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Volatility dynamics of agricultural futures markets under uncertainties

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ABSTRACT

The objective of this study is to examine the effect of various uncertainty measures on the realized volatility of agricultural futures markets. In doing so, we use a range of uncertainty indicators in our analysis to investigate whether news-based uncertainty measures (e.g., geopolitical risk and economic policy uncertainty) have better predictive contents than the market-based uncertainty measures (e.g., crude oil volatility index, the US equity market VIX and exchange rate VIX). This comparison is important given that employing both measures has some specific benefits. Methodologically, we consider the application of the LASSO (least absolute shrinkage and selection operator) method as well as the heterogenous autoregressive (HAR) process. The in-sample estimates indicate that among the various news-based and market-based risk measures the latter provide better forecasts for the realized volatility of agricultural futures markets. The out-of-sample forecasts also confirm the same with the LASSO method outperforming the HAR process.

1. Introduction

Global food prices have increased significantly amid the ongoing Russo–Ukrainian war. Wheat prices, for example, experience a record 40% upsurge since the inception of this conflict (World Bank, 2022). The price levels of other basic food commodities such as corn and soybean oil are also mounting rapidly. The export restrictions due to the Russian invasion of Ukraine are particularly disrupting the production of food commodities and transportation chains, which leads to food shortages.[1] Such scarcities shake the entire agricultural systems which raises food prices globally. It would not be an exaggeration to say that food commodities have emerged as a key geopolitical tool over the past decade.

Notably, the uncertainty in international crude oil markets, generated by geopolitics, is also considered as a major driver to substantially influence the commodity markets (Antonakakis et al., 2017; Su et al., 2020; Saâdaoui et al., 2022; Raza et al., 2022; Lee and Lee, 2023; Lee et al., 2023). Raza et al. (2022), for instance, claim that geopolitics is often responsible for oil market boom, which eventually promotes food prices. In addition, Saâdaoui et al. (2022) empirically show that the current geopolitical tensions due to the war in Ukraine cause a huge increment in oil and gas prices,[2] leading to a major growth in the price levels of basic food commodities.

However, the literature showing the impact of energy prices on food commodities is not new (Fasanya and Akinbowale, 2019). This strand of research tends to grow abundantly following the 2008 global financial crisis as several studies claim that the significant linkages between energy and food markets are the consequence of great recessions (Chen et al., 2010; Du et al., 2011). In fact, the existence of such associations is

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[1] A recent report, published by the European Council (www.consilium.europa.eu), shows that the Russian invasion of Ukraine leads to a significant drop in Ukrainian grain exports, causing a lasting effect on global food prices. Fig. A1 demonstrates how the production and export of agricultural products (e.g., wheat, maize, edible oils) tend to decline due to this ongoing war.

[2] Several studies document that geopolitical risk (GPR) has predictive contents for crude oil prices. For example, Qian et al. (2022) find empirical evidence that oil price volatility is highly sensitive to GPR and that the impact varies across the market conditions. In addition, Li et al. (2023) show that the effect of GPR on crude oil markets is time-varying and asymmetric. Another recent study by Jiao et al. (2023) also confirms that geopolitical uncertainty exerts both positive and negative effects on oil price volatility.

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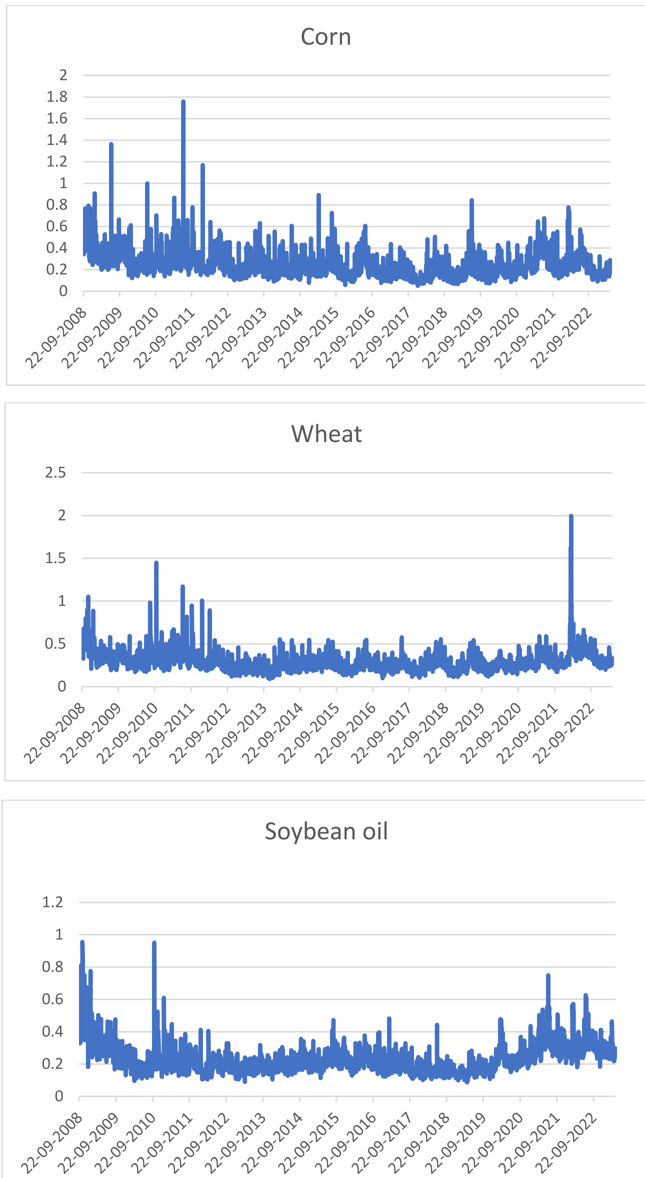

Fig. 1. Realized volatility of agricultural futures prices.

not surprising given that oil is a key production input for agricultural commodity markets (Baumeister and Kilian, 2014; Wei et al., 2019). Besides, the cost of transporting food commodities is heavily dependent on fuel prices as well (Adam, 2016; Rafiq et al., 2009). Moreover, some researchers also contend that energy prices impact food commodities indirectly through the channel of exchange rates (Nazlioglu and Soytas, 2011; Raza et al., 2022). These authors argue that rising oil prices seem to cause the current account deficit, which might result in depreciation of the national currency. Such fluctuations in currency markets influence the prices of various agricultural inputs, leading to an increase in global food prices.[3]

While geopolitical risk (GPR), oil price volatility and currency risk appear to be the key determinants of food price changes, several other uncertainty measures affecting food markets are also identified in prior works. Wen et al. (2021), for example, show that economic policy uncertainty (EPU) has a positive effect on the Chinese food prices both in the long run and in the short run. The study further reveals that negative shocks of uncertainty lead to a higher impact on food commodities when compared to positive shocks, indicating the presence of an asymmetric association. More recently, Cao et al. (2023) find a similar linkage between EPU and global food price volatility. Such significant connections could be attributed to the recurrence of trade tensions between China and the US which creates uncertainty, thereby reducing the total import potential. This in turn elevates trade costs and as a consequence food prices experience an upsurge (Li and Li, 2021). Thus, agricultural prices can also be driven by EPU as it has policy implications for food price stabilization.

Additionally, as evidenced by a number of studies, climate risk is another emergent factor, which causes large swings in food price volatility. A recent analysis by Le et al. (2023) shows that extreme weather events such as heatwaves, natural disasters and draughts are responsible for crop damages, thereby promoting global food prices. Similar studies also argue that due to high temperatures and extreme levels of CO_2 emissions, there could be a 24% decrease in maize production by the end of 21st century (Jacobs et al., 2019; Dhifaoui et al., 2023).

While numerous empirical works have investigated the volatility dynamics of agricultural markets over the years, proper knowledge on appropriate volatility measures for food commodities is still lacking. This is because precise forecasts of food price volatility are somewhat complicated as agricultural markets have been highly volatile in recent years (Cao et al., 2023). Nevertheless, researchers and academics are constantly in search of better models for obtaining accurate measures of food price volatilities. The motivation of this research also arises from the desire to produce more precise measures of food price volatilities. This strand of research is crucial given the sharp increases in global food prices. In particular, our analysis offers valuable insights to policymakers which might be useful in formulating proper strategies for food price stabilization amid the uncertainties.

The contributions of this study are two-fold. Firstly, we use a range of uncertainty indicators in our analysis with a view to investigating whether news-based uncertainty measures (e.g., geopolitical risk, economic policy uncertainty) have better predictive contents than the market-based uncertainty measures (e.g., crude oil volatility index, the US equity market VIX, exchange rate VIX). This comparison is important given that employing both measures has some specific benefits. For instance, the market-based measure such as the VIX index is largely focused on the macroeconomic fluctuations, but unlike GPR and EPU, it disregards the key role of public media and investor attentions. On the other hand, VIX not only contains historical volatility information, but also captures investors' perception on future uncertainty, which makes it a leading indicator of market uncertainty. Since the results of previous studies comparing these measures are somewhat conflicting (Zhu et al., 2019), our analysis nicely complements such works.

Secondly, this empirical research is aimed at finding the accurate forecasts of food price volatilities during the Russia-Ukraine conflicts. To serve this purpose, we split our sample in such a way that the out-of-sample forecast period encompasses the ongoing war period. Based on our knowledge, this is among the initial studies comparing the performance of various uncertainty indicators when forecasting the food price volatility amid the phases of geopolitical tensions. This sort of analysis could be beneficial for investors searching for appropriate hedges during the periods of uncertainties induced by geopolitical conflicts. In addition, the findings of our dynamic risk prediction process might also be useful for regulators in formulating timely containment strategies to diminish the long-term impacts of the Russian invasion of Ukraine on global food prices.

It is also worth noting that while prior studies mainly employ the

[3] Several researchers provide empirical evidence that exchange rates exert significant effects on agricultural markets. For example, Reboredo and Ugando (2014) find that while soybean oil is sensitive to the US dollar exchange rate, such impacts are weak for corn, wheat and rice. Nazlioglu and Soytas (2012) also report a similar result for a range of food commodities. More recently, Núñez et al. (2023) show that exchange rates and food prices are highly cointegrated.

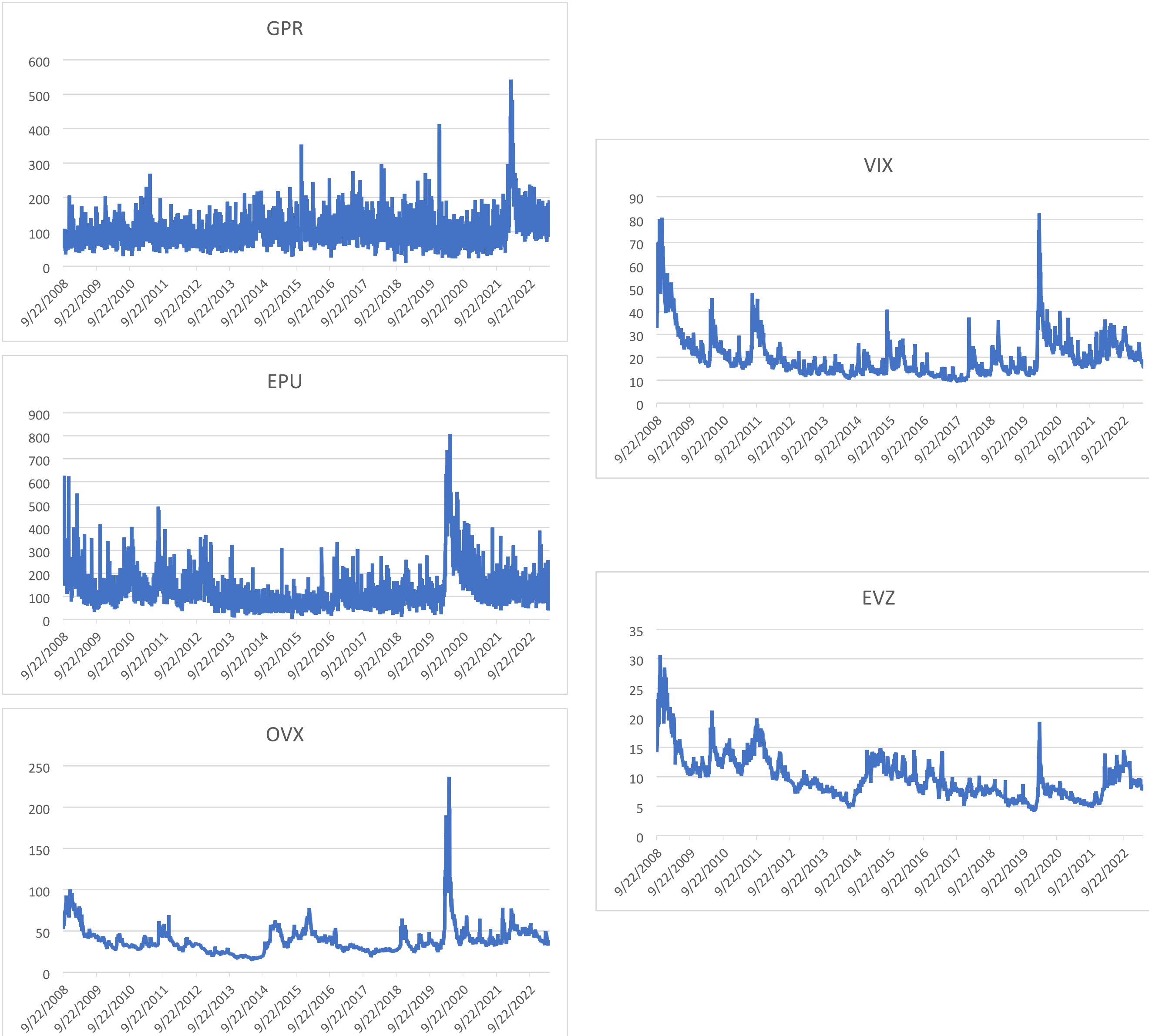

Fig. 2. News-based and market-based uncertainty indicators.

heterogenous autoregressive (HAR) process for forecasting the realized volatility of agricultural markets,[4] we consider the application of a machine learning approach (MLA) in our empirical analysis. The immense popularity of HAR process is rational given that it is presumed to be the dominant approach for predicting the realized volatility of financial markets (Dutta et al., 2023). However, recent evidence shows that MLA such as the LASSO (least absolute shrinkage and selection operator) model outperforms the HAR process (Ding et al., 2021). The LASSO method has attracted the academics vastly due to the fact that it has the potential to improve model selection and thereby produce better forecasts. Notably, the HAR process could be regarded as a restricted autoregressive (AR) process of order 22 (Corsi, 2009). Therefore, our analysis involves estimating an AR(22) model using the LASSO method. Hence, our main objective is to explore whether this machine learning approach (i.e., LASSO) provides additional information which is not contained in the baseline HAR model. To the best of our knowledge, this is the first paper to compare the predictive power of HAR model and MLA in the context of agricultural markets.

On the whole, this study seeks answers to the following research questions. First, are news-based risk measures better predictors than market-based indicators? Second, does the LASSO method outperform the HAR process? Overall, our findings demonstrate that food price volatility is not vulnerable to GPR and EPU shocks, whereas it is highly sensitive to the fluctuations in different VIX indexes. Hence, the results conclude that among the various news-based and market-based risk measures the latter provide better forecasts for the realized volatility of agricultural futures markets. The out-of-sample forecasts also confirm

[4] A number of recent studies have used the HAR models for predicting the realized volatility of food markets. Some notable contributions include Tian et al. (2017), Yang et al. (2017), Luo et al. (2022) and Degiannakis et al. (2022). Yang et al. (2017), for instance, combine the baseline HAR model with bagging and principal component (PC) to forecast the volatility of Chinese agricultural futures markets. More recently, Luo et al. (2022) apply the HAR process to model the volatility of several agricultural commodities including Corn, Cotton, Indica rice, Palm oil and Soybeans. The authors show that HAR models with infinite Hidden Markov regime-switching structures outperform the benchmark HAR approach.

Table 1
Estimates of daily HAR-RV models for corn futures.

Models	HAR-RV	HAR-RV-GPR	HAR-RV-EPU	HAR-RV-OVX	HAR-RV-VIX	HAR-RV-EVZ
τ_0	0.0209***	0.0209***	0.0209***	0.0205***	0.0163***	0.0174***
	(0.0040)	(0.0041)	(0.0041)	(0.0045)	(0.0042)	(0.0044)
τ_d	0.2012***	0.2011***	0.2012***	0.1956***	0.1917***	0.1997***
	(0.0198)	(0.0199)	(0.0199)	(0.0199)	(0.0198)	(0.0198)
τ_w	0.3460***	0.3461***	0.3460***	0.3282***	0.3386***	0.3304***
	(0.0367)	(0.0367)	(0.0367)	(0.0373)	(0.0371)	(0.0369)
τ_m	0.3620***	0.3621***	0.3620***	0.3821***	0.3520***	0.3544***
	(0.0337)	(0.0338)	(0.0338)	(0.0349)	(0.0359)	(0.0359)
θ		0.0000				
		(0.0001)				
γ			0.0000			
			(0.0000)			
ψ_d				0.0012***		
				(0.0003)		
ψ_w				−0.0006		
				(0.0004)		
ψ_m				−0.0005**		
				(0.0002)		
δ_d					0.0028***	
					(0.0007)	
δ_w					−0.0015*	
					(0.0009)	
δ_m					−0.0007	
					(0.0005)	
ϕ_d						0.0016
						(0.0024)
ϕ_w						0.0033
						(0.0031)
ϕ_m						−0.0040***
						(0.0015)
R^2 (%)	48.60	48.59	48.59	48.87	49.04	48.79
HET test	0.31	0.31	0.30	0.39	0.43	0.37
Log-likelihood	3864.46	3864.49	3864.47	3875.06	3880.88	3872.15

Notes: We report the findings of daily HAR models for corn futures. Our data span from 22.09.2008 to 30.04.2023. The *p*-values are computed for the heteroscedasticity (HET) test. The parentheses show the standard errors. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

the same with the LASSO method outperforming the HAR process.

2. Data

Our data include the realized volatility of corn, wheat and soybean oil futures prices. In addition, two news-based risk measures such as geopolitical risk (GPR) and economic policy uncertainty (EPU) are considered in our analysis. As the market-based uncertainty indicators, we choose crude oil volatility index (OVX), the US equity market VIX and the eurocurrency volatility index (EVZ). The information on realized volatility, based on the 5-min intra-day squared returns for the agricultural futures, is collected from Professor Dacheng Xiu's risk lab (https://dachxiu.chicagobooth.edu/#risklab). Besides, the uncertainty indexes are retrieved from the Thomson Reuter's DataStream database. Our sample period runs from 22 September 2008 to 30 April 2023.[5]

Fig. 1 displays the realized volatility of various food commodities. It is evident from this graph that food futures prices remain highly volatile during the 2008 financial crisis. Notably, wheat prices appear to be more volatile than corn and soybean oil prices amid the ongoing Russo–Ukrainian war. It seems that the sanctions on Russian banks and companies create chaos in exporting wheat, thereby increasing its volatility.

Next, Fig. 2 exhibits the news-based and market-based risk measures. The GPR index, for example, reaches new heights after the inception of the Russo–Ukrainian war. EPU mainly increases during the periods of market downturns (e.g., COVID-19 pandemics). The implied volatility indexes, on the other hand, experience large increases during the 2008 financial crisis as well as the COVID-19 pandemics. As for instance, the crude oil volatility index (i.e., OVX) has witnessed a huge jump following the downturns due to coronavirus outbreak in April 2020.

3. Methodology

3.1. The HAR process

The HAR models receive ample attention in prior studies for forecasting the realized volatility (RV) of financial markets. Such significant attention could be attributed to the fact that the HAR process considers separation of realized volatility into short-, medium-, and long-term volatility components, which improves the predictive power of this model (Dutta and Das, 2022). The existing literature (Andersen et al., 2007; Andersen et al., 2011; Forsberg and Ghysels, 2007; Giot and Laurent, 2007; Ma et al., 2014) also confirms its superiority over the GARCH-type, SV-type, VAR-RV, MIDAS-RV, and ARFIMA-RV approaches.

In line with Corsi (2009) and Busch et al. (2011), we define the baseline HAR-RV model as follows:

$$RV_{t,t+h} = \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \varepsilon_t \quad (1)$$

where h equals 1, 5 and 22 depending on the daily, weekly and monthly forecast horizons, respectively and

$$RV_{t_1,t_2} = \frac{1}{t_2 - t_1} \sum_{t=t_1+1}^{t_2} RV_t \quad (2)$$

Consistent with Andersen and Bollerslev (1998), the day t RV for food prices is given as:

$$RV_t = \sum_{i=1}^{N} \left(r_{t,i}\right)^2 \quad (3)$$

[5] Summary statistics are presented in Table A1.

Table 2
Estimates of weekly HAR-RV models for corn futures.

Models					HAR-RV	HAR-RV-GPR	HAR-RV-EPU	HAR-RV-OVX	HAR-RV-VIX	HAR-RV-EVZ
τ_0					0.0297***	0.0298***	0.0298***	0.0297***	0.0246***	0.0251***
					(0.0026)	(0.0026)	(0.0026)	(0.0029)	(0.0027)	(0.0028)
τ_d					0.0910***	0.0910***	0.0909***	0.0854***	0.0821***	0.0891***
					(0.0128)	(0.0129)	(0.0128)	(0.0128)	(0.0127)	(0.0127)
τ_w					0.4061***	0.4060***	0.4062***	0.3930***	0.3992***	0.3859***
					(0.0238)	(0.0238)	(0.0238)	(0.0240)	(0.0239)	(0.0238)
τ_m					0.3734***	0.3734***	0.3734***	0.3908***	0.3549***	0.3625***
					(0.0218)	(0.0219)	(0.0219)	(0.0226)	(0.0231)	(0.0231)
θ		−0.0000								
		(0.0000)								
γ			0.0000							
			(0.0000)							
ψ_d				0.0011***						
				(0.0002)						
ψ_w				−0.0008***						
				(0.0003)						
ψ_m				−0.0004***						
				(0.0001)						
δ_d					0.0025***					
					(0.0004)					
δ_w					−0.0014**					
					(0.0006)					
δ_m					−0.0004					
					(0.0003)					
ϕ_d							0.0014			
							(0.0015)			
ϕ_w							0.0052***			
							(0.0019)			
ϕ_m							−0.0053***			
							(0.0010)			
R^2 (%)	67.02	67.01	67.02	67.38	67.71		67.63			
HET test	0.42	0.40	0.43	0.48	0.49		0.51			
Log-likelihood					5387.03	5387.03	5387.05	5407.78	5425.28	5418.09

Notes: We report the findings of weekly HAR models for corn futures. Our data span from 22.09.2008 to 30.04.2023. The *p*-values are computed for the heteroscedasticity (HET) test. The parentheses show the standard errors. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

with $r_{t,i}$ indicating the log return of a particular food commodity price on day t and i-th intraday interval.

Next, eq. (1) is extended using the information on different uncertainty measures. For the news-based indicators, we form the following two equations:

$$RV_{t,t+h} = \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \theta \Delta GPR_t + \varepsilon_t \tag{4}$$

$$RV_{t,t+h} = \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \gamma \Delta EPU_t + \varepsilon_t \tag{5}$$

Note that for each of the market-based uncertainty indexes, we consider the heterogeneous structure. Some recent studies confirm that doing so raises the prediction power of HAR-type methods (Liang et al., 2022; Dutta et al., 2023). Thus, we have following three equations for the financial market implied volatility indexes:

$$\begin{aligned} RV_{t,t+h} = {} & \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \psi_d OVX_t + \psi_w OVX_{t-5,t} \\ & + \psi_m OVX_{t-22,t} + \varepsilon_t \end{aligned} \tag{6}$$

$$\begin{aligned} RV_{t,t+h} = {} & \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \delta_d VIX_t + \delta_w VIX_{t-5,t} \\ & + \delta_m VIX_{t-22,t} + \varepsilon_t \end{aligned} \tag{7}$$

$$\begin{aligned} RV_{t,t+h} = {} & \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \phi_d EVZ_t + \phi_w EVZ_{t-5,t} \\ & + \phi_m EVZ_{t-22,t} + \varepsilon_t \end{aligned} \tag{8}$$

We specify Eqs. (4)–(8) as the HAR-RV-GPR, HAR-RV-EPU, HAR-RV-OVX, HAR-RV-VIX and HAR-RV-EVZ models respectively, whereas Eq. (1) is termed as the baseline HAR-RV process.

3.2. The LASSO method

The Lasso model, proposed by Toshigami (1996), has been extensively used in recent literature due to the fact that it produces a parsimonious parameter specification in a linear process (Friedman et al., 2010) and can strengthen the predicting power of volatility models (Ding et al., 2021). In particular, the LASSO, being a continuous shrinkage process, improves the forecast accuracy due to the bias–variance trade-off (Fang et al., 2020; Cheng et al., 2021). Besides, this machine learning approach is designed to operate for a large array of predictors (Çepni et al., 2022). Although the current literature recommends the application of HAR approach to modeling the volatility dynamics, recent evidence also supports the use of LASSO approach (Ding et al., 2021; Çepni et al., 2022). This is because the HAR model is estimated using the ordinary least squares (OLS) method, which produces unbiased estimates with large variances. The LASSO estimates, on the other hand, sacrifice some bias to reduce the variance, thereby improving the overall forecast accuracy (Zhang et al., 2019). In this study, we thus employ both methods to compare the results.

As mentioned earlier, the HAR approach could be regarded as a restricted autoregressive (AR) process of order 22 (Corsi, 2009). Hence, the LASSO estimator for an AR(p) structure is given as:

$$\widehat{\beta}_{LASSO} = argmin\left\{ \sum_{t=p}^{T} \left(RV_{t+h} - \varphi_0 - \sum_{i=1}^{p} \varphi_i RV_{t-i+1} \right)^2 + \lambda \sum_{i=1}^{p} |\beta_i| \right\} \tag{9}$$

with T being the number of available observations and λ denoting the tuning parameter which controls the shrinkage estimators in term of penalty strictness (Ding et al., 2021). Then the LASSO estimator in our case is defined as:

Table 3
Estimates of monthly HAR-RV models for corn futures.

Models	HAR-RV	HAR-RV-GPR	HAR-RV-EPU	HAR-RV-OVX	HAR-RV-VIX	HAR-RV-EVZ
τ_0	0.0519***	0.0520***	0.0520***	0.0535***	0.0459***	0.0457***
	(0.0024)	(0.0024)	(0.0024)	(0.0026)	(0.0025)	(0.0026)
τ_d	0.0661***	0.0660***	0.0661***	0.0627***	0.0591***	0.0635***
	(0.0116)	(0.0117)	(0.0117)	(0.0117)	(0.0115)	(0.0115)
τ_w	0.2575***	0.2577***	0.2576***	0.2532***	0.2456***	0.2435***
	(0.0216)	(0.0215)	(0.0216)	(0.0219)	(0.0217)	(0.0216)
τ_m	0.4467***	0.4467***	0.4467***	0.4595***	0.4193***	0.4222***
	(0.0198)	(0.0199)	(0.0199)	(0.0206)	(0.0209)	(0.0209)
θ		0.0000				
		(0.0000)				
γ			0.0000			
			(0.0000)			
ψ_d				0.0007***		
				(0.0002)		
ψ_w				−0.0006**		
				(0.0003)		
ψ_m				−0.0001		
				(0.0001)		
δ_d					0.0017***	
					(0.0004)	
δ_w					−0.0005	
					(0.0005)	
δ_m					−0.0003	
					(0.0002)	
ϕ_d						0.0049***
						(0.0014)
ϕ_w						−0.0007
						(0.0018)
ϕ_m						−0.0027***
						(0.0009)
R^2 (%)	65.61	65.59	65.60	65.75	66.54	66.28
HET test	0.41	0.39	0.39	0.42	0.44	0.46
Log-likelihood	5659.31	5659.45	5659.33	5668.23	5708.51	5695.21

Notes: We report the findings of monthly HAR models for corn futures. Our data span from 22.09.2008 to 30.04.2023. The *p*-values are computed for the heteroscedasticity (HET) test. The parentheses show the standard errors. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

$$\widehat{\beta}_{LASSO} = argmin\left\{\sum_{t=p}^{T}\left(RV_{t+h} - \varphi_0 - \sum_{i=1}^{p}\varphi_i RV_{t-i+1} - \theta X_t\right)^2 + \lambda\sum_{i=1}^{p}|\beta_i|\right\} \quad (10)$$

where X represents a particular uncertainty measure. Note that when an implied volatility index is used as a predictor of realized volatility, X includes its daily, weekly and monthly components.

At this stage, it is important to clarify that the LASSO method is mainly used for the out-of-sample exercise, whereas we report the results of HAR models for both in-sample and out-of-sample tests. The in-sample estimates of HAR models are crucial to understand the effects of different uncertainty indicators on the realized volatility of agricultural futures markets.

3.3. Out-of-sample forecasts

3.3.1. Forecasting evaluation

For comparing the accuracy of different forecasting models, we compute the heteroskedasticity adjusted root mean square error (HRMSE), proposed by Bollerslev and Ghysels (1996), as follows:

$$HRMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{RV_t - \widehat{RV}_t}{RV_t}\right)^2} \quad (11)$$

where T implies the number of observations to be predicted with RV_t and $\widehat{RV}_t$ being the observed and estimated volatilities on day t, respectively.

For robustness check, the mean absolute error (MAE) is also estimated. We define MAE as:

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|RV_t - \widehat{RV}_t| \quad (12)$$

Note that the in-sample estimation period spans from 22 September 2008 to 30 April 2021 and the out-of-sample period runs from 1 May 2021 to 30 April 2023.

3.3.2. Diebold and Mariano test

In order to verify the null hypothesis that two forecasts have the same accuracy, we apply the Diebold and Mariano (hereafter, DM) test (1995). This test assumes that $\boldsymbol{e_{it}} = \boldsymbol{RV_t} - \widehat{\boldsymbol{RV_t}}$ $(\boldsymbol{i} = \boldsymbol{1}, \boldsymbol{2})$ refers to the forecast errors and that $\boldsymbol{d_t} = \boldsymbol{f}(\boldsymbol{e_{1t}}) - \boldsymbol{f}(\boldsymbol{e_{2t}})$, with $\boldsymbol{f}(.)$ denoting a function of forecast errors. We then wish to test:

$$H_0 : E(d_t) = 0$$

Diebold and Mariano (1995) shows that the approximate asymptotic variance of $\overline{d}$ is given as:

$$Var(\overline{d}) \approx k^{-1}\left[\eta_0 + 2\sum_{l=1}^{p-1}\eta_l\right] \quad (13)$$

where η_l indicates the l-th autocovariance of d_t, which is estimated as:

$$\widehat{\eta} = k^{-1}\sum_{t=l+1}^{k}(d_t - \overline{d})(d_{t-l} - \overline{d}) \quad (14)$$

The DM test statistic is then defined as:

$$\mathbf{DM} = \left(\widehat{\boldsymbol{Var}(\overline{\boldsymbol{d}})}\right)^{-\mathbf{1}/\mathbf{2}}\overline{\boldsymbol{d}} \quad (15)$$

Given that $\boldsymbol{H_0}$ is true, the probability distribution of DM statistic is asymptotically normal.

Table 4
Estimates of daily HAR-RV models for wheat futures.

Models	HAR-RV	HAR-RV-GPR	HAR-RV-EPU	HAR-RV-OVX	HAR-RV-VIX	HAR-RV-EVZ
τ_0	0.0256***	0.0257***	0.0256***	0.0285***	0.0222***	0.0235***
	(0.0044)	(0.0044)	(0.0044)	(0.0046)	(0.0045)	(0.0046)
τ_d	0.2174***	0.2176***	0.2179***	0.2111***	0.2094***	0.2135***
	(0.0202)	(0.0201)	(0.0202)	(0.0202)	(0.0201)	(0.0201)
τ_w	0.5116***	0.5113***	0.5109***	0.5058***	0.5008***	0.4958***
	(0.0330)	(0.0330)	(0.0330)	(0.0335)	(0.0333)	(0.0334)
τ_m	0.1815***	0.1815***	0.1816***	0.1878***	0.1739***	0.1787***
	(0.0284)	(0.0285)	(0.0285)	(0.0295)	(0.0302)	(0.0302)
θ		−0.0000				
		(0.0000)				
γ			−0.0000			
			(0.0000)			
ψ_d				0.0012***		
				(0.0003)		
ψ_w				−0.0009**		
				(0.0004)		
ψ_m				−0.0002		
				(0.0002)		
δ_d					0.0021***	
					(0.0006)	
δ_w					−0.0006	
					(0.0008)	
δ_m					−0.0009**	
					(0.0004)	
ϕ_d						0.0032
						(0.0022)
ϕ_w						0.0018
						(0.0028)
ϕ_m						−0.0041***
						(0.0014)
R^2 (%)	55.93	55.93	55.94	56.13	56.30	56.13
HET test	0.52	0.51	0.48	0.54	0.55	0.51
Log-likelihood	4156.90	4157.07	4157.39	4166.58	4173.24	4166.49

Notes: We report the findings of daily HAR models for wheat futures. Our data span from 22.09.2008 to 30.04.2023. The *p*-values are computed for the heteroscedasticity (HET) test. The parentheses show the standard errors. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

4. Empirical findings

4.1. In-sample estimates

Tables 1–9 exhibit the in-sample estimates of daily, weekly and monthly HAR models for different agricultural markets. We first discuss the results for the corn futures market, which are presented in Tables 1–3. For instance, the estimates of Table 1 reveal that for the baseline daily HAR-RV process the coefficients of short-, medium- and long-term volatility components all appear to be statistically significant at 1% level. This finding indicates that corn futures volatility has a long memory. Next, the estimates of HAR-RV-GPR model suggest that the impact of geopolitical risk is insignificant, though the coefficients of short-, medium- and long-term volatility components are still significant. This result is quite unexpected as geopolitics often plays a pivotal role in food price fluctuations (Goyal and Steinbach, 2023). Interestingly, the effect of economic policy uncertainty is also found to be statistically insignificant as evidenced by the outcomes of HAR-RV-EPU process. Hence, corn price volatility seems to be insulated from the effects of news-based uncertainty indicators. It is also worth noting that the R^2 statistics do not increase either when we insert GPR and EPU to the HAR models. This holds for the log-likelihood values as well. Proceeding further, we find that OVX exerts a significant impact on corn futures volatility and that such effect is heterogeneous. In particular, both daily and monthly components for OVX are statistically significant implying that crude oil volatility has a short- and long-term impact on corn prices. The R^2 statistic also increases slightly confirming the importance of crude oil market uncertainty in predicting corn price volatility. Next, the results of the HAR-RV-VIX process show that the US equity market volatility has a short-term effect on corn futures volatility, though we do not find any evidence of long-term effects. More importantly, we notice a further improvement in the R^2 statistic. Finally, the estimates of the HAR-RV-EVZ model demonstrate that exchange rate volatility influences corn prices mainly in the long run as both short- and mid-term effects are found to be statistically insignificant.

When referring to the estimates of Table 2, which display the results of the weekly HAR models, we report similar findings. For example, the coefficients of all the volatility components (i.e., τ_d, τ_w and τ_m) for the baseline HAR process remain statistically significant at 1% level, thereby confirming the long memory property for corn futures volatility. Besides, the food price volatility is still insensitive to GPR or EPU shocks. In addition, the market-based uncertainty indicators have substantial effects on corn market volatility. Some exceptions are, however, also observed. As for instance, the mid-term volatility components are now significant for both crude oil and exchange rate implied volatility indexes. Notably, the R^2 statistics appear to be higher for the weekly HAR models when compared to the daily approaches.

Now, the results of the monthly HAR models, shown in Table 3, are mostly consistent with what we report in Tables 1 and 2. The main discrepancy is that we do not find any evidence of long-term effects for the OVX index. Moreover, the monthly component is now significant for the exchange rate VIX, suggesting that it exerts both short- and long-term impacts on corn futures volatility.

Looking at Table 4, we observe that for the baseline HAR-RV process the coefficients of short-, medium- and long-term volatility components are statistically significant at 1% level, which confirms the long memory property of wheat futures volatility. We also notice that wheat futures volatility does not react to GPR and EPU shocks. This finding is in line with what we report in Table 1, indicating that the volatility of two basic food commodities such as corn and wheat is not sensitive to news-based uncertainties. The findings further show that oil price uncertainty has mainly short-run impacts on the realized volatility of wheat futures

Table 5
Estimates of weekly HAR-RV models for wheat futures.

Models	HAR-RV	HAR-RV-GPR	HAR-RV-EPU	HAR-RV-OVX	HAR-RV-VIX	HAR-RV-EVZ
τ_0	0.0398***	0.0398***	0.0398***	0.0387***	0.0352***	0.0363***
	(0.0032)	(0.0032)	(0.0032)	(0.0034)	(0.0032)	(0.0033)
τ_d	0.1863***	0.1864***	0.1863***	0.1790***	0.1755***	0.1795***
	(0.0148)	(0.0148)	(0.0148)	(0.0148)	(0.0146)	(0.0143)
τ_w	0.4389***	0.4389***	0.4390***	0.4376***	0.4327***	0.4233***
	(0.0242)	(0.0243)	(0.0242)	(0.0244)	(0.0242)	(0.0243)
τ_m	0.2348***	0.2348***	0.2348***	0.2383***	0.2141***	0.2256***
	(0.0209)	(0.0209)	(0.0208)	(0.0216)	(0.0220)	(0.0220)
θ		0.0000				
		(0.0000)				
γ			0.0000			
			(0.0000)			
ψ_d				0.0014***		
				(0.0002)		
ψ_w				−0.0012***		
				(0.0003)		
ψ_m				−0.0001		
				(0.0002)		
δ_d					0.0032***	
					(0.0004)	
δ_w					−0.0019***	
					(0.0006)	
δ_m					−0.0005*	
					(0.0003)	
ϕ_d						0.0076***
						(0.0016)
ϕ_w						−0.0021
						(0.0021)
ϕ_m						−0.0042***
						(0.0010)
R^2 (%)	67.09	67.08	67.08	67.44	67.98	67.69
HET test	0.63	0.60	0.61	0.65	0.66	0.65
Log-likelihood	5268.48	5268.48	5268.49	5289.02	5319.43	5303.06

Notes: We report the findings of weekly HAR models for wheat futures. Our data span from 22.09.2008 to 30.04.2023. The *p*-values are computed for the heteroscedasticity (HET) test. The parentheses show the standard errors. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

prices as the long-term components for OVX is insignificant. VIX, on the other hand, exerts both short- and long-run effects. Finally, in case of the exchange rate volatility, only the long-term component is statistically significant. Note that the R^2 statistics tend to increase slightly when VIX indexes replace the news-based measures.

The estimates of the weekly HAR models for wheat futures market reveal that equity VIX along with exchange rate VIX influence the realized volatility both in the short run and long run, whereas OVX exerts only a short-term impact on the RV. The results of Table 5 further confirm that we are yet to find any statistically significant impact of geopolitical risk and economic policy uncertainty. The results of Table 6 are also in line with those shown in Table 5. The main inconsistency is that the US stock price implied volatility has only short-run impacts on the RV of wheat futures prices. Notably, the R^2 statistics appear to be higher for the monthly HAR models when compared to the daily and weekly approaches. This is also the case for the corn futures market.

The results for the Soybean oil futures market are presented in Tables 7–9. The estimates of daily HAR models, as shown in Table 7, suggest that the realized volatility of soybean oil futures also has a long memory. The results further confirm that all the implied volatility indexes have both short- and long-term effects on the RV, though the mid-term component for the exchange rate VIX index is found to be insignificant. Consistent with the earlier findings, we do not find statistically significant impacts of GPR and EPU on the RV of soybean oil futures prices. Next, the results of weekly and monthly HAR models also lead to similar conclusions. The only discrepancy is that crude oil volatility index only exerts a short-term impact on the RV as the coefficient of long-term component is not statistically significant. One interesting finding of the monthly HAR models is that the R^2 statistic is higher for the exchange rate VIX index (76.43) when compared to OVX (76.17) and VIX (76.12).

Overall, the in-sample estimates indicate that among the news-based and market-based risk measures the latter provide better forecasts for the realized volatility of agricultural futures markets. In fact, we do not find any evidence that the RV of food prices sensitive to shocks stemming from geopolitical risk or economic policy uncertainty. This finding is quite surprising given that prices of basic food commodities have increased substantially amid the Russo–Ukrainian war. However, one could expect that news-based measure such as GPR might exert an indirect effect on food prices through the energy markets. This argument could be valid, since oil prices witness a huge jump due to the recent geopolitical tensions which could have raised the price levels of agricultural commodities. Some recent studies including Raza et al. (2022), Saâdaoui et al. (2022) and Goyal and Steinbach (2023) also conclude the same.

4.2. Out-of-sample forecasts

Tables 10–15 report the forecast errors and the results of DM tests. Table 10, for instance, displays the HRMSE statistics for the corn futures market. Both HAR and LASSO models (see Panel A and Panel B, respectively) confirm that VIX index has better predictive contents than other risk measures. This result hold for daily, weekly and monthly horizons. The DM test also supports this by rejecting the null hypothesis that two forecasts have the same accuracy. Hence, both in-sample estimates and out-of-sample forecasts provide evidence in favour of market-based risk measures. We further observe that the LASSO model consistently outperforms the HAR process irrespective of the forecast horizons. This finding is in line with Ding et al. (2021) and Çepni et al. (2022). These studies also document that the forecast errors for LASSO are much lower than HAR.

Next, the numbers shown in Table 11 are also consistent with what

Table 6
Estimates of monthly HAR-RV models for wheat futures.

Models	HAR-RV	HAR-RV-GPR	HAR-RV-EPU	HAR-RV-OVX	HAR-RV-VIX	HAR-RV-EVZ
τ_0	0.0778***	0.0779***	0.0779***	0.0775***	0.0726***	0.0732***
	(0.0032)	(0.0032)	(0.0032)	(0.0034)	(0.0032)	(0.0034)
τ_d	0.1204***	0.1202***	0.1204***	0.1163***	0.1115***	0.1139***
	(0.0147)	(0.0148)	(0.0148)	(0.0148)	(0.0146)	(0.0146)
τ_w	0.2722***	0.2725***	0.2723***	0.2747***	0.2664***	0.2583***
	(0.0242)	(0.0242)	(0.0242)	(0.0246)	(0.0242)	(0.0243)
τ_m	0.3302***	0.3303***	0.3302***	0.3311***	0.2900***	0.3122***
	(0.0209)	(0.0209)	(0.0209)	(0.0217)	(0.0219)	(0.0220)
θ		0.0000				
		(0.0000)				
γ			0.0000			
			(0.0000)			
ψ_d				0.0008***		
				(0.0002)		
ψ_w				−0.0008**		
				(0.0003)		
ψ_m				0.0001		
				(0.0002)		
δ_d					0.0022***	
					(0.0005)	
δ_w					−0.0011*	
					(0.0006)	
δ_m					−0.0000	
					(0.0003)	
ϕ_d						0.0069***
						(0.0016)
ϕ_w						−0.0017
						(0.0021)
ϕ_m						−0.0035***
						(0.0010)
R^2 (%)	57.46	57.46	57.45	57.56	58.59	58.32
HET test	0.43	0.42	0.40	0.47	0.48	0.44
Log-likelihood	5270.55	5270.92	5270.56	5276.12	5320.10	5305.79

Notes: We report the findings of monthly HAR models for wheat futures. Our data span from 22.09.2008 to 30.04.2023. The *p*-values are computed for the heteroscedasticity (HET) test. The parentheses show the standard errors. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

we report in Table 10. Hence, for the both corn and wheat futures markets, we find that VIX and LASSO are the front-runners. However, for the soybean oil futures market, we find slightly different outcomes. Firstly, the results of Table 12 reveal that while VIX beats other risk measures for the daily horizon, OVX and EVZ are the winners for weekly and monthly horizons, respectively. Both HAR and LASSO conclude the same. Secondly, For the daily horizon, HAR produces better forecasts as evidenced by the HRMSE values, though LASSO outperforms HAR in other cases.

While looking at Tables 13–15, where MAE statistics are presented, it is further confirmed that market-based uncertainty measures have additional information which in not contained in the news-based indicators. Besides, LASSO consistently beats HAR irrespective of the forecast horizons. Hence, we conclude that volatility indexes are better predictors for food market risk than the news-based measures and that machine learning approach could be adopted when forecasting such risk.

It is also noteworthy that while our results are in line with earlier studies (Tian et al., 2017; Luo et al., 2022; Degiannakis et al., 2022), which find that the HAR model can effectively capture the volatility dynamics of food commodities, we stretch the existing literature in several aspects. Firstly, unlike the prior studies, we show that HAR models extended with the information on various market- and text-based uncertainty measures produce superior forecasts than the benchmark HAR models. Secondly, to the best of our knowledge, this is one of a few studies to provide empirical evidence that LASSO approach has better precision than the HAR model when predicting the realized volatility of agricultural futures markets. Hence, this is a novel finding given that the application of LASSO approach to modeling the volatility of food commodities is very limited.

4.3. *Asymmetric impact of various uncertainty measures*

In this section, we examine whether the impact of different uncertainty indicators on food commodities is asymmetric. This strand of analysis has important implications for risk valuation and hedging strategies. For instance, Shahzad et al. (2018) show that positive and negative changes in oil price uncertainty can lead to cyclical fluctuations in agricultural market investments. Besides, Sun et al. (2023) also argue that since food prices are sensitive to asymmetric shocks stemming from oil and currency markets, appropriate non-linear models should be employed to understand the food price risk more precisely.

In our analysis, we estimate the following model to capture the asymmetric effect of various risk measures:

$$RV_{t,t+h} = \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \varphi^+ \Delta X_t^+ + \varphi^- \Delta X_t^- + \varepsilon_t \tag{16}$$

where, $\Delta X_t^+ = max(\Delta X_t, 0)$ and $\Delta X_t^- = min(\Delta X_t, 0)$ with $\Delta X_t = X_t - X_{t-1}$. Note that X indicates a particular risk meausre. To assess whether there exist any asymmetric effects, we test for the following null hypothesis

$$H_0 : \varphi^+ = \varphi^-$$

Table 16 reports the results (*t*-statistics) of testing H_0. These findings indicate that mainly market-based risk measures have asymmetric effects on the volatility of agricultural futures markets. More specifically, GPR has no asymmetric effects at all, whereas EPU exerts only a long-term impact on the corn and soybean oil price volatilities as the corresponding monthly volatility components are significant at conventional levels.

One interesting finding is that OVX does not have any asymmetric effects on the corn and wheat futures volatility, although the soybean oil

Table 7
Estimates of daily HAR-RV models for soybean oil futures.

Models	HAR-RV	HAR-RV-GPR	HAR-RV-EPU	HAR-RV-OVX	HAR-RV-VIX	HAR-RV-EVZ
τ_0	0.0122***	0.0122***	0.0122***	0.0131***	0.0108***	0.0130***
	(0.0026)	(0.0026)	(0.0025)	(0.0026)	(0.0025)	(0.0029)
τ_d	0.2328***	0.2329***	0.2330***	0.2197***	0.2032***	0.2266***
	(0.0199)	(0.0199)	(0.0198)	(0.0199)	(0.0200)	(0.0199)
τ_w	0.4856***	0.4855***	0.4855***	0.4679***	0.4817***	0.4487***
	(0.0329)	(0.0330)	(0.0329)	(0.0341)	(0.0341)	(0.0339)
τ_m	0.2268***	0.2267***	0.2267***	0.2565***	0.2476***	0.2694***
	(0.0270)	(0.0271)	(0.0271)	(0.0294)	(0.0299)	(0.0287)
θ		−0.0000				
		(0.0000)				
γ			−0.0000			
			(0.0000)			
ψ_d				0.0011***		
				(0.0002)		
ψ_w				−0.0007***		
				(0.0002)		
ψ_m				−0.0003***		
				(0.0001)		
δ_d					0.0033***	
					(0.0004)	
δ_w					−0.0024***	
					(0.0005)	
δ_m					−0.0007**	
					(0.0003)	
ϕ_d						0.0043***
						(0.0014)
ϕ_w						−0.0006
						(0.0018)
ϕ_m						−0.0037***
						(0.0009)
R^2 (%)	69.99	69.98	69.98	70.28	70.68	70.22
HET test	0.27	0.26	0.23	0.32	0.34	0.31
Log-likelihood	5840.94	5841.01	5841.07	5859.79	5884.23	5856.01

Notes: We report the findings of daily HAR models for soybean oil futures. Our data span from 22.09.2008 to 30.04.2023. The *p*-values are computed for the heteroscedasticity (HET) test. The parentheses show the standard errors. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

volatility reacts significantly to the positive and negative changes in oil price uncertainty. This finding is in line with Shahzad et al. (2018), but differs from what documented by Sun et al. (2023). One possible explanation is that these results might be sensitive to the sample periods used. Nevertheless, the findings are crucial for biofuel policymaking given that soybean oil is the main feedstock for the US biodiesel market. Hence, appropriate hedging strategies need to be developed to deal with such asymmetric oil price risks.

Next, looking at the impact of VIX and EVZ indexes, we find that the volatility of these food commodities responds differently to the rise and fall in equity and currency market implied volatility indexes. For example, while all the volatility components for corn futures are sensitive to these two market-based risk measures, only the weekly component is found significant for the wheat futures volatility. Besides, for the soybean oil futures, we do not notice any significant long-term shocks emanating from VIX and EVZ.

Overall, we can conclude that investors and policymakers should closely observe the VIX indexes of energy, equity and currency markets, since these indicators contain important information for prediciting the volatility pattern of agricultural commodity markets.

4.4. Impact of biofuel volatility on food price volatility

Over the last few decades, a growing body of literature has investigated the linkage between biofuel and agricultural commodity prices (Chakravorty et al., 2012; Trujillo-Barrera et al., 2012; Zilberman et al., 2012; Kristoufek et al., 2012; Natanelov et al., 2013; Chiu et al., 2016; Dutta et al., 2018; Guo and Tanaka, 2022). The aforesaid nexus has received such attention due to the fact that the first generation of biofuels is produced mainly from key food commodities such as corn and soybean oil (Dutta et al., 2018; Guo and Tanaka, 2022). In the US, for instance, 40% of the corn goes into fuel ethanol (USDA Economic Research Service, 2019) and nearly 30% of field corn is used to produce this leading biofuel (FAOSTAT, 2019). In addition, as mentioned earlier, soybean oil remains the main feedstock for the biodiesel production with inputs reaching 8.3 billion pounds in 2020, which indicates that soybean oil represents nearly 70% of the US biodiesel feedstocks. The food-biofuel nexus, therefore, requires a continuous assessment as understanding such time-varying linkage is essential for the stability of both markets. To that end, we revisit this important association by estimating the following HAR model:

$$RV_{t,t+h} = \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \lambda_d BV_t + \lambda_w BV_{t-5,t} + \lambda_m BV_{t-22,t} + \varepsilon_t \tag{17}$$

where, BV refers to the volatility of S&P GSCI global biofuel index,[6] which is estimated from the GARCH (1,1) process given below[7]:

$$h_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^2 \tag{18}$$

where ω, α and β refer to the parameters of GARCH (1,1) process and h_t^2 indicates the conditional variance for the biofuel return index.

Table 17 reports the estimates of the above HAR model for daily horizon.[8] For the corn futures market, we find that all the volatility components are statistically significant, implying that biofuel uncertainty has both short- and long-term effects on the corn futures volatility.

[6] The data on biofuel prices are retrieved from the Bloomberg terminal.

[7] Table A2 reports that ARCH effects do exist in the S&P GSCI global biofuel index

[8] Table 17 reports the finding of daily HAR models for various food commodities. For weekly and monthly models, we find similar results.

Table 8
Estimates of weekly HAR-RV models for soybean oil futures.

Models	HAR-RV	HAR-RV-GPR	HAR-RV-EPU	HAR-RV-OVX	HAR-RV-VIX	HAR-RV-EVZ
τ_0	0.0197***	0.0197***	0.0198***	0.0204***	0.0187***	0.0213***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0020)
τ_d	0.1503***	0.1505***	0.1502***	0.1336***	0.1293***	0.1440***
	(0.0141)	(0.0141)	(0.0141)	(0.0141)	(0.0142)	(0.0141)
τ_w	0.4971***	0.4969***	0.4971***	0.4959***	0.4865***	0.4526***
	(0.0234)	(0.0234)	(0.0234)	(0.0239)	(0.0242)	(0.0239)
τ_m	0.2628***	0.2627***	0.2629***	0.2856***	0.2829***	0.3154***
	(0.0192)	(0.0192)	(0.0192)	(0.0207)	(0.0212)	(0.0203)
θ		−0.0000				
		(0.0000)				
γ			0.0000			
			(0.0000)			
ψ_d				0.0013***		
				(0.0001)		
ψ_w				−0.0012***		
				(0.0002)		
ψ_m				−0.0001		
				(0.0001)		
δ_d					0.0023***	
					(0.0003)	
δ_w					−0.0015***	
					(0.0004)	
δ_m					−0.0007***	
					(0.0002)	
ϕ_d						0.0042***
						(0.0010)
ϕ_w						0.0002
						(0.0012)
ϕ_m						−0.0046***
						(0.0006)
R^2 (%)	80.87	80.87	80.87	81.36	81.37	81.27
HET test	0.53	0.52	0.50	0.58	0.57	0.54
Log-likelihood	7071.27	7071.42	7071.32	7118.80	7119.69	7109.96

Notes: We report the findings of weekly HAR models for soybean oil futures. Our data span from 22.09.2008 to 30.04.2023. The *p*-values are computed for the heteroscedasticity (HET) test. The parentheses show the standard errors. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table 9
Estimates of monthly HAR-RV models for soybean oil futures.

Models	HAR-RV	HAR-RV-GPR	HAR-RV-EPU	HAR-RV-OVX	HAR-RV-VIX	HAR-RV-EVZ
τ_0	0.0412***	0.0412***	0.0412***	0.0423***	0.0405***	0.0461***
	(0.0018)	(0.0018)	(0.0018)	(0.0019)	(0.0018)	(0.0020)
τ_d	0.1067***	0.1067***	0.1066***	0.0975***	0.0921***	0.0991***
	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0145)	(0.0142)
τ_w	0.2745***	0.2746***	0.2746***	0.2831***	0.2689***	0.2367***
	(0.0237)	(0.0238)	(0.0238)	(0.0245)	(0.0247)	(0.0242)
τ_m	0.4279***	0.4279***	0.4279***	0.4536***	0.4451***	0.4888***
	(0.0195)	(0.0195)	(0.0195)	(0.0212)	(0.0217)	(0.0206)
θ		0.0000				
		(0.0000)				
γ			0.0000			
			(0.0000)			
ψ_d				0.0006***		
				(0.0001)		
ψ_w				−0.0009***		
				(0.0002)		
ψ_m				0.0001		
				(0.0001)		
δ_d					0.0016***	
					(0.0003)	
δ_w					−0.0011***	
					(0.0003)	
δ_m					−0.0004**	
					(0.0002)	
ϕ_d						0.0051***
						(0.0010)
ϕ_w						−0.0019
						(0.0013)
ϕ_m						−0.0040***
						(0.0007)
R^2 (%)	75.88	75.85	75.86	76.17	76.12	76.43
HET test	0.39	0.37	0.37	0.45	0.46	0.51
Log-likelihood	7018.42	7018.42	7018.42	7043.03	7039.60	7063.21

Notes: We report the findings of monthly HAR models for soybean oil futures. Our data span from 22.09.2008 to 30.04.2023. The *p*-values are computed for the heteroscedasticity (HET) test. The parentheses show the standard errors. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table 10
HRMSE statistics and DM test results for the corn futures market.

	Daily		Weekly		Monthly	
	HRMSE	DM statistic	HRMSE	DM statistic	HRMSE	DM statistic
Panel A: HAR models						
HAR-RV	0.070105	−1.60**	0.056750	−2.00**	0.066978	−4.09***
HAR-RV-GPR	0.070102	−1.62**	0.056777	−1.96**	0.066979	−4.10***
HAR-RV-EPU	0.070112	−1.62**	0.056749	−1.99**	0.066977	−4.09***
HAR-RV-OVX	0.069872	-1.24	0.056501	−1.49*	0.067103	−4.58***
HAR-RV-VIX	**0.069500**		**0.056043**		**0.065964**	
HAR-RV-EVZ	0.070342	−1.82**	0.057437	-2.87***	0.068425	−5.87***
Panel B: LASSO methods						
AR(22)	0.069610	-1.77**	0.055956	−2.58***	0.064739	−1.98**
AR(22)-GPR	0.069375	−1.35*	0.055867	−2.99***	0.064730	−1.92**
AR(22)-EPU	0.069375	−1.31*	0.055917	-1.34*	0.064731	−1.96**
AR(22)-OVX	0.069155	-0.85	0.055423	-1.72**	0.064731	−1.96**
AR(22)-VIX	**0.068906**		**0.055378**		**0.064711**	
AR(22)-EVZ	0.069342	−2.00**	0.055466	−1.68**	0.064745	−2.28**

Note: In this table we present the HRMSE statistics and the findings of Diebold-Mariano (DM) tests for the corn futures market. Panel A shows the out-of-sample forecasts for the HAR models, while Panel B demonstrates the same for the LASSO methods. The in-sample estimation period spans from 22 September 2008 to 30 April 2021 and the out-of-sample period runs from 1 May 2021 to 30 April 2023. The highlighted observations indicate the lowest errors for different methods. ***, ** and * refer to statistical significance at 1%, 5% and 10% levels, respectively.

Table 11
HRMSE statistics and DM test results for the wheat futures market.

	Daily		Weekly		Monthly	
	HRMSE	DM statistic	HRMSE	DM statistic	HRMSE	DM statistic
Panel A: HAR models						
HAR-RV	0.096688	−2.21**	0.082175	−3.26***	0.095194	−5.23***
HAR-RV-GPR	0.096682	−2.17**	0.082178	−3.51***	0.095198	−5.39***
HAR-RV-EPU	0.096661	−1.76**	0.082175	−3.26***	0.095195	−5.28***
HAR-RV-OVX	0.101562	−3.42***	0.082626	−1.43*	0.095217	−5.96***
HAR-RV-VIX	**0.096614**		**0.082162**		**0.094743**	
HAR-RV-EVZ	0.097029	−2.92***	0.082880	−1.93**	0.099202	−2.81***
Panel B: LASSO methods						
AR(22)	0.095964	−1.33*	0.081957	−2.01**	0.093192	−2.00**
AR(22)-GPR	0.095712	−1.88**	0.081956	−2.11**	0.093191	−1.96**
AR(22)-EPU	0.095719	−1.91**	0.081959	−1.98**	0.093192	−2.01**
AR(22)-OVX	0.095453	-0.69	0.081955	−2.03**	0.093194	−2.08**
AR(22)-VIX	**0.095320**		**0.081878**		**0.093099**	
AR(22)-EVZ	0.095931	−1.56*	0.081949	−1.87**	0.093163	−1.34*

Note: In this table we present the HRMSE statistics and the findings of Diebold-Mariano (DM) tests for the wheat futures market. Panel A shows the out-of-sample forecasts for the HAR models, while Panel B demonstrates the same for the LASSO methods. The in-sample estimation period spans from 22 September 2008 to 30 April 2021 and the out-of-sample period runs from 1 May 2021 to 30 April 2023. The highlighted observations indicate the lowest errors for different methods. ***, ** and * refer to statistical significance at 1%, 5% and 10% levels, respectively.

Table 12
HRMSE statistics and DM test results for the soybean oil futures market.

	Daily		Weekly		Monthly	
	HRMSE	DM statistic	HRMSE	DM statistic	HRMSE	DM statistic
Panel A: HAR models						
HAR-RV	0.053135	−1.10	0.047276	−2.01**	0.061430	−3.54***
HAR-RV-GPR	0.053177	−1.21	0.047307	−2.41**	0.061436	−3.61***
HAR-RV-EPU	0.053129	−1.03	0.047275	−1.99**	0.061431	−3.51***
HAR-RV-OVX	0.052936	−0.72	**0.046907**		0.061282	−3.48***
HAR-RV-VIX	**0.052746**		0.047213	−1.20	0.061349	−3.57***
HAR-RV-EVZ	0.052963	−0.76	0.047206	−1.45*	**0.060742**	
Panel B: LASSO methods						
AR(22)	0.053378	−1.01	0.047239	−1.86**	0.061161	−3.36***
AR(22)-GPR	0.053395	−0.97	0.047285	−2.14**	0.061142	−3.67***
AR(22)-EPU	0.053321	−0.79	0.047260	−2.05**	0.061144	−3.66***
AR(22)-OVX	0.053141	−0.33	**0.046884**	−1.43*	0.060970	−3.18***
AR(22)-VIX	**0.053047**		0.047250	−1.38*	0.061078	−3.71***
AR(22)-EVZ	0.053313	−1.01	0.047163		**0.060463**	

Note: In this table we present the HRMSE statistics and the findings of Diebold-Mariano (DM) tests for the soybean oil futures market. Panel A shows the out-of-sample forecasts for the HAR models, while Panel B demonstrates the same for the LASSO methods. The in-sample estimation period spans from 22 September 2008 to 30 April 2021 and the out-of-sample period runs from 1 May 2021 to 30 April 2023. The highlighted observations indicate the lowest errors for different methods. ***, ** and * refer to statistical significance at 1%, 5% and 10% levels, respectively.

Looking at the estimates for the wheat futures market, we document that the short- and mid-term volatility components for BV appear to be statistically significant. Hence, the impact of biofuel volatility on the wheat futures market seems to be diminishing in the long run. Similar findings are also observed for the soybean oil futures market. In sum, we find that biofuel volatility exerts heterogeneous effects on these major food commodities.

These results have key implications for policymakers. For instance, our analysis shows that the global biofuel market has a long-term impact on the corn futures volatility, indicating that uncertainty in biofuel prices might cause a chaos in corn prices. While we do not find such long-term effects in case of wheat and soybean oil futures, volatility might transmit from one market to another as a consequence of market integration. Therefore, governments should increase the levels of biofuel feedstock reserves in order to reduce the volatility of corn and soybean oil futures. Besides, promoting better market monitoring systems (e.g., introducing the biofuel futures market globally) will also play a pivotal role in minimizing the adverse impact of biofuel volatility on feedstock markets. Adopting such policies are crucial for stabilizing the prices of important food commodities.

4.5. *Does food price volatility react to climate risk?*

Given that extreme weather events often cause high uncertainties in global food prices, several recent studies (Nam, 2021; Makkonen et al., 2021) have investigated the impact of climate risk on agricultural commodity markets. Makkonen et al. (2021) for instance, find that environmental risk exerts a negative impact on corn and soybean oil futures prices. Nam (2021), however, find that higher climate risk leads to a growth in agricultural commodity prices. Overall, the results of prior studies are somewhat conflicting and hence the effect of climate risk on agricultural commodity markets merits further investigations.

Our study differs from the aforementioned articles in several aspects. Firstly, we examine the impacts of climate risk on the realized volatility

Table 13
MAE statistics and DM test results for the corn futures market.

	Daily		Weekly		Monthly	
	MAE	DM statistic	MAE	DM statistic	MAE	DM statistic
Panel A: HAR models						
HAR-RV	0.044205	−2.17**	0.032664	−0.90	0.050043	−3.02***
HAR-RV-GPR	0.044213	−2.19**	0.032660	−0.87	0.050044	−3.01***
HAR-RV-EPU	0.044203	−2.16**	0.032663	−0.04	0.050042	−3.01***
HAR-RV-OVX	0.044197	−1.92**	**0.032500**		0.050069	−2.87***
HAR-RV-VIX	0.044161	−1.96**	0.032652	−0.50	**0.049244**	
HAR-RV-EVZ	**0.043384**		0.032727	−0.47	0.050266	−2.44**
Panel B: LASSO methods						
AR(22)	0.043734	−2.27**	0.031289	−2.81***	0.049222	−2.26**
AR(22)-GPR	0.043678	-1.77**	0.031254	−2.54***	0.049213	−2.08**
AR(22)-EPU	0.043664	−1.72**	0.031284	−2.20**	0.049213	−2.08**
AR(22)-OVX	0.043741	−1.74**	0.030856	−2.16***	0.049212	−2.06**
AR(22)-VIX	0.043823	−2.17**	0.030753	−1.78**	**0.049194**	
AR(22)-EVZ	**0.043057**		**0.030401**		0.049218	−1.91**

Note: In this table we present the MAE statistics and the findings of Diebold-Mariano (DM) tests for the corn futures market. Panel A shows the out-of-sample forecasts for the HAR models, while Panel B demonstrates the same for the LASSO methods. The in-sample estimation period spans from 22 September 2008 to 30 April 2021 and the out-of-sample period runs from 1 May 2021 to 30 April 2023. The highlighted observations indicate the lowest errors for different methods. ***, ** and * refer to statistical significance at 1%, 5% and 10% levels, respectively.

Table 14
MAE statistics and DM test results for the wheat futures market.

	Daily		Weekly		Monthly	
	MAE	DM statistic	MAE	DM statistic	MAE	DM statistic
Panel A: HAR models						
HAR-RV	0.048717	−3.75***	0.043230	−2.69***	0.054421	−2.49**
HAR-RV-GPR	0.048742	−4.06***	0.043236	−2.71***	0.054422	−2.51**
HAR-RV-EPU	0.048698	−2.81***	0.043231	−2.66***	0.054421	−2.49**
HAR-RV-OVX	0.051583	−5.74***	0.043004	−2.01**	0.054431	−2.83***
HAR-RV-VIX	0.048288	−2.17**	0.042731	−1.62*	**0.053870**	
HAR-RV-EVZ	**0.047643**		**0.042105**		0.054253	−0.88
Panel B: LASSO methods						
AR(22)	0.047733	−1.83**	0.041261	−1.71**	0.052238	−1.69**
AR(22)-GPR	0.048424	−3.35***	0.041316	−1.87**	0.052237	−1.79**
AR(22)-EPU	0.048383	−3.01***	0.041305	−1.91**	0.052237	−1.79**
AR(22)-OVX	0.048199	−2.93***	0.041334	−2.14**	0.052231	−1.63**
AR(22)-VIX	0.048083	−2.58***	0.041265	−1.77**	0.052220	−1.35*
AR(22)-EVZ	**0.047296**		**0.041202**		**0.052100**	

Note: In this table we present the MAE statistics and the findings of Diebold-Mariano (DM) tests for the wheat futures market. Panel A shows the out-of-sample forecasts for the HAR models, while Panel B demonstrates the same for the LASSO methods. The in-sample estimation period spans from 22 September 2008 to 30 April 2021 and the out-of-sample period runs from 1 May 2021 to 30 April 2023. The highlighted observations indicate the lowest errors for different methods. ***, ** and * refer to statistical significance at 1%, 5% and 10% levels, respectively.

of agricultural futures markets, while Makkonen et al. (2021) and Nam (2021) explore such impacts on the return data. Besides, unlike the existing literature, we use intraday high frequency trading data to measure the realized volatility of different futures markets. Finally, we measure climate risk using the recently published climate policy uncertainty (CPU) index introduced by Gavriilidis (2021). Employing this index, which is a text-based indicator of environmental risk, could be advantageous for assessing the aforesaid linkage given that this measure is developed using several keywords relevant to climate and environmental uncertainties (see Gavriilidis, 2021).

Note that the only monthly data are available for the CPU index. Therefore, we employ the MIDAS (mixed-data sampling) process, proposed by Ghysels et al. (2004), to examine whether the daily realized volatility of various agricultural commodities is sensitive to climate risk. The MIDAS model is particularly useful as it allows for data sampled at different frequencies to be used in the same regression. Hence, we consider applying the MIDAS process to manage the data frequency mismatch between the daily realized volatility data and the monthly CPU index.

The MIDAS process is defined as follows:

$$RV_{t+1} = \alpha + \beta W\left(L^{\frac{1}{m}};\theta\right)x_t^{(m)} + \varepsilon_t \tag{19}$$

Where, R_t indicates the realized volatility of a specific agricultural futures market at time t, $W\left(L^{\frac{1}{m}};\theta\right) = \sum_{k=0}^{K}\omega(k;\theta)L^{k/m}$ with $\omega(k;\theta)$ implying a parameterized weight function and $L^{1/m}$ denotes a lag operator such that $L^{1/m}x_t^{(m)} = x_{t-1/m}^{(m)}$. In our analysis, we replace x with CPU.

Table 15
MAE statistics and DM test results for the soybean oil futures market.

	Daily		Weekly		Monthly	
	MAE	DM statistic	MAE	DM statistic	MAE	DM statistic
Panel A: HAR models						
HAR-RV	0.036078	−2.37**	0.031695	−2.78***	0.041443	−3.52***
HAR-RV-GPR	0.036092	−2.40**	0.031723	−2.86***	0.041451	−3.62***
HAR-RV-EPU	0.036090	−2.39**	0.031689	−2.74***	0.041444	−3.54***
HAR-RV-OVX	0.03815	−4.61***	**0.031214**		0.041089	−2.06**
HAR-RV-VIX	**0.035400**		0.031252	-0.16	0.041194	−2.42**
HAR-RV-EVZ	0.035758	−1.38*	0.031446	−1.10	**0.040751**	
Panel B: LASSO methods						
AR(22)	0.036160	−0.83	0.031740	−1.72**	0.041197	−3.71***
AR(22)-GPR	0.036496	−2.11**	0.031976	−3.18***	0.041181	−3.35***
AR(22)-EPU	0.036501	−2.13**	0.031947	−3.02***	0.041182	−3.32***
AR(22)-OVX	0.036182	−1.08	**0.031437**		0.040796	−1.46*
AR(22)-VIX	**0.035907**		0.031480	-0.19	0.040973	−2.32**
AR(22)-EVZ	0.036135	−0.96	0.031707	−1.33*	**0.040553**	

Note: In this table we present the MAE statistics and the findings of Diebold-Mariano (DM) tests for the soybean oil futures market. Panel A shows the out-of-sample forecasts for the HAR models, while Panel B demonstrates the same for the LASSO methods. The in-sample estimation period spans from 22 September 2008 to 30 April 2021 and the out-of-sample period runs from 1 May 2021 to 30 April 2023. The highlighted observations indicate the lowest errors for different methods. ***, ** and * refer to statistical significance at 1%, 5% and 10% levels, respectively.

Table 16
Test of asymmetric impacts.

Models	Corn futures	Wheat futures	Soybean oil futures
Panel A: Daily horizon			
GPR	0.2052	−0.9720	0.0972
EPU	−1.4734	0.1670	−1.8492*
OVX	0.0227	1.0924	2.2336**
VIX	2.4487**	1.1166	2.7710***
EVZ	3.0355***	4.2197***	1.7663*
Panel B: Weekly horizon			
GPR	0.1212	0.3929	0.5529
EPU	−1.4275	−0.9694	−1.4155
OVX	0.2009	0.5501	1.4990
VIX	3.1039***	2.5662**	3.5485***
EVZ	3.4840***	6.4580***	2.5899***
Panel C: Monthly horizon			
GPR	−0.3193	1.3631	0.7401
EPU	−1.1928*	−1.5410	−2.1405**
OVX	−0.9798	−0.8666	−2.1357**
VIX	3.1384***	2.8745***	0.3660
EVZ	3.5642***	4.7709***	−0.1685

Notes: This table presents the results (t-statistics) of testing the null hypothesis $H_0 : \varphi^+ = \varphi^-$. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table 17
Impact of biofuel volatility on agricultural commodity markets.

Models			Corn futures	Wheat futures	Soybean oil futures
τ_0			0.0270***	0.0302***	0.0123***
			(0.0045)	(0.0046)	(0.0026)
τ_d			0.2012***	0.2164***	0.2339***
			(0.0198)	(0.0201)	(0.0199)
τ_w	0.2783***	0.4709***	0.4338***		
	(0.0393)	(0.0345)	(0.0360)		
τ_m	0.3637***	0.1789***	0.2797***		
	(0.0430)	(0.0328)	(0.0321)		
λ_d	0.0032***	0.0028***	0.0014***		
	(0.0007)	(0.0007)	(0.0004)		
λ_w	−0.0019**	−0.00018**	−0.0011**		
	(0.0009)	(0.0008)	(0.0005)		
λ_m	−0.0007*	−0.0004	−0.0003		
	(0.0004)	(0.0003)	(0.0002)		
R^2 (%)	48.91	56.28	69.84		
HET test	0.27	0.31	0.42		
Log-likelihood			3877.65	4169.26	5848.38

Notes: This table presents the effect of biofuel volatility (BV) on various food commodities. We report the findings of daily HAR models. Our data span from 22.09.2008 to 30.04.2023. The p-values are computed for the heteroscedasticity (HET) test. The parentheses show the standard errors. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

It is noteworthy that we employ the unrestricted MIDAS or U-MIDAS model instead of the conventional MIDAS approach, since the unrestricted version can be estimated by the ordinary least squares (OLS) method, thereby simplifying the estimation procedure relative to the traditional approach. Besides, the U-MIDAS process has the advantage of a higher flexibility than the conventional MIDAS model given that no structure is imposed on the shape of the weight function (Foroni et al., 2015).[9]

Table 18 shows the estimates of the U-MIDAS models. We find that climate risk exerts a positive effect on the realized volatility of both corn and soybean oil futures markets. For the wheat futures, however, we do not find any significant result. Such a positive linkage indicates that increasing climate risk leads to an upsurge in the volatility levels for

Table 18
Impact of climate policy uncertainty on the realized volatility of agricultural commodities.

	Estimate	Standard error	t-statistic	p-value
Corn futures	0.000066***	0.000023	2.93	0.00
Wheat futures	0.000031	0.000021	1.45	0.14
Soybean oil futures	0.000067***	0.000014	4.77	0.00

Notes: This table reports the estimates of U-MIDAS model. *** refers to statistical significance at 1% level.

[9] The estimation of the traditional MIDAS model requires. Earlier studies show that (Ghysels, 2016; Zhang and Wang, 2019; Gong et al., 2022) several weight functions such as the Almon polynomial weight function, the Exponential Almon polynomial weight function, and the Beta weight function can be applied to the traditional MIDAS model.

corn and soybean oil futures markets. This finding could be attributed to the fact that during the periods of high climate risk, both consumers and investors might delay their decision-making process, which raises the volatility of these commodities.

5. Conclusions

In this study, we aim to model the realized volatility of agricultural futures markets using the information on various uncertainty measures. In doing so, the future prices of three basic food commodities such as corn, wheat and soybean oil are analyzed. Methodologically, we employ the HAR process to investigate the realized volatility of these futures markets. For comparison purpose, the LASSO model is also applied. The in-sample estimates indicate that among the various news-based and market-based risk measures the latter provide better forecasts for the realized volatility of agricultural futures markets. The out-of-sample forecasts also confirm the same with the LASSO method outperforming the HAR process.

Our findings offer important implications to commodity market investors and policymakers. Investors, for instance, need to have sound knowledge on the time-varying associations between various uncertainty indicators and the realized volatility of agricultural futures prices for developing appropriate hedging strategies. In particular, market participants should closely observe the implied volatility indexes when making asset allocation decisions on agricultural futures markets. Moreover, our findings should be beneficial for those stakeholders who apply financial derivatives to hedge food price uncertainty. Note that although news-based risk measures do not have any significant effects on the agricultural futures markets, they should still receive proper attention as these indicators (e.g., geopolitical uncertainty) could transmit risk to food prices through oil, stock and exchange markets.

Decision makers, on the other hand, could utilize our results for policy formulations. One major policy could be increasing the application of clean energies. The growing use of renewable fuels such as ethanol could reduce the dependence on fossil fuels. The energy transition is also crucial for bringing greater energy self-sufficiency, thereby decreasing the adverse effects of geopolitical conflicts. However, when lifting the use of biofuels, key concerns for policymakers are food price stability and food security given that biofuel production often competes for land with agricultural production. Hence, precise policies should be developed to moderate such risks so that global agricultural markets remain stable.

A limitation of this empirical research is that the list of the agricultural commodity futures considered in our analysis is not exhaustive. To this end, future studies could investigate the impact of various uncertainties on additional commodities such as rapeseed oil, cocoa, coffee etc. Moreover, future research could also assess the time-varying linkages between food commodities and other important financial markets (e.g., metal markets) during the periods of high uncertainties. Besides, it is also crucial to examine how agricultural market investors should adjust their portfolio to hedge climate risk following extreme weather events. Such investigations would help investors develop precise portfolio strategies, which might offer long-term benefits through compensating the losses due to weather anomalies.

CRediT authorship contribution statement

Anupam Dutta: Writing – original draft, Investigation, Formal analysis, Data curation, Conceptualization. **Gazi Salah Uddin:** Writing – original draft, Project administration, Investigation, Conceptualization. **Lin Wen Sheng:** Writing – original draft, Methodology, Data curation. **Donghyun Park:** Writing – review & editing, Writing – original draft, Supervision. **Xuening Zhu:** Methodology, Project administration, Supervision, Writing – original draft.

Appendix A

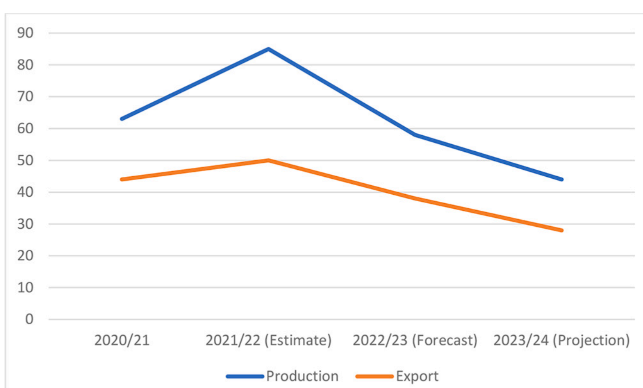

Fig. A1. The production and export of Ukrainian crops (in million tons).

Table A1
Summary statistics.

	Corn RV	Wheat RV	Soybean oil RV	GPR	EPU	OVX	VIX	EVZ
Mean	0.2360	0.2900	0.2300	105.90	125.06	39.12	20.32	9.95
Std. Dev.	0.1140	0.1157	0.0896	47.26	84.65	18.19	9.62	3.80
Skewness	2.49	3.16	2.02	2.37	2.32	3.67	2.33	1.42
Kurtosis	18.77	29.33	10.18	15.12	11.43	27.29	10.62	5.97
Jarque-Bera	41,213.80***	110,426.9***	10,218.23***	25,517.62***	13,984.91***	96,966.48***	12,030.83***	2556.87***
ADF	−7.72***	−8.68***	−6.29***	−11.84***	−6.64***	−5.43***	−5.66***	−3.84***
PP	−53.56***	−45.55***	−34.04***	−49.86***	−39.02***	−6.22***	−5.70***	−3.80***

Notes: *** indicates statistical significance at 1% level.

Table A2
Testing for ARCH effects in the S&P GSCI global biofuel index.

F-statistic	*p*-value	Decision
83.77198***	0.00	ARCH effects exist

Notes: *** indicates statistical significance at 1% level.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107754.

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