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The Role of Energy on the Price Volatility of Fruits and Vegetables: Evidence from Turkey

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Abstract. In agricultural economics, fluctuations in food prices and the factors affecting these fluctuations have always been an important research topic. From production to delivery to consumers, the supply chain of agricultural products has a dynamic structure with continuous changes. In this dynamic process, analyzing the intensive use of energy at each stage has gained more importance with its deepening effects in comparison to the past. This study will empirically explore the volatility spillovers between energy price index and fruit-vegetables price index in the period of 2007-2020 in Turkey using the Kanas and Diebold-Yilmaz approaches. According to the results obtained from the Kanas approach in the study, it has been observed that there is a statistically significant volatility spillover from the energy price index to the vegetable price index, whereas there is no statistically significant volatility spillover to the fruit price index. This finding was supported by the results obtained from the Diebold-Yilmaz approach showing that there is a volatility spillover of 13.52% to the vegetable price index and 0.86% to the fruit price index from the energy price index.

Keywords: volatility spillover, energy, agricultural prices, EGARCH, agricultural markets.
JEL codes: Q11, Q18, Q41, Q47, C32.

1. INTRODUCTION

Volatility in food prices and the reasons behind this volatility have recently become a trending topic of discussions throughout the world, while they are often discussed in literature as well. In this regard, pricing process of sub-product groups must also be analyzed in addition to general food prices. Indeed, due to the difficulties in storing these products for a long period, changing vegetable and fruit prices might well cause producers and consumers to be deeply affected by price volatility. On the other hand, it is also highly important to examine the reasons that may affect the price fluctuations of these products.

Fresh fruit and vegetables sector is considered one of the most essential sectors in the agricultural industry as it is vital for sustaining human life. In this context, the United Nations declared the year of 2021 as the "International Year of Fruits and Vegetables", highlighting the importance of fruits and vegetables in nourishment, the problems experienced in the process from production to consumption, food wastes and losses, the importance of farming in the fight against famine and small family businesses generating incomes. Thus, the factors that underlie price changes in agricultural markets is currently a hot topic. Prices in agricultural markets have recently been affected by macroeconomic factors such as exchange rate, inflation (Algieri, 2016), interest rates, energy prices and demand for biofuels, monetary policies, financial investments and speculations, sudden trade restrictions or lack of information, transaction costs, agricultural policies and international prices (Kalkuhl et al., 2016; Algieri, 2016; Kornher and Kalkuhl, 2013).

This study will focus on Turkey from an empirical perspective within its scope. While the country stands out in fruit and vegetable production across the world, Turkey is experiencing frequent price volatility at recent times. According to the World Food Organization's 2019 statistics, Turkey is the 4th largest producer of fresh vegetables in the world (Statista, 2021a). In addition, it is the 6th largest producer of fresh fruits in the world (Statista, 2021b). Therefore, Turkey is one of the most important agricultural producers in the world. However, Turkey's currency is one with the highest volatility among emerging market markets and this causes fluctuations in the fruit and vegetable price indices. Besides, fluctuations in energy prices due to the volatility of the exchange rate and global markets has become significant as energy is an input item in production processes. Considering upward fluctuations in particular, the practices for direct sale points and mediators in the supply chain have been heavily discussed in recent years. In the same vein, the fluctuations in food prices have been the hot topic in Turkey too due to the recent global crises, the climate change and foreign-source dependency on energy. It is stated that the reason behind these fluctuations in agricultural product prices is the increasing production input prices by farmers. Besides seasonal effects on the price fluctuations in agricultural commodities, it can be observed that increasing energy prices have a direct or indirect aggravating effect on the costs of agricultural inputs such as fertilizers, chemicals, irrigation, production, storage and transportation (Fasanya and Akinbowale, 2019; Tadasse et al., 2016; Algieri, 2016). Moreover, the use of modern technology applications in agriculture also increases energy consumption. The use of agricultural machinery and pesticides requires the consumption of fossil fuels, and indeed, intense energy consumption is particularly observed in the field of pesticide production (Öztürk et al., 2010). Besides, price volatility in the categories of electricity, coal, petroleum products and natural gas has an extremely deep negative impact on the economic performance of Turkey, as an energy importer. As a matter of fact, oil and natural gas reserves are limited in Turkey leading to foreign-source dependence in the field of energy. Thus, it is observed that Turkey has been the country with the fastest increase in energy demand among the Organization for Economic Cooperation and Development (OECD) countries in the past 20 years. Within this framework, Turkey ranks second in the world after China in the increase in electricity and natural gas demands. Existing energy sources cannot unfortunately meet Turkey's increasing energy needs and thus, the country meets nearly 74% of its energy needs via imported sources (MFA, 2020). Considering that Turkey is a country dependent on imports of oil in its consumption, there is an urging need to address the effects of changing energy prices on the performance of several sectors and industries (Algan et al., 2017). On the other hand, the increase in energy prices in recent years is one of the most crucial cost items threatening agricultural production (Yıldırım, 2020). Hence, the fluctuations in these costs reflect on product prices and cause difficulties in production plans (Fasanya and Akinbowale, 2019: 186; Tadasse et al., 2016: 63; Algieri, 2016: 210).

For the reasons mentioned above, this study aims to investigate the effects of changes in energy prices on other price indices for Turkey. In this regard, we analyzed the volatility spillover between the Energy Price Index (EPI), the Fruit Price Index (FPI) and the Vegetable Price Index (VPI) using monthly data sets from January 2007 to December 2019 by two different methods: The Kanas (1998) Approach for volatility spillover effect and the Diebold-Yilmaz (2009, 2012) spillover index, analyzed respectively. As for the content of the study, the second section consists of an extensive literature review. This part is followed by a detailed description of the methodology. The fourth section summarizes the data set used in the study. In the fifth part, empirical results of the analyses are given in two subsections. Finally, the last section covers comments, discussions and policy recommendations based on the study results.

2. BACKGROUND AND LITERATURE REVIEW

Energy consumption is one of the main determinants of the socio-economic development of countries. More specifically, oil and its derivatives are considered one of the main production factors in an economy. They are used in the energy supply of various sectors including agriculture, transportation, industry and households, in addition to their extensive use as raw materials in the production of other energy products like electricity and petrochemistry. Thus, oil and its derivatives have a vast impact on other commodities (Sarwar et al., 2020; Taghizadeh-Hasery et al., 2019).

At recent times, agricultural products and energy markets have been growingly intertwined (Koirala et al, 2015: 431). From this perspective, energy consumption in agriculture can be evaluated in two categories: (1) Direct energy use: Energy inputs such as electricity, fuel, oil, coal, petroleum products, natural gas, biomass can be used in agricultural activities. (2) Indirect energy use: The amount of energy consumed in human and animal labor, agricultural tools or machineries, fertilizers, pesticides, irrigation or seed production. In this regard, energy prices affect the costs of inputs necessary for faming including inorganic fertilizers and fuel for agricultural machinery. Moreover, it is commonly observed that energy prices increase transportation costs and therefore, affect food transportation and distribution costs. The primary energy products directly consumed in agricultural production include fuels such as coal, petroleum products, natural gas and biomass. Also, electricity is widely used as power carrier in farming and particularly irrigation operations. It is a source commonly benefited in the agricultural industry (Akder et al., 2020: 9; Radmehr and Henneberry, 2020: 2; Sarwar, 2020: 1; Öztürk et al., 2010: 2; Mawejje, 2016: 2; Nwoko et al., 2016: 2; Gilbert and Mugera 2014: 201).

Yet, the history is marked by many crises related to food supply and demand. In this vein, it can be observed that the recent price volatility in food has had a destructive effect. The increased volatility in prices in this field can be associated with the transition from the labor-intensive to a more capital-intensive agricultural production in recent years as well as the regional and national differences in terms of farming. The use of energy is naturally essential in agricultural production. Today's technology enables growing even tropical products in cold regions thanks to the heat provided by energy sources. Hence, technology allows countries that are rich in energy sources to produce fruits and vegetables despite their cold climate. On the other hand, especially developing countries that import energy seem to have hardship in their agricultural operations due to the high energy prices increasing the costs of inputs. This leads to an intricate relationship between energy and prices of agricultural products. From this perspective, various studies analyze the effects of oil and other energy prices on agricultural product prices. For example, Hau et al. (2020) and Koirala et al. (2015) discuss the relations between oil and agricultural prices in terms of futures. Sarwar et al. (2020), Hesary et al. (2019), Alghalith (2010) and Zhang et al. (2010) examine the effects of the changing crude oil prices on agricultural products. On the other hand, Radmehr and Henneberry (2020), Balcılar and Bekun (2019) and Huchet-Bourdon (2011) scrutinize the effects of energy and exchange rates on agricultural products' prices. Mawejje (2016) further dwells upon the importance of energy and climate shocks in the case of Uganda and the food prices in this country.

In their study, Volpe et al (2013) also investigate how fuel prices in the USA affect the prices of wholesale products and their transportation costs. Since agricultural products themselves have been used for energy production at recent times, Baffes (2011) examines the relations between oil, biofuel and prices of agricultural products.

The literature in this field contains many other similar studies analyzing the volatility in the prices of energy and agricultural product using the econometric techniques that are also benefited in this study. Table 1 summarizes these studies in detail:

3. METHODOLOGY

3.1 The Kanas approach for the volatility spillover effect

Engle (1982) developed a new method to measure the volatility in a time series by modeling conditional variance. He revealed that the conditional variance is a function of the lagged values of the error term squares and modeled the change of the error term squares with respect to time using the ARCH process. Thanks to the introduction of the GARCH model in the literature, many other conditional variance models started to be widely used (Bollerslev, 1986). Although the standard GARCH model captures various features of financial series such as excess kurtosis and volatility clustering, they are not successful in capturing the leverage effect of financial time series. Standard GARCH models tend to ignore the negative correlation between current return and future return volatility. Further, the constraints on parameters to ensure the stationarity of the GARCH process can make parameter estimation difficult. Lastly, another difficulty is to interpret whether shocks persist on the conditional variance in the standard GARCH model. An alternative model developed by Nelson (1991) is the EGARCH model that removes these defects in the standard GARCH modeling of the financial time series, prevents the model from giving symmetrical responses in cases of positive and nega-

Table 1. Summary Literature Review.

Authors	Goal	Methodology	Industry	Region	Results
Hau et al. (2020)	To explore the volatility between global crude oil and China's agricultural futures.	- Time-dependent parameter stochastic volatility - Conditional volatility	Agriculture, Energy, Futures and Options Market	China	There is a heterogeneous dependence between the volatility of agricultural futures and the volatility of crude oil. While crude oil volatility does not affect agricultural volatility in the normal mode of the crude oil market, oil volatility at high or low amounts has been found to have an extremely significant effect.
Tiwari et al. (2020)	To analyze the progression-regression relationship between the price indices of energy fuels and food, industrial inputs, agricultural raw materials, metals, and beverages (lead-lag relation) in the time-frequency domain.	- Wavelet coherence and phase differences, - Diebold & Yilmaz (2012) and Barunik & Krehlik (2017) volatility spillover indices	Food &Energy	Global	The results revealed significant relationships between fuel and food prices, fuel and industry prices, and fuel and metal prices. The results also showed that there are phase relationships between these paired prices. The volatility spillover results showed that the agricultural industry was the most affected industry by shocks from other markets.
Balcılar and Bekun (2019)	To examine the structure of the interconnectedness between the returns of oil and foreign exchange prices with selected agricultural commodity prices.	- Diebold & Yilmaz (2012) volatility spillover index	Food, Energy & Finance	Nigeria	Analyses demonstrate that banana, cocoa, peanut, corn, soybean, and wheat are net transmitters of spillover. Moreover, there is weak spillover between the variables of rice and sorghum, in addition to price inflation, nominal effective exchange rate, and oil prices.
Fasanya and Akinbowale (2019)	To analyze the returns and volatility of crude oil and food prices.	- Diebold & Yilmaz (2012) volatility spillover index	Food &Energy	Nigeria	Evidence of the interconnectedness between crude oil and food prices was found based on spillover indices.
Adrangi et al. (2017)	To examine the daily volatility spillovers between crude oil prices and a selected group of basic agricultural products.	- Johansen-Juselius cointegration test, - Dynamic conditional correlations, - Spectral and cross spectral analyses, - The Bivariate EGARCH model and Granger causality tests.	Food &Energy	USA	The Johansen-Juselius cointegration test reveals that the long-run equilibrium relationships between crude oil prices and the commodities in question have disappeared. The dynamic conditional correlations show that the relationship between agricultural products and crude oil changes over time. The spectral and cross-spectral analyses confirm that volatility in crude oil prices is associated with volatility in agricultural products given in the sample. The Bivariate EGARCH model and Granger causality tests confirm this relationship. Analyses also confirm that the fluctuations in crude oil prices are related with the volatility of agricultural products given in the sample.
Judith et al. (2017)	To investigate the cause of increased food price volatility.	- Descriptive statistics - Correlation analysis	Food	USA	The results show that the main source of food price volatility is mainly the oil price shock.

Authors	Goal	Methodology	Industry	Region	Results
Cabrera and Schulz (2016)	To investigate the risk of price and volatility arising from the correlation between energy and agricultural commodity prices and to examine their changing dynamics over time.	- The asymmetric dynamic conditional correlation GARCH model, - The multivariate multiplicative volatility model	Food &Energy	Germany	It is revealed that prices move together in the long run and both rapeseed and biodiesel prices react to deviations from the equilibrium. In the short run, biodiesel prices do not affect rapeseed and crude oil price levels, but rather react to price changes in the other two markets. Moreover, the volatility of biodiesel is related to the volatility of crude oil and rapeseed, while the correlation between the fluctuation of rapeseed and crude oil has been increasing in recent years.
Lucotte (2016)	To analyze the dynamics of co-movements in crude oil and food prices.	- Correlations of VAR estimation errors (variance decompositions)	Food &Energy	Global	Empirical results manifest that after the spikes in the commodity prices, strong positive co-movements were observed between the crude oil price and food price indices, while significant correlation coefficients were not observed in the period before the spikes in the commodity prices.
Nwoko et al. (2016)	To examine the long-run and short-run relationships between oil price and food price volatility and the causality relationships between them.	- Johansen and Juselius co-integration test, - The vector error correction model, - Granger causality test	Food &Energy	Nigeria	Analyses reveal that there is a long-run relationship between oil price and local food price volatility and that causality is one-way from oil price volatility to food price volatility.
Gilbert and Mugera (2014)	To investigate the role of biofuels in explaining the increased volatility in food products.	- The multivariate GARCH model - The Dynamic Conditional Correlation model	Food &Energy	USA	Analyzing a sample between 2000 and 2011, the study found increases in the correlation and joint movements between grain and crude oil prices after 2006 and especially in 2008 when crude oil prices were high. Researchers concluded that the increased volatility in grains during the 2008-2009 increase was largely due to shocks transferred from crude oil to grains, particularly corn, wheat, and soybean prices.
Tadesse et al. (2014)	To search for empirical evidence on the quantitative significance of supply, demand, and market shocks for price changes in international food commodity markets. To explore the main drivers of food price spikes and volatility for wheat, corn, and soybeans and show how these factors triggered the crisis in extreme price swings.	- The price spike model by differentiated regression - The volatility model by panel regression - The prediction of extreme volatility by quantile regression	Food	Global	They concluded that oil prices are a statistically significant factor in explaining the increases and volatility in food prices.

Authors	Goal	Methodology	Industry	Region	Results
Gardebroek and Hernandez (2013)	To examine the volatility spillovers in oil, ethanol, and corn prices.	Multivariate GARCH models	Food &Energy	USA	In the study, significant volatility spillover is observed only from corn and not vice versa. Also, researchers do not detect cross-volatility effects from oil to corn markets. The results do not provide any evidence that volatility in energy markets has a significant effect on price volatility in the US corn market.
Nazlıoğlu et al. (2013)	To examine the volatility transmission between oil and selected agricultural commodity prices which are wheat, corn, soybean, and sugar.	The variance causality test	Food &Energy	Global	Data are analyzed in two periods as the pre-crisis period (January 1986 - December 2005) and the post-crisis period (January 2006-March 2011) to determine the impact of the food price crisis. The results showed that although there was no risk of spillover between oil and agricultural commodity markets in the pre-crisis period, there was actual oil market volatility spillover to agricultural markets - excluding sugar - in the post-crisis period.
Serra (2011)	To investigate price relations between crude oil, ethanol and sugar	a semiparametric GARCH model	Food &Energy	Brazil	The results reveal that in the long run, ethanol prices increase along with the increase in both crude oil and sugar prices.

tive shocks in volatility, and thus is more convenient for modeling conditional variance. In this model, the logarithmic conditional variance depends on both the size and the sign of the residuals (Nelson, 1991; Bollerslev et al., 1994). EGARCH (p, q) is:

$$\ln(\sigma^2_t)=\omega+\sum^{p}_{i=1}[\alpha_i z_{t-i}+(\gamma_i|z_{t-i}|-E[|z_{t-i}|])]+\sum^{q}_{i=1}\beta_i\ln(\sigma^2_{t-i}) \quad (1)$$

where $z_t=\varepsilon_t/\sigma_t$ and the coefficient α_i captures the sign effect and γ_i captures the size effect. So, the EGARCH (1, 1) model can be expressed as follows

$$\ln(\sigma^2_t)=\omega+\alpha_1 z_{t-i}+(\gamma_i|z_{t-i}|-E[|z_{t-i}|])]+\beta_1\ln(\sigma^2_{t-i}) \quad (2)$$

where γ_i is also referred to as the asymmetry coefficient and β_1 indicates volatility persistence. It can be said that there is a leverage effect on the conditional variance when has a value other than 0.

In this study, the Kanas (1998) approach is taken as basis in determining the volatility spillover. Before volatility modeling, it is first necessary to determine the most convenient Autoregressive Moving Average (ARMA) models for the conditional mean process. By testing the ARCH effect on the residuals obtained from these models, the most convenient EGARCH (1, 1) model is determined according to the information criteria and likelihood value. The assumed distributions for EGARCH models are Normal Distribution (norm), Skewed-Normal Distribution (snorm), Student-t Distribution (std), Skewed-Student-t Distribution (sstd), Generalized Error Distribution (ged), Skewed-Generalized Error Distribution (sged), Normal Inverse Gaussian Distribution (nig) and Johnson's SU Distribution (jsu). EGARCH (1,1) models with different distributions are compared according to Akaike Information Criteria (AIC), Bayes Information Criteria (BIC), Shibata Information Criteria (SIC), Hannan-Quinn Information Criteria (HQIC) and likelihood values.

Kanas (1998) defines the residual squares of other variables obtained from the conditional variance model as exogenous variables and made parameter estimates in order to determine the volatility spillover. Accordingly, the EGARCH (1,1) model to be estimated is as follows:

$$\ln(\sigma^2_t)=\omega+\alpha_1 z_{t-i}+(\gamma_i|z_{t-i}|-E[|z_{t-i}|])]+\beta_1\ln(\sigma^2_{t-i})+\tau_1\ln(u^2_{t-i}) \quad (3)$$

In the above equation, u_t is the residuals obtained from the conditional variance model, and τ_1 is the coefficient showing the volatility spillover. If the coefficient τ_1 is statistically significant, it is concluded that there is a volatility spillover.

3.2 The Diebold-Yilmaz approach for the volatility spillover effect

Diebold and Yilmaz (2009) describe the return and volatility spillover on the basis of the Vector Autoregressive (VAR) model. Here, the total spillover index is measured based on the Cholesky decomposition. Nevertheless, Diebold and Yilmaz (2012) developed a methodology in a later study to evaluate directional spillover in a generalized VAR framework. This VAR framework approach offers variance decomposition that is invariant to the order of variables after that of Koop et al. (1996) and Pesaran and Shin (1998). In the N-component standard *VAR* model, each entity *xi* with = 1,…, *N* is expressed as follows:

$$y_t = \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t \tag{4}$$

where y_t is $Nx1$ matrix of dependent variables and φ_i are NxN matrix of coefficients. ε_t is the vector of independently and identically distributed innovations (iid) and follows $\varepsilon_t \sim N(0,\Sigma)$ where Σ is variance-covariance matrix. The moving average representation of the *VAR* model is as follows:

$$y_t = \sum_{i=1}^{\infty} A_i \varepsilon_{t-i} \tag{5}$$

where A_i are NxN matrix of moving average coefficients and $A_i=\varphi 1 A_{i-1}+\varphi_2 A_{i-2}+\ldots+\varphi_p A_{i-p}$. Then, given the VAR framework, H-step-forecast error-variance decompositions are defined as follows:

$$\theta_{ij}^{g} = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} \left(\Delta_i^T A_h \Sigma \Delta_j\right)^2}{\sum_{h=0}^{H-1} (\Delta_i^T A_h \Sigma A_h^T \Delta_i)} \tag{6}$$

where σ_{ij} represents the standard deviation of the error term, Σ is variance-covariance matrix and Δ_i is the selection vector of which i[th] element is equal to 1 and the other elements are 0. If each element of the decomposition matrix is divided by row sums, each forecasting error decomposition variance will be normalized, thus using the available information in the decomposition matrix to compute the spillover effects as follows:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{7}$$

with $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H)=1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)=N$.

In the light of the above definitions and equations from 4.4 to 47, Diebold and Yilmaz (2012) defined total, directional and net spillovers as described below:

The total volatility spillovers index based on h-step-ahead forecasts with the following equation:

$$TS^g(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} x100 = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} x100 \tag{8}$$

Directional volatility spillovers to i market from other *j* markets:

$$DS_{j\to i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} x100 \tag{9}$$

Directional volatility spillovers from market *i* to other *j* markets:

$$DS_{i\to j}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} x100 \tag{10}$$

The net spillover index is obtained using Equations 4.9 and 4.10 as follows

$$NS_i^g(H) = DS_{i\to j}^{g}(H) - DS_{j\to i}^{g}(H) \tag{11}$$

4. DATA ANALYSIS

As signified in the introduction, this study aimed to analyze the relationship between the fruit and vegetable price volatility and the energy price volatility in Turkey. Both energy and product prices consist of the data sets obtained from Eurostat within the scope of the Harmonized Index of Consumer Prices (HICP). The scope of energy index includes "electricity, gas and other fuels". The energy price index is a variable with broader content than the crude oil price, which is widely cited in the literature. It is considered noteworthy to refer to this energy price index in this analysis.

The monthly data set obtained from Eurostat consists of the Energy Price Index (EPI), the Fruit Price Index (FPI) and the Vegetable Price Index (VPI) between January 2007 and December 2020. Appendix-A, Table-A1 and Table-A2 demonstrate the descriptive statistics and Augmented Dickey-Fuller Unit Root Test results for the data set of these indexes and their loga-

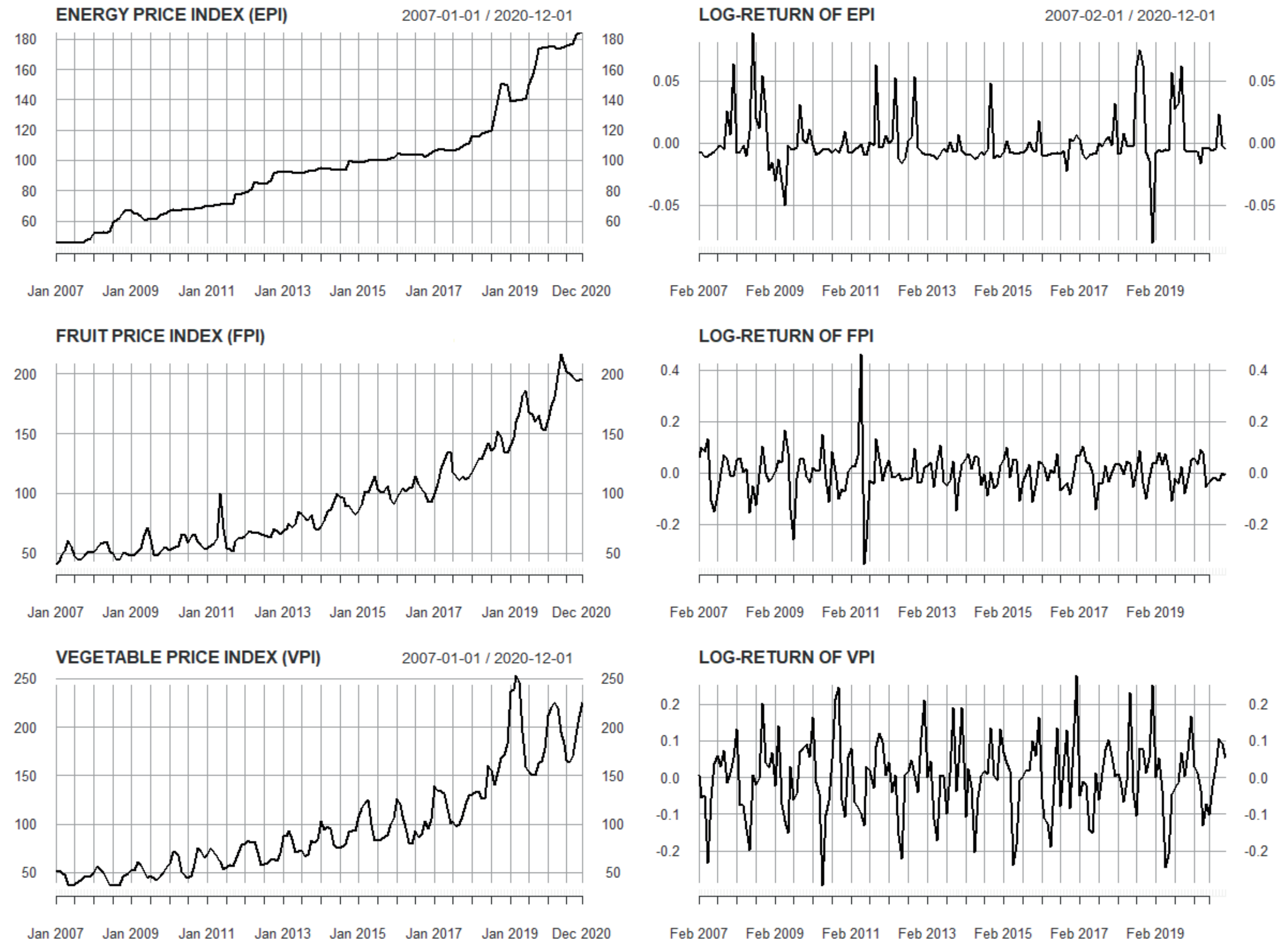

Figure 1. Time-series Plot of Indexes and Log-returns.

rithmic returns. Figure 1 shows the time-series plot of the variables.

5. EMPIRICAL RESULTS

5.1 Empirical results for Kanas Approach

The convenient conditional mean models for EPI, FPI, and VPI were found to be AR (1), ARMA (2,2), and MA (1), respectively. The output of conditional mean models and ARCH test results are given in Table A3 in Appendix-A. The evaluation of the volatility models is given in Table 2.

The results[1] in Table 2 manifest that the most adequate models are as follows: Sged-EGARCH (1,1) for EPI; std-EGARCH (1,1) for FPI and norm-EGARCH (1,1) models for VPI. Table A2 points out to the parameter estimation results and diagnostic test results of the models.

It is evident in all three models that all parameters are statistically significant. According to the diagnostic test results, the results of Ljung-Box (LB) and Langrange-Multiplier (LM) tests indicate that there are no autocorrelation problems in the residuals and heteroscedasticity problem in the residual squares. The Nyblom Stability Test (NST) results show that there is no structural break according to the NST critical value of 1.49 at 10% confidence level. As in NST, common statistical values calculated for Sign Bias Test (SBT) are given and according to these test statistics, there is no functional error in the conditional volatility model. Looking at the results of the Pearson Goodness of Fit (GoF) test, it can be understood that the empirical distribution of standard residuals and the theoretical distribution are aligned.

[1] EGARCH-type volatility models were estimated using "rugarch" R package developed by Ghalanos (2020a, 2020b).

Table 2. EGARCH(1,1) Model Evaluation depending on Information Criteria and Likelihood Values.

dist	EPI					FPI					VPI				
	AIC	BIC	SIC	HQIC	L	AIC	BIC	SIC	HQIC	L	AIC	BIC	SIC	HQIC	L
norm	-5.18	-5.10	-5.18	-5.15	436.5	-2.54	-2.44	-2.54	-2.50	216.9	**-1.91**	**-1.81**	**-1.91**	**-1.87**	**164.2**
snorm	-5.33	-5.23	-5.33	-5.29	449.8	-2.56	-2.45	-2.56	-2.52	219.9	-1.90	-1.78	-1.90	-1.85	164.3
std	-5.63	-5.53	-5.63	-5.59	474.7	**-2.71**	**-2.59**	**-2.71**	**-2.66**	**232.0**	-1.87	-1.76	-1.87	-1.83	162.3
sstd	-5.63	-5.53	-5.63	-5.59	474.7	-2.71	-2.59	-2.71	-2.66	232.0	-1.87	-1.76	-1.87	-1.83	162.3
ged	-5.54	-5.44	-5.54	-5.50	467.3	-2.62	-2.51	-2.62	-2.57	224.7	-1.90	-1.79	-1.90	-1.86	164.9
sged	**-6.17**	**-6.06**	**-6.17**	**-6.13**	**521.2**	-2.65	-2.52	-2.66	-2.60	228.6	-1.88	-1.75	-1.89	-1.83	164.2
nig	-6.14	-6.03	-6.15	-6.10	519.0	-2.68	-2.55	-2.68	-2.63	230.8	-1.88	-1.75	-1.88	-1.83	163.9
jsu	-6.16	-6.04	-6.16	-6.11	520.1	-2.69	-2.56	-2.70	-2.64	232.0	-1.87	-1.74	-1.88	-1.82	163.5

Normal Distribution (norm), Skewed-Normal Distribution (snorm), Student-t Distribution (std), Skewed-Student-t Distribution (sstd), Generalized Error Distribution (ged), Skewed-Generalized Error Distribution (sged), Normal Inverse Gaussian Distribution (nig) and Johnson's SU Distribution (jsu), Akaike Information Criteria (AIC), Bayes Information Criteria (BIC), Shibata Information Criteria (SIC), Hannan-Quinn Information Criteria (HQIC), Llikelihood (L).

Table 3. The Parameter Estimation of EGARCH(1,1) Models for Price Indices.

Parameters	sged-EGARCH(1,1) for EPI				std-EGARCH(1,1) for FPI				norm-EGARCH(1,1) for VPI			
	est	Std.Err	t-stat	sig	est	Std.Err	t-stat	sig	est	Std.Err	t-stat	sig
omega	-1.49	0.01	-194.71	0.00	-2.47	1.14	-2.16	0.03	-0.33	0.00	-3793.40	0.00
alpha1	0.35	0.03	11.90	0.00	0.12	0.11	1.05	0.29	0.26	0.00	2136.50	0.00
beta1	0.81	0.00	1176.69	0.00	0.56	0.21	2.71	0.01	0.93	0.00	4454.40	0.00
gamma1	-0.08	0.00	-16.82	0.00	0.39	0.15	2.63	0.01	-0.30	0.00	-2522.70	0.00
shape	0.47	0.01	76.08	0.00	5.69	1.84	3.08	0.00				
skew	1.44	0.01	163.05	0.00								
		stat	sig			stat	sig			stat	sig	
LB on SR		1.48	0.75			3.71	0.29			0.25	0.82	
LB on SSR		1.19	0.82			0.13	1.00			3.59	0.31	
ARCH LM		1.15	0.69			0.10	0.99			2.04	0.46	
SBT Joint		0.12	0.99			3.26	0.35			0.60	0.90	
Perason GoF		47.67	0.53			42.88	0.72			35.10	0.93	
NST Joint		2.41				1.57				1.48		
Persistence		0.81				0.56				0.94		
Half-life		3.36				1.19				9.94		

LB: Ljung-Box SR: Standardized Residuals SSR: Standardized Squared Residuals LM: Langrange Multiplier SBT: Sign Bias Test NST: Nyblom Stability Test GoF: Goodness-of-Fit. "omega" is the constant term. "alpha1"is the the ARCH coefficient that is a measure of sign effect. "beta1" is the the ARCH coefficient that is a measure of volatility persistence "gamma1" is the asymmetry coefficient that is a measure of leverage effect. "Normal Distribution (norm), Student-t Distribution (std), Skewed-Student-t Distribution (sstd), Skewed-Generalized Error Distribution (sged).

Negative values for EPI and VPI can be found by analyzing the values of "gamma1" parameters that show the leverage effect. In this case, it can be concluded that the effect of bad news on EPI and VPI volatility is higher the effect of good news and increases the volatility persistence. The persistent values indicate that the volatility persistence is high for EPI and VPI variables. It is also found that the half-life of persistence in VPI was 9.94 days. Thus, the effect of good news on the volatility is higher for FPI, while the volatility persistence and half-life are lower. This is an indication that good news has a less impact than bad news in the leverage effect. The time-series graph of the volatilities obtained from the models is as described in Figure 2.

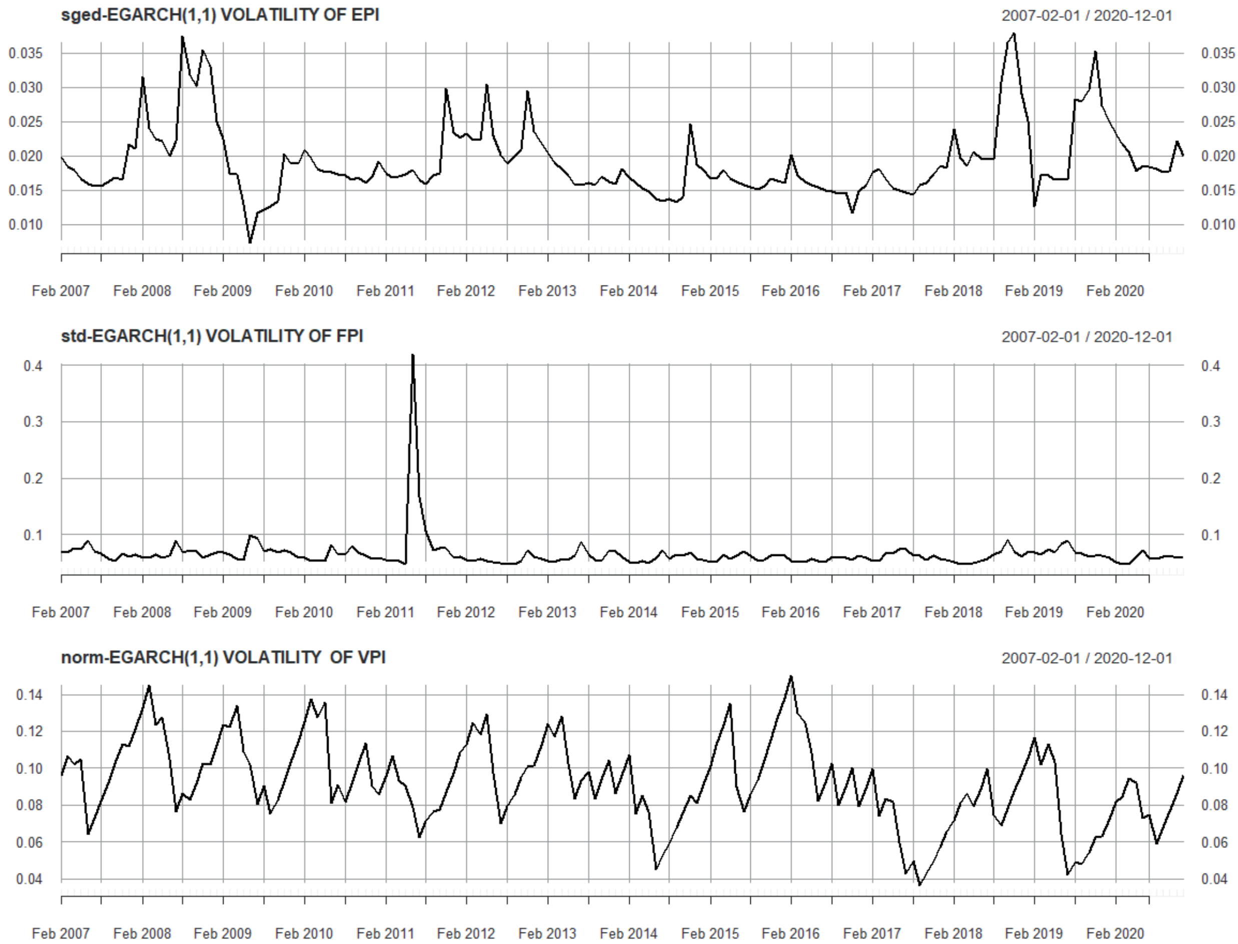

Figure 2. Time-Series Plot of Volatilities Obtained from EGARCH Processes.

It can be said that there was a fluctuation in FPI volatility in May 2011 similar to a big shock effect. In this regard, the Iterative Cumulative Sum of Squares (ICSS) introduced by Inclan and Tiao (1994) was applied to all three indexes to locate any structural break in the variance. However, the results showed no break in the variance. To test the volatility spillover of EPI on other variables in this study, the residual squares obtained from the sged-EGARCH (1, 1) model (given in Table 3) were added as an exogenous variable to the volatility models. This step was followed by the parameter estimation. The results are given in Table 4.

The diagnostic test results in Table 4 indicate that the models support the hypotheses. According to the results of FPI parameter estimation, it is understood that the "tau1" coefficient (which shows the volatility spillover from EPI to FBI) is not statistically significant, and therefore there is no volatility spillover from EPI to FBI. On the other hand, according to the VPI parameter estimations, the "tau1" coefficient is found to be statistically significant leading to the understanding that there is a volatility spillover from EPI to VPI. Hence, it can be concluded that the volatility in the EPI negatively affects the VPI volatility.

4.2 Empirical Results for the Diebold-Yilmaz Approach

Table 3 demonstrates the most suitable volatility models determined for EPI, FPI and VPI indexes. Derived from volatility data obtained from these models, the lag value of the VAR model was found to be 1. In addition to this calculation, the VAR (1) model parameter was estimated. The results of the model estimated by the lag value of selection criteria are respectively presented in Appendix-B, Table B1 and Table B2. The Die-

Table 4. The Parameter Estimation of EGARCH(1,1) Models for Spillover from EPI to FPI and VPI with Diagnostics Tests.

Parameters	std-EGARCH(1,1) for FPI				norm-EGARCH(1,1) for VPI			
	est	Std.Err	t-stat	sig	est	Std.Err	t-stat	sig
omega	-2.52	1.08	-2.33	0.02	-0.28	0.00	-7553.23	0.00
alpha1	0.13	0.11	1.11	0.27	0.28	0.00	5849.33	0.00
beta1	0.56	0.19	2.90	0.00	0.94	0.00	7751.43	0.00
gamma1	0.38	0.15	2.57	0.01	-0.28	0.00	-10783.22	0.00
shape	5.74	1.85	3.10	0.00				
tau1 (EPI spillover)	14.36	115.70	0.73	0.47	-7.75	0.01	-686.85	0.00
		stat	sig			stat	sig	
LB on SR		9.76	0.01			3.54	0.32	
LB on SSR		3.21	0.37			0.12	1.00	
ARCH LM		1.87	0.50			0.08	0.99	
SBT Joint		0.40	0.94			3.17	0.37	
Perason GoF		48.87	0.48			36.89	0.90	
NST Joint		1.60				1.53		
Persistence		0.56				0.94		
Halflife		1.19				11.68		

LB: Ljung-Box SR: Standardized Residuals SSR: Standardized Squared Residuals LM: Langrange Multiplier SBT: Sign Bias Test NST: Nyblom Stability Test GoF: Goodness-of-Fit. “omega” is the constant term. “alpha1”is the the ARCH coefficient that is a measure of sign effect. “beta1” is the the GARCH coefficient that is a measure of volatility persistence “gamma1” is the asymmetry coefficient that is a measure of leverage effect. “tau1” is the coefficient showing the volatility spillover Normal Distribution (norm), Student-t Distribution (std), Skewed-Student-t Distribution (sstd), Skewed-Generalized Error Distribution (sged).

bold-Yilmaz approach results[2] obtained on the basis of the VAR model can be seen in Table 5.

Before moving on to the results, it is worth reiterating that the spillover index shows how much of the total variance that occurs in the variables themselves is caused by other variables. In other words, the Diebold-Yilmaz spillover index demonstrates the contribution of the volatility in price indices to the forecasting error variance. Thus, the results of the total volatility spillovers index are based on a 10-step-ahead approach.

As these results suggest, it is observed that the volatility spillover from EPI index to other indexes is higher than the others. Furthermore, the VPI is the index that is exposed to the highest volatility transfers. The total spillover from EPI to the other indexes is 14.38% and 13.52% of this value belongs to the VPI and the rest belongs to the FPI index. This case points out to shocks in energy prices exhibiting a higher possibility to affect the pattern of other prices in the investigated area. Here, the EPI can be defined as a volatility transmitter. It can be deduced that the risk that the FPI index is exposed to from the outside is low. Indeed, only 2.68% of its current volatility results

Table 5. Diebold-Yilmaz Generalized Directional Spillover Output.

	EPI	FPI	VPI	Contribution from others
EPI	91.80	0.27	7.92	8.20
FPI	0.86	97.32	1.82	2.68
VPI	13.52	4.45	82.03	17.97
Contribution to others (spillover)	14.38	4.72	9.75	9.62
Contribution to others including own	106.18	102.04	91.78	300.00
Net Spillover	6.18	2.04	-8.22	
Total Spillover Index	9.62%			

from other indexes. On the other hand, it is seen in the VPI index that the externally exposed volatility spillover is 17.97%, and 75.23% of it (13.52%) is due to the EPI. These results also support the outputs obtained from the Kanas (1998) approach. The fact that the total spillover index value is 9.62% points out to a low connectedness between these indexes. Nevertheless, it can be seen that the risk in energy prices is transferred to vegetable prices. Due to the high energy prices in Turkey, for instance, people can only heat their greenhouses only to protect them from frost rather than proper

[2] Diebold-Yılmaz analysis was performed using “Spillover” R package developed by Urbina (2020).

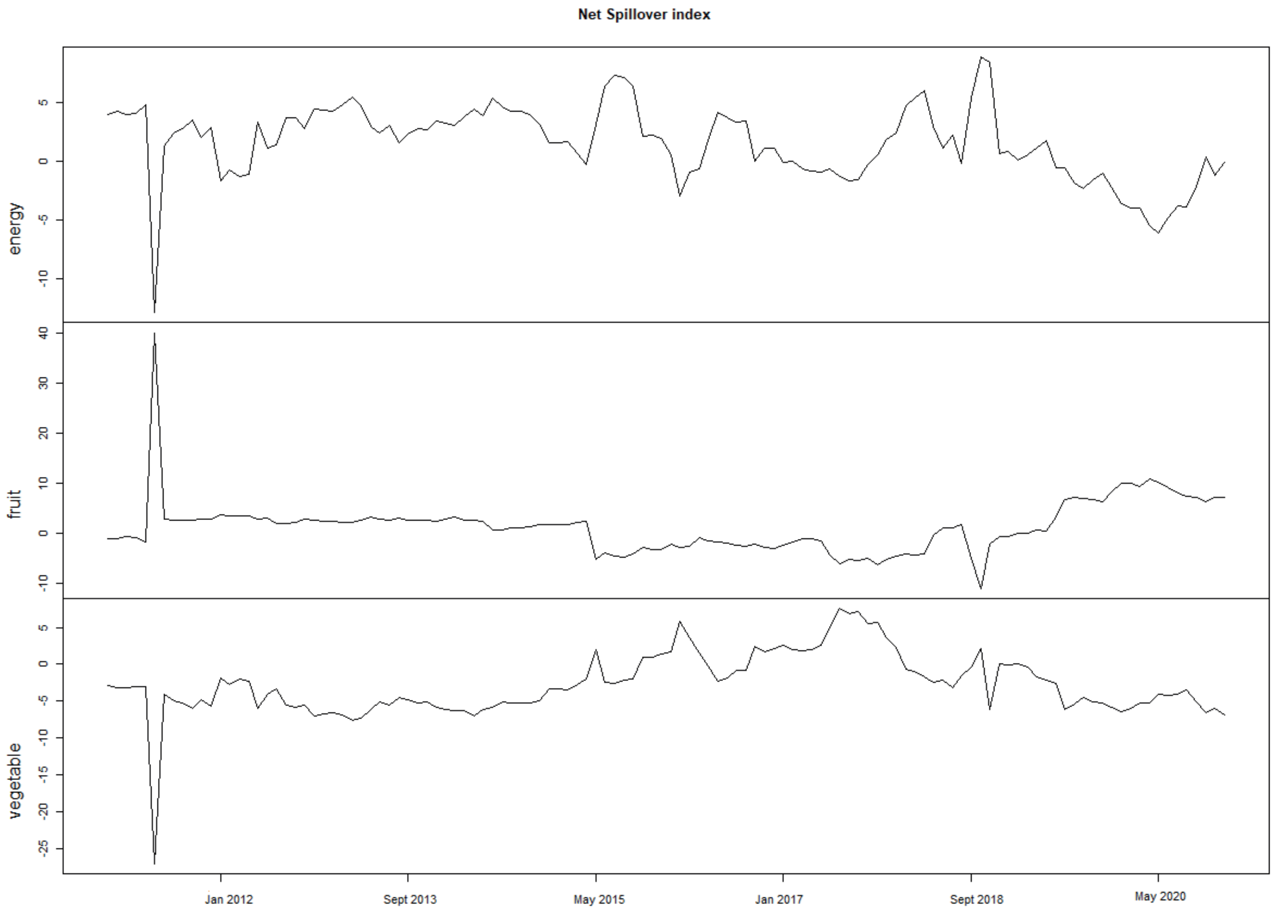

Figure 3. The Top-Down Rolling Net Spillovers Indexes for EPI, FPI and VPI.

heating. Despite this widespread use of limited energy, volatility in energy prices affects greenhouse costs. 31 million tons of vegetables were produced in Turkey in 2019 as the world's 4th largest producer of fresh vegetables. 23.2 million tons of these crops were grown in agricultural or open areas, and 7.8 million tons were produced in greenhouses. As a matter of fact, around 0.6 million tons of fruits are produced in greenhouses (MAF, 2021). According to the results of the analysis, this explains the reason why the vegetable price index is subject to volatility from the spillover of the fluctuating energy prices.

Within this framework, the average spillover effects over the full sampling period are obtained by generalized spillover analysis. Diebold and Yilmaz (2009, 2012) stated that full sample spillover measurements cannot clearly reflect the important sustained and cyclical movement in spillovers. Thus, they developed a rolling window framework that allows time-varying spillover indices to overcome their shortcomings in the spillover index, using a 48-month subsample. In this line, the following graphs show the estimation of the dynamic net and total spillover indexes. These rolling windows were obtained using the 10-step-ahead forecasting spillovers.

The date that stands out at first glance in the rolling net spillover index is May 2011, when consumer prices increased by 2.42% and annual inflation rose to 7.17 %. Coupled with the base effect, the high increases in fresh fruit prices due to seasonal transitions marked the rationale behind this rise. In this period, fresh fruit prices increased by 76.12% on a monthly basis, well above the average of the previous period (TCBM, 2011). Therefore, the FPI became the volatility transmitter in May 2011 and created a net volatility spillover of 40.05% on the forecasting error variances of other indices. Thus, the total spillover index was estimated as 44.33%.

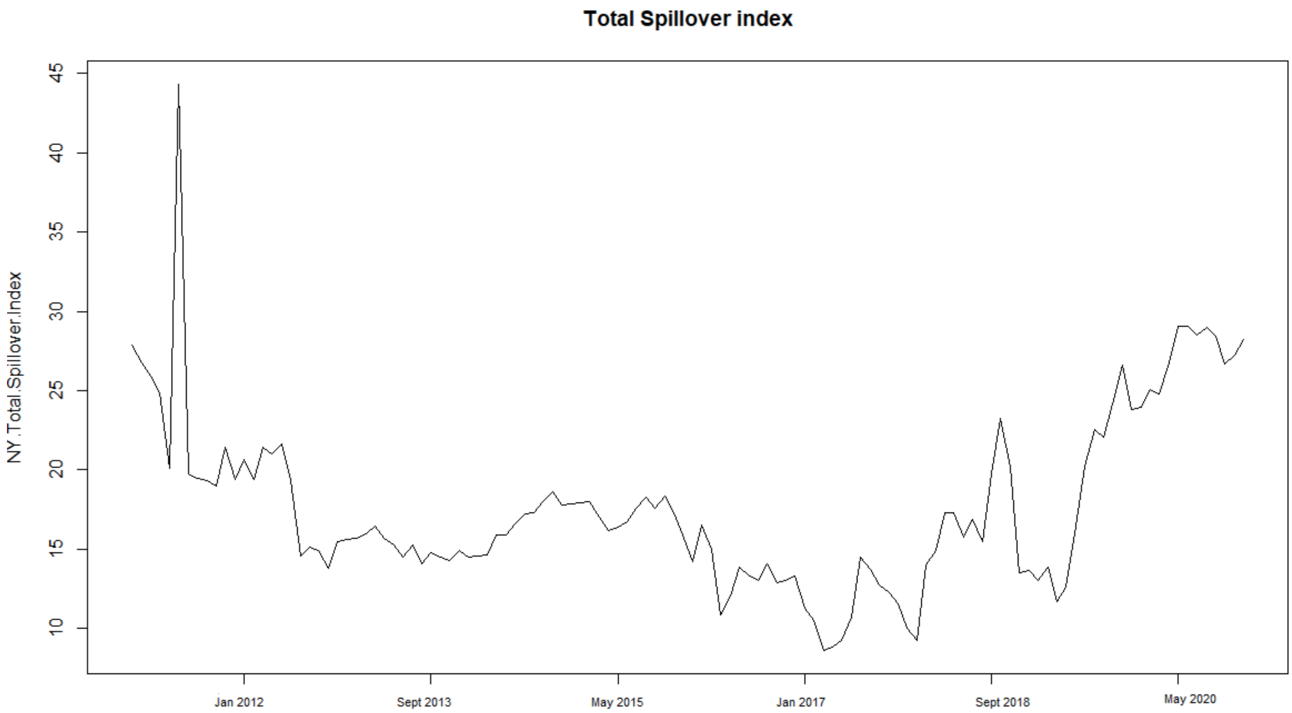

Figure 4. The Rolling Total Spillovers Index.

6. CONCLUSION

Input costs have a significant share in setting the prices of agricultural products and ensuring sustainable production. Increases especially in energy prices may have an effect on many items from production to delivery of products to final consumers. These items include but are not limited to fertilizers, chemicals, irrigation, production, storage and transportation costs. In this context, stable pricing in the field of energy is essential for the price stability of agricultural products. However, energy prices are not reflected on every agricultural product at the same level. Thus, this study analyzed the prices of fruits and vegetables as the category containing the highest price fluctuations compared to other agricultural products.

Two different analysis methods, Kanas (1998) and Diebold-Yilmaz (2012), were used in the study and it is concluded that the results obtained from both methods support each other. After the parameter estimation of the relevant ARMA models for logarithmic changes of energy, fruit and vegetable price indices, the ARCH effect was determined in the residuals of conditional mean models. To identify the residuals of conditional mean models, volatility modelling was performed through the EGARCH conditional variance model introduced to the literature by Nelson (1991). Parameter estimations were made for the EGARCH models by assuming eight different conditional probability distributions. In this regard, sged-EGARCH, std-EGARCH and norm-EGARCH were found to be the most compatible models for EPI, FPI and VPI, respectively. Considering the outputs of these models indicating the leverage effect, it can be seen that the volatility of energy and vegetable price indexes is more affected by bad news in the market. On the other hand, the volatility of fruit price index appears to be mostly affected by good news. At the same time, it can be understood that the volatility persistence and half-life of energy and vegetable price indexes are higher according to the fruit price index. As an exogenous variable in other variables' volatility modelling, we used the residual squares obtained from the volatility model estimated for the energy price index on the basis of the Kanas (1998) approach. Consequently, it is concluded that there is a statistically significant volatility spillover from the energy to the vegetable price index, while not from the energy index to the fruit price index. This clarifies that the fluctuations in energy prices increase the risk and uncertainty in vegetable prices. In the Diebold-Yilmaz (2012) approach, the volatility spillover index results were obtained by using the VAR model for the volatilities attained from the EGARCH models, which were found to be most compatible for the indexes. Accordingly, it is understood that the volatility spillovers from the energy to the vegetable price index and the fruit price index are 13.52% and 0.86%, respectively. In addition, these calculations show that the risk that the fruit price index is exposed to from the outside is rather low, and only 2.68% of the current volatility are due to other indexes. In the case of the vegetable price index, however, it is found that 75.23% of the net volatility index is from energy prices. These results are well overlapping with the results obtained by applying the Kanas (1998) approach. The fact that the total spillover index value is 9.62% points out to a low connectedness between these indexes. As we mentioned in the findings section, the share of greenhouse cultivation in vegetable production is considerably higher than in fruit production. At the same time, vegetable production is higher than fruit production in Turkey. In this case, the amount of energy input needed in vegetable production is naturally higher than fruit production. In addition to these, Turkey's dependence on foreign energy, increases in the exchange rate, and price increases in the global energy market are other factors to be considered. Thus, it is an expected result that the spillover effect of the energy price index volatility on the vegetable price index is greater than the fruit price index.

Another production input that has an indirect effect on energy prices (which, in turn, affect vegetable and fruit prices) is the price of fertilizers used in farming. Indeed, it may well be observed that fertilizer production is decreasing due to the increasing costs of natural gas and electricity all over the world. This is the indirect factor that causes the upward volatility trend of fruit and vegetable price indices in Turkey. In other words, the volatility of energy prices is quite high in the country.

Elaborated in this study from a scientific perspective, the increasing energy prices can be associated with expensive foods due to the increasing costs of processing, transportation, and distribution of agricultural products. In addition, the effect of energy prices on food prices also varies depending on the distance traveled by road.

Largely focusing on the fluctuating energy prices and their impact on agricultural products, the results of this study provide important implications for policymakers. In this sense, policymakers should urgently do make improvements in their exchange rate policies and the oil reserve system in order to reduce the negative impact of fluctuations in oil prices on the agricultural sector in Turkey, which is an oil importer country. They should also pay as much attention as possible to the global oil markets and their impact on transportation costs. In parallel with the developments in the energy industry, there is also a need to design preventive/protective regulations to mitigate the agricultural price risks and stabilize the market. In addition, policymakers should take measures to prevent speculative behaviors in the markets in an attempt to prevent price increases of food. In addition to these measures and regulations, governments must support farmers so that they maintain their resilience, while also protecting consumers against price changes. On the other hand, it is necessary to expand the use of alternative energy sources such as biofuels, wind, and solar energy in order to reduce Turkey's dependence on foreign-sourced oil consumption.

Similar to the rest of the world, Turkey can grow fruits for a much longer time period than vegetables. According to the results obtained from our study, the time-wise conclusion is that that energy prices have a greater effect on agricultural products grown in a shorter time. Also, the study results are reasonable in the sense that vegetable production in greenhouses is often in greater amounts than fruit production, while requiring a high amount of energy consumption.

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APPENDIX-A

Table A1. Summary Statistics.

Variable	Mean	Median	Min	Max	Std. Dev.	Skewness	Ex. kurtosis	5% Perc.	95% Perc.	IQrange
energy	96.50	93.68	45.33	184.46	36.02	0.82	0.07	45.75	175.00	39.66
fruit	94.05	82.58	40.38	217.00	43.83	0.98	0.06	47.88	194.70	56.74
vegetable	96.89	82.71	36.15	253.72	51.55	1.15	0.63	41.24	216.29	68.24
logret(energy)	0.00	-0.01	-0.08	0.09	0.02	1.60	5.25	-0.02	0.06	0.01
logret(fruit)	0.00	0.00	-0.36	0.46	0.08	0.16	7.82	-0.14	0.10	0.08
logret(vegetable)	0.00	0.01	-0.30	0.28	0.10	-0.06	0.42	-0.19	0.19	0.12

Table A2. Augmented Dickey-Fuller Unit Root Test Results.

		energy	fruit	vegetable	logret(energy)	logret(fruit)	logret(vegetable)
With Constant	t-Statistic	1.39	5.28	1.02	-9.08	-6.10	-8.42
	Prob.	1.00	1.00	1.00	0.00	0.00***	0.00***
With Constant & Trend	t-Statistic	-0.49	2.15	-1.31	-9.05	-6.98	-8.46
	Prob.	0.98	1.00	0.88	0.00	0.00***	0.00***
Without Constant & Trend	t-Statistic	3.64	6.46	2.80	-9.11	-6.09	-8.43
	Prob.	1.00	1.00	1.00	0.00	0.00***	0.00***

*** indicates that log-returns of EPI, FPI and VPI has no unit root.

Table A3. ARMA Model Outputs for EPI, FPI and VPI.

Coefficients	AR(1) for EPI		ARMA(2,2) for FPI		MA(1) for VPI	
	est	sig	est	sig	est	sig
const	−3.99718e-05	0.99	−0.000537185	0.71	0.00	0.99
phi_1	0.33	0.00	1.55	0.00		
phi_2			−0.795506	0.00		
theta_1			−1.76350	0.00	0.41	0.00
theta_2			0.83	0.00		
Mean dependent var	0.00		−1.91e-17		0.00	
Mean of innovations	0.00		0.00		−0.000061	
R-squared	0.11		0.27		0.13	
Log-likelihood	417.55		206.90		154.05	
Schwarz criterion	−819.7365		−383.0893		−292.7434	
S.D. dependent var	0.02		0.08		0.10	
S.D. of innovations	0.02		0.07		0.10	
Adjusted R-squared	0.11		0.26		0.13	
Akaike criterion	−829.0905		−401.7972		−302.0974	
Hannan-Quinn	−825.2939		−394.2041		−298.3008	
ARCH LM test	56.00 (9.65e-10)***		51.3 (7.91e-09)***		15.33 (3.20e-02)**	

** and *** indicate that there is an ARCH effect on residuals.

APPENDIX-B

Table B1. VAR Lag Selection.

lags	loglik	p(LR)	AIC	BIC	HQC
1	1484.04		-18.51*	-18.28*	-18.42*
2	1485.41	0.97	-18.42	-18.01	-18.26
3	1487.78	0.86	-18.34	-17.76	-18.10
4	1494.17	0.17	-18.30	-17.55	-18.00
5	1499.96	0.24	-18.26	-17.34	-17.89
6	1508.76	0.04	-18.26	-17.16	-17.81
7	1521.01	0.00	-18.30	-17.03	-17.78
8	1526.37	0.30	-18.26	-16.81	-17.67

*The most convenient VAR Lag is selected 1.

Table B1. VAR(1) Model Output.

Dependent Var	Energy Volatility (evol)		Fruit Volatility (fvol)		VegetableVolatility (vvol)	
	est	sig	est	sig	est	sig
const	0.01	0.00	0.05	0.00	0.01	0.07
evol[-1]	0.77	0.00	−0.381	0.35	0.44	0.03
fvol[-1]	−0.0063	0.49	0.30	0.00	−0.0383	0.29
vvol[-1]	−0.0263	0.02	−0.0193	0.83	0.82	0.00
Mean dependent var	0.02		0.06		0.06	
Sum squared resid	0.00		0.13		0.13	
R-squared	0.60		0.10		0.10	
F(3, 162)	82.29		5.79		5.79	
rho	−0.021		−0.004		−0.004	
S.D. dependent var	0.01		0.03		0.03	
S.E. of regression	0.00		0.03		0.03	
Adjusted R-squared	0.60		0.08		0.08	
sig(F)	0.00		0.00		0.00	
Durbin-Watson	2.04		2.01		2.01	
All lags of evol F(1, 162)	241.41	[0.0000]	0.86818	[0.3528]	5.0403	[0.0261]**
All lags of fvol F(1, 162)	0.4696	[0.4942]	15.226	[0.0001]	1.1422	[0.2868]
All lags of vvol F(1, 162)	5.6895	[0.0182]	0.044003	[0.8341]	354.2	[0.0000]

**The test statistics of all lags of evol in vvol model indicates that evol Granger causes vvol.