https://doi.org/10.17221/147/2022-AGRICECON

The volatility connectedness among fertilisers and agricultural crop prices: Evidence from selected main agricultural products

Harun Uçak[1]*, *Yakup Arı*[1], *Esin Yelgen*[2]

[1]*Department of Economics, Faculty of Economics, Administrative and Social Sciences, Alanya Alaaddin Keykubat University, Alanya, Turkey*

[2]*Department of Business Administration, Faculty of Economics, Administrative and Social Sciences, Alanya Alaaddin Keykubat University, Alanya, Turkey*

**Corresponding author: harun.ucak@alanya.edu.tr*

Citation: Uçak H., Arı Y., Yelgen E. (2022): The volatility connectedness among fertilisers and agricultural crop prices: Evidence from selected main agricultural products. Agric. Econ. – Czech, 68: 348–360.

Abstract: The price of fertiliser, which is one of the most important inputs of agricultural production, has increased significantly in recent years. In this study, we empirically analysed the effect of volatility in fertiliser prices on selected agricultural products by using the Diebold-Yilmaz connectedness approach, which is based on time-varying parameter (TVP) vector auto-regression (VAR). The findings showed that the spread of volatility and the interconnectedness between these variables increased in times of crisis and that the risk pass-through was due to fertiliser prices. However, empirical results showed that the price volatility of phosphate rock and urea was highly correlated to the volatility of other products. Furthermore, we found that sugar, soybean and cotton were the agricultural products most vulnerable to the effects of external shocks.

Keywords: Diebold-Yilmaz approach; dynamic connectedness; time-varying parameter vector auto-regression; volatility spillover

The global food system faces many challenges, including wars, disease, climate change, resource depletion and population growth, as well as changes in diets and agricultural land-use practices. Many inputs, such as seeds, seedlings and saplings, fertilisers, pesticides, labour, energy, machinery, equipment, vehicles, and land, are needed to produce agricultural products, and the costs of these inputs are important for the sustainability of agricultural production. Fertiliser, one of the most important of these inputs, is a substance applied to the soil to increase productivity and quality by preventing the formation of diseases and disorders in agricultural products. This substance provides the nutritional components, nitrogen, phosphorus and potassium, elements that enable plants to grow. Fertiliser is used when the soil is not able to supply the nutritional components necessary for adequate growth. Although nitrogen should be applied every year for plants that need nitrogen, there is no requirement for phosphorus and potassium because phosphorus and potassium are relatively stable in the soil unless they are depleted by agricultural activities. Therefore, it is necessary to measure the levels of phosphorus and potassium in the soil at regular intervals. However, the types of crops grown also affect the requirements for fertilisers. For example, legumes and soybeans can produce their own nitrogen from the air, so they do not require nitrogen fertiliser. However, fertiliser application is of great importance for crops such as wheat, maize, rice, sugar beet and peanuts (Ali and Habib 2022; Yang et al. 2022a; Zhao et al. 2022). Increases in the prices of fertilisers, which are of great importance for

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some product types, may adversely affect the agricultural activities of the producers. For example, in the face of price increases, many producers may switch products (e.g. soybean instead of corn) or use insufficient or no fertiliser (Brunelle et al. 2015). Chandio et al. (2015) found that an increase in fertiliser prices led to less fertiliser use, so agricultural productivity decreased. They found that when fertiliser prices increased by 1%, sugar cane, corn, and rice production decreased. Regarding this issue, Tan et al. (2005) stated that the continued depletion of nitrogen, phosphorus, and potassium in the soil as a result of agricultural activities, combined with the decrease in fertiliser use, caused low production levels and posed a threat to agricultural sustainability.

Fertilisers that are used to increase yields within the framework of agricultural sustainability have a link with the availability of energy and natural gas. For example, natural gas is the most important variable in the production of nitrogen-supplying fertilisers. Therefore, energy prices are one of the main factors that increase fertiliser prices (Gardebroek and Hernandez 2013; Brunelle et al. 2015; Etienne et al. 2016). Chojnacka et al. (2022) stated that with the increase in natural gas prices, there was a 300% increase in the price of nitrogen fertilisers in 2021. Thorn et al. (2022) stated, that considering the recent price increases, phosphorus fertiliser prices doubled in 2021 (643 USD/metric ton) compared with what they were in 2017 (326 USD/metric ton). Russia is one of the top three producers of natural gas, nitrogen, phosphorus and potassium. Therefore, the war between Russia and Ukraine is expected to cause a further increase in world fertiliser prices (Randive et al. 2021). In addition, approximately 45% of phosphorus resources are found in so-called geopolitically unstable regions in Algeria, Iraq, Jordan, and Syria. This fact makes sustainable access to sources and a consistent phosphorus supply uncertain (Olagunju et al. 2021).

Theoretical background. Price volatility can cause instability and uncertainty in agricultural markets. Increasing volatility in prices can lead to negative effects such as food shortages, political crises, poverty and unstable conditions in agricultural markets (Santeramo and Lamonaca 2019). Many factors can affect price volatility. There is a vast literature on the dynamics and causes of price volatility in agricultural markets. For example, Zhang et al. (2010), Serra (2011), Gardebroek and Hernandez (2013), Tadesse et al. (2014), Gozgor and Memis (2015), Nwoko et al. (2016), Adrangi et al. (2017), Fasanya and Akinbowale (2019), Chen et al. (2020), and Sarwar et al. (2020), all examined the effects of oil price changes on selected agricultural products. Among them, Zhang et al. (2010) and Gardebroek and Hernandez (2013) concluded that there is no price relationship between oil and agricultural commodity prices, whereas the results of other studies showed that oil and food prices move together. In other words, as oil prices increase, food prices also increase. Moreover, Yanıkkaya et al. (2013), Balcılar and Bekun (2019), Radmehr and Henneberry (2020), and Uçak et al. (2022) examined the effects of energy and exchange rates on agricultural product prices. They found that selected food prices increased in response to increases in energy and real exchange rates. Furthermore, Mawejje (2016) examined the importance of energy and climate shocks in food price processes and concluded that energy prices have a long-term cointegration relationship with food prices and that temperature shocks are more important than precipitation shocks in explaining the variability in food prices. Matoskova (2011), Santeramo et al. (2018), and Santeramo and Lamonaca (2019) discussed the effects of supply-and-demand movements and arbitrage factors on agricultural product prices. Santeramo and Lamonaca (2019) found that demand shocks diminished price volatility, whereas supply shocks exacerbated it. They also found a negative relationship between arbitrage and grain price volatility.

It is possible to divide the studies dealing with the effects of fertiliser prices on fertiliser use within the framework of agricultural activities basically into two groups. The study investigators in the first group examine the factors affecting fertiliser prices, whereas those in the second group examine the use of fertilisers. We see that the first group of studies focused on the effects of oil and natural gas prices on fertiliser prices. For example, Sanyal et al. (2015) evaluated the effects of volatility in crude oil and natural gas prices on fertiliser price changes. The results showed that changes in oil and natural gas prices increased fertiliser prices from June 2007 to June 2008. Chen et al. (2012) evaluated the effect of crude oil prices on global fertiliser prices in terms of both average and volatility. The results showed that most fertiliser prices were significantly affected by the price of crude oil. They also found that the volatility of global fertiliser prices and crude oil prices between March and December 2008 was higher than in other periods. Baffes (2007) found that crude oil prices had the highest pass-through on the fertiliser index. The second group consists of studies that specifically examine the effect of fertiliser subsidy programs on fertiliser use. These studies were gener-

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Table 1. Studies of volatility in agricultural product prices caused by volatility in fertiliser prices

Reference	Goal	Variables and sampling period	Methodology	Results
Yang et al. (2022b)	They discussed the price and volatility transmission among natural gas and fertiliser and corn markets.	The prices of natural gas, fertiliser and corn markets. 2 219 observations used in the study. The sample period was from 25 May 2011 to 30 November 2021.	VECM-MGARCH model and BEKK model	They could not find a relationship between fertiliser prices and corn prices, but fertiliser markets were negatively affected by natural gas prices. In the long run, they found that fertiliser was the only statistically significant parameter among the adjustment parameters. This finding indicated that there were strong statistical associations between manure (ammonium) and maize.
Olagunju et al. (2021)	They aimed to analyse the dynamic causal relationships among phosphate rock, fertilisers and wheat prices.	Phosphate rock, fertilisers (such as TSP, DAP, urea and potassium chloride fertilisers), crude oil and wheat prices. 147 monthly price observations. The sample period was from March 2007 to April 2019.	directed acyclic graphs and VECM	The results showed that an increase in the price of wheat had a large effect on both fertiliser and phosphorus prices. In addition, they provided empirical evidence that increases in the price of phosphorus were due to demand factors as well as supply factors.
Ismail et al. (2017)	They aimed to investigate the factors affecting the volatility of selected food and agricultural commodities.	The price data of tea, barley, rice, wheat, beef, poultry, lamb, sugar, rapeseed oil, soybean oil, sunflower oil, cotton, crude oil, urea, exchange rate and interest rate. 360 monthly price observations. The sample period was from April 1983 to April 2013.	GARCH, GJR GARCH, EGARCH	The results showed that the volatility in fertiliser prices was transmitted only through the volatility of sunflower oil.
Etienne et al. (2016)	They investigated the transfer of price and volatility between the natural gas, fertiliser (ammonia) and corn markets.	Natural gas, ammonia and corn prices. 1 094 weekly observations. The sample period was from January 1994 to December 2014.	VECM-MGARCH model and BEKK model	The results showed a significant interaction between fertiliser and corn markets. There was not only a positive relationship between maize and ammonium prices in the short run, but both prices also responded to deviations from the long-term parity. In addition, the lagged conditional volatility of ammonium prices positively affected the conditional volatility in the corn market, but *vice versa*.

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Table 1. To be continued

Reference	Goal	Variables and sampling period	Methodology	Results
Dillon and Barrett (2016)	They investigated how global crude oil price shocks affect local food prices, particularly in countries with high levels of subsistence food production in the four major East African economies: Ethiopia, Kenya, Tanzania and Uganda.	Maize, fertiliser and petrol prices. 144 monthly price observations. The sample period was from 2000 to 2012.	Johansen cointegration tests	The results showed that fertiliser prices had a negligible effect on the determination of local corn prices after controlling for changes in global corn prices.

TSP – triple superphosphate; DAP – diammonium phosphate; VECM – vector error correction model; GARCH – generalised autoregressive conditional heteroskedasticity; MGARCH – multivariate GARCH; EGARCH – exponential GARCH; BEKK – Baba, Engle, Kraft and Kroner; GJR – Glosten-Jagannathan-Runkle

ally conducted for African and South Asian countries. For example, the results of Tsiboe et al. (2021), who examined the effect of fertiliser subsidy on grain production at the household level in Ghana, showed that the grain yield increase attributable to the fertiliser subsidy program was 24.5%. Gono and Takane (2019) examined the effect of the price increase of subsidised fertilisers on poor farmers in Southern Malawi. They found that the price increase of fertilisers caused a decrease in the use of fertilisers. Nasrin et al. (2018) examined the effect of fertiliser subsidy on farming productivity in Bangladesh. The results of the study showed that fertiliser subsidy had a significant effect on increasing farming efficiency for small farms. Komarek et al. (2017) investigated the effects of changes in inorganic nitrogen fertiliser prices on agricultural households for farmers in central Malawi. They found that higher fertiliser prices increased legume cultivation areas but decreased household incomes. Takeshima and Liverpool-Tasie (2015) investigated the effect of a fertiliser subsidy program on seasonal growth rates of grain prices in Nigeria. The results showed that the fertiliser subsidy program had very small effects on grain price growth rates between the post-planting and post-harvest seasons. Holden and Lunduka (2012) evaluated the effects of the Malawi Farm Input Subsidy Program on fertiliser use at the farmland level. They stated that a 1% increase in the average fertiliser price was associated with a 0.43% to 0.76% increase in the probability of fertiliser use and a 3.5% to 5.3% increase in fertiliser use intensity. Ramli et al. (2012) examined the effects of fertiliser subsidy on the Malaysian paddy and rice industry. The results of the study showed that fertiliser subsidy had a significant effect on the paddy and rice industry – namely, the removal of fertiliser support reduced paddy and rice production. Finally, the limited number of studies in which the investigators examined the volatility in agricultural product prices caused by the volatility in fertiliser prices, which is the main purpose of this study, are summarised in Table 1.

The studies conducted within the scope of our literature review focus on the advantages and disadvantages of fertiliser use and the factors affecting fertiliser prices. In addition, it is noteworthy that there are few studies in the literature that contribute to understanding the volatility in fertiliser prices and, moreover, the relationship between fertiliser volatility and the volatility of agricultural products. In this article, we test the hypotheses that changes in fertiliser prices affect the changes in agricultural product prices and that there is a relatively high connectedness between these changes. Another hypothesis we test is to show that the interconnectedness and risk contagion between the variables increase in times of crisis. Accordingly, in this study, we aimed to empirically test the spillover and interconnectedness between the volatility of fertiliser and selected agricultural product prices through the Diebold-Yilmaz approach based on the time-varying parameter (TVP) vector auto-regression (VAR) model. With this approach, while revealing the volatility pass-

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-through between the variables, we also saw the change in the relationship between the variables in crisis periods via the dynamic structure of the method. Diebold and Yılmaz (2014) estimate the dynamics via a rolling window VAR approach that causes losing data. Therefore, we used the same method as Antonakakis et al. (2020) because the dynamics of TVP-VAR do not influence the size of the rolling window.

MATERIAL AND METHODS

Data set. The data set consists of monthly price changes from January 2000 to March 2022 downloaded from the World Bank commodity price data site (World Bank 2022). We included selected commodity price indexes as proxies for world prices. The abbreviations of the variables consisting of fertilisers and agricultural products and their coding in the data source are listed in Table 2. Our primary goal in choosing these fertiliser types and agricultural products was to avoid data loss because data are missing on the prices of other agricultural products. In addition, the World Bank uses prices in some countries and regions to determine global prices. We assumed these prices as approximate world prices and used them in our analysis. Figure 1 demonstrates commodity prices.

Poon (2005) indicated that using absolute monthly values to represent macroeconomic volatility creates a proxy value for volatility, as many macroeconomic series exist only at monthly intervals. Therefore, we used absolute logarithmic price changes as the volatility of commodities in the connectedness analysis. Figure 2 presents the volatility series. The skewness and the excess kurtosis statistics in Table S1 in electronic supplementary material (ESM; for the ESM see the electronic version) indicate that all the volatility series are skewed to the right and have excess kurtosis with respect to the normal distribution. These results are supported by Jarque-Bera test statistics that also indicate the series are not normally distributed at the 1% significance level. Therefore, we can use an Elliot-Rothenberg-Stock test to check for stationarity of the volatility series, and these statistics show that all volatility series are stationary.

TVP-VAR-based dynamic volatility connectedness. Antonakakis et al. (2020) used the TVP-VAR method to enhance Diebold and Yilmaz's (2014) proposed connectedness approach by allowing the variance-covariance matrix to fluctuate by using a Kalman filter estimation with forgetting factors, as in the study of Koop and Korobilis (2014). To investigate the time-varying linkage between price volatilities of fertilisers and agricultural products, we estimated a TVP-VAR(2) model, which we determined to be the most appropriate by means of Bayes information criteria, and it is as in Equations (1, 2).

Table 2. Variables and data description

Product	Unit	Description
Phosphate rock	USD/metric ton	FOB North Africa
Urea	USD/metric ton	Ukraine, FOB Black Sea
DAP	USD/metric ton	spot, FOB US Gulf
TSP	USD/metric ton	spot, import US Gulf
Sugar	USD/kg	world, International Sugar Agreement daily price, raw, FOB and stowed at greater Caribbean ports
Cotton	USD/kg	Cotton Outlook A index, middling 1–3/32 inch, traded in Far East, CIF beginning 2006; previously Northern Europe, CIF
Soybeans	USD/metric ton	from January 2021, US Gulf Yellow Soybean #2, CIF Rotterdam; December 2007 to December 2020, US No. 2 yellow meal, CIF Rotterdam; previously US origin, nearest forward
Maize	USD/metric ton	US, No. 2, yellow, FOB US Gulf ports
Rice	USD/metric ton	Thailand, 5% broken, white rice, milled, indicative price based on weekly surveys of export transactions, government standard, FOB Bangkok
Wheat	USD/metric ton	US, No. 2, soft red winter, export price delivered at the US Gulf port for prompt or 30 days shipment

FOB – free on board; CIF – cost, insurance and freight; DAP – diammonium phosphate; TSP – triple superphosphate
Source: The metadata and definitions of the variables are available in the Pink Sheet data (World Bank 2022)

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$$y_t = A_t z_{t-1} + \epsilon_t \qquad \epsilon_t \sim N\left(0, \Sigma_t\right) \tag{1}$$

$$\text{vec}(A_t) = \text{vec}(A_{t-1}) + \upsilon_t \qquad \upsilon_t \sim N\left(0, S_t\right) \tag{2}$$

where: y_t, z_{t-1} – $k \times 1$ and $2k \times 1$ vectors, respectively; A_t – $k \times 2k$ dimensional matrix; ϵ_t, υ_t – $k \times 1$ and $2k^2 \times 1$ dimensional vectors, respectively; Σ_t, S_t – time-varying variance-covariance matrices of which the dimensions are $k \times k$ and $2k^2 \times 2k^2$, respectively; vec(A_t) – $2k^2 \times 1$ dimensional vector.

The Diebold-Yilmaz approach is based on the generalised forecast error variance decomposition (GFEVD) analysis. Thus, TVP-VAR needs to be transformed into a TVP-vector moving average Wold representation:

$$y_t = \sum_{h=0}^{\infty} A_{ht} \epsilon_{t-h}, \text{ where: } A_0 = I_k \tag{3}$$

where: I_k – identity matrix; A_{ht} – $k \times k$ dimensional time-varying vector moving average coefficient matrix

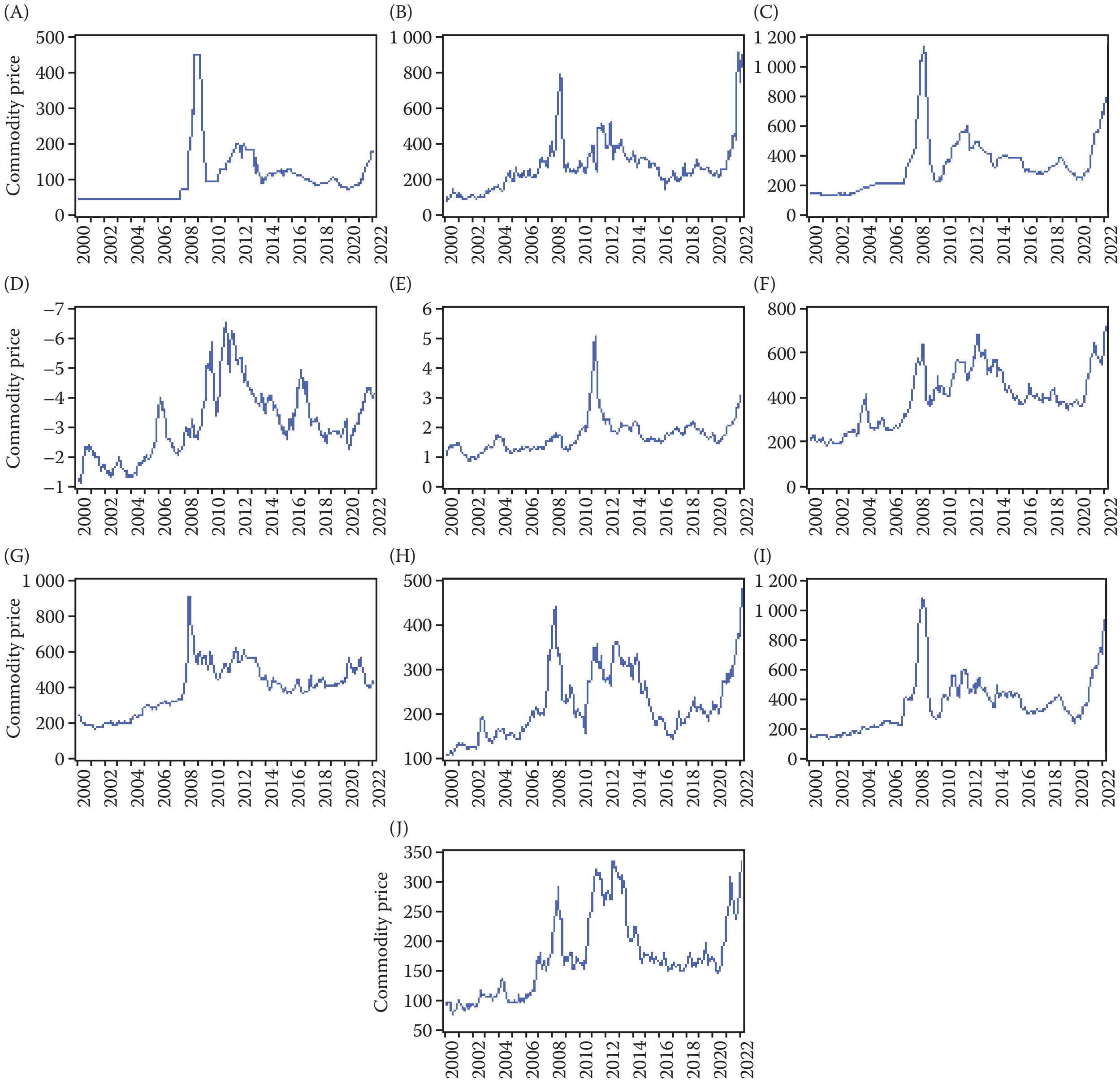

Figure 1. Commodity price series: (A) phosphate rock (USD/metric ton), (B) urea (USD/metric ton), (C) TSP (USD/metric ton), (D) sugar (USD/kg), (E) cotton (USD/kg), (F) soybeans (USD/metric ton), (G) rice (USD/metric ton), (H) wheat (USD/metric ton), (I) DAP (USD/metric ton), and (J) maize (USD/metric ton)

DAP – diammonium phosphate; TSP – triple superphosphate
Source: World Bank (2022)

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As a result, using the h-step forward GFEVD, one can predict (pairwise directional connectedness) the influence of a shock in variable j on variable i as follows:

$$\tilde{\phi}^{g}_{ij,t}(H) = \frac{\sum_{h=0}^{H-1}\left(\in_i^T A_{ht}\Sigma_t \in_j\right)^2}{\left(\in_i^T \Sigma_t \in_j\right)\sum_{h=0}^{H-1}\left(\in_i^T A_h \Sigma_t A_{ht}^T \in_i\right)} \quad (4)$$

with $\sum_{j=1}^{m}\tilde{\phi}^{g}_{ij,t}(H) = 1$ and $\sum_{i,j=1}^{m}\tilde{\phi}^{g}_{ij,t}(H) = k$.

where: $\tilde{\phi}$– (scaled) GFEVD (pairwise directional connectedness from j to i); H – forecast horizon; $\in_i, \in_j$ – selection vector with 1 on the i^{th} position and 0 otherwise

Thus, the total connectedness index (TCI) of the Diebold-Yilmaz (2014) approach via GFEVD is calculated as in Equation (5).

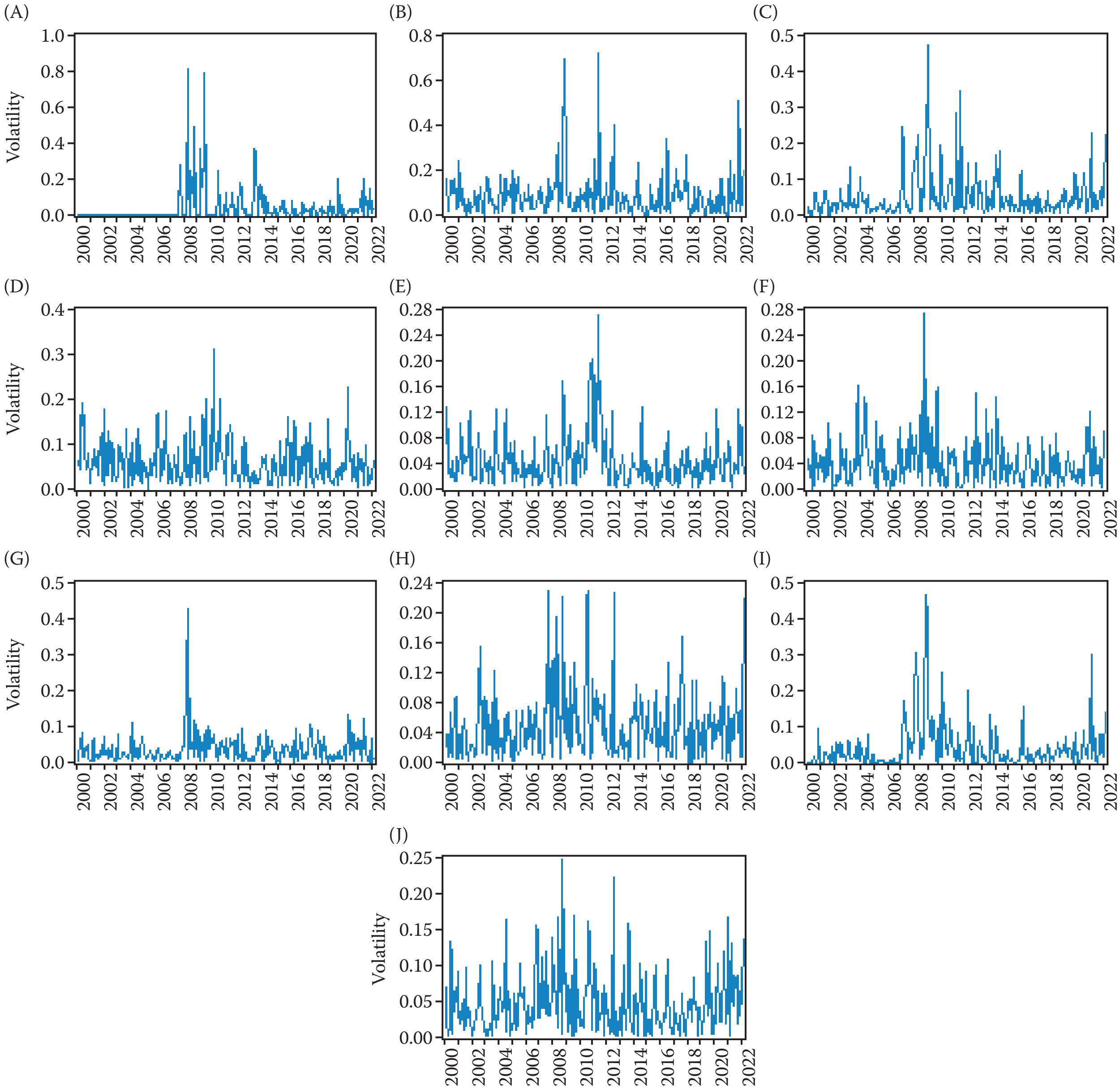

Figure 2. Volatility series (absolute log-price changes): (A) phosphate rock, (B) urea, (C) DAP, (D) sugar, (E) cotton, (F) soybeans, (G) rice, (H) wheat, (I) TSP, and (J) maize

DAP – diammonium phosphate; TSP – triple superphosphate

Source: Authors' own elaborations

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$$C_t(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{k} \tilde{\phi}_{ij,t}^{g}(H)}{\sum_{i,j=1}^{k} \tilde{\phi}_{ij,t}^{g}(H)} = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{k} \tilde{\phi}_{ij,t}^{g}(H)}{k} \tag{5}$$

TCI can be used to model how a shock in one variable affects other variables. To put it another way, we may quantify the transmission of a shock in variable i to all other variables by using the following formula (total directional connectedness to others):

$$C_{i \to j,t}(H) = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{k} \tilde{\phi}_{ij,t}^{g}(H)}{\sum_{j=1}^{k} \tilde{\phi}_{ij,t}^{g}(H)} \tag{6}$$

The calculation for receiving the shock, known as total directional connectedness from others, is as follows:

$$C_{i \leftarrow j,t}(H) = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{k} \tilde{\phi}_{ij,t}^{g}(H)}{\sum_{i=1}^{k} \tilde{\phi}_{ij,t}^{g}(H)} \tag{7}$$

The net total directional connectedness (NTDC) shows the effect of the variable i on the analysed macroeconomic network. Therefore, the NTDC is:

$$C_{i,t} = C_{i \to j,t}(H) - C_{i \leftarrow j,t}(H) \tag{8}$$

We can investigate bidirectional interactions by calculating the net pairwise directional connectedness to see which variable dominates the other, which is:

$$NPDC_{ij}(H) = \tilde{\phi}_{ji,t}^{g}(H) - \tilde{\phi}_{ij,t}^{g}(H) \tag{9}$$

RESULTS AND DISCUSSION

Antonakakis et al. (2020) considered the benchmark values for forgetting factors provided by Koop and Korobilis (2014), who used the TVP-VAR forgetting factor of 0.99 and the exponentially weighted moving average forgetting factor of 0.96. The fixed values decreased the computation burden of the Kalman filter algorithm significantly. In addition, they determined that these decay factors showed the minimum error in simulations. Therefore, we used the same forgetting factors values while estimating the TVP-VAR model with Minnesota prior, which Antonakakis et al. (2020) used in their study. Table 3 presents the results of the TCI derived

Table 3. Averaged dynamic connectedness table

Variables and connectedness	Phosphate rock	Urea	DAP	TSP	Sugar	Cotton	Soybeans	Maize	Rice	Wheat	From others
Phosphate rock	65.88	4.40	2.21	2.68	0.40	1.16	1.43	2.61	15.80	3.44	34.12
Urea	4.25	61.06	12.92	10.24	1.39	2.87	0.81	2.30	2.87	1.30	38.94
DAP	6.98	18.02	48.72	17.05	1.08	1.29	0.91	1.61	3.00	1.35	51.28
TSP	7.37	14.86	18.41	49.76	0.86	1.24	0.91	1.89	3.37	1.32	50.24
Sugar	3.11	5.21	3.31	3.14	74.27	3.20	1.73	2.36	2.41	1.26	25.73
Cotton	5.51	5.18	2.62	4.93	2.20	65.41	4.29	3.46	2.04	4.36	34.59
Soybeans	4.41	2.85	2.13	3.80	0.83	4.52	64.61	9.98	2.62	4.24	35.39
Maize	5.92	3.64	2.32	2.60	2.46	3.65	8.65	58.43	3.51	8.81	41.57
Rice	16.73	5.48	3.09	6.49	1.68	1.83	0.61	0.93	59.87	3.31	40.13
Wheat	7.24	2.28	2.10	4.01	1.12	3.89	3.51	9.26	4.14	62.45	37.55
To others	61.53	61.92	49.10	54.92	12.04	23.64	22.85	34.40	39.75	29.39	389.53
Including own	127.41	122.98	97.82	104.68	86.31	89.05	87.47	92.82	99.62	91.84	**TCI**
Net	**27.41**	**22.98**	–2.18	**4.68**	–13.69	–10.95	–12.53	–7.18	–0.38	–8.16	**38.95**

DAP – diammonium phosphate; TSP – triple superphosphate; TCI – total connectedness index; results are based on a time-varying parameter vector auto-regression [TVP-VAR(2)] model and a 10-step-ahead generalised forecast error variance decomposition (GFEVD); for TVP-VAR-based connectedness analysis, one can use the R-package 'Connectedness Approach', as well as the online connectedness approach platform prepared by Gabuer (2022); bold – volatility transmitters in the network

Source: Authors' own elaborations

https://doi.org/10.17221/147/2022-AGRICECON

from the TVP-VAR(2) model through GFEVD with a forecast horizon of 10 months.

The TCI among the variables was 38.95%. According to this result, approximately 39% of the forecasting error variance in the variables was caused by the transition and connectedness between these variables. Although the diagonal elements of the 10 × 10 matrix given in Table 3 show the forecasting error variance caused by the variables themselves, the other elements are the decomposition of the error variances. The columns show the variance decompositions of spillover to other variables, and the row elements show the volatility spillover from other variables. The difference between them gives the average net directional connectedness rates. Accordingly, phosphate rock, triple superphosphate (TSP) and urea are net shock transmitters, and other variables are shock receivers. The fact that phosphate rock and urea had a net directional connectedness of 27.41% and 22.98%, respectively, indicates that price volatility in these fertilisers is highly contagious to the volatility of other products. The agricultural products most vulnerable to the effects of external shocks were sugar, soybeans and cotton. although the risk of volatility in rice prices was transferred to other variables at a rate of 39.75%, the fact that other products were affected by 40.13% from volatility spillover reveals that the net interconnectedness of rice was almost non-existent. This means that derivatives on rice can be used for portfolio diversification. In other words, rice had a low connection to other variables because its NTDC was −0.38. Thus, in a portfolio with futures contracts for other products, contracts on rice can be used for risk reduction. These products can be used for portfolio diversification and hedging transactions in derivative markets, considering the net interconnectedness. The network of connectivity shown in Figure 3 can also be interpreted as a visual result that supports our findings. Blue (yellow) knuckle dots indicate the clear transmitter (receiver) of the shocks. The vertices are weighted by their mean net pairwise connectedness measures. The size of the knuckles represents the weighted average NTDC. The network plot indicates that there is a spread of volatility from phosphate rock and urea to the other fertiliser types of TSP and diammonium phosphate (DAP), and cotton was the biggest net receiver of the shocks in phosphate rock price volatility among agricultural products.

To elaborate further on the situation revealed in the network analysis, we present the net pairwise connectedness values in Table 4. The volatility in urea fertiliser price dominates all variables, including phosphate rock. Although phosphate rock had the highest diffusion rate, it was affected by volatility in urea prices. We calculated the total exposure rates from the spillover of fertiliser price volatility; in other words, the risk created by the change in fertiliser prices were as follows: cotton (11.68%), sugar (11.04%), soybeans (9.13%), wheat (8.22%), rice (6.75%) and maize (6.07%).

Figure 4 presents the total dynamic TCI over the entire period via TVP-VAR spillover analysis. Increases in both fertiliser and agricultural product prices in the last quarter of 2007 and the first quarter of 2008 showed their effects in April 2008. The price data show that fertiliser prices increased by 44.26% on average in April 2008 compared with the previous month and realised the highest increase. Although agricultural product prices increased by 4.6% on average, the highest increase was realised in rice with 52.69%. The peak value in April 2008 in Figure 4 illustrates that the connectedness reached the highest value of 82.34% throughout the entire period, for other reasons beyond only the 2007–2008 financial crisis. The biggest source of volatility spillover in April 2008 was phosphate rock because its price increased by 124.30%. The net pairwise connectedness between phosphate rock and agricultural products were sugar (31.15%), maize (31.47%), cotton (23.26%), soybeans (19.90%)

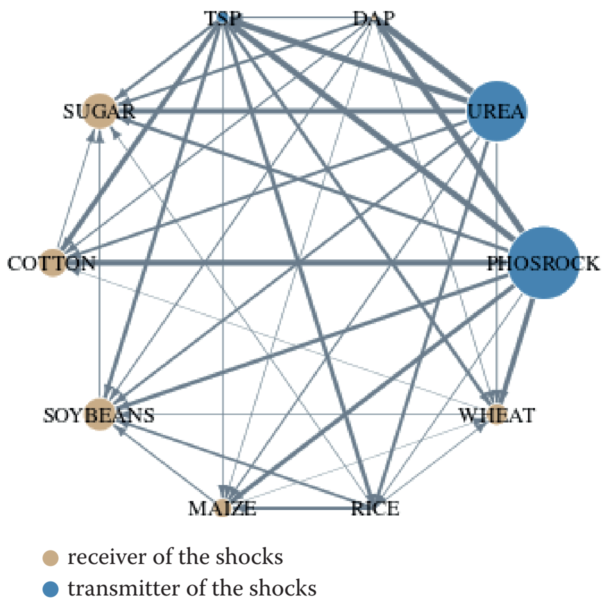

Figure 3. Network plot

DAP – diammonium phosphate; TSP – triple superphosphate; PHOSROCK – phosphate rock; results are based on a time-varying parameter vector auto-regression [TVP-VAR(2)] model and a 10-step-ahead generalised forecast error variance decomposition (GFEVD)

Source: Authors' own elaborations

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Table 4. Net pairwise volatility connectedness

Variables	Phosphate rock	Urea	DAP	TSP	Sugar	Cotton	Soybeans	Maize	Rice
Wheat	–3.80	–0.98	–0.75	–2.68	0.13	0.47	0.73	–0.45	–0.83
Rice	–0.93	–2.60	–0.09	–3.11	0.72	0.22	2.01	2.58	–
Maize	–3.31	–1.35	–0.71	–0.71	–0.10	–0.19	1.33	–	–
Soybeans	–2.98	–2.04	–1.22	–2.90	0.90	–0.23	–	–	–
Cotton	–4.35	–2.31	–1.33	–3.69	0.99	–	–	–	–
Sugar	–2.71	–3.82	–2.23	–2.27	–	–	–	–	–
TSP	–4.70	–4.62	–1.37	–	–	–	–	–	–
DAP	–4.77	–5.10	–	–	–	–	–	–	–
Urea	0.15	–	–	–	–	–	–	–	–

DAP – diammonium phosphate; TSP – triple superphosphate; results are based on a time-varying parameter vector auto-regression [TVP-VAR(2)] model and a 10-step-ahead generalised forecast error variance decomposition (GFEVD)
Source: Authors' own elaborations

and rice (0.02%). The second biggest price fluctuation in fertilisers occurred in June 2011. As fertiliser prices increased by 37.71% on average, agricultural product prices increased by 0.22%. Thus, the volatility propagation remained low, and TCI increased to just 39.39%. The World Health Organisation declaration of the COVID-19 pandemic in March 2020 slightly increased the connectedness. The high demand that occurred when the pandemic weakened, the availability of the vaccine in the post-pandemic period and the normalisation process increased prices of fertilisers by 22.51% and agricultural products by 3.31% in February 2021. This fluctuation created by the third-highest average increase in fertiliser prices affected the contagion of volatility among the variables. Therefore, the TCI reached 55.22%. The TCI tended to decrease during 2021, when strong demand, increasing input costs, production cuts and trade policies were influential in the price increase. Furthermore, with the start of the Russia-Ukraine war in February 2022, it tended to increase again. Although the average increase in fertiliser prices was 16.61% in March 2022, it was 9.26% in agricultural products. As a result, TCI increased to 41.22%, moving above the average value. The TCI showed that the shock in one of the variables in the upcoming period tended to increase the risk in the others more.

The results of the analysis showed that there is a relatively high connectedness among the variables and that the volatility connectedness between fertiliser and agricultural product prices increased especially during crisis periods. With the use of up-to-date data, we can expect that the crisis caused by the Ukraine-Russia war will further increase the connectedness. Because other studies do not have dynamic structures or at least do not include methods such as rolling window analysis, they arrive at only average volatility spillover over the entire period. Therefore, although Dillon and Barrett (2016) and Yang et al. (2022b) did not find sig-

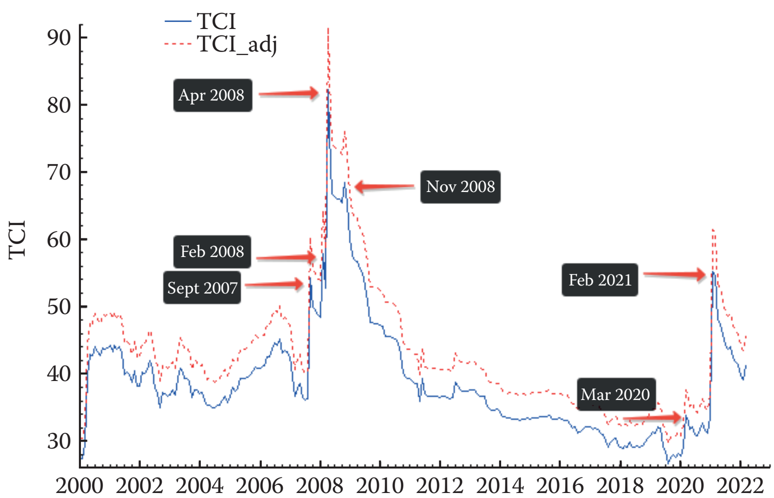

Figure 4. Total dynamic connectedness index

TCI – total connectedness index; results are based on a time-varying parameter vector auto-regression [TVP-VAR(2)] model and a 10-step-ahead generalised forecast error variance decomposition (GFEVD)
Source: Authors' own elaborations

https://doi.org/10.17221/147/2022-AGRICECON

nificant volatility pass-through between fertiliser and corn prices, we found that corn price was a volatility receiver, especially in times of crisis. Ismail et al. (2017) found a volatility transmission from fertiliser prices only to sunflower oil, but we found a volatility pass-through for rice, wheat, sugar and cotton. Although our method is different from those of the studies in the literature, it shows similarities in terms of results. For example, phosphate rock had a huge effect on the network, and we found that the agricultural product for which phosphate rock provided the highest risk pass-through after cotton was wheat, which is in line with the results of Olagunju et al. (2021).

CONCLUSION

We used the TVP-VAR-based Diebold-Yilmaz connectedness approach to reveal the volatility spillover and connectedness between fertiliser prices and some agricultural product prices. The TCI revealed that 38.95% of the forecasting error variance in the variables was due to contagion and connectedness. According to the results, the price volatility of phosphate rock and urea was highly contagious to the volatility of other products. The findings showed that the agricultural products most vulnerable to the effects of external shocks were sugar, soybeans and cotton. The net connectedness of rice was almost zero, resulting in derivatives on rice being able to be used for portfolio diversification. According to the net pairwise connectedness rates, the volatility of urea fertiliser price dominated all variables. In addition, the TCI showed that the interconnectedness reached its highest value in April 2008 for the entire period. The crisis created by the increase in food prices in 2007 and 2008 was also revealed in the analysis results. Moreover, we observed that TCI increased slightly in March 2020 because of the COVID-19 pandemic. The volatility pass-through between variables emerged because of high demand and the normalisation process in the post-pandemic period. Therefore, high prices, or more precisely, the volatility affected the TCI, which increased to 55.22% in April 2021. The findings showed that volatility spillover and interconnectedness among the variables increased during crisis periods and that the risk pass-through was due to the prices of fertiliser as a raw material. These results are consistent with volatility spillover and connectedness theory.

Because some farmers cannot afford fertiliser because of post-pandemic high inflation, high loan rates and lack of equity capital, increases in fertiliser prices may cause low yields because producers use less fertiliser or none at all. This is one of the reasons for the high prices of agricultural products. The regulation of the prices of inputs used in agriculture and the amount of support and payment periods by policymakers is an urgent and strategic issue. In addition, they should ensure that the efficient use of fertilisers is increased within the scope of improved nutrient management planning. However, in terms of reducing fertiliser costs, sustainable food production can be improved by using recycled bio-based (from biological waste) fertilisers that support the local microorganisms that are important for agricultural production. Legumes also should be added to rotations in a planned manner when there is insufficient fertiliser. Relevant government departments should carry out their inspection and control activities regularly and take measures to keep the market prices of agricultural inputs such as fertilisers and pesticides constant. Subsidy programs for agriculture and food sector inputs can help to create a general equilibrium in decreasing food prices by reducing the negative effects of high costs, especially for small producers. In addition, financial institutions such as banks should provide short-term, medium-term and long-term agricultural loans on flexible terms to support sustainable agricultural production. Lastly, for agricultural producers to have easy access to agricultural loans or support programs provided by the public or private sector, all kinds of electronic and print media should be used regularly.

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Received: May 17, 2022
Accepted: August 5, 2022
Published online: September 15, 2022