infectious zoonotic diseases: The neglected role of food animals. One Health, 13: 100323.

Pu M., Zhong Y. (2020): Rising concerns over agricultural production as COVID-19 spreads: Lessons from China. Global Food Security, 26: 100409.

Qin M., Chang H.L., Su C.W., Racataian R.I., Craciun A.F. (2024a): Substitution or creation? Identifying the role of artificial intelligence in employment. Technological and Economic Development of Economy: 1–22.

Qin M., Su A.H., Li R., Su C.W. (2024b): Speculation, climate or pandemic: Who drives the Chinese herbal medicine bubbles? China Economic Review, 87: 102213.

Roubík H., Lošťák M., Ketuama C.T., Procházka P., Soukupová J., Hakl J., Karlík P., Hejcman M. (2022): Current coronavirus crisis and past pandemics – What can happen in post-COVID-19 agriculture? Sustainable Production and Consumption, 30: 752–760.

Saboori B., Radmehr R., Zhang Y.Y., Zekri S. (2022): A new face of food security: A global perspective of the COVID-19 pandemic. Progress in Disaster Science, 16: 100252.

Silvestrini A., Veredas D. (2008): Temporal aggregation of univariate and multivariate time series models: A survey. Journal of Economic Surveys, 22: 458–497.

Smith K.M., Machalaba C.C., Seifman R., Feferholtz Y., Karesh W.B. (2019): Infectious disease and economics: The case for considering multi-sectoral impacts. One health, 7: 100080.

Su C.W., Song X.Y., Dou J., Qin M. (2025): Fossil fuels or renewable energy? The dilemma of climate policy choices. Renewable Energy, 238: 121950.

Sun T.T., Su C.W., Mirza N., Umar M. (2021): How does trade policy uncertainty affect agriculture commodity prices? Pacific-Basin Finance Journal, 66: 101514.

Udmale P., Pal I., Szabo S., Pramanik M., Large A. (2020): Global food security in the context of COVID-19: A scenario-based exploratory analysis. Progress in Disaster Science, 7: 100120.

Urak F., Bilgic A., Florkowski W.J., Bozma G. (2024): Confluence of COVID-19 and the Russia-Ukraine conflict: Effects

https://doi.org/10.17221/323/2023-AGRICECON

on agricultural commodity prices and food security. Borsa Istanbul Review, 24: 506–519.

Vercammen J. (2020): Information-rich wheat markets in the early days of COVID-19. Canadian Journal of Agricultural Economics, 68: 177–184.

Verikios G. (2020): The dynamic effects of infectious disease outbreaks: The case of pandemic influenza and human coronavirus. Socio-Economic Planning Sciences, 71: 100898.

Woolhouse M.E., Scott F., Hudson Z., Howey R., Chase-Topping M. (2012): Human viruses: Discovery and emergence. Philosophical Transactions of the Royal Society B: Biological Sciences, 367: 2864–2871.

Yao H., Zuo X., Zuo D., Lin H., Huang X., Zang C. (2020): Study on soybean potential productivity and food security in China under the influence of COVID-19 outbreak. Geography and Sustainability, 1: 163–171.

Zhou X.Y., Lu G., Xu Z.C., Yan X.Q., Khu S.T., Yang J.F., Zhao J. (2023): Influence of Russia-Ukraine war on the global energy and food security. Resources, Conservation & Recycling, 188: 106657.

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