

Food insecurity and sovereignty threat to uncontrolled price spillover effects in financialized agricultural products: The red meat case in Türkiye

Faruk Urak^{1,*}, Abdulkaki Bilgic²

¹ *The Turkish Radio and Television Corporation (TRT), Erzurum Directorate, 25080 Palandöken/Erzurum, Türkiye*

² *Department of Management Information Systems, College of Economics and Administrative Sciences, Bilecik Şeyh Edebali University, Bilecik, Türkiye*

Received 2 June 2022; revised 14 December 2022; accepted 14 December 2022

Available online 4 January 2023

Abstract

The objective of this study is to examine the long-term uncertainty transmission between cattle and lamb carcass markets and the feed wheat market in terms of exogenous variables (e.g., gasoline price, exchange rate, and import variables) and whether the volatility is symmetrical, using the daily data from January 2005 to June 2019, and VAR (1)–BEKK–GARCH (1, 1) Model. The empirical results indicate that short- and long-term indirect and direct shocks and long-term uncertainty propagation significantly affect the conditional variances of the beef carcass, lamb carcass, and feed wheat returns, which poses a threat to producers in terms of product sovereignty and consumers in terms of food security. We also discovered that the conditional variances of the beef carcass, lamb carcass, and feed wheat returns were significantly affected by any increase in foreign exchange rates in times of import in comparison with those in the times of nonimport. Similarly, the fluctuations in the energy (gasoline) market increased the ongoing risk propagations in the lamb carcass and feed wheat markets, whereas they decreased it in the beef carcass market. Meanwhile, asymmetrical effects played a role in uncertainty in transitions for product markets. Additionally, the optimal portfolio weight of beef carcasses on lamb carcasses and feed wheat was 0.645 and 0.553, respectively, whereas the optimal portfolio weight of lamb carcasses on feed wheat remained at approximately 0.188.

Copyright © 2022 Borsa İstanbul Anonim Şirketi. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

Keywords: Beef and lamb carcasses; Feed wheat; Gasoline; Exchange rate; Prices; Volatility

1. Introduction

Due to economic and noneconomic driving forces globally, perturbations result in volatility in food prices. Sidhoum and Sera (2016) reported the spillover of volatility throughout the tomato market, whereas Pal and Mitra (2017) reported the spillover of volatility in crude oil prices into the long-term global food price index. Food prices have major correlations with both crude oil and ethanol prices (Al-Maadid et al., 2017). The biofuel industry, growing in line with the ever-increasing demand of countries for more and more foods,

has become an increasingly important bridge between the energy and agricultural product markets and has enabled the easy volatility transmission from one market to another, from the basic dynamics of the market to all other obscure events (Reboredo, 2012). The increase in input prices increased the cost of livestock, causing food prices to rise (Tejeda and Goodwin, 2009). The increase in prices has also caused several problems in the supply chain of the agricultural sector, which threatens food security in all nations globally. For all sectors, grains are a fundamental input. Hence, grains closely correlate with the price volatility of food (Tejeda and Goodwin, 2009). Moreover, the literature has emphasized that any volatility in oil prices would affect the prices of red meat (Cabrera and Schulz, 2016; Tejeda and Goodwin, 2009). As emphasized by a similar study, the effect of corn prices on pork prices is nonlinear and asymmetrical (Wang et al., 2018).

* Corresponding author.

E-mail addresses: farukurak.trt@gmail.com (F. Urak), abdulkaki.bilgic@bilecik.edu.tr (A. Bilgic).

Peer review under responsibility of Borsa İstanbul Anonim Şirketi.

Von Braun and Tadesse (2012) also showed that the price volatility of agricultural commodities is impacted by the increasing connections between agriculture, energy commodities, and financial markets.

In recent years, red meat prices have skyrocketed, posing a threat to protein-based food security, especially in low- and middle-income families. Increasing input costs, including oil prices, is one of the main reasons for this price increase. Oil and petroleum derivatives are frequently utilized in the supply chain of various industries, including transportation, agriculture, industry, and households. They are also used as raw materials for the production of petrochemical products (Taghizadeh-Hesary et al., 2019). According to some studies, high oil prices are the primary cause of persistently high inflation and a decline in the gross domestic product. For example, Hamilton (1983) claimed that nearly all economic downturns in the United States followed an increase in oil prices. According to Cunado and Perez de Gracia (2003), oil price shocks have a major impact on economic development in the case of the European economy, whereas global oil prices have a significant impact on China's economic growth and inflation, as stated by Du et al. (2010). In developing economies such as Türkiye, the increase in crude oil prices has led to a surge in animal-based foods. In Türkiye, for example, the increase in meat prices over the past decade appears to have been driven by demand, since breeders have been compelled to sell off animals due to the import of milk powder and extreme spikes in feed prices, and some breeders have halted breeding operations. Meanwhile, most developing countries require foreign currency since they are net importers of crude oil and petroleum derivatives used as inputs for agricultural production. Since such products are purchased based on the United States dollar (USD), fluctuations in crude oil prices affect the foreign exchange markets of countries that trade in USDs (Adom, 2014; Salisu and Mobolaji, 2013). Hence, the global increase in crude oil prices, which increases import costs and production costs of inputs such as machinery, animals, shipping, distribution, and biochemical (manure, pesticides, and herbicides), results in a loss of income in net oil-importing countries (Adom, 2014; Gilbert, 2010; Pal and Mitra, 2017; Salisu and Mobolaji, 2013). Türkiye is susceptible to fluctuations in the USD exchange rate because it relies heavily on imported resources for oil and petroleum derivatives as well as other agricultural inputs.

Countries attempt to increase self-sufficiency to protect their food supply and domestic markets from the sudden and unexpected negative aspects of foreign markets (Guo and Tanaka, 2020). The autarky system, owing to its rigidity, causes welfare losses for consumers, although it has beneficial aspects. In the case of high food self-sufficiency, for instance, it ensures the availability of food in the event of war or natural calamities such as earthquakes and tsunamis. In a peacetime or normal-time economy, however, households and consumers lose welfare by purchasing unreasonably expensive products as a result of protectionist policies such as high import taxes and strict quota restrictions, as well as by incurring the cost of substantial subsidies that encourage domestic farmers to produce more

goods. Moreover, if domestic production is extremely volatile compared to foreign production, the autarky policy does not always fulfill its market regulatory purpose by absorbing abrupt, unanticipated shocks. Therefore, the majority of economists and policymakers oppose autarky, in which more limitations on imports distort market signals and result in inefficient resource allocation (Guo and Tanaka, 2020). In this context, for instance, in Türkiye, the Central Bank of the Republic of Türkiye (CBRT) is responsible for ensuring stability in monetary policies such as inflation (Akgunduz et al., 2020; Chadwick and Bastan, 2017), whereas the Ministry of Agriculture and Forestry (MAF) is liable for providing adequate income to farmers through effective policies such as direct income and subsidy measures. Nevertheless, the price transmission mechanism between producers, wholesalers, retailers, and consumers was difficult to manage despite the efforts of both organizations (Akgunduz et al., 2020; Chadwick and Bastan, 2017; Cinar, 2018). As a result of the continual imbalance between supply and demand for agricultural products in Türkiye, price fluctuations are a constant occurrence. Türkiye's rising socioeconomic prosperity has resulted in a spike in the price of red meat as the demand could not be met. For example, red meat consumption per capita in Türkiye declined from 6.42 to 6.39 kg between 2019 and 2020 and was projected to remain at approximately 6.37 kg in 2021 (OECD, 2022). Similarly, red meat prices increased significantly since red meat production did not expand despite Türkiye's rapid population growth (e.g., in 2011, approximately 4 million Syrian nationals took refuge in Türkiye due to the civil war). Although real red meat prices follow a fluctuating course, the worldwide food crisis in 2007 and the global financial crisis in 2010 led to a significant increase in prices. In September 2007, the prices of genuine lamb and genuine beef were 27.65 and 23.86 Türkiye Lira (henceforth, ₺), respectively. In September 2011, these prices increased by 83% (50.63 ₺) and 46% (34.69 ₺), respectively (TSI, 2019). Similarly, the nominal price of beef in Türkiye was approximately 45.64 ₺/kg in 2019 but increased to 51.38 and 62.66 ₺/kg in 2020 and 2021, respectively (TSI, 2022). These prices may triple within the next few months and years. Özertan et al. (2015) noted that asymmetric price transmission in Türkiye's red meat supply chain is indicative of imperfect competition and oligopolistic market behavior, as well as supermarkets in the country. A price adjustment role can be obtained by developing marketing power through persistent imperfect retail competition. In 2009, Türkiye abolished the autarky system and began to support cattle producers with heavy subsidies in order to alleviate the regular red meat supply shortages caused by supply and demand shocks in the country (Akgunduz et al., 2020; Chadwick and Bastan, 2017; TOB, 2018; Urak et al., 2022b). Although support for forage crops and livestock increased by 89% between 2009 and 2017, reaching 189 million ₺ and 4 billion ₺ in real terms, respectively (TSI, 2022), the country has not yet achieved the targeted level of production.

As emphasized by Guo and Tanaka (2022), price is one of the most important determinants of efficient resource allocation in an economy. If high market efficiency is maintained, price

fluctuations are transmitted between markets in a sensitive yet synchronized manner, maximizing both producer and consumer welfare. Economists and decision-makers are exerting great efforts to simplify market mechanisms in an effort to boost market efficiency. To ensure food sovereignty for producers and easy accessibility to food options and food security for consumers, policymakers in Türkiye must understand the effects and aspects of uncertainty pass-through between agricultural commodity markets in order to lay the groundwork for more sound decision making. Furthermore, in recent years, research on the theoretical and empirical unpredictability pass-through for agricultural commodity markets has increased in vertical integration dimensions (e.g., producer–wholesaler–retailer), as have several scientific studies focusing on spillover effects between agricultural commodity markets and energy markets (Ben Abdallah et al., 2020; Reztis, 2018; Sidhoum and Sera, 2016; Urak et al., 2022c; Özertan et al., 2015). Nevertheless, models that include macroeconomic variables as exogenous factors in conditional heteroscedasticity equations are uncommon, as are studies that consider such factors externally in conditional volatility models to measure the propagation effect between agricultural commodity markets. Moreover, among the products to be examined in the present study, beef and lamb carcasses constitute almost the entire red meat sector in Türkiye, whereas feed wheat has a large share in animal feed. Concurrently, such product markets are impacted by rapid economic decisions, as well as other geopolitical, cultural, and social changes in daily life in the country, causing producers and consumers to be concerned about food sovereignty and food security. Being a haven for investors in the meat and feed sector in an environment where institutional price controls are inadequate in comparison to intense price escalations in the country depends, at least in part, on the ability to discern the impact and direction of the persistent uncertainty pass-through from and between the markets. The need to understand the liaisons of the increased price volatility, the effects and extent of possible volatility spillovers, the nature of the underlying risks, and the relationships between them creates the need for eclectic empirical analysis. Hence, using macroeconomic markets (gasoline, exchange rate, and imports) as external stimuli in both the mean and conditional heteroscedasticity equations in Türkiye, this study aims to examine for the first time the volatility spillovers between forage (feed) wheat, beef carcass, and lamb carcass markets. To achieve this objective, the Baba, Engle, Kraft, and Kroner (BEKK) model of Engle and Kroner, one of the multivariate generalized conditional heteroscedasticity models (GARCH), was used in the analysis together with the mean return equations of the vector autoregressive model (VAR), henceforth VAR–BEKK GARCH. In developed economies, the bioethanol market is typically the conduit for the propagation of uncertainty between the agricultural products and energy markets. However, the volatility transmission from energy, foreign exchange markets, and structural policy changes to animal and agricultural products, as well as the identification of embedded relationships among them, can provide crucial information for decision-makers and stakeholders, as the bioethanol market is almost nonexistent in emerging countries such as Türkiye.

Additionally, the present study provides optimal portfolio weights of beef and lamb carcass and feed wheat markets for one another, and their hedging ratios in quantity. Furthermore, the derived findings from this study can provide important insights into countries with structural conditions such as Türkiye.

This study consists of four sections including the introduction. The second section introduces the empirical method and data sets to be adopted for variables. The empirical results of the study are reported in the third section. The findings and policy recommendations are presented in the final section.

2. Literature review

Unfortunately, studies on red meat markets are extremely limited in scope. Using the Granger causality test, Ziemer and Collins (1984) reported bidirectional propagation clues for corn, wheat, beef, and pork, which they utilized to determine the relationships between livestock and grain prices in the United States. Using the GARCH model to estimate price volatility in beef and pork products in the United States, Kesavan et al. (1992) found that volatility in cattle and pig farm prices is propagated by information from previous periods. Reztis and Stavropoulos (2010) used several different symmetrical, asymmetrical, and nonlinear GARCH models to predict volatility in the Greek beef market. Likewise, they confirmed an asymmetrical interaction and uncertainty propagation in price levels by examining the transmission of nonlinear vertical price level adjustment and price volatility between consumer and producer prices in the broiler sector in Greece (Reztis and Stavropoulos, 2011). Conversely, another study (Luo and Liu, 2011) using various GARCH models to investigate meat price volatility between 2000 and 2007 in China (constituting a large supply chain) found that beef has high risk and low return in the GARCH-M model. Nevertheless, as determined in the ARCH and E-GARCH models, whereas an asymmetrical relationship between beef, sheep, and chicken meat prices exists, the volatility transmission from price decreases was much lower than the volatility propagation from price hikes.

Both the supply chain and the demand side contribute to price fluctuations in red meat, which are directly related to increasing input costs (Rask and Rask, 2011). For instance, a study (Reztis, 2012) examining the vertically related producer–consumer price volatility of beef, lamb, pork, and poultry in Greece between 1993 and 2008 discovered that pork and poultry prices had a lasting effect on lamb and beef volatility, whereas the predicted producer–consumer vertical price volatility transmission was mainly attributed to agricultural policy changes, imports, and market structure in the country. Reztis and Stavropoulos (2012) discussed the supply side response patterns of beef, chicken, lamb, and pork markets in Greece within the framework of rational expectations in their study based on the 1993 and 2006 periods. Multivariate GARCH (henceforth MGARCH) and Cholesky analysis were utilized for the joint price volatility transmission. Empirical results indicate that meat producers behave rationally in four markets, whereas price volatility is the main risk factor for

Greek meat production. Nonetheless, they discovered that the European Common Agricultural Policy Reform had seriously damaged lamb and beef production in Greece. Zhen (2015) reported that corn price volatility was higher than forage barley price volatility, in which the asymmetric bivariate BEKK GARCH model was employed to investigate the spillovers of cattle and feed price volatility in the cattle supply chain in Alberta, Canada. Furthermore, it was emphasized that there are very weak market interdependencies between the cattle and feed grain markets. Çelik (2015) highlighted that there is a causal relationship between the exchange rate and goat meat, in which he examined the effects of exchange rate and inflation on red meat production in Türkiye. Fakari et al. (2016), who used the multivariate BEKK–GARCH model to study the volatility and spread of cattle, sheep, and chicken prices per week in Iran, stated that the volatility in sheep meat prices was higher than in beef and chicken meat prices due to the production structure. Nevertheless, they emphasized that the volatility of mutton and beef prices was interrelated. Using the EGARCH model, Chadwick and Bastan (2017) examined whether unexpected price changes for 90 retail food items in the Turkish consumer price index asymmetrically affected price volatility. To analyze the pass-through between world crude oil and some basic food prices covering the period 1990–2015, Damba et al. (2017) employed the multivariate BEKK–GARCH model. They determined that a strong bilateral cross-correlation relationship existed between the crude oil price return and meat, grain, edible oils, and sugars. Meanwhile, the effect of corn prices on pork prices was found to be nonlinear and asymmetrical (Wang et al., 2018). Fiszeder and Orzeszko (2018) argued that there were strong nonlinear relationships between live cattle and pig price returns and corn and wheat price returns.

Çınar and Keskin (2018) stressed that there are strong nonlinear relationships between animal (live cattle and pigs) price returns and corn and wheat price returns in Türkiye. In their study using the GARCH-BEKK model to investigate the volatility of producer and consumer meat prices in Finland, Abdallah et al. (2020) found an asymmetrical volatility spillover effect in poultry meat and reported a one-way consumer–producer volatility spillover effect in pork prices. Similarly, beef and lamb carcass prices have been volatile in the last 10 years, especially between 2009 and 2012, when imports were high, and red meat prices have a very important relationship with oil prices in Türkiye (Akay, 2021). In a study they conducted in Türkiye, Urak et al. (2022b) reported that the uncertainties occurring in the live calf, live sheep, and feed wheat markets are due to both their long-term uncertainties and those of other markets. According to their findings, the conditional variances of the returns of live calves, live sheep, and forage wheat are significantly affected by the price fluctuations in the exchange rate and the import periods compared to the periods when imports were not made in Türkiye. Conversely, Tejeda and Goodwin (2009) investigated beef, soybean, and corn price correlations in the United States using weekly average futures prices from 1998 to 2008. The lack of a significant relationship between cattle prices and corn and

soybean prices in their study could be attributed to the fact that meat producers altered their feed combinations when corn or soybean prices increased.

Given that the importance of price connectivity research in international beef markets has been largely disregarded, Guo and Tanaka (2020) and Tanaka and Guo (2020) employed a generalized autoregressive conditional time-varying volatility (GARCH) model with a dynamic conditional correlation (DCC) specification that permits it to elicit dynamics of the market connectivity in question. They analyzed the relationship between global and local prices in some countries, as well as price volatility in the market. They also permitted structural modifications to the overall processes in their study in order to improve the estimation reliability. Their main findings were as follows: (1) After the global food crisis of 2007–2009, local retail prices for Azerbaijan, Georgia, Japan, Kazakhstan, Kyrgyzstan, Tajikistan, and the United Kingdom showed a structural change in mean or variance. (2) International prices are unidirectional, with regional prices in Georgia, Tajikistan, and the United States causing Granger both in terms of mean and time-varying volatility. (3) Volatility relationships between global and domestic beef markets are generally weak, but price volatility exhibited a closer synchronization around the 2008 global food crisis, which led to structural changes during the period. Finally, Wan and Li (2022) recently applied an asymmetric MGARCH-BEKK model to examine asymmetric price volatility transmission through a structural break in agricultural supply chains, with an application to the Chinese pork market, based on the fact that the issue of asymmetric price volatility transmission in agricultural supply chains is neglected in the literature. In March 2007, the authors discovered a structural change in pork market prices, where they determined that there was an asymmetrical volatility spillover in Chinese pork supply chains and that the propagation was different before and after the corresponding break.

When examining the literature on the spread of uncertainty for meat and meat types, studies on volatility spillovers in livestock and feed wheat markets in emerging countries with a fragile economic structure, such as Türkiye, where both the exchange rate market and oil markets predominantly influence other economic structures, have been scarce. This study will fill the gap. To capture the differential effects on the returns of the explored agricultural commodity markets, we employed returns of the energy and exchange rate series and the dummy import variable in the average return equations. Our study also deviates from the existing literature by presenting the lean variables of energy, exchange rate, and binary imports in the time-varying volatility equations to elicit their effects on risk propagation levels of the Turkish meat market and feed wheat markets.

3. Data and methods

3.1. Data

Daily gasoline price, real exchange rate, and import data for the period of January 2005–June 2019 were obtained in order

to analyze the volatility between agricultural commodities, daily beef carcass, lamb carcass, and feed wheat prices. The prices of agricultural products including beef and lamb carcasses and feed wheat are collected from the daily exchange figures of the database run by the Union of Chambers and Commodity Exchanges of Türkiye. Additionally, macroeconomic variables of gasoline, foreign exchange rate, and imports were included as indicators of the energy and other markets. The real exchange rate series were obtained from the Electronic Data Delivery System of the Central Bank of the Republic of Türkiye. Moreover, imports of agricultural products are required during periods of insufficient supplies of beef carcasses, lamb carcasses, and feed wheat in Türkiye. Thus, the effect of the “import” variable on the agricultural markets was investigated during the import periods in contrast to the non-import periods. In this context, the “import” variable series was obtained from the Turkish Statistical Institute (TSI) database.

Returns are a source of synergy for investors to invest and have a tendency to fluctuate over time. These familiar sources of change can be economic as well as political, cultural, social, and environmental, which are the impulse reactions to everyday events (Tosun and Demirbas, 2020). The volatility of agricultural commodity returns and the level of risk they pose are known by the volatility of the data. Volatility is the directionless movement of a commodity in a given period. In a very short time frame, the high amplitude of commodity price fluctuation implies high volatility, whereas low amplitude implies low volatility. Unless such fluctuations remain stable or constant in the time dimension, they represent a property with a heteroscedastic form. The return level of the three agricultural commodity markets was calculated as follows: $R_t = 100 \cdot \ln(P_t/P_{t-1})$, where P_t shows the real price (e.g., deflated) of the agricultural commodity in question, whereas \ln represents the natural logarithm symbol. Conversely, P_{t-1} expresses the lag operator of P_t . R_t generally represents a vector; for example, in our study, beef carcass (bc), lamb carcass (lc), and feed wheat (fw) were subjected to a vector, $R_t = [R_{bc,t} \ R_{lc,t} \ R_{fw,t}]'$.

3.2. Econometric method

This study is based on the vector autoregressive (VAR) model and Baba–Engle–Kraft–Kroner's (BEKK) asymmetric generalized autoregressive conditional variable variance (GARCH) model. Combining these three terms results in VAR(q)–BEKK GARCH(1,1), where q is the number of lags in the VAR model (Engle and Kroner, 1995; Rahman and Serlitis, 2012; Salisu and Oloko, 2015). The model includes conditional vector autoregression on the one hand and dependent multivariate GARCH in a conditional heteroscedasticity equation on the other hand. The model is superior to other models as it adds asymmetrical effects to the conditional variance equation based on the assumption that positive and negative shocks have equal sizes (Rahman and Serlitis, 2012; Salisu and Oloko, 2015). The VECM model, known as the vector stacking covariance matrix, is unattractive since the covariance matrix known as H does not meet the semidefinite

positive condition and has intensive computation and non-convergence problems in the face of an excessive number of parameters. Alternatively, the constant conditional correlation model loses its attractiveness because it has an overload of parameters and a time-independent nature of the conditional correlation, although it satisfies the semidefinite positive condition of the variance–covariance matrix. Although the DCC model, which has a time-varying (dynamic) conditional correlation due to less parameter load, provides the semidefinite positive condition in the variance–covariance matrix, we preferred to use the BEKK model, which is more of an information source cube because it allows asymmetric information flow during the modeling phase (Engle and Kroner, 1995; Rahman and Serlitis, 2012; Salisu and Oloko, 2015). In this context, the BEKK model served as a motive behind our choice of modeling interdependencies between variables of financial time series in the days under study when the asymmetrical effect of shocks in financial markets is often studied. Additionally, the model has the advantage of warranting fewer BEKK parameters and positive definiteness of the conditional variance–covariance parameters (Rahman and Serlitis, 2012; Salisu and Oloko, 2015). The equations of conditional averages and conditional variances of each return are presented in equations (1) and (2) (Ling and McAleer, 2003; Rahman and Serlitis, 2012; Salisu and Oloko, 2015).

$$R_t = \mu + \sum_{i=1}^p \Gamma_i R_{t-i} + \Psi R_{G,t-1} + \Phi R_{E,t-1} + \omega I + \varepsilon_t, \quad (1)$$

where R_t is as defined before. Parameters such as μ , Ψ , Φ , and ω are each a 3×1 column vector. Moreover, index i indicates the level of lag specified by the Akaike, Bayesian, and Hannan–Quinn information criteria (AIC, BIC, and HQ, respectively). R_{t-i} and ε_t represent the lagged return vector for agricultural commodity markets and the error shocks vector of these markets, respectively. G , E , and I represent the gasoline return, exchange rate return, and dummy import variables, respectively. Conversely, Ψ , Φ , and ω coefficients are used to measure the effect of these subsequent variables, respectively. Moreover, dummy variable I was set to have a value of 1 in the months in which beef and lamb carcasses are imported, and 0 in other months. When the price change in feed wheat, beef carcasses, and lamb carcasses is greater than anticipated, market actors consider this to be good news; conversely, when the price change is less than expected, they generally consider this to be bad news. In this case, the residuals of each return variable will be positive and will be displayed as follows: $\xi_{1,t} = \max\{\varepsilon_{1,t}, 0\}$, ..., $\xi_{m,t} = \max\{\varepsilon_{m,t}, 0\}$ (Rahman and Serlitis, 2012), where m equals 3. These values derived from the market return equations characterized as 1 when negative and 0 otherwise were used to allow for asymmetry in the conditional heteroscedasticity equations.

Considering the preference for the multilagged BEKK form, the nonlinearity of the parameters, and the almost impossibility of convergence of the model with the number of parameters as much as ammo at the maximum point of the function in question, only the first-order BEKK form was preferred in this

study. We can express the conditional heteroscedasticity equation for the first-order asymmetric BEKK–GARCH model as (Grier et al., 2004):

$$H_t = \Upsilon \Upsilon' + A' \varepsilon_{t-1} \varepsilon'_{t-1} A + B' H_{t-1} B + D' \xi_{t-1} \xi'_{t-1} D, \quad (2)$$

where matrix H consists of two parts. The first part consists of the constants of the equation plus the exogenous variables G , E , and I in $\Upsilon = (C + \Psi G + \Phi E_t + \varphi I_t)$. The second part consists of the following variables: short-term shocks (ε_{t-1}), long-term volatility (H_{t-1}), and asymmetric effect (ξ_{t-1}). This first part can be displayed as $\Upsilon \Upsilon'$, whereas the second part can be presented as follows: $A' \varepsilon_{t-1} \varepsilon'_{t-1} A + B' H_{t-1} B + D' \xi_{t-1} \xi'_{t-1} D$. Moreover, C is the lower diagonal matrix, and ψ , ϕ , and φ are respectively the constant coefficients and corresponding parameters for gasoline, exchange rate, and imports in the conditional variance equation. A and B matrices display short-term shocks and long-term volatility parameters, respectively, whereas D matrix emerges as a parameter displaying the asymmetric effect. Although the diagonal coefficients in A, B, and D matrices are related exclusively to the shocks, volatility, and asymmetry of the relevant market, respectively, non-diagonal parameters in these matrices define the short- and long-term persistent transmission from other markets to the relevant market. The measurability of the BEKK model ensures the positive definition of H_t for ε_t residuals, and it allows different relative responses to positive–negative shocks via conditional variance and covariance (H_t) by relaxing the assumption of symmetry.

The parameters of the BEKK model's conditional mean and conditional variance–covariance equation were effectively obtained by maximizing the log-likelihood function. Moreover, Student's t-distribution proposed by Bollerslev (1987) was applied for the parameter evaluation. This distribution can produce the estimators for the distribution of the leptokurtic of conditional residuals that solve the problem of nonnormal distribution. The likelihood function of this distribution is defined as follows:

$$L_t = \ln \left[\frac{\Gamma(\frac{v+n}{2}) v^{\frac{n}{2}}}{(vn)^{\frac{n}{2}} \Gamma(\frac{v}{2}) (v-n)^{\frac{n}{2}}} \right] - \frac{1}{2} \ln |H_t| - \frac{1}{2} (v+n) \ln \left(1 + \frac{\varepsilon_t' H_t^{-1} \varepsilon_t}{v-2} \right), \quad (3)$$

where the average number of n equations, ε_t , shows the residuals of n mean equations and v and $\Gamma(\cdot)$ stand for a degree of freedom (provided that $v > 2$) and gamma function, respectively (Urak et al., 2022b).¹

¹ This log-likelihood function value was compared with the log-likelihood function value obtained under normal distribution to elicit which model was statistically more congruent with the data.

3.3. Optimal portfolio weights and hedge ratios

Based on the VAR(q)–BEKK–GARCH (1,1) model, the hedge ratio of feed wheat, beef carcass, and lamb carcass markets and other optimal ratios were ascertained. The purpose is to minimize the risk of an investor's expected return on investment. Kroner and Ng (1998) expressed the optimal portfolio weight as the i weight in the i portfolio with a single currency for the t time and j sector (Kroner and Ng, 1998; Gencer and Musaoglu, 2014). These variables are shown in equations (4)–(6), respectively:

$$w_t^{ij} = \frac{h_t^i - h_t^{ij}}{h_t^i - 2h_t^{ij} + h_t^j}, \quad i = 1, \dots, m \text{ and } j = \text{alternative market} \quad (4)$$

where agricultural product markets can extend from $i = 1, \dots, m$. Correspondingly, whereas h_t^i expresses the conditional variance of each chosen agricultural product, h_t^i displays the foreseen conditional variance for the alternative market. h_t^{ij} exhibits the foreseen conditional covariance between each chosen agricultural product and the alternative agricultural market. In this context, hedging strategies mitigate the price volatility of the products or variables, whereas enabling the investors to make exact price projections for future investment decisions. Hence, the portfolio weight is expressed as follows:

$$w_t^{ij} = \begin{cases} 0, & \text{if } w_t^{ij} < 0 \\ w_t^{ij}, & \text{if } 0 \leq w_t^{ij} \leq 1 \\ 1, & \text{if } w_t^{ij} > 1 \end{cases} \quad (5)$$

The average weight here displays how much an investor should invest 1 ₺ in agricultural product A and the rest in agricultural product B. Kroner and Sultan (1993), conversely, estimated hedge ratios of asset portfolios as follows:

$$\beta_t^{ij} = \frac{h_t^{ij}}{h_t^i}, \quad i = 1, \dots, m \text{ and } j = \text{alternative market} \quad (6)$$

where β_t^{ij} in the i market in the sector indicates the short-term position amount for hedging against the long-term position of 1 ₺ in the j market.

4. Results and discussion

In the present study, after converting the series into real prices,² the analyses were performed by obtaining the return series. Table 1 shows some descriptive statistics including the correlation relationships of the price, returns, and return squares series. Given the correlation relationship between product prices, we observe that the correlation levels between the beef carcass and lamb carcass prices and between the beef

² The prices of beef and lamb carcasses and feed wheat have been deflated using the food price index based 2003 = 100 and the fuel price using energy prices index based 2003 = 100. The exchange rate series was adjusted using the real effective exchange rate.

Table 1
Descriptive statistics and unit root test results.

Statistics	Returns ($R_{j,t}$)				
	$R_{bc,t}$	$R_{lc,t}$	$R_{fw,t}$	$R_{g,t}$	$R_{e,t}$
Mean	-0.025	0.044	0.067	-0.102	0.675
Std. dev.	4.325	5.735	6.305	4.775	5.915
Skewness	0.071 (0.629)	0.375** (0.011)	-0.187 (0.202)	-0.681*** (0.000)	3.727*** (0.000)
Kurtosis	1.955*** (0.000)	3.002*** (0.000)	4.099*** (0.000)	34.926*** (0.000)	32.734*** (0.000)
Jarque-Berra	45.007*** (0.000)	112.138*** (0.000)	198.351*** (0.000)	14303.500*** (0.000)	13196.344*** (0.000)
Correlations between real prices ($Pr_{j,t}$, $j = bc, lc, fw, gasoline(g),$ and exchange rate (e)):					
$Pr_{bc,t}$		0.989	0.988	0.981	0.804
$Pr_{lc,t}$			0.979	0.976	0.819
$Pr_{fw,t}$				0.989	0.793
$Pr_{g,t}$					0.780
Correlations between return series ($R_{j,t}$, $j = bc, lc, fw, g,$ and e)					
$R_{bc,t}$		0.240	0.026	0.032	-0.013
$R_{lc,t}$			0.098	-0.111	0.045
$R_{fw,t}$				-0.089	0.006
$R_{g,t}$					-0.142
Correlations between squared return series ($R_{j,t}^2$, $j = bc, lc,$ and fw)					
$R_{bc,t}^2$		0.351	0.467	0.043	0.116
$R_{lc,t}^2$			0.235	0.225	0.328
$R_{fw,t}^2$				0.087	0.067
$R_{g,t}^2$					0.177
Serial correlations in returns ($R_{j,t}$, $j = bc, lc,$ and fw)					
LB-Q (10)	25.992 (0.004)	16.675 (0.082)	106.303 (0.000)		
McLeod-Li (10)	24.822 (0.006)	5.137 (0.882)	65.769 (0.000)		
HM-Q (10)	225.739 (0.000)				
ARCH effects in return squared series ($R_{j,t}^2$, $j = bc, lc,$ and fw)					
ARCH-LM (10)	2.509 (0.007)	0.354 (0.965)	7.061 (0.000)		
MARCH-LM (10)		979.400 (0.000)			
HM-Q ² (10)		204.941 (0.000)			
Unit Root Tests (Return series ($R_{j,t}$, $j = bc, lc,$ and fw))					
ADF	13.130*** (lags = 1)	-12.500*** (lags = 1)	-15.499*** (lags = 1)		
KPSS	0.026 (lags = 1)	0.027 (lags = 1)	0.027 (lags = 1)		

Note: The critical values vary with the lags selected. In parenthesis are associative p-values. *, **, and *** are statistically significant at 10%, 5% and 1% respectively.

carcass and feed wheat prices are much higher than in other relationships. Moreover, the synchronized relationship between red meat and feed wheat prices, which indicates the easy transmission of the volatility propagation, is immediately striking (Fig. 1). However, the synchronized mobility between the two meat types is more pronounced. The graph confirming the above statistics also shows that feed wheat prices show high volatility, followed by lamb and beef carcass prices. The close relationship of agricultural commodities with the energy market is also noteworthy, as energy costs account for almost half of price formation in the country. The relationship level between the dollar exchange rate and agricultural commodity markets is quite solid. In this context, we observed that market sensor is particularly effective at price transmission, where innovations in one market are instantly transmitted by price sensors to other markets, resulting in either price inflation or a

slight price contraction. Such a relationship may stem from features such as substitutions or complementarities of products, but generally, the purchase and sale of products in digital environments through financial instruments in the last quarter-century have led to a gradual integration between commodities, which ultimately increased the levels of correlation and diffusion volatility of commodities (Adams and Glück, 2015; Karyotis and Alijani, 2016; Olson et al., 2014).

The beef carcass return is negative (-0.025), which has the lowest unconditional return and volatility (standard deviation) among the series. We can assert that the high demand or low supply of lamb was influential in the period in which the lamb carcass return was higher than the beef carcass return (Table 1). Alternatively, we observed an asymmetrical distribution of the return series. The coefficient of kurtosis exposed that the return series exhibit a leptokurtic (fat-tailed) distribution (Table 1).

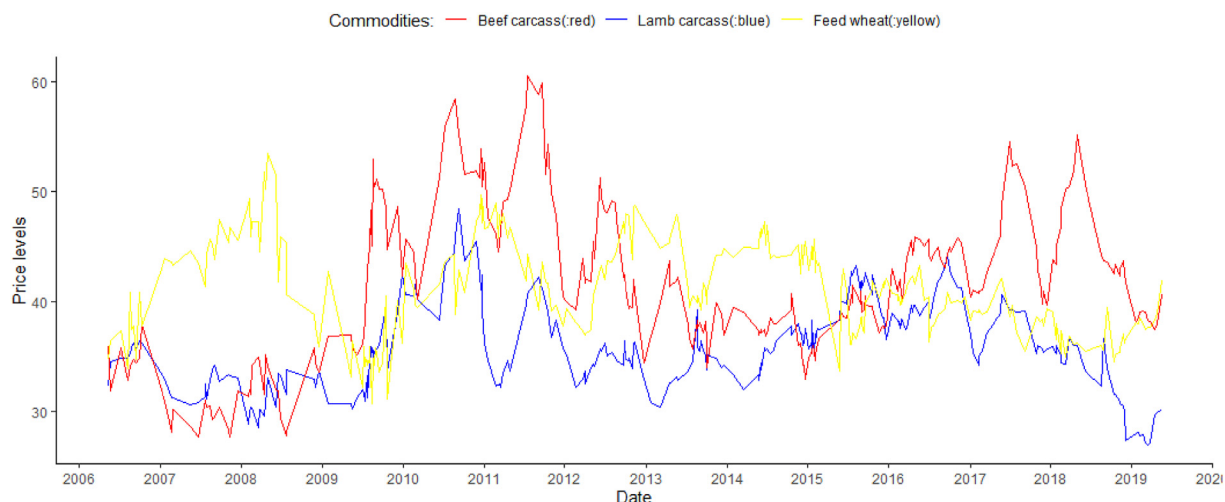


Fig. 1. Co-movements of commodity prices in question. Note: Feed wheat prices were magnified 30 times to show the synchronous relationship between the products examined.

The leptokurtic distribution of the return series implies a possible autoregressive conditional variance (ARCH) effect on the series. Such a notion was initiated using the Jarque–Bera test statistic, confirming that the series was not normally distributed at the 1% significance level (Table 1). Then, using many statistical tests, the presence of both autocorrelation and time-varying volatility (heteroscedasticity) in returns and return squares, respectively, was examined. Although Ljung–Box Q (henceforth, LB–Q) and McLeod–Li statistical tests were applied to individual return series, we preferred Hosking's Multivariate Q–statistic (henceforth, HM–Q) as a multivariate test for detecting serial correlation. Individual and multivariate tests all confirm each other (Table 1), indicating the presence of autocorrelation in the return series of the explored agricultural commodities. Therefore, an increased return can lead to an increased return, and a decreased return can lead to a decreased return in the three agricultural markets in question. The results also imply an autoregressive (AR) process in the return equation. Alternatively, to capture the presence of the time-varying volatility (heteroscedasticity), the individual ARCH–Lagrange Multiplier (henceforth, ARCH–LM) test was applied to the squares of the return series, whereas the multivariate ARCH–LM (henceforth, MARCH–LM) and HM–Q² tests were also applied to the squares of the return series for a joint decision. The purpose of such tests is to elicit which periods of exciting and disappointing returns are more affected, as increasing returns track increasing returns during periods of exciting returns and decreasing returns track decreasing returns during periods of a letdown in volatility clustering. While evaluating the individual ARCH–LM test statistics, we observed that there was an ARCH effect in the series except for the lamb carcass return (Table 1). However, given the multivariate ARCH–LM and HM–Q² statistic for joint return squared series, an ARCH effect on the squares of the return series exists, which indicates that the squared series are characterized by volatility clustering. This shows that the series holds the ARCH effect simultaneously and requires analysis with a multivariate

generalized ARCH (henceforth, GARCH) model. When considering the results of the augmented Dickey–Fuller and Kwiatkowski–Phillips–Schmidt–Shin unit root tests, the return series are stationary at the I(1) level with a 1% statistical significance, which meets the requirement for the series to be stationary in the use of the BEKK–GARCH model (Table 1).

In Fig. 2, which shows the unconditional time-varying volatility of the series returns, we observed that the highest volatility detected between 2008 and 2011 corresponds to the global crisis period in the financial and food sectors of the world. Crude oil prices peaked in 2008 when there was a global crisis in the finance and food sectors, with an increase of 94%, and achieved \$133/barrel per year (Baffes and Haniotis, 2010). Likewise, the high volatility of the return series in the period after 2017 may be due to the positive influence of the restrictions on imports within the context of policy measures implemented in Turkey in 2017. Conversely, between 2011 and 2016, when there was no global economic crisis, particularly in Turkey, we observed that the return series have the lowest and most stable trend volatility. The divergent expansion of the series over time amplitude is an obvious implication that the series is under the influence of ARCH. For this purpose, Fig. 3 depicts the squares of the time-dependent return series. The sharp peaks observed in the markets, especially between 2008 and 2011 and some other years, are clear evidence of the ARCH effect. Such an extreme effect is mostly felt in the feed wheat return followed by lamb carcass and beef carcass returns. The continuous volatility of the feed wheat return in such a situation is significant as its production is directly related to the high and unpredictable volatility of energy inputs in the country. Meanwhile, as can be easily observed in Fig. 3, the fact that the three products act synchronously in peak and decline periods in a sense shows the joint effect of shocks or innovations in the markets, whereas at the same time, it is evidence of the easy pass-through of the volatility between the corresponding markets. In terms of the unconditional variances of such markets, the beef carcass prices are very weak and quite stable when

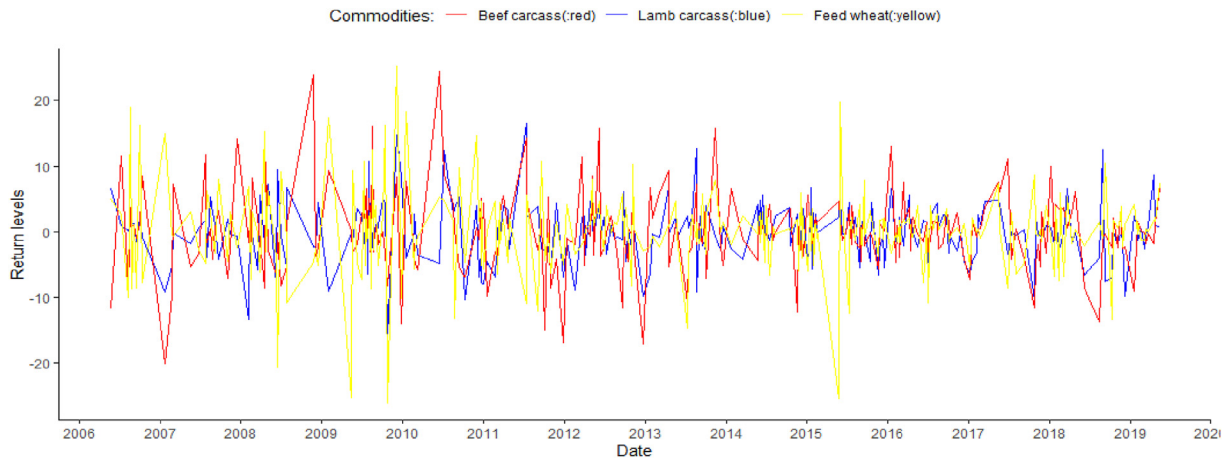


Fig. 2. Comovement of returns of the beef carcass, lamb carcass, and feed wheat over time.

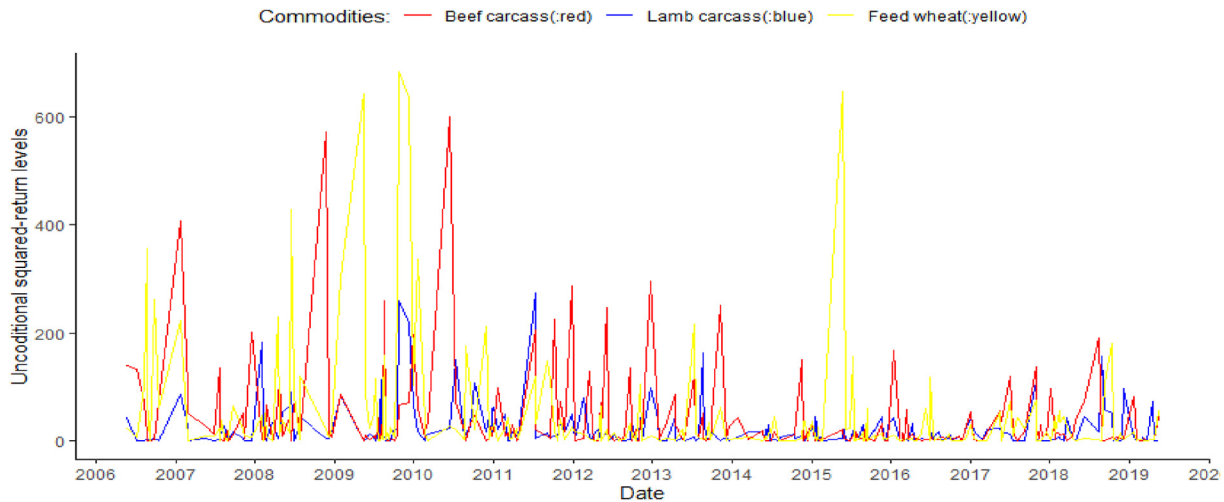


Fig. 3. Comovement of squares of the beef carcass, lamb carcass, and feed wheat returns over time.

compared to the other two competing markets, especially after 2010. This can be interpreted as a positive influence on the government’s implementation of meat imports to cope with the overwhelming demand in the country. Such a finding is in line with the literature results (Chadwick and Bastan, 2017; Urak et al., 2022b).

Before analyzing the model results, we deemed it necessary to evaluate the series fit of the log-likelihood function derived under the t distribution and the log-likelihood function derived under the normal distribution.³ The likelihood ratio (LR) statistic ($LR = 85.504$ and $p < 0.000$) and Wald (W) statistic ($W = 359.821$ and $p < 0.000$), all under chi-squared distribution (χ^2) and along with different information criteria (see Table 4), show that the parameters derived under the t distribution are more robust in explaining the mean and time-variant conditional heteroscedasticity. Using these statistical tests, the

Table 2
Parameter estimates for the mean returns.

Parameters	Returns		
	$R_{bc, t}$	$R_{lc, t}$	$R_{fw, t}$
μ	2.103*** (0.115)	-0.096 (0.075)	1.346*** (0.076)
Γ_{bc}	-0.143*** (0.044)	0.086* (0.050)	0.091* (0.049)
Γ_{lc}	0.082*** (0.023)	-0.043** (0.020)	0.016 (0.040)
Γ_{fw}	-0.059*** (0.019)	-0.088*** (0.030)	-0.393*** (0.039)
Ψ	0.018 (0.023)	-0.060*** (0.017)	0.015 (0.028)
Φ	0.002 (0.032)	-0.086*** (0.016)	-0.040** (0.016)
ω	-2.257*** (0.117)	0.228* (0.122)	-1.176*** (0.085)

Note: In parenthesis are associative standard errors. *, **, and *** are statistically significant at 10%, 5%, and 1%, respectively.

³ We would like to express our gratitude to the anonymous referee for drawing our attention to this point.

Table 3
Parameter estimates for the conditional variances.

Parameters	Returns		
	$R_{bc, t}$	$R_{lc, t}$	$R_{fw, t}$
$c_{bc,i}$	2.433*** (0.079)	–	–
$c_{lc,i}$	–13.955*** (0.203)	–9.921*** (0.080)	–
$c_{fw,i}$	1.494*** (0.082)	–0.682*** (0.102)	1.049*** (0.129)
$a_{bc,i}$	0.667*** (0.038)	0.632*** (0.062)	0.400*** (0.055)
$a_{lc,i}$	–0.518*** (0.033)	–0.714*** (0.048)	–0.153*** (0.043)
$a_{fw,i}$	0.174*** (0.045)	–0.003 (0.043)	0.292*** (0.004)
$b_{bc,i}$	0.166*** (0.025)	–0.094*** (0.019)	–0.038 (0.048)
$b_{lc,i}$	–0.342*** (0.036)	–0.026 (0.021)	0.074*** (0.016)
$b_{fw,i}$	–0.244*** (0.014)	0.157*** (0.020)	0.663*** (0.014)
$d_{bc,i}$	–0.131*** (0.024)	0.400*** (0.015)	–0.370*** (0.046)
$d_{lc,i}$	–0.318*** (0.047)	0.093*** (0.019)	0.013 (0.022)
$d_{fw,i}$	0.108*** (0.022)	–0.002 (0.048)	0.422*** (0.011)
$\psi_{bc,i}$	–0.286*** (0.006)	–	–
$\psi_{lc,i}$	1.098*** (0.021)	1.714*** (0.011)	–
$\psi_{fw,i}$	0.564*** (0.010)	0.138*** (0.013)	–0.073*** (0.016)
$\phi_{bc,i}$	1.063*** (0.056)	–	–
$\phi_{lc,i}$	0.808*** (0.048)	–0.260*** (0.029)	–
$\phi_{fw,i}$	–0.180*** (0.019)	0.054 (0.045)	–0.470*** (0.032)
$\varphi_{bc,i}$	–0.697*** (0.104)	–	–
$\varphi_{lc,i}$	5.348*** (0.123)	2.416*** (0.072)	–
$\varphi_{fw,i}$	–3.511*** (0.083)	–0.848*** (0.100)	1.828*** (0.035)
Shape (t degrees)	4.206*** (0.222)	–	–

Note: In parenthesis are associative standard errors. *, ** and *** are statistically significant at 10%, 5%, and 1%, respectively.

Table 4
Optimal portfolio weights and hedging rates.

Product	Optimal Portfolio Weights (w_i^*)			Hedging Rates (β_i^*)		
	bc	lc	fw	bc	lc	fw
bc	–	0.645	0.553	–	0.188	0.121
Testing bc = 0		40.995*** (0.000)	37.499*** (0.000)		8.893*** (0.000)	5.227*** (0.000)
lc	0.355	–	0.420	0.232	–	0.150
Testing lc = 0	22.568*** (0.000)		33.308*** (0.000)	8.638*** (0.000)		6.694*** (0.000)
fw	0.467	0.580	–	–0.021	0.061	–
Testing fw = 0	32.815*** (0.000)	46.058*** (0.000)		–0.813 (0.947)	4.090*** (0.000)	

Note: *, ** and *** are statistically significant at 10%, 5%, and 1%, respectively.

existence of a leptokurtic nonnormal distribution problem of conditional residuals was elicited. Additionally, robust standard errors were used to derive the statistics of parameter values of both models. In the subsequent discussion, we will now proceed by referring to the maximum likelihood function with the t distribution and performing it on parameters of statistical significance.

When different information criteria in the VAR return equation presented different lag values, one (1) with the lag value specified by the AIC was referenced throughout all estimation procedures. Table 2 shows the results of the return equations, which is the first part of the VAR (1)–BEKK–GARCH (1, 1) model. The beef carcass market is significantly affected by a lag of both its own ($\Gamma_{bc} = -0.143$) and the lamb carcass market ($\Gamma_{lc} = 0.082$). Increased lag return from the beef carcass market shrinks the current conditional mean return, whereas the lag lamb carcass market value has an increasing role. Although the increased return in the previous period is expected to create an attraction for the beef carcass sector, by contrast, there may be some fundamental problems behind the decreasing return. Although increased returns are expected to scale up the business, such a reduced return may be due to the high additional cost of raising cattle, the high number of intermediaries, and the small scale of most farms in the country. Alternatively, increases in the feed wheat return in the previous period negatively affect the beef carcass return. In other words, the increase in real prices in the feed wheat market means an increased cost in this market as it acts as an input for beef production.

Imports have an adverse effect on the beef carcass return, which can undermine domestic producer decisions. Such an empirical finding must be reached because opening the import gate to overcome the bottleneck in red meat has been a subject of great debate in the country. Confronted with high breeding costs and lower world prices than local prices, additional incentives should be offered by the government to ensure that domestic cattle producers do not deviate from their long-term production decisions as they face the risks of breeding sovereignty (Akgunduz et al., 2020; Chadwick and Bastan, 2017; Urak et al., 2022b). The same effect is unfortunately also present in feed wheat returns. As domestic beef carcass prices regress to import prices, the demand for feed

wheat decreases, which leads to reduced incentives for its cultivation.

The current lamb carcass market is positively affected by the gain in the beef carcass market ($\Gamma_{bc} = -0.086$) but negatively impacted by its lagged return ($\Gamma_{lc} = -0.043$) and feed wheat market return ($\Gamma_{fw} = -0.088$). Lagging gains in the beef market also boost returns in the rival lamb market. In this case, whereas the lagged gains in the cattle market make producers or traders experience a loss of return in their market, the lamb market shows return gains. Furthermore, given that the main input in beef and lamb breeding is feed wheat, the positive atmosphere surrounding this market reflects negatively on the lamb carcass market. The gains in gasoline and dollar exchange rates, unfortunately, negatively impact the lamb carcass return ($\Psi = -0.060$ and $\Phi = -0.086$), and import decisions caused a significant gain in the lamb carcass market ($\omega = 0.228$). Although import decisions cause a loss of earnings for veal breeders as the calf carcass market is impacted, it opens a door to additional income earnings for lamb breeders. In the face of high returns in gasoline and exchange rates, producers or traders might be directed to alternative financial commodity markets and may leave the country in bottlenecks in terms of food sovereignty. Although the increases in lagged earnings in the beef carcass market reflect positively on the gains in the feed wheat market ($\Gamma_{bc} = 0.091$), unfortunately, the lagged earnings in its market make the current returns negative ($\Gamma_{fw} = -0.393$). Conversely, the exchange rate and import decision significantly negate the gains in the feed wheat market ($\Phi = -0.040$ and $\omega = -1.176$). We might conclude that such results might lead producers or traders to other profitable portfolios, especially in the foreign exchange market. We might also infer that import decisions to mitigate food inflation and increase consumer welfare hit the beef carcass sector the most, followed by the feed wheat market, which unfortunately may cause red meat producers and feed wheat growers to lower their production.

Table 3 presents the maximum likelihood estimates for the second part of the VAR (1)–BEKK–GARCH model (e.g., the conditional heteroscedasticity model). Conditional variances among all three agricultural commodities are statistically affected by their shocks in the short term and the shocks in counter markets. Such results show that the beef carcass, lamb carcass, and feed wheat markets were significantly affected by bad and good news (e.g., innovations) that disseminate into the agricultural markets. For instance, the conditional variance of beef carcass returns was affected by both its short-term shocks ($a_{bc,1} = 0.667$) and rival market shocks, that is, negative lamb carcass ($a_{lc,1} = -0.518$) and positive feed wheat ($a_{fw,1} = 0.174$), with the largest impact stemming from the lamb carcass market. Such results show that the events entering both its market and the counter markets (lamb and feed wheat) are perceived by the receptors in the beef carcass market and conveyed to the market itself. However, the short-term fluctuations in both the own market and the feed wheat market deepen the uncertainty in the beef carcass market. The above results agree with the theory as the beef carcass market is a close substitute for the lamb carcass market and the feed wheat

market is complementary to the beef carcass market. The uncertainty that spreads in both the beef carcass and feed wheat markets may disrupt producers' future cattle breeding plans, which may cause the country to experience persistent problems in the red meat supply chain. Kesavan et al. (1992) emphasized that fluctuations in bovine meat and pork are due to their short-term shocks, whereas Zhen et al. (2018), in their study conducted in Canada, showed that there was neither a spillover transmission from barley price shocks to fed cattle returns nor the reverse but each lagged spread of market fluctuations affected its market volatility. Our findings confirm the similar results of Urak et al. (2022b).

Considering the extent to which the two counterfactual markets are affected by transmission in the beef carcass market, the beef carcass market has similar spillover volatilities in both markets ($a_{bc,2} = 0.632$ for lamb carcass market and $a_{bc,3} = 0.400$ for feed wheat market). There is a positive spread from the beef carcass market to other counter markets, whereas there is a negative spillover from the lamb carcass market to the beef carcass market. Considering the market scales, these findings are in line with expectations since the beef carcass market has the highest weight in the meat sector. Although short-term shocks from the beef carcass and feed wheat markets cause permanent uncertainty in the beef carcass market, the short-term shocks from the beef carcass market similarly deepen the volatility in the other two competing markets, which will adversely affect the production decisions of the producers and thus consumer food security. Low- and middle-income consumer families and subsistence producers will suffer greatly from this unpredictable volatility.

Given the short-term spread between and within the remaining two markets, lamb carcass is negatively affected by its market ($a_{lc,2} = -0.714$), while feed wheat is positively affected by its market ($a_{fw,3} = 0.292$). Although the current short-term unpredictability in the lamb carcass market mitigates the permanent uncertainty in its market, such a situation does not exist for the feed wheat market. Since the feed wheat market is an energy-intensive process, short-term external factors inevitably shape both the price and the ongoing uncertainty in the market. There was a negative spread from the lamb carcass market to the feed wheat market ($a_{lc,3} = -0.153$), whereas the reverse spillover was statistically insignificant from the feed wheat to the lamb carcass market. Although feed wheat can be stored, storage times for red meats are very limited as Zhen et al. (2018) stated. Given supply shocks, demand for the relevant product becomes more inelastic as stocks erode and spillover transmission mostly occurs when higher prices are involved. Beef and lamb are nonstorable products and when animals reach a certain weight, they move to the next stage in the supply chain, either for fattening or for slaughter; hence, volatility pass-through occurs when prices decrease (Zhen et al., 2018). Our findings derived from market-induced shocks overlap with those of national and international studies (Abdelradi and Serra, 2015a, 2015b; Cabrera and Schulz, 2016; Gardebroeck and Hernandez, 2016; Mensi et al., 2013; Mensi et al., 2014; Sadorsky, 2014; Sidhoum and Sera, 2016; Urak et al., 2022b; Urak et al., 2022c; Zhen et al., 2018).

Focusing on the parameters in the persistent volatility spillovers across the three markets (e.g., long-term volatility parameters), all parameters except the spillover from beef carcass to feed wheat and the lamb carcass itself were statistically significant. The conditional variance of beef carcass returns was directly affected by its long-run market volatility ($b_{bc,1} = 0.166$), whereas it was indirectly affected by persistent spillovers of the lamb carcass market ($b_{lc,1} = -0.342$) and feed wheat market ($b_{fw,1} = -0.244$). Long-term uncertainties in the cattle market make its uncertainty even more permanent. Although such a situation causes foreign exchange outflow from the country by importing cattle, it threatens consumer food security in the face of increasing prices with supply constraints, which made it inevitable for the country to pay concessions in the red meat supply chain. Additionally, the long-term uncertainty that occurs in a market owing to the substitution effect between red meat prices leads to fluctuations in the prices of other markets (Fakari et al., 2016). Although the persistent spillovers from the two other markets to the beef carcass market are negative, similar negative uncertainty is conveyed from this market to the others; however, the impact on the feed wheat market is negligible ($b_{bc,2} = -0.094$ to lamb carcass and $b_{bc,3} = -0.038$ to feed wheat market), which confirms the effects of the above short-term shocks we obtained earlier. Due to the persistent long-term uncertainties in the counter markets, red meat investors in the market probably took precautions by putting the existing animals on sale (Zhen et al., 2018). Many agricultural commodity-based international studies have also reported that most agricultural markets are affected by both long-term volatility and the fluctuations of crude oil (Abdelradi and Serra, 2015a; 2015b; Cabrera and Schulz, 2016; Gardebroek and Hernandez, 2016; Mensi et al., 2014; Sadorsky, 2014). Information on both agricultural input and retail food prices caused volatility in retail, wholesale, and consumer agricultural product prices (Ben Abdallah et al., 2020; Khiyavi et al., 2012; Rezitis, 2018; Sidhoum and Sera, 2016). The literature also found that among the inputs used in red meat production, there are linear (Ziemer and Collins, 1984) and nonlinear (Fiszeder and Orzeszko, 2018) relationships.

Although persistent uncertainties in the lamb carcass market do not have a significant impact on long-term persistent volatilities in its market ($b_{lc,2} = -0.026$), long-term uncertainties in the feed wheat market significantly worsen the persistent uncertainties in its market ($b_{fw,3} = 0.663$). Inevitably, the uncertainties that have become permanent in the feed wheat market will cause deep wounds in its market, for instance, exposing producers to the risk of high input costs and lower production. Uncertainties that may arise from the supply–demand imbalance in this market will inevitably produce problems in the red meat sector and other sectors where feed wheat is predominantly used as an input for raising livestock. Persistent spillover transmission from the lamb carcass market to the feed wheat market ($b_{lc,3} = 0.074$) and from the feed wheat market to the lamb carcass market ($b_{fw,2} = 0.157$) is positive, which further worsens each market, whereas the effect of spillover transmission from the feed wheat to the lamb

carcass market is more severe. As Zhen et al. (2018) highlighted, uncertainties in the red meat sector continued to worsen during the downturn of storable feed barley or wheat. The literature states that all volatility expansions predicted throughout the supply chain are one-directional and these expansions derive from the market channel to the input–output markets (Apergis and Rezitis, 2003; Pozo and Schroeder, 2012; Zhen et al., 2018). Fakari et al. (2016) focused on the substitute goods effect on red meat prices and stated that the shock in one market will create a fluctuation in the prices of another market. The fact that long-term uncertainty in the beef carcass and feed wheat markets is limited to long-term uncertainties only in their markets should be perceived as positive news, and policymakers must approach each market with a separate structural reform and take precautions to eliminate price fluctuations in the markets. For example, reducing the number of intermediaries in the beef carcass market and establishing a contractual partnership between cattle breeders and supermarkets can increase the traceability of price propagations in the country. Moreover, various subsidies can be offered to feed wheat producers including contract farming, licensed warehousing, and digital programs that will allow small- and medium-sized businesses to produce their feed for their farm animals (Urak et al., 2022b). Excessive price volatility may also be prevented by establishing centers in cities where supermarkets or medium- and large-scale butcher businesses can report their daily meat purchase quantities and prices in a synchronized manner.

There is an asymmetric spillover transmission of negative news to conditional variances within and between markets. For example, asymmetric shocks in the beef carcass market are negatively conveyed in both its market ($d_{bc,1} = -0.131$) and feed wheat market ($d_{bc,3} = -0.370$) but positively conveyed in the lamb carcass market ($d_{bc,2} = 0.400$). Negative shocks were transmitted from the lamb carcass market to the beef carcass market ($d_{lc,1} = -0.318$) but positively to the own market ($d_{lc,2} = 0.003$) in a more distinct amplitude than the positive information. Conversely, negative news originating from the feed wheat market increases both the ongoing fluctuations in the beef carcass market ($d_{fw,3} = 0.108$) and its markets ($d_{fw,3} = 0.422$), adversely impacting its market the most. The lamb carcass market is most affected by asymmetric information derived from its internal supply–demand and other external imbalances, followed by the beef and lamb carcass markets. As stated by Zhen et al. (2018), lagged barley returns had an asymmetric effect on the uncertainties of 30-week fed cattle returns, and there is no such tandem spread from fed cattle uncertainty to barley market uncertainty. An asymmetric relationship was also confirmed between energy prices and food prices (Chowdhury et al., 2021). Likewise, Rezitis and Stavropoulos (2009) and Luo and Liu (2011) found asymmetric effects on pork, beef, mutton, and chicken meat price uncertainties.

Remarkably, the increase in energy prices mitigates the persistent fluctuations in the beef carcass ($\psi_{bc,1} = -0.286$) and feed wheat ($\psi_{fw,3} = -0.073$) markets while increasing the persistent uncertainty in the lamb carcass market ($\psi_{lc,2} =$

1.714), which is likely because producers or intermediaries may want to be minimally affected by the damage that may occur by placing their commodities on the market. The impact of rising energy prices on the uncertainties of the three markets is much more evident in the lamb carcass market. There is a spread of risk from the lamb carcass market to the beef carcass market, which was badly affected by increases in the energy market. In other words, price hikes in the energy market deepen the persistent uncertainties in the beef market through the lamb market ($\psi_{lc,1} = 1.098$) or vice versa. Furthermore, the increase in energy prices traded in the feed wheat market is causing continued deepening and ingrained volatility, largely in beef ($\psi_{fw,1} = 0.560$) and later in the lamb ($\psi_{fw,1} = 0.138$) markets or vice versa. Our findings are supported by the fact that feed wheat prices, which are influenced by high energy costs in the country, contribute to the ongoing volatility in the beef carcass and lamb carcass markets. Fossil fuels are inevitably shaping the long-term volatility of red meat markets (with the largest impacts on the lamb carcass market) since they have a wide presence in all possible stages of red meat production. As stated earlier, we found that price increases in the gasoline market also mitigate the risk (e.g., conditional variance) in beef carcass returns in the long run. Since petroleum and petroleum derivatives are frequently used in the production and transportation of beef carcasses, the increase in fossil fuel prices will boost the cost of meat production. Since a farmer is forced to sell the animals that he/she has, the risk of beef carcass returns can be expected to decrease in the long run with the increase in the animal supply in the market. The findings of this study are supported by the existence of a long-term and integrative relationship between food prices and energy prices in the literature (Cabrera and Schulz, 2016; Du et al, 2010; Mcfarlane, 2016; Pal and Mitra, 2017; Peri and Baldi, 2010; Shahzad et al., 2018; Sun et al., 2021; Taghizadeh-Hesary et al., 2019; Trujillo-Barrera et al., 2012). Furthermore,

changes in the value of national currencies influence both the high cost of agricultural products in foreign-dependent countries and the import and export of agricultural products, hence the prices of agricultural products. In this context, through foreign exchange, fluctuations in fuel prices impact food prices (Chen et al., 2010; Ismail et al., 2017; Özdemir et al., 2020). As in fossil fuels, volatility in the explored markets is under the influence of the dollar exchange rate ($\phi_{bc,1} = 1.063$ for beef, $\phi_{bc,1} = -0.260$ for lamb, and $\phi_{fw,3} = -0.470$ for feed wheat). Interestingly, the increase in the dollar exchange rate increases the long-term risks in the beef carcass market and makes it more permanent while minimizing the existing risks in the lamb carcass and feed wheat markets. Since cattle breeding is a long-term operation compared to the other two markets, the fluctuation in the exchange rate creates a disadvantage for a market rather than an advantage. Since most red meat imports are in the form of beef, the market volatility of beef carcass is persistently high with the dollar impact when compared with that of lamb carcass. The effect of the dollar on the lamb carcass or beef carcass market has a significant lasting effect on the uncertainty risk in the beef carcass (or lamb carcass) market ($\phi_{lc,2} = 0.808$). The dollar effect reflected on the feed wheat market or the beef carcass market indirectly mitigates the persistent risk in the beef carcass (or feed wheat market) market ($\phi_{lc,2} = -0.180$), which is directed by feed wheat producers who switch to alternative production options, possibly forcing cattle breeders to stop raising animals. Urak et al. (2022a) and Askan et al. (2020) found that agricultural products were significantly affected by their fluctuations and the volatility of the real exchange rate.

Although the spillover volatility in the beef carcass market is dampened by red meat imports ($\phi_{bc,1} = -0.697$), the fluctuations in the other remaining markets intensify ($\phi_{lc,2} = 2.416$ and $\phi_{fw,3} = 1.828$). Although the interaction between beef and lamb carcasses in imports made the market risks much worse

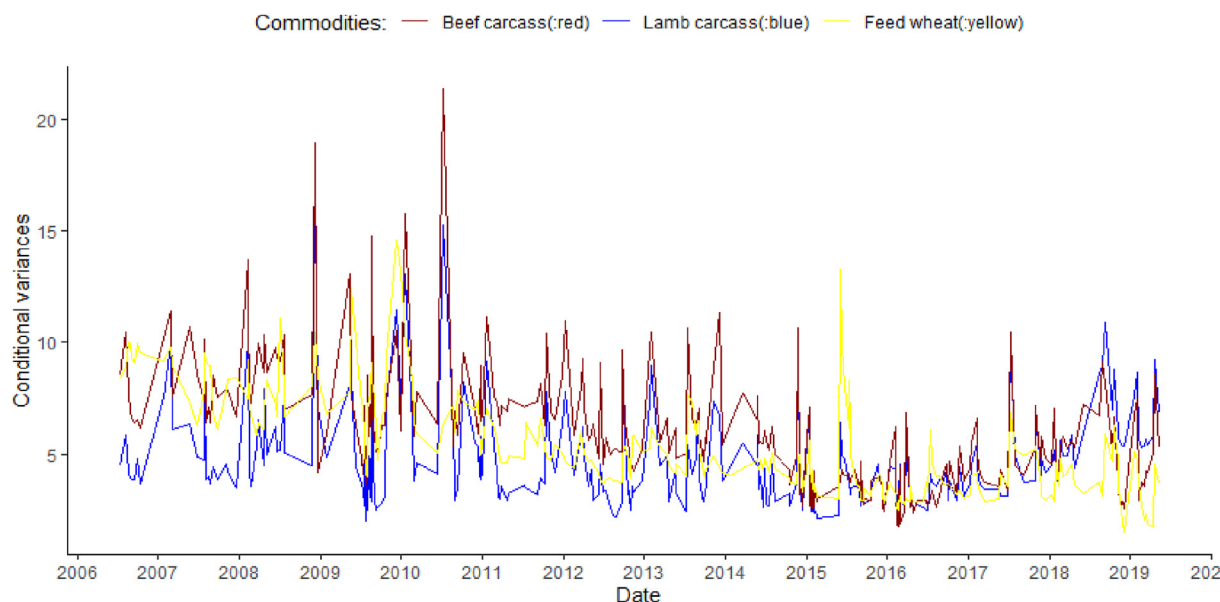


Fig. 4. Comovement of conditional variance of the beef carcass, lamb carcass, and feed wheat over time.

($\varphi_{lc,1} = 5.348$), the interactions between the feed wheat market and the two meat markets interestingly reduced the risks from imports ($\varphi_{fw,1} = -3.511$ and $\varphi_{fw,2} = -0.848$) or vice versa. Additionally, the import effect reflected on the feed wheat market and caused the spillover in the red meat markets to continue for a longer period. Though meat import decisions have a negative widespread impact on the lamb carcass and feed wheat markets, such an impact is more severe than the effects across the entire analysis. Meat import decisions have been successful in keeping food inflation relatively under control by shelving the autarky system and generally have a positive effect on consumers' welfare. However, inevitably, some producers (meat and feed wheat) will lose welfare in contrast to the gains for consumers. Although our findings overlap with the results of other studies conducted in Turkey (Chadwick and Bastan, 2017; Urak et al., 2022b), they differ from those of Chadwick and Bastan (2017) on behalf of the Central Bank of the Republic of Turkey. They reported that red meat imports played a constructive role in the volatility of red meat in the short run but lost their impact in the long run. Our results echoed the findings of Urak et al. (2022b) who showed that continued red meat imports mitigate long-term widespread risk in the sector and lowered food inflation. Although import decisions provide consumers with the opportunity to access relatively cheap meat, they may cause producers to lose their production sovereignty because of low profits. In such a dilemma, the state should resort to measures to compensate for welfare losses (producers) resulting from excessive welfare gains (consumers). To prevent such a loss of tare, supporting animal breeders with incentives within the scope of different support programs can resolve the conflict arising from the supply–demand imbalance in the country.

Fig. 4 depicts the movements of conditional variances of returns in time. The conditional mean variances of the beef carcass, lamb carcass, and feed wheat returns were determined to be 4.64, 6.00, and 5.32, respectively, indicating that the lamb carcass market is the most volatile among the three markets. Fig. 4 also shows the oscillation course of the conditional variance of the lamb carcass market by years. It is found that the volatility decreased after 2011 when the import of lamb carcasses was started but increased again in 2017. This happened because of the shortage of domestic production and the savings measures implemented in Turkey after 2017 as well as restrictions on importation. The conditional variance of lamb carcass returns soared in the analyzed period owing to this bottleneck in the domestic supply and possibly the pressure originating from the overwhelming demand on the market. Total red meat imports amounted to 110,371 tons in Turkey back in 2011, whereas they fell to 18,879 tons in 2017, which is an 83% decline (TSI, 2018). When the conditional variance of the beef carcass market is analyzed periodically, we can observe that the highest trend belongs to the period between 2008 and 2011, with a constant trend in 2012–2017, and increasing volatility in the post-2017 period. The conditional variance of the beef carcass may return, reaching its highest value in the period 2008–2011, and the financial and food crises that occurred worldwide were influential. When the import of red meat and livestock (bovine) began (some periods excepted), the conditional variance of beef carcass returns decreased from 2011 to 2017. The conditional variances of all three products showed less volatility and a decreasing trend toward a stable mean, particularly after the 2008 world food and financial crises, indicating strong pairwise correlations across the respective markets. Such strong positive

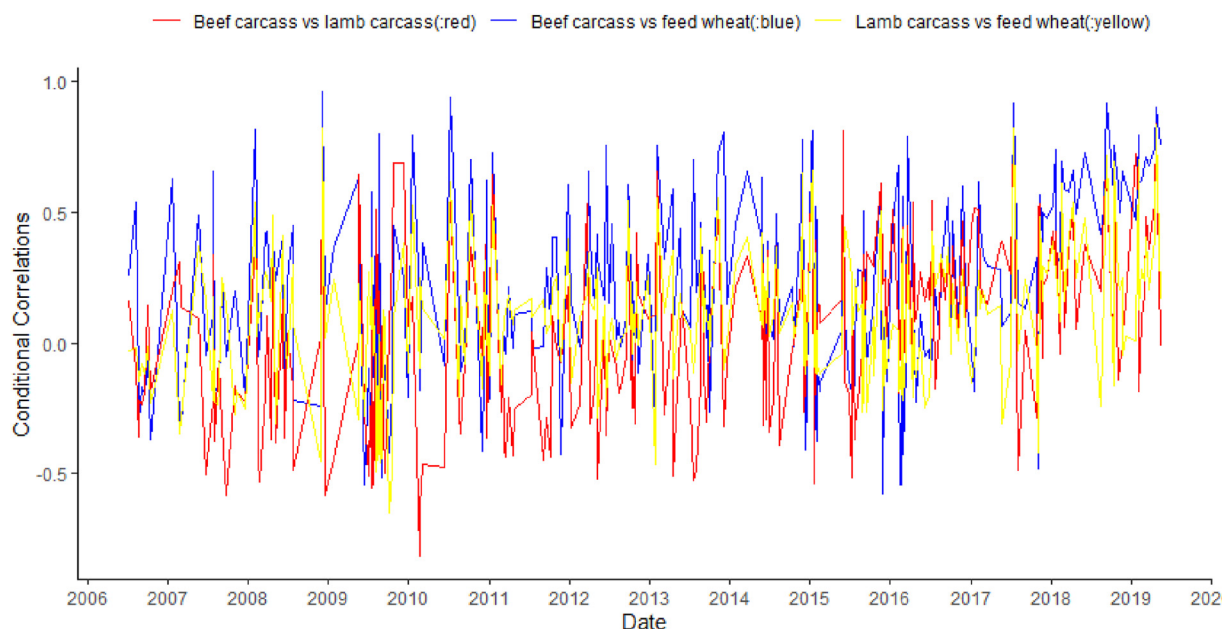


Fig. 5. Comovement of conditional correlations of the beef carcass, lamb carcass, and feed wheat over time.

relationships that have developed between products in recent years are indicative of such a phenomenon.

Fig. 5 presents the movement of conditional correlation between beef carcass, lamb carcass, and feed wheat returns over time. During the evaluation of the correlation of the conditional variance of beef carcasses and lamb carcasses, an average value of 0.20 is detected. Such a situation shows that beef carcasses and lamb carcasses trigger each other in terms of volatility. Increased risk in the beef carcass market will be reflected in the lamb carcass market (or vice versa). The correlation of the conditional variance of beef carcasses and lamb carcasses was six times higher than the conditional correlation of beef carcasses with feed wheat, three times higher than the conditional correlation of lamb carcasses with feed wheat, and three times higher than the conditional correlation of beef with feed wheat as this relationship could be due to substitution of beef and lamb carcasses. Furthermore, we determined that the average negative and positive correlations of beef carcasses and lamb carcasses between the years 2005–2007, 2008–2011, and 2012–2019 were respectively -0.12 and 0.36 , -0.25 and 0.20 , and -0.17 and 0.21 . Considering the correlations in question, we can conclude that the highest volatility (considering the margin between negative and positive volatility, the volatility is

equal to 0.48 units) is a reflection of the world financial and food crises in 2008–2011. When the period volatility values are analyzed, they correspond exactly to the results of the study. The average and positive correlations of beef carcasses and feed wheat for the period 2005–2007, 2008–2011, and 2012–2019 were found to be -0.19 and 0.40 , -0.33 and 0.28 , and -0.24 and 0.22 , respectively. When looking at this amplitude range (2008–2011) in which the financial and food crises occurred, the result is clear. Similar results were obtained for lamb carcasses and feed wheat for the subsequent three periods (e.g., 2005–2007, 2008–2011, and 2012–2019) determined to be -0.20 and 0.40 , -0.22 and 0.30 , and -0.13 and 0.25 , respectively, confirming the above-mentioned results. Correlations between products tend to be significantly positive as can be inferred in Fig. 5, especially after the 2013–2014 period. The existence of such a relationship may be an indication of the financialization of the markets in recent years in the country. At the same time, these results imply that the volatility propagation between the respective agricultural markets will be aggressively and synchronously positive with less volatility around a weaker variance in the country.

The understanding of volatility transmission and spillover from one to another market may help in managing risk

Table 5
Some specification tests for VAR (1) - BEKK GARCH (1,1) model.

Parameters	$R_{bc, t}$	$R_{lc, t}$	$R_{fw, t}$
Panel A: Residual Diagnostic Tests			
Serial Correlation in residuals:			
LB-Q (10)	19.879 (0.030)	11.916 (0.291)	14.378 (0.156)
McLeod-Li (10)	11.047 (0.354)	3.393 (0.971)	6.980 (0.727)
HM-Q(10) 106.261 (0.116)			
ARCH Effects in residual squares:			
ARCH-LM (10)	1.075 (0.382)	0.323 (0.975)	0.120 (0.998)
HM-Q ² (10)	59.796 (0.994)		
MARCH-LM (10)	341.020 (0.757)		
Additional Statistics:			
z	-0.007 (0.896)	0.018 (0.759)	-0.065 (0.311)
z^2	0.868 (0.108)	0.931 (0.419)	1.143 (0.098)
AIC	4906.858		
SBC	5172.717		
HQC	5013.470		
LogFPE	4760.858		
Log-Likelihood Value	-2380.429		
Panel B: Model Specification Tests			
Granger Causality Tests:			
H ₀ :lc, fw, gasoline, exchange rate, and import do not granger cause bc			405.758 (0.000)
H ₀ :bc, fw, gasoline, exchange rate, and import do not granger cause lc			45.669 (0.000)
H ₀ :bc, lc, gasoline, exchange rate, and import do not granger cause fw			265.674 (0.000)
No GARCH	H ₀ : $a_{ij} = b_{ij} = d_{ij} = 0$ for all $i, j = 1, 2, 3$		301809.807 (0.000)
Diagonal GARCH	H ₀ : All off-diagonal elements of A, B, and D are jointly zero		19007.127 (0.000)
No Asymmetry	H ₀ : $d_{ij} = 0$ for all $i, j = 1, 2, 3$		31062.156 (0.000)
H ₀ :Off-diagonal gasoline estimates in the conditional variance equations are jointly zero			6684.297 (0.000)
H ₀ :Off-diagonal exchange rate estimates in the conditional variance equations are jointly zero			488.309 (0.000)
H ₀ :Off-diagonal import estimates in the conditional variance equations are jointly zero			6543.247 (0.000)

Note: *, **, and *** are statistically significant at 10%, 5%, and 1% respectively and standard errors are in parenthesis. z and z^2 stand for the mean and variance values for the standardized residuals of the model in question. All values in parentheses indicate the p-value. AIC, SBC, HQC, and log FPE stand for Akaike, Schwarz Bayesian, Hannan-Quinn, and Final Prediction Error Criterion, respectively, while p-values for standardized residuals and residual squares (z and z^2) are derived under t and chi-square tests.

exposure to avoid future unexpected losses (Albulescu, 2021; Gil-Alana et al., 2020; Phan and Narayan, 2020; Sun et al., 2021). This is among the principal reasons to conduct the underlying study on energy and agricultural commodities like oil and agricultural products prices, which experience large fluctuations (Al-Maaidid et al., 2017). The optimal portfolio weights and hedging ratios of beef carcasses, lamb carcasses, and feed wheat price returns are therefore calculated and presented in Table 4. The optimal portfolio weights of the beef carcass with lamb carcass and feed wheat prices were determined to be 0.645 and 0.553, respectively. Based on this result, farmers or investors must spend 0.645 ₺ per 1 ₺ of their portfolio for lamb carcasses and 0.355 ₺ per 1 ₺ for beef carcasses. Considering the hedging ratios, beef carcasses can be hedged against the long position of 1 ₺, whereas the investor designates 18.80 Kuruş (K) (equivalent to cents) as a lamb carcass (period). By separating it into feed wheat, 12.10 K can be preserved. Based on these results, one can argue that a lamb carcass poses more risks than a beef carcass. This can be attributed to the shorter supply chain of lamb carcasses compared to beef carcasses in agricultural products and food markets in the country. Most of the analyses obtained were statistically significant, indicating significant stimuli for the economy.

Table 5 includes some specification tests regarding the outputs of the model. In panel A of Table 5, we performed several individuals and multivariate statistical tests on post-diagnosis standardized residuals ($z_{j,t} = \varepsilon_{j,t}/\sqrt{h_{j,t}}$, $j = 1, 2, 3$) from a VAR(1)–BEKK–GARCH (1,1) model to diagnose the presence of both autocorrelation and ARCH effects. All individual and multivariate tests conducted on 10 lagged standardized residuals (standardized for GARCH variances) showed neither the presence of autocorrelation nor the ARCH effect in the remaining serial residuals and residual squares, respectively. For example, there is no evidence of autocorrelation in all serial residuals (LB–Q and McLeod–Li statistic), nor is there evidence of autocorrelation in contemporaneous residuals (HM–Q statistic). Likewise, there is no ARCH effect in the residual squares of each series (ARCH–LM statistic), nor is it present in the residual squares of the system at 10 lags (MARCH–LM and HM–Q² statistic). Such findings provide proof of the suitability of the chosen model, and the series can now be characterized as white noise (Table 5). Moreover, confirming the above tests, additional tests using the *t*-test for $E(z) = 0$ and chi-squared test for $E(z^2) = 1$ show the absence of both autocorrelation and time-varying conditional variances in the model (Table 5), respectively, which indicates no remaining misspecification issues in the GARCH application and proof of fit of the selected model to the data (Rahman and Serletis, 2012).

In panel B of Table 5, we questioned the existence of the Granger causality of some variables in the mean returns and conditional variance equations, as well as the existence of some constraints on the parameters of the conditional variances of

the model. For example, GARCH effects, off-diagonal effect in GARCH, and asymmetric effect in GARCH were all rejected using the Wald test ($W = 301809.807$, $W = 19007.127$, and $W = 31062.156$, respectively), expressing the appropriateness of the analysis that includes all possible effects in the system and the transmission of shock or persistent volatility spillovers including asymmetric spillovers from one market to the counter market. Additionally, the hypothesis that the effects of lamb carcasses, feed wheat, gasoline, exchange rate returns, and imports on beef carcass returns are simultaneously 0 is statistically rejected ($p < 0.000$). Comparable results were also obtained for lamb carcass and feed wheat markets. All these test results strengthen the argument implying a significant relationship between the conditional mean returns series that we obtained above. In this case, no inconsistency in modeling the conditional average return series against both the lags and other market lags can be found. This shows the existence of volatility transmission between return series. Similar results were obtained for gasoline returns, exchange rate returns, and import variables in the conditional variances of the agricultural markets. The effect of energy, dollar exchange rate, and imports, which interact with the opposite markets on the market in question, has been elicited by using the Wald test statistic. Therefore, price formations formed by such macroeconomic indicators provide a pass-through to the volatility of the market in question.

5. Conclusions and recommendations

This study established that the time-varying conditional variances in the return series are significantly affected by their shocks and shocks among other rival return markets in the short term. Volatility (uncertainty) is conveyed to markets in either indirect (by conditional variance) or direct (by conditional covariance) ways. The impact of short- and long-term volatility increases in proportion to the market share of the products. Although the beef carcass and feed wheat markets are badly affected by their market uncertainty, the lamb carcass market is positively affected. However, such positivity is masked by the interaction from both the beef carcass and/or feed wheat markets, causing the lamb carcass market to show more volatility than the other two markets. This means that the lamb carcass market has a more sensitive and fragile structure than the other two markets. Therefore, such a result shows that short-term shocks and long-term uncertainties in the other markets greatly affect the uncertainty in the lamb carcass, which can be attributed to the very low trading volume of the lamb carcass market compared to the two markets. In this context, in terms of proactive measures, policymakers can protect the lamb carcass market as long as they focus on the other two markets by eliminating their structural problems. Long-standing uncertainties in the cattle carcass and feed wheat markets in Turkey may cause producers to lose product sovereignty by giving up their production or investment decisions and threaten

the nutritional needs and food choices of consumers, which can be especially harmful to low-income families.

The results of our study confirm that the volatility transmitted directly or indirectly to the markets by foreign currency-based oil and petroleum derivatives causes permanent uncertainties. Hence, the concept that the adoption of a stable national monetary policy leads to a more stable environment not only for the entire economy but also for the correlation between beef carcass, lamb carcass, and feed wheat markets should not be disregarded. Additionally, the creation of energy alternatives to fossil fuels could be expected to mitigate long-term uncertainties for agricultural products in general. In line with the European Union's goal to phase out fossil fuels for transportation services by 2030, setting similar goals in Türkiye can be expected to mitigate long-term uncertainties in agricultural markets. The determination of energy prices is made by the Turkish Energy Market Regulatory Board. For example, depending on the volatility in the exchange rate and the course of world oil prices, oil prices are determined every 2 days, every 3 days, or sometimes once a week. Instead of such an arrangement, if oil prices are traded instantly on the Istanbul Stock Exchange, other commodity markets will have the chance to catch such sudden price movements by preventing a cumulative effect and possible speculative behavior of energy prices on commodities and will determine their position in the market in price formation. Additionally, the concentration on domestic production for most of the inputs of the beef carcass, lamb carcass, and feed wheat production could help keep uncertainties in the agricultural market under control.

The studied markets are primarily affected by their market fluctuations, which threaten product sovereignty for producers and food security for consumers. Comprehensive analyses that consider both consumer-induced tare loss (which includes all the burdens of high food inflation) and producer-induced tare loss can assure price stability in the country. Such situations depend on the existence of very robust national commodity markets, the behavior of world markets, and the level of relations with them, as well as internal and external dynamics such as hedging positions against fluctuations in energy, exchange rates, and international financial markets. When a country destroys the individual power of domestic producers by opening the door to imports, it follows a policy based on heavy subsidies against the risks of giving up domestic production decisions. Given that most livestock enterprises in Türkiye are subsistence and low- and middle-income consumer families spend most of their income on food, uncertainties in the agricultural sector pose a particular threat to these demographics. In this context, we will note specific policy recommendations resulting from our research findings. Large retail companies, which primarily eliminate intermediaries and wholesalers, have the authority to establish a single price mechanism by establishing production centers with the farmers they have contracted with. These enterprises can slaughter animals in their slaughterhouses, given that all purchases are made through livestock exchanges. Transactions on the livestock exchange can further strengthen price traceability and

prevent possible price speculation. Furthermore, partial price controls can be achieved by reducing the number of possible intermediaries, even by determining the number of times an animal changes ownership in its lifetime by requiring that all animals be sold on livestock exchanges established in provinces throughout the country. Additionally, price traceability centers established within the MAF in city centers across the country can increase price traceability by synchronously displaying the sales prices of the animals to be slaughtered or the market values of the animals exchanged in their systems by digitally extracting the prices from the livestock exchanges. Different support schemes can be provided to small- and medium-sized livestock producers to produce animal feed from their farms. Finally, since both live animals and carcass meats are imported to combat food inflation in the country, subsidies can be transferred by the state to animal breeders under different schemes so that they do not lose or harm product sovereignty.

Further studies may concentrate more on the product markets inside the supply chain and may even investigate the impact of the coronavirus disease 2019 pandemic. Future research can also examine the relationship between the vertical integration of these items and risk transmission among producers, distributors, and retailers.

Information about funding sources

None.

Conflict of Interest

The authors declare no conflicts of interest.

Acknowledgments

We would like to express our sincere gratitude to Laura L. Alfonso of the Department of Agriculture and Applied Economics in the College of Agricultural and Environmental Sciences at the University of Georgia for her selfless contribution to the grammar corrections of the present study.

Appendix.

Table A1
Parameter estimates for the mean returns under the normal distribution

Parameters	Returns		
	R _{bc, t}	R _{lc, t}	R _{fw, t}
μ	1.704*** (0.061)	0.254 (0.184)	1.703*** (0.059)
Γ_{bc}	-0.161*** (0.039)	0.091 (0.069)	0.193*** (0.051)
Γ_{lc}	0.096** (0.038)	-0.054*** (0.058)	-0.077 (0.046)
Γ_{fw}	-0.054** (0.026)	-0.066 (0.042)	-0.482*** (0.054)
Ψ	-0.041 (0.039)	-0.074* (0.043)	-0.096** (0.046)
ϕ	-0.052 (0.037)	-0.099*** (0.034)	-0.026 (0.018)
ω	-1.883*** (0.133)	0.026 (0.237)	-1.665*** (0.048)

Note: In parenthesis are associative standard errors. *, **, and *** are statistically significant at 10%, 5%, and 1%, respectively.

Table A2
Parameter estimates for the time-varying conditional variances under the normal distribution

Parameters	Returns		
	$R_{bc, t}$	$R_{lc, t}$	$R_{fw, t}$
$c_{bc,i}$	2.889*** (0.129)	–	–
$c_{lc,i}$	–13.996*** (0.208)	–9.110*** (0.156)	–
$c_{fw,i}$	4.007*** (0.073)	–2.257*** (0.098)	–0.0001 (0.722)
$a_{bc,i}$	0.534*** (0.053)	0.413*** (0.092)	0.434*** (0.062)
$a_{lc,i}$	–0.401*** (0.062)	–0.639*** (0.128)	–0.110** (0.051)
$a_{fw,i}$	0.155*** (0.036)	0.045 (0.066)	0.259*** (0.045)
$b_{bc,i}$	0.382** (0.081)	0.168* (0.089)	0.008 (0.051)
$b_{lc,i}$	–0.294*** (0.041)	–0.269*** (0.061)	0.076** (0.031)
$b_{fw,i}$	–0.316*** (0.022)	0.250*** (0.028)	0.558*** (0.018)
$d_{bc,i}$	0.097** (0.061)	0.513*** (0.103)	–0.237*** (0.072)
$d_{lc,i}$	–0.327*** (0.060)	–0.023 (0.114)	0.036 (0.048)
$d_{fw,i}$	0.075 (0.060)	–0.028 (0.081)	0.309*** (0.085)
$\psi_{bc,i}$	–0.365*** (0.007)	–	–
$\psi_{lc,i}$	1.130*** (0.037)	1.384*** (0.021)	–
$\psi_{fw,i}$	0.210*** (0.014)	0.293*** (0.008)	0.00001 (0.103)
$\phi_{bc,i}$	1.161*** (0.062)	–	–
$\phi_{lc,i}$	0.302*** (0.013)	–0.235*** (0.053)	–
$\phi_{fw,i}$	–0.639*** (0.040)	0.330*** (0.045)	0.00003 (0.098)
$\varphi_{bc,i}$	–1.291*** (0.094)	–	–
$\varphi_{lc,i}$	6.908*** (0.194)	3.460*** (0.180)	–
$\varphi_{fw,i}$	–1.375*** (0.122)	–1.717*** (0.089)	–0.0002 (0.505)
Useful Statistics			
AIC	4990.362		
SBC	5252.579		
HQC	5095.514		
LogFPE	4846.362		
Log-Likelihood Value	–2423.181		

Note: In parenthesis are associative standard errors. *, **, and *** are statistically significant at 10%, 5%, and 1%, respectively.

References

Abdallah, M. B., Farkas, M. F., & Lakner, Z. (2020). Analysis of meat price volatility and volatility spillovers in Finland. *Agricultural Economics*, 66(2), 84–91. <https://doi.org/10.17221/158/2019-AGRICECON>

Abdelradi, F., & Serra, T. (2015a). Food-energy nexus in Europe. price volatility approach. *Energy Economics*, 48, 157–167. <https://doi.org/10.1016/j.eneco.2014.11.022>

Abdelradi, F., & Serra, T. (2015b). Asymmetric price volatility transmission between food and energy markets. The case of Spain. *Agricultural Economics*, 46(4), 503–513. <https://doi.org/10.1111/agec.12177>

Adams, Z., & Glück, T. (2015). Financialization in commodity markets: A passing trend or the new normal? *Journal of Banking & Finance*, 60, 93–111. <https://doi.org/10.1016/j.jbankfin.2015.07.008>

Adom, P. K. (2014). Determinants of food availability and access in Ghana. what can we learn beyond the regression results? *Studies in Agricultural Economics*, 6(3), 153–164. <https://doi.org/10.7896/j.1423>

Akay, M. (2021). Red meat price volatility and its relationship with crude oil and exchange rates in Turkey with the approach of GARCH (p,q) model. *Yuzuncu Yil University Journal of Agricultural Sciences*, 31(4), 915–927. <https://doi.org/10.29133/yyutbd.984277>

Akgunduz, Y. E., Cilasun, S. M., & Tok, E. O. (2020). *Dana eti ve sut sektorlerinde tedarik zinciri ve karlilik analizi (No. 2007)*. Research and Monetary Policy Department, Central Bank of the Republic of Turkey. https://scholar.google.com/scholar_lookup?title=Dana+Eti+ve+Sut+Sektorlerinde+Tedarik+Zinciri+ve+Karlilik+Analizi&author=Akgunduz,+Y.E.&author=Cilasun,+S.M.&author=Tok,+E.O.&publication_year=2020

Al-Maadid, A., Caporale, G. M., Spagnolo, F., & Spagnolo, N. (2017). Spillovers between food and energy prices and structural breaks. *International Economics*, 150, 1–18. <https://doi.org/10.1016/j.inteco.2016.06.005>

Albulescu, C. T. (2021). COVID-19 and the United States financial markets' volatility. *Finance Research Letters*, 38, Article 101699. <https://doi.org/10.1016/j.frl.2020.101699>

Apergis, N., & Reztis, A. (2003). Agricultural price volatility spillover effects: The case of Greece. *European Review of Agricultural Economics*, 30, 389–406. <https://doi.org/10.1093/erae/30.3.389>

Askan, E., Urak, F., & Bilgic, A. (2020). Revealing asymmetric spillover effects in hazelnut, gasoline, and exchange rate markets in Turkey: The VECM-BEKK MGARCH Approach. *Panoeconomicus*, 69(1), 35–54. <https://doi.org/10.2298/PAN190509005A>

Baffes, J., & Haniotis, T. (2010). *Placing the 2006/08 commodity price boom into perspective*. The World Bank Development Prospects Group. July 2010 <https://ssrn.com/abstract=1646794>.

Ben Abdallah, M., Farkas, M. F., & Lakner, Z. (2020). Analysis of meat price volatility and volatility spillovers in Finland. *Agricultural Economics-Czech*, 66(2), 84–91. <https://doi.org/10.17221/158/2019-AGRICECON>

Bollerslev, T. (1987). A conditionally heteroskedastic time series model for speculative prices and rates of return. *The Review of Economics and Statistics*, 69(3), 542–547. <https://www.jstor.org/stable/1925546>.

von Braun, J., & Tadesse, G. (2012). Food security, commodity price volatility, and the poor. In *Institutions and comparative economic development* (pp. 298–312). London: Palgrave Macmillan. https://link.springer.com/chapter/10.1057/9781137034014_16.

Cabrera, B., & Schulz, F. (2016). Volatility linkages between energy and agricultural commodity prices. *Energy Economics*, 54, 190–203. <https://doi.org/10.1016/j.eneco.2015.11.018>

Çelik, Ş. (2015). Impact of inflation, dollar exchange rate and interest rate on red meat production in Turkey, Vector Autoregressive (VAR) Analysis. *Chinese Business Review*, 14(8). <http://www.davidpublisher.com/Public/uploads/Contribute/564ad164e72da.pdf>.

Chadwick, M., & Bastan, M. (2017). News impact for Turkish food prices. *Central Bank Review*, 17(2), 55–76. <https://doi.org/10.1016/j.cbrev.2017.05.001>

Chen, S. T., Kuo, H. I., & Chen, C. C. (2010). Modeling the relationship between the oil price and global food prices. *Applied Energy*, 87(8), 2517–2525. <https://doi.org/10.1016/j.apenergy.2010.02.020>

Chowdhury, M. A. F., Meo, M. S., Uddin, A., & Haque, M. (2021). Asymmetric effect of energy price on commodity price: New evidence from NARDL and time frequency wavelet approaches. *Energy*, 231, Article 120934. <https://doi.org/10.1016/j.energy.2021.120934>

Cinar, G. (2018). Price volatility transmission among cereal markets. The evidences for Turkey. *New Medit (Mediterranean Journal of Economics, Agriculture and Environment)*, 17(3), 93–104. <https://newmedit.iamb.it/2018/09/15/price-volatility-transmission-among-cereal-markets-the-evidences-for-turkey/>.

Cinar, G., & Keskin, B. (2018). The spillover effect of imported inputs on broiler prices in Turkey. *New Medit*, 17(1). https://www.researchgate.net/profile/Gokhan-Cinar/publication/324476619_The_spillover_effect_of_imported_inputs_on_broiler_prices_in_Turkey/links/5acf251ba6fdcc87840fce9d/The-spillover-effect-of-imported-inputs-on-broiler-prices-in-Turkey.pdf.

Cunado, J., & Perez de Gracia, F. (2003). Do oil price shocks matter? Evidence for some European countries. *Energy Economics*, 25(2), 137–154. [https://doi.org/10.1016/S0140-9883\(02\)00099-3](https://doi.org/10.1016/S0140-9883(02)00099-3)

Damba, O. T., Bilgic, A., & Aksoy, A. (2017). Estimating price volatility transmission between world crude oil and selected food commodities, a BEKK approach. *Atatürk Üniversitesi Ziraat Fakültesi Dergisi*, 48, 41–49.

Du, L., Yanan, H., & Wei, C. (2010). The relationship between oil price shocks and China's macro-economy, an empirical analysis. *Energy Policy*, 38(8), 4142–4151. <https://doi.org/10.1016/j.enpol.2010.03.042>

Engle, R. F., & Kroner, K. (1995). Multivariate simultaneous generalized ARCH. *Econometric Theory*, 11(1), 122–150. <https://doi.org/10.1017/S0266466600009063>

- Fakari, B., Aliabadi, M. M. F., Mahmoudi, H., & Kojori, M. (2016). Volatility spillover and price shocks in Iran's meat market. *Custos e Agronegocio On Line*, 12(2), 84–98. https://www.researchgate.net/profile/Mohammad-Mehdi-Farsi-Aliabadi/publication/309379065_Volatility_Spillover_and_Price_Shocks_in_Iran's_Meat_Market/links/580c454e08ae2cb3a5da70bd/Volatility-Spillover-and-Price-Shocks-in-Irans-Meat-Market.pdf.
- Fiszeder, P., & Orzeszko, W. (2018). Nonlinear Granger causality between grains and livestock. *Agricultural Economics–Czech*, 64(7), 328–336. <https://doi.org/10.17221/376/2016-AGRICECON>
- Gardebroeck, C., & Hernandez, M. A. (2016). Market interdependence and volatility transmission among major crops. *Agricultural Economics*, 47(2), 141–155. <https://doi.org/10.1111/agec.12184>
- Gencer, G. H., & Musaoglu, Z. (2014). Volatility transmission and spillovers among gold, bonds and stocks, an empirical evidence from Turkey. *International Journal of Economics and Financial Issues*, 4(4), 705–771. <https://dergipark.org.tr/en/download/article-file/362903>.
- Gil-Alana, L. A., Abakah, E. J. A., & Rojo, M. F. R. (2020). Cryptocurrencies and stock market indices. Are they related? *Research in International Business and Finance*, 51, Article 101063. <https://doi.org/10.1016/j.ribaf.2019.101063>
- Gilbert, C. L. (2010). How to understand high food prices. *Journal of Agricultural Economics*, 61(2), 398–425. <https://doi.org/10.1111/j.1477-9552.2010.00248.x>
- Grier, K. B., Henry, T. O., Olekalns, N., & Shields, K. (2004). The asymmetric effects of uncertainty on inflation and output growth. *Journal of Applied Econometrics*, 19(5), 551–565. <https://doi.org/10.1002/jae.763>
- Guo, J., & Tanaka, T. (2020). The effectiveness of self-sufficiency policy: International price transmissions in beef markets. *Sustainability*, 12(15), 6073. <https://doi.org/10.3390/su12156073>
- Guo, J., & Tanaka, T. (2022). Potential factors in determining cross-border price spillovers in the pork sector: Evidence from net pork-importing countries. *Humanities and Social Sciences Communications*, 9(1), 1–14. <https://www.nature.com/articles/s41599-021-01023-1>.
- Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. *Journal of Political Economy*, 91(2), 228–248. <https://doi.org/10.1086/261140>
- Ismail, A., Ihsan, H., Khan, S. A., & Jabeen, M. (2017). Price volatility of food and agricultural commodities: A case study of Pakistan. *Journal of Economic Cooperation and Development*, 38(3), 77–120.
- Karyotis, C., & Alijani, S. (2016). Soft commodities and the global financial crisis: Implications for the economy, resources and institutions. *Research in International Business and Finance*, 37, 350–359. <https://doi.org/10.1016/j.ribaf.2016.01.007>
- Kesavan, T., Aradhyula, S. V., & Johnson, S. R. (1992). Dynamics and price volatility in farmretail livestock price relationships. *Journal of Agricultural and Resource Economics*, 17(2), 348–361. <https://www.jstor.org/stable/40986765>.
- Khiyavi, P. K., Moghaddasi, R., Eskandarpur, B., & Mousavi, N. (2012). Spillover effects of agricultural products price volatilities in Iran. *Journal of Basic and Applied Scientific Research*, 2(8), 7906–7914.
- Kroner, K. F., & Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. *Review of Financial Studies*, 11(4), 817–844. <https://doi.org/10.1093/rfs/11.4.817>
- Kroner, K. F., & Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Financial and Quantitative Analysis*, 28(4), 535–551. <https://doi.org/10.2307/2331164>
- Ling, S., & McAleer, M. (2003). Asymptotic theory for A vector ARMA-GARCH model. *Econometric Theory*, 19(2), 280–310. <https://doi.org/10.1017/S0266466603192092>
- Luo, W. C., & Liu, R. (2011). Analysis of meat price volatility in China. *China Agricultural Economic Review*, 3(3), 402–411. <https://doi.org/10.1108/175613711111165815>
- McFarlane, L. (2016). Agricultural commodity prices and oil prices, mutual causation. *Outlook on Agriculture*, 45(2), 87–93. <https://doi.org/10.1177/0030727016649809>
- Mensi, W., Beljid, M., Boubaker, A., & Managi, S. (2013). Correlations and volatility spillovers across commodity and stock markets, Linking energies, food, and gold. *Economic Modelling*, 32, 15–22. <https://doi.org/10.1016/j.econmod.2013.01.023>
- Mensi, W., Hammoudeh, S., Nguyen, D. K., & Yoon, S. M. (2014). Dynamic spillovers among major energy and cereal commodity prices. *Energy Economics*, 43, 225–243. <https://doi.org/10.1016/j.eneco.2014.03.004>
- OECD (Organisation for Economic Co-operation and Development). (2022). *Meat consumption organisation for economic co-operation and development*. <https://doi.org/10.1787/fa290fd0-en>. (Accessed 6 April 2022)
- Olson, E., Vivian, A. J., & Wohar, M. E. (2014). The relationship between energy and equity markets: Evidence from volatility impulse response functions. *Energy Economics*, 43, 297–305. <https://doi.org/10.1016/j.eneco.2014.01.009>
- Özdemir, F. N., Urak, F., Bilgic, A., & Yavuz, F. (2020). Estimating volatility transmission in real prices of mutton, fattening fodder, gasoline, and exchange rate in Turkey using VAR-asymmetric BEKK-GARCH (1, 1) model. *KSU Journal of Agricultural and Nature*, 23, 1270–1285. <https://doi.org/10.18016/ksutarimdogavi.631256>
- Özertan, G., Saghaian, S. H., & Tekgüç, H. (2015). Dynamics of price transmission and market power in the Turkish beef sector. *Iktisat İslatme ve Finans*, 30(349), 53–76. <http://www.iif.com.tr/index.php/iif/article/view/iif.2015.349.4317>.
- Pal, D., & Mitra, S. K. (2017). Time-frequency contained co-movement of crude oil and world food prices: A wavelet-based analysis. *Energy Economics*, 62, 230–239. <https://doi.org/10.1016/j.eneco.2016.12.020>
- Peri, M., & Baldi, L. (2010). Vegetable oil market and biofuel policy, an asymmetric cointegration approach. *Energy Economics*, 32(3), 687–693. <https://doi.org/10.1016/j.eneco.2009.09.004>
- Phan, D. H. B., & Narayan, P. K. (2020). Country responses and the reaction of the stock market to COVID-19-a preliminary exposition. *Emerging Markets Finance and Trade*, 56(10), 2138–2150. <https://doi.org/10.1080/1540496X.2020.1784719>
- Pozo, V. F., & Schroeder, T. C. (2012). *Price and volatility spillover between livestock and related commodity markets (No. 323-2016-11484)*.
- Rahman, S., & Serletis, A. (2012). Oil price uncertainty and the Canadian economy, Evidence from a VARMA, GARCH-in-Mean, asymmetric BEKK model. *Energy Economics*, 34(29), 603–610. <https://doi.org/10.1016/j.eneco.2011.08.014>
- Rask, K. J., & Rask, N. (2011). Economic development and food production–consumption balance: A growing global challenge. *Food Policy*, 36(2), 186–196. <https://doi.org/10.1016/j.foodpol.2010.11.015>
- Reboredo, J. C. (2012). Do food and oil prices co-move? *Energy Policy*, 49, 456–467. <https://doi.org/10.1016/j.enpol.2012.06.035>
- Rezitis, A. N. (2012). Modelling and decomposing price volatility in the Greek meat market. *International Journal of Computational Economics and Econometrics*, 2(3), 197–222, 4 <https://ssrn.com/abstract=2113502>.
- Rezitis, A. N. (2018). Empirical analysis of price relations along the Finnish supply chain of selected meat, dairy, and egg products: A dynamic panel data approach. *Agribusiness*, 34, 542–561. <https://doi.org/10.1002/agr.21536>
- Rezitis, A. N., & Stavropoulos, K. S. (2009). Modeling pork supply response and price volatility: The case of Greece. *Journal of Agricultural & Applied Economics*, 41(1), 145–162. <https://doi.org/10.1017/S1074070800002601>
- Rezitis, A. N., & Stavropoulos, K. S. (2010). Modeling beef supply response and price volatility under CAP reforms: The case of Greece. *Food Policy*, 35(2), 163–174. <https://doi.org/10.1016/j.foodpol.2009.10.005>
- Rezitis, A. N., & Stavropoulos, K. S. (2011). Price transmission and volatility in the Greek broiler sector: A threshold cointegration analysis. *Journal of Agricultural & Food Industrial Organization*, 9(1). <https://doi.org/10.2202/1542-0485.1340>
- Rezitis, A. N., & Stavropoulos, K. S. (2012). Greek meat supply response and price volatility in a rational expectations framework: A multivariate GARCH approach European. *Review of Agricultural Economics*, 39(2), 309–333. <https://doi.org/10.1093/erae/jbr038>
- Sadorsky, P. (2014). Modeling volatility and correlations between emerging market stock prices and the prices of copper, oil and wheat. *Energy Economics*, 43, 72–81. <https://doi.org/10.1016/j.eneco.2014.02.014>
- Salisu, A. A., & Mobolaji, H. (2013). Modeling returns and volatility transmission between oil price and US–Nigeria exchange rate. *Energy Economics*, 39, 169–176. <https://doi.org/10.1016/j.eneco.2013.05.003>

- Salisu, A. A., & Oloko, T. F. (2015). Modeling oil price–US stock nexus, A VARMA–BEKK–AGARCH approach. *Energy Economics*, 50, 1–12. <https://doi.org/10.1016/j.eneco.2015.03.031>
- Shahzad, S. J. H., Hernandez, J. A., & Al-Yahyaee, K. H. (2018). Asymmetric risk spillovers between oil and agricultural commodities. *Energy Policy*, 118, 182–198. <https://doi.org/10.1016/j.enpol.2018.03.074>
- Sidhoum, A., & Serra, T. (2016). Volatility spillovers in the Spanish food marketing chain, the case of tomato. *Agribusiness*, 32(1), 45–63. <https://doi.org/10.1002/agr.21418>
- Sun, Y., Mirza, N., Qadeer, A., & Hsueh, H. P. (2021). Connectedness between oil and agricultural commodity prices during tranquil and volatile period. Is crude oil a victim indeed? *Resources Policy*, 72, Article 102131. <https://doi.org/10.1016/j.resourpol.2021.102131>
- Taghizadeh-Hesary, F., Rasoulinezhad, E., & Yoshino, N. (2019). Energy and food security, linkages through price volatility. *Energy Policy*, 128, 796–806. <https://doi.org/10.1016/j.enpol.2018.12.043>
- Tanaka, T., & Guo, J. (2020). How does the self-sufficiency rate affect international price volatility transmissions in the wheat sector? Evidence from wheat-exporting countries. *Humanities and Social Sciences Communications*, 7(1), 1–13. <https://www.nature.com/articles/s41599-020-0510-8>.
- Tejeda, H., & Goodwin, B. (2009). Price volatility, nonlinearity, and asymmetric adjustments in corn, soybean, and cattle markets, implications of ethanol-driven (market) shocks. In *Paper presented at the 2009 NCCC-134 Conference on applied commodity price analysis, forecasting, and market risk management*, St. Louis, MO, April 20-21. <https://ageconsearch.umn.edu/record/53039>.
- TOB. (2018). *Tarım ve orman Bakanlığı (Ministry of agriculture and Forestry)*. <https://www.tarimorman.gov.tr/Konular/Hayvancilik>.
- Tosun, D., & Demirbaş, N. (2020). What are the problems of the red meat processing industry?: A case study from Turkey. *Food Science and Technology*, 41, 522–528. <https://doi.org/10.1590/fst.27220>
- Trujillo-Barrera, A., Mallory, M., & Garcia, P. (2012). Volatility spillovers in U.S. crude oil, Ethanol, and corn futures markets. *Journal of Agricultural and Resource Economics*, 37(2), 247–262. <https://www.jstor.org/stable/23496711>.
- TSI (Turkish Statistical Institute). (2018). *Consumption spending statistics*. https://www.tuik.gov.tr/PreTablo.do?alt_id=1012.
- TSI (Turkish Statistical Institute). (2019). *Foreign trade statistics*. <https://biruni.tuik.gov.tr/disticaretapp/disticaret.zul?param1=22¶m2=0&sitcrev=0&isicrev=0&sayac=5802>.
- TSI (Turkish Statistical Institute). (2022). *Inflation & price*. www.tuik.gov.tr.
- Urak, F., Bilgic, A., Bozma, G., Florkowski, W. J., & Efehan, E. (2022b). Volatility in live calf, live sheep, and feed wheat return markets: A threat to food price stability in Turkey. *Agriculture*, 12, 566. <https://doi.org/10.3390/agriculture12040566>
- Urak, F., Bilgiç, A., Dağdemir, V., & Özer, H. (2022a). Estimating the conditional variance volatilities of beef carcass, lamb carcass, and fodder wheat markets in the context of exchange rate using VAR(2)- asymmetric BEKK-GARCH (1,1) model. *Atatürk University Journal of Agricultural Faculty*, 53(1), 31–41.
- Urak, F., Bilgiç, A., Dağdemir, V., & Özer, H. (2022c). Empirically eliciting the volatility transmission between red meat and forage wheat markets in Turkey. *KSU Journal of Agricultural and Nature*, 25(5), 1168–1180. <https://doi.org/10.18016/ksutarimdogu.vi.955565>
- Wang, G. Y., Si, R. X., Li, C. X., Zhang, G. T., & Zhu, N. Y. (2018). Asymmetric price transmission effect of corn on hog: Evidence from China. *Agricultural Economics – Czech*, 64, 186–196. <https://doi.org/10.17221/227/2016-AGRICECON>
- Wan, X., & Li, C. (2022). Asymmetric price volatility transmission in agricultural supply chains: Evidence from the Chinese pork market. *Mathematical Problems in Engineering*, 11. <https://doi.org/10.1155/2022/4801898>
- Zhen, M. (2015). *Two essays on market interdependencies, price volatility and volatility spillovers in the Western Canadian feed barley, U.S. Corn and Alberta cattle markets*. <https://doi.org/10.7939/R3Q372>
- Zhen, M., Rude, J., & Qiu, F. (2018). Price volatility spillovers in the Western Canadian feed barley, U.S. Corn, and Alberta cattle markets. *Canadian Journal of Agricultural Economics*, 66, 209–229. <https://doi.org/10.1111/cjag.12146>
- Ziemer, R. F., & Collins, G. S. (1984). Granger causality and US crop and livestock prices. *Southern Journal of Agricultural Economics*, 16(1), 115–120. <https://doi.org/10.1017/S0081305200016599>