Revealing asymmetric spillover effects in hazelnut, gasoline, and exchange rate markets in Turkey: The VECM–BEKK–MGARCH Approach

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Summary: The study used the VECM–BEKK–MGARCH method to model the volatility transmission between the markets of gasoline, exchange rates, and the hazelnut market for the period of 21.07.2005-20.3.2018. The suitability of the VECM–BEKK–MGARCH method was confirmed by statistical testing. The changes in hazelnut prices were not affected by the changes in the prices or final values in the other two sectors (Granger causality). Moreover, the Granger causality tests revealed that, while the change in the gasoline market was not affected by the other two markets, the change in the exchange rates market was affected by the other two markets. Furthermore, especially the volatilities (long–term uncertainties) of the markets were affected by both their own short– and long–term volatilities and other sectors' short– and long–term volatilities. It was shown that the long–term swings in these three markets were affected by the cross-interaction in the markets. Additionally, as opposed to the case in the positive news, it was observed that pieces of negative news affected the markets.

1. Introduction

Turkey produces on average 550,000 tons of hazelnut per year, which corresponds to approximately 70-75% of the global production (Osman Kilic 2006; Lisanne de Wit

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2014; Muhammet Y. Şişman 2017). However, hazelnut prices have been volatile for the last few years due to extreme weather conditions in the country. Despite the latest price soars, hazelnut prices have fallen to a level lower than in 2014 and 2015, when the Black Sea region was exposed to bad weather conditions. In 2014, heavy frosts destroyed crops at high altitude places in the region. In 2017, the government intervened in the market by buying hazelnuts against price fluctuations that would harm producers. This was the first intervention of the government by authorizing the Turkish Grain Board (TGB) in the market within eight years. TGB was a regular buyer of hazelnuts between 2006 and 2009. It has now created a backdrop for farmers who will either sell their products to the state or hope to sell their products at higher prices in the market (de Wit 2014; Şişman 2017).

While all this was happening, Turkish Lira (TL), on the other hand, gradually depreciated against the US dollar and the Euro recently, making Turkish export products cheaper. Volatility (e.g., fluctuations) in exchange rates used as a means of payment in foreign trade can also lead to fluctuations in the import and export values of the finished products. Turkey has the power to determine the world price of many agricultural products such as hazelnuts, dried apricots, dried figs, lentil, and chickpea (Gülistan Erdal, Hilmi Erdal, and Kemal Esengün 2012).

The fact that long–term uncertainties are determined by the amount and aspects of cross–market pass–through actually leads to the evolution of more robust and reliable policies in the markets. While determining how the volatility in exchange rates and gasoline prices passes to the hazelnut market being chosen as the main purpose of the study, empirically revealing the volatility pass–through from the hazelnut market to these two markets is as important as the previous goal. The study also aims to show how the market reacted to the good and bad news by utilizing asymmetric information in the conditional volatilities of the markets, whilst it is crucially important to examine the long–term price dynamics between the three markets and how each market reacts to deviations from the long–run equilibrium. On the other hand, while such issues have been documented in a wide range in international literature, unfortunately, it has remained almost scant in Turkey. In this context, this study will provide a novelty to the literature by revealing such issues mentioned above along with putting forth its aspects that overlap and diverge with international findings.

In the next section, the literature will be discussed. Subsequently, after the material and method section is presented in greater detail, the results and discussion section will be reported. Finally, a summary of the study findings will be presented in the conclusion section along with the deliberate recommendations.

2. Literature Review

Nowadays, many researchers are investigating the spreading effects of uncertainty between the markets and especially the studies investigating the volatility transmission between prices of agricultural product, biofuels, and crude oil have gained more importance and became a forefront in the literature (Teresa Serra, David Zilberman, José M. Gil, and Barry K. Goodwin 2008; Jonathan Balcombe 2010; Serra and Gil 2012; Serra and Zilberman 2013; Perry Sadorsky 2014; Fadi Abdelradi, and Serra 2015a,

2015b; Amer A. Sidhoum, and Serra 2016; Miao Zhen, James Rude, and Feng Qiu 2017; Sayed Saghaian, Mehdi Nemati, Cory Walters, and Bo Chen 2018; and among others). The fact that developed and some developing countries like the USA, Germany, Brazil, and China allocated a large part of their natural resources to biofuel production especially after 2006 has been the beginning of a new era. While the production of biofuels from agricultural products has gained a great meaning, it has also contributed to the establishment of a nexus between crude oil and the agricultural sector (Serra and Zilberman 2013; Tsion T. Assefa, Miranda P. M. Meuwissen, and Alfons G. J. M. Oude Lansink 2015). The introduction of this link in a quantitative dimension has been the focus of interest for economists as well as agricultural economists for many years. While some researchers attempted to present this relationship level with the help of either Vector Autoregressive Model (VAR) or the Vector Error Correction Model (VECM) (Rabobank 2011; Serra 2011; Anthony N. Rezitis 2012; Robert J. Myers, Stanley R. Johnson, Michael Helmar, and Harry Baumes 2014; Abdelradi and Sera 2015a, 2015b; Mansor H. Ibrahim 2015; Ladislav Kristoufek, Karel Janda, and Zilberman 2016; Sidhoum and Serra 2016), others used the Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) model predominantly whether the spillover transmission of volatility between markets is symmetrical (Islam Hassouneh, Serra and Gil 2010; Serra et al. 2011; Serra and Gil 2012; Harry de Gorter, Dusan Drabik, and David R. Just 2013; Walid Mensi, Makram Beljid, Adel Boubaker, and Shunsuke Managi 2013; Mensi, Shawkat Hammoudeh, Duc K. Nguyen, and Seong-Min Yoon 2014; Sadorsky 2014; Abdelradi and Serra 2015a, 2015b; Sidhoum and Sera 2016; Brenda L. Cabrera, and Franziska Schulz. 2016; Fakhri J. Hasanov, Lester C. Hunt, and Ceyhun I. Mikayilov 2016; Zhen et al. 2017; Saghaian et al. 2018; and among others).

The volatility of surging food prices and its detrimental effects have unexpected high-cost impacts on economic activities and raising concerns among consumers, producers, and policymakers (Sidhoum and Sera 2016; Saghaian et al. 2018). These adverse effects can be stated as follows: First, high price volatility creates a bottleneck for food security by pushing farmers to poverty and income instability. Second, rising food prices drag down both the income and purchasing power of poor consumers, leading them to more poverty, malnutrition, and hunger. Lastly, it negatively affects farmers' future profound and efficient production plans and investment decisions. As a result, the rapid and unexpected price instability in food prices can disrupt both markets and the governments' actions on political and social stabilities (Mensi et al. 2014; Abdelradi and Serra 2015a, 2015b; Sidhoum and Sera 2016; Cornelis Gardebroek, Manuel A. Hernandez, and Miguel Robles 2016; Saghaian et al. 2018).

Although the volatility transmission between agricultural product markets and macroeconomic indicators have been recently addressed in international studies, similar studies in Turkey, unfortunately, remains limited. For all purposes mentioned in the introduction section, the VECM – MGARCH model is used with the daily data set covering the period of 07.21.2005-03.20.2018. In general, in previous studies, unitary (marginal) effects of the short– and long–term volatility spillovers and asymmetric

effects on the conditional volatility of each market in question were neglected. We, however, presented them in this study.

3. Material and Method

3.1. Time Series Econometric Method

Time-series econometric model was used in this study. A preliminary assessment of the statistical properties of time series is crucially important in the selection of a suitable econometric model (Sidhoum and Sera 2016). In this context, in this study, non-stationarity, covariance, and clustering are discussed in preliminary statistics of the series. Non-stationary arises where a high autocorrelation that causes the mean and variance to change over time has a tendency to host within the series. In this context, time-series analysis ignoring non-stationarity in the series leads to the generation of counterfeit (spurious) results (Sidhoum and Sera 2016). Today, fortunately, there are several tests that reveal the statistical properties of the time series to decipher inherited traits. Non-stationarity is inevitable in both macroeconomic markets and most of the agricultural products markets (Apostolos Serletis and Ricardo Rangel-Ruiz 2004; Neil Kellard and Mark E. Wohar 2006; Svetlana Maslyuk and Russell Smyth 2008; Saghaian 2010; Atanu Ghoshray 2011). Another characteristic of the time series is that the linear combinations of the non-stationary series exhibit a long–run relationship and may exhibit the cointegration with an established tendency to adapt to this equilibrium (Goodwin and Nicholas E. Piggott 2001; Serra et al. 2006; Sidhoum and Sera 2016). If there is an equilibrium in the linear composition of the time series variables, deviations that occur in the long–run equilibrium due to economic and/or non-economic shocks are rectified and brought back to the long–run equilibrium. Robert F. Engle and Clive W. J. Granger (1987) have been able to demonstrate both short– and long–term equilibrium of co–integrating series with the help of error correction models. In this context, while short–term dynamics determine how current price volatility is affected by lagged price volatility, long–term (run) dynamics determine the adjustment of deviations in the long–run equilibrium of time series (Sidhoum and Sera 2016). On the other hand, both independent and identical distribution, which are the common assumption of time series data, are interrupted by time-varying and clustered variability. Different suggestions have been put forward by researchers to overcome this problem. While Engle (1982) identifies the above problem with the autoregressive conditional heteroskedasticity (ARCH) model, the improved generalized ARCH (GARCH) model presented by Tim Bollerslev (1986) plays a major role in diagnosing the above problem. While time-series studies are usually focused on univariate volatility studies, the multivariate aspects of volatility have increased in recent years to an incredible extent (Sidhoum and Sera 2016). In this context, especially in recent years, the multivariate GARCH (MGARCH) models have been used to demonstrate the spillover effects between agricultural products and energy markets (Stacie Beck 2001; Octavio A. Ramírez, and Mohamadou Fadiga 2003; Serra 2011; Sidhoum and Sera 2016; Saghaian et al. 2018).

In this study, we used the Vector Error Correction Model (VECM)–BEKK (Baba, Engle, Kraft, and Kroner) Multivariate Generalized Autoregressive Conditional Variance (VECM–BEKK–MGARCH) model, which contains two main equations in

order to investigate the volatility relations between hazelnut, gasoline prices, and real exchange rate. While the first model is designed to explain the conditional mean equation of the VECM based on the BEKK–GARCH method developed by Engle and Kenneth F. Kroner (1995) for the hazelnut, gasoline prices, and real exchange rate, the second equation, BEKK–MGARCH model, was used to explain the conditional variance of the mean equation. As can be seen, this main model consists of two basic equations. While the first part of the model contains the conditional mean equation put forward with the help of VECM, the second part consists of the conditional variance equation explained with the help of the BEKK–MGARCH model. In this context, the first part of the model shows how prices (for hazelnut and gas) or closing values (exchange rates) shape each other, whereas the second part of the model shows how the current short–term, long–term and existing symmetrical relationships in the markets affect long–term volatility in the markets. However, in some studies, Vector Autoregressive Model (VAR) was preferred to VECM in the conditional mean equation (Gardebroek and Hernandez 2013; Serra and Zilberman 2013; Mensi et al. 2014; Sadorsky 2014; Assefa et al. 2015; Afees A. Salisu and Tirimisiyu F. Oloko 2015; Cabrera and Schulz 2016; Zhen et al. 2017; Saghaian et al. 2018). Here, the conditional mean equation derived from the VECM[4] is integrated into the BEKK–MGARCH model. The conditional mean equations used for this model are:

$$\Delta P_t = \delta_i + \alpha_i z_{t-1} + \sum_{j=1}^{p} \beta_{ik,j} \Delta P_{t-j} + \varepsilon_{i,t}, \quad i,k = h,g,e \quad \text{ve} \quad j = 1,...,p$$

$$\text{where} \begin{pmatrix} \Delta P_t^h \\ \Delta P_t^g \\ \Delta P_t^e \end{pmatrix} = \begin{pmatrix} \delta_h \\ \delta_g \\ \delta_e \end{pmatrix} + \begin{pmatrix} \alpha_h \\ \alpha_g \\ \alpha_e \end{pmatrix} z_{t-1} + \sum_{j=1}^{p} \begin{pmatrix} \beta_{hh,j} & \beta_{hg,j} & \beta_{ge,j} \\ \beta_{gh,j} & \beta_{gg,j} & \beta_{ge,j} \\ \beta_{eh,j} & \beta_{eg,j} & \beta_{ee,j} \end{pmatrix} \begin{pmatrix} \Delta P_{t-j}^h \\ \Delta P_{t-j}^g \\ \Delta P_{t-j}^e \end{pmatrix} \quad (1)$$

and $\varepsilon_t \square (0, H_t)$

Equation (1) shows the conditional mean equation and defines price or closing level behavior where h, g, and e stand for hazelnut, gasoline, and exchange rate markets, respectively, whilst j stands for the lag length. The symbol Δ in the equation represents the first difference operator, while P_t and P_{t-1} represents the n-dimensional vector of the current and lagged levels of the series (prices and closing values), respectively. The number n indicates the total number of endogenous variables studied in the study (e.g., three markets), while the vector $\varepsilon_{i,t}$ contains n number of white noise residuals associated with each series in question. z_{t-1} represents the vector of the lagged value

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[4] We, however, chose to use VECM in this study because of some of its superior features such as cointegration, short‒ and long‒term equilibrium that we have mentioned above.

of the error correction variable, α_i parameters represent the long–run dynamic relationship and indicates the rate at which the long–run equilibrium deviations of the series are set back to long–term equilibrium. At the same time, the dynamic changes in the short–run are determined by the $\beta_{ik,j}$ parameters and show how the current price or closing changes react to the lagged price or closing changes (where "i and k" represent the variable level and "j" represents the lag length (Sidhoum and Sera 2016).

Volatility measures fluctuation in our price or closing series and its size and different MGARCH models are recommended in the literature. Here, the BEKK–MGARCH model is used, which allows estimating the conditional covariance matrix, and at the same time can precisely define the conditional covariance matrix. The model implies the specific parametrization of the MGARCH model and is a dynamic conditional model with the attractive feature where the conditional covariance matrices are positive definite (Sidhoum and Sera 2016; Saghaian et al. 2018). The algebraic representation of this equation is as:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\xi_{t-1}\xi'_{t-1}D \tag{2}$$

In Equation (2), C, A, B, and D are 3x3 matrices. The matrix A and B show short–term shocks and long–term volatility, respectively. The matrix D shows the asymmetric effect as a parameter. Here, since the matrix H_t is positive definite, the matrix H_{t-1} must also be defined as positive definite.

The analytical form of the conditional variances of the matrix given in Equation (2) is:

$$
\begin{aligned}
h_{jj,t} = c^*_{jj} &+ \left(a^2_{j1}\varepsilon^2_{1,t-1} + 2a_{j1}a_{j2}\varepsilon_{2,t-1}\varepsilon_{1,t-1} + 2a_{j1}a_{j3}\varepsilon_{3,t-1}\varepsilon_{1,t-1} \right) & + \\
&\left(a^2_{j2}\varepsilon^2_{2,t-1} + 2a_{j2}a_{j3}\varepsilon_{3,t-1}\varepsilon_{2,t-1} \right) + \left(a^2_{j3}\varepsilon^2_{3,t-1} \right) & + \\
&\left(b^2_{j1}h_{11,t-1} + 2b_{j1}b_{j2}h_{21,t-1} + 2b_{j1}b_{j3}h_{31,t-1} \right) & + \\
&\left(b^2_{j2}h_{22,t-1} + 2b_{j2}b_{j3}h_{32,t-1} \right) + \left(b^2_{j3}h_{33,t-1} \right) & + \\
&\left(d^2_{j1}\xi^2_{1,t-1} + 2d_{j1}d_{j2}\xi_{2,t-1}\xi_{1,t-1} + 2d_{j1}a_{j3}\xi_{3,t-1}\xi_{1,t-1} \right) & + \\
&\left(d^2_{j2}\xi^2_{2,t-1} + 2d_{j2}d_{j3}\xi_{3,t-1}\xi_{2,t-1} \right) + \left(d^2_{j3}\xi^2_{3,t-1} \right), j = 1,2,3
\end{aligned}
\tag{3}
$$

Equation (3) expresses how conditional variances in hazelnut, gasoline, and real exchange rate markets are affected both by their own short–term shocks and by long–term uncertainties. The equation also shows how markets are affected by short–term shocks and long–term uncertainties among themselves. In Equation (3), $\varepsilon_{j,j}$ represents the short–term shocks of each market price, $\varepsilon_{i,j}$ represents the cross-short–term shocks

between markets, $h_{j,j}$ represents the uncertainty (volatility) in markets, $h_{i,j}$ represents the cross uncertainty (volatility) in markets, and $\xi_{j,j}$ represents short–term negative shocks in markets that are different from positive shocks. Because Equation (3) is nonlinear, marginal effects must be measured. Therefore, the delta method was used in conjunction with the standard deviation to measure the marginal effects in this study.

3.2. Data Set

Hazelnut prices were obtained from the database of the Turkish Union of Chambers and Commodity Exchange. Chubby hazelnut data include daily average trading prices. Crude oil prices are not used as fuel prices. Because high taxes taken from fuel prices in Turkey are thought to be the cause of volatility in the hazelnut prices. The gasoline pump price is used as an indicator of fuel price and data were obtained from the Republic of Turkey Energy Market Regulatory Authority (RTEMRA) database. A free exchange rate can swing fluctuations in the price of nuts because hazelnuts are ranked first among Turkey's most important export products. The real exchange rate series was obtained from the Republic of Turkey Central Bank database (RTCB). Daily data for the period of 2005:03 – 2018:03 were used to examine the volatility between the series. In the examined period, the dates of these three variables were overlapped and a total of 478 observations was obtained. Since the pump price for gasoline in Turkey has changed once or twice per week or two weeks, the data of the other variables are adjusted accordingly based on the day the gasoline pump prices change.

In the study, after the series were converted to their corresponding real values[5], the analysis was carried out on the level series. Levels of the series against time are given in Figure 1. As seen in the figure, especially the chubby hazelnut prices show great variability and all three variables showed an increasing tendency towards time. In Table 1, some descriptive statistics including the correlation of price series and autocorrelation relations are presented. Given the unconditional variance obtained from the standard deviation of hazelnut, it is seen that the volatility is higher than the gasoline and real exchange rate price levels. When the real exchange rate, gasoline price levels, and standard deviations are taken into consideration, it is determined that gasoline price has higher mean and variance levels than the real exchange rate. Moreover, it has been determined that the real exchange rate has the least volatility among the series. The kurtosis coefficient indicates that the level series exhibits a leptokurtic[6] (fat-tail) distribution. Leptokurtic distribution of the level series indicates that the ARCH effect may be present in the series. The ARCH–LM test developed by Engle (1982) was applied for the presence of the ARCH effect in the level series. The ARCH–LM test shows that the ARCH effects were observed in the level series. It has been observed that the level series include autocorrelation as revealed by the Ljung–Box (LB) statistical

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[5]The price of hazelnuts is 2003 = 100 based on food prices, while the price of fuel is revaluated by using energy prices index based on 2003 = 100. The exchange rate series are redeemed using the real effective exchange rate.

[6] Spike-tipped and fat-tailed distribution.

test. The Jarque–Bera statistic indicates that the level series are not normally distributed. Finally, the Augmented Dickey and Fuller (ADF) unit root test developed by David A. Dickey and Wayne A. Fuller (DF) (1979) was applied when the series were tested for stationary and the results are presented in Table 1. For all three series, the zero hypotheses were not rejected in the ADF unit root test and the series were found to exhibit a non-stationarity feature. At the same time, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests confirmed the ADF unit root results, indicating the series are not stationarity at a 1% significance level. There is also a very high correlation between the levels of the series. In this context, the observed short– and long–term bustling fluctuations in the series shows that it can be comfortably transmitted to the levels of other series. This high correlation may be closely linked to each other in terms of the functionality of the markets, especially in the context of foreign trade, while it also indicates the use of MGARCH model.

Please insert Figure 1 and Table 1 here

4. Results and Discussion

Before discussing the results of VECM–BEKK MGARCH, the long–run relationship (co–integration) between the hazelnut, gasoline, and exchange rate markets was questioned using the Johansen test procedure. The lag length in the Johansen co-integration analysis was determined to be "two" by implementing the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and Hannan-Quinn Criterion (HQ). When two lags were used in the model, we found that there was only a co–integration vector at the 6% significance level between the three markets (Table 1). When this co–integration vector is taken into consideration, a unitary increase in the real price of gasoline and the closing value of the exchange rate leads to a decrease of about 10 TL in the long–term shelled hazelnut real price level. In this context, the long–term relationship between these two variables has great implications on the true price of shelled hazelnut. This is not surprising because shelled hazelnuts are traded on a dollar basis in the world market and fuels make up a large part of the cost of production from the evolution of the hazelnut growing to its different value–added final products. Another point worth noting is that the degree of intensive relationship between fuel and exchange rate in the country might be a cause in these relations.

Before considering the VECM–BEKK–GARCH results from a broad perspective, it is useful to state some specification test results done here. Three Granger causality tests were applied in this study. Among these, first, the null hypothesis that the gasoline price, exchange rate, and error correction factor are not causal for the current change in chubby hazelnut prices has been tested and the hypothesis has been rejected with a high level of statistical significance ($\chi^2_{5,0.05} = 168.197$, and p < 0.000). Thus, the lagged values of gasoline, exchange rate, and error correction factor are a Granger cause of price change in the chubby hazelnut market. In other words, the behavior of the price level in the chubby hazelnut market will depend on the changes in the other two markets, as well as the drift that will occur in the long–run equilibrium between these three markets. Conversely, the statistical test result showed that the chubby hazelnuts,

exchange rate, and error correction factor were not a Granger causality in the gasoline market ($\chi^2_{5,0.05} = 8.335$, and p = 0.138), showing that the oil market is perhaps affected by the changes in the other macroeconomic environment (i.e., the inflation rate, industry index, and etc.) rather than the swings in these markets in the country. However, it has been also determined that the current exchange rate is simultaneously affected by the changes in lagged the prices of chubby hazelnut, gasoline, and lagged value in the error correction factor ($\chi^2_{5,0.05} = 241.386$, and p < 0.000), indicating that these three lagged changes significantly determine the current exchange rate. In this context, we can easily say that the effect of the change in the oil market on this change can be substantially high. The fact that the rising oil prices in the world markets expose the country to more import bills causes the exchange rate to move upwards while consequently triggering inflation in the food prices in the country.

Please insert Table 2 and Table 3 here

One of the other important statistical tests was to test the hypothesis that there is no GARCH effect on the conditional variances of the markets in question. The conducted Wald test showed that the null hypothesis that all parameters in matrices A, B, and D are simultaneously equally zero is rejected with a very high significance level ($\chi^2_{27,0.05} = 12795.589$, and p < 0.000). In this context, we can say that a market is affected by both short–term shocks and long–term volatility including different spillover effects of negative and positive swings, indicating that the markets have ARCH, GARCH, and asymmetric effects within both themselves and cross–markets. Meanwhile, the hypothesis that the diagonal GARCH effect is absent, i.e., that a market is not affected by the cross–interaction of other markets, is rejected with a high significance value ($\chi^2_{18,0.05} = 604.128$, and p < 0.000) pointing out that markets are related to each other, and long–term uncertainties in the markets are caused by uncertainties in their own markets as well as uncertainties in other markets. The latest specification test in this study rejected the hypothesis that the negative and positive news on the market had an equal weight over the long–run volatility of a market with a very high statistical value ($\chi^2_{6,0.05} = 209.482$ and p < 0.000). Hence, both the negative and positive atmospheres in the markets have different effects on the long–term volatilities of the markets. While negative news usually worsens markets, positive news does not show as much as an effect as negative news did. In this context, negative speculative news appearing in the market may be more effective, suggesting that the actors or stakeholders in the market should resort to preventive measures against these negative reports.

On the other hand, the individual Ljun–Box (LB–Q) and McLeod–Li tests applied to standardized residuals and their squares, respectively, derived from the VECM–BEKK MGARCH model showed no autocorrelation, while the multivariate ARCH test (MARCH–LM test) also showed that both autocorrelation and time–varying

conditional variance were not present (see Table 3). Thus, the selected VECM–BEKK MGARCH model is consistent with the data.

Parameter estimates of the conditional mean equation of the VECM–BEKK MGARCH model are presented in Table 2. The VECM parameters were found statistically significant in the three markets. If there is a deviation between the three markets due to a change in prices of chunky hazelnuts, the mechanism on the market will bring this drift back to a long–run equilibrium of about 0.001. In the same way, the current divergence in the price of gasoline is corrected by approximately 0.0001, resulting in a long–run equilibrium between the markets, whilst deviations in current exchange rates indicate that they are gradually moving away from the long–run equilibrium. On the other hand, it has been determined that current changes in chubby hazelnut real prices are generally affected by changes in the prices of the two lagged markets. Similarly, it has been determined that the real price of gasoline will be negatively affected by the changes in the current average value from the two–term lagged change in own market. Likewise, current exchange rates generally indicate that the three markets will be negatively affected by two lagged price changes.

Parameter estimates of the time–varying conditional variances forming the second equation of the VECM–BEKK MGARCH model are given in Table 3. Marginal effects on the conditional variance of the variables in the equation are also given in Table 4. In this section, we will focus on the marginal effects of the variables on the conditional variances. At the same time, the discussion here will be based on statistically significant marginal effects.

The conditional variance of the chubby hazelnut market is positively affected by its short–term shocks ($\varepsilon_{1,t}^2$). In this context, short–run shocks in the chubby hazelnut market will have a lasting effect on the long–run volatility of the market. As the short–run shocks in this market increase, its long–run volatility will swing more while it will erode as the information loses its effects in the short–run. Their short–run shocks of the other two markets (gasoline and exchange rate, $\varepsilon_{2,t}^2$ and $\varepsilon_{3,t}^2$, respectively) do not acquire a statistically significant effect on the chubby hazelnut market. In this context, short–run negative or positive news in these two markets will not be significantly transmitted to the hazelnut market. These results coincided with findings of international literature (Mensi et al. 2013; Mensi et al. 2014; Sadorsky 2014; Abdelradi and Serra 2015a, 2015b; Sidhoum and Sera 2016; Cabrera and Schulz 2016; Gardebroek et al. 2016). It was concluded in many international studies that short–run shocks have a one-way spreading effect in agricultural products markets (Mensi et al. 2014; Sadorsky 2014; Abdelradi and Serra 2015a, 2015b; Cabrera and Schulz 2016; Gardebroek et al. 2016). On the other hand, short–term shocks originating from the simultaneous joint market between the chubby hazelnut market and the other two markets ($\varepsilon_{1,t}\varepsilon_{2,t}$ and $\varepsilon_{1,t}\varepsilon_{3,t}$) will have a lasting impact on the hazelnut market volatility. For example, while the simultaneous joint shocks of the hazelnut and the gasoline markets

($\varepsilon_{1,t}\varepsilon_{2,t}$) increase the volatility of the hazelnut market, short–term joint shocks between the hazelnut and the exchange rate market ($\varepsilon_{1,t}\varepsilon_{3,t}$) diminish the long–term uncertainty of the hazelnut market. Similarly, the short–term joint shocks between the gasoline and the exchange rate markets ($\varepsilon_{2,t}\varepsilon_{3,t}$) reduce the volatility in the hazelnut market. The results show that short–term good and bad news between the three markets will provide transmission to the hazelnut market. The degree of interaction between the hazelnut and the exchange rate markets ($\varepsilon_{1,t}\varepsilon_{2,t}$) is higher than that of the two other joint short–run shocks ($\varepsilon_{1,t}\varepsilon_{3,t}$ and $\varepsilon_{2,t}\varepsilon_{3,t}$) and this is expected because the hazelnut has the foreign market potential in the country both as raw materials and processed products.

Please insert Table 4 here

The conditional volatility of the hazelnut market is positively affected both by its own ($h_{1,t}$) and by the conditional volatilities of the other two markets ($h_{2,t}$ and $h_{3,t}$). In this context, the occurrence of long–term uncertainties in these markets will be a trigger for a swing in the hazelnut market. In particular, the marginal impact of the conditional volatility of the exchange rate ($h_{3,t}$) on the hazelnut market is higher than that of the other two markets, including the hazelnut market. This shows that the volatility in the exchange rate will drive the hazelnut industry into even more permanent swings because the hazelnut product has an important potential in the foreign trade volume. Many international studies have indicated that most agricultural products are affected by both their long–term volatilities and crude oil uncertainty (Mensi et al. 2014; Sadorsky 2014; Abdelradi and Serra 2015a, 2015b; Cabrera and Schulz 2016; Gardebroek et al. 2016). In addition, considering the fact that the hazelnut product is the main raw material for beer nuts, dessert, chocolate, hazelnut cream with cocoa, and hazelnut butter industries worldwide, the volatility in exchange rates is expected to be transmitted to the hazelnut market. Similarly, the long–run uncertainties ($h_{12,t}, h_{13,t}$, and $h_{23,t}$) in pairwise joint interactions between these three markets influence the conditional volatility of the hazelnut market in various directions and magnitudes. As expected, the greatest share of the effects of these joint volatilities lies in the interaction of hazelnut and exchange rate markets ($h_{13,t}$).

The asymmetrical effects that can occur in the hazelnut market are seen to shape the long–term uncertainty of the hazelnut market. Therefore, the negative news in the hazelnut market was seen to increase its volatility in the market when compared to positive news. In this context, it should be remembered that the negative atmosphere that the governments can experience in determining the base prices of hazelnuts would ultimately have permanent effects on the hazelnut market. Therefore, on-site and on-time determination of base prices without subjecting to speculations will serve the robust and more efficient operation in the market. On the other hand, in the case of

natural disasters such as drought, it would be very useful for the government to effectively monitor market regulations to avoid further damage to the hazelnut market. Likewise, the negative news in the exchange rate market is likely to significantly increase the volatility of the hazelnut market compared to the positive news. Thus, the negative speculation in the exchange rate will worsen the uncertainties in the hazelnut market as compared to the positive news, and it is, therefore, necessary to avoid the negative speculative news in the market. In particular, as the TL has depreciated against the dollar nowadays, a deterrent measure by the authorities should be taken into account against those who have turned it into an opportunity to gain more power in the market.

While the conditional variance of the gasoline market is positively affected only by the short–term shocks of the exchange market ($\varepsilon_{3,t}^2$), the volatility in three markets, including itself ($h_{1,t}, h_{2,t}$, and $h_{3,t}$), has a permanent impact on the volatility of the gasoline market. In the international studies, it has been determined that there is a bi–directional uncertainty transmission between the markets and our findings support this notion (Mensi et al. 2013; Mensi et al. 2014; Sadorsky 2014; Abdelradi and Serra 2015a, 2015b; Sidhoum and Sera 2016; Cabrera and Schulz 2016; Gardebroek et al. 2016; Saghaian et al. 2018). However, as expected, while the effect of a unitary (marginal) change in the conditional variance of the chubby hazelnut market ($h_{1,t}$) on the conditional volatility of the gasoline market was negligible, the long–run uncertainty in the exchange rate market ($h_{3,t}$) had a permanent impact on the gasoline market volatility. In this context, the impact of long–term uncertainties in the exchange rate market on the gasoline market will not be underestimated due to the close link between gasoline and exchange rate markets. This is because the purchase of crude oil is traded in dollars worldwide and therefore, the volatility in the exchange rate market in the country is directly transmitted to the oil market. Likewise, cross–bilateral relations between markets ($h_{12,t}, h_{13,t}$, and $h_{23,t}$), have been found to influence the conditional volatility of the gasoline market in different directions with varying magnitudes. Interestingly, the negative news on each market ($d_{1,t}, d_{2,t}$, and $d_{3,t}$), and the news from the simultaneous joint events in the pair markets ($d_{12,t}, d_{13,t}$, and $d_{23,t}$), were all observed to have permanent impacts on the conditional volatility of the gasoline market. As expected, the impact of negative news derived from the exchange rate on the gasoline market has been observed to be much more pronounced.

While the conditional volatility of the exchange rate is positively affected by short–term shocks in the chubby hazelnut market with a negligible spillover spread ($\varepsilon_{1,t}^2$), it is also positively affected by its own short–term shocks ($\varepsilon_{3,t}^2$). The fact that the pass–through from the hazelnut market to the exchange rate market is as low as possible is, in a sense, an expected result because there are more primary macroeconomic variables affecting the uncertainty in the exchange rate in the country. However, finding

this variable statistically significant is an important finding. Moreover, the long–term volatility of the exchange rate market is positively affected by the joint market shocks between the chubby nuts and the exchange rate ($\varepsilon_{1,t}\varepsilon_{3,t}$). The increased demand for chocolate, beer nuts, hazelnut cream with cocoa, and hazelnut butter in the world and Turkey and the continued growth of the sector accordingly may lead to such an outcome. For example, the size of the global chocolate industry exceeds \$ 75 billion, whilst its corresponding market size in Turkey reached 5.3 billion TL in 2016 (Euromonitor International 2018). On the other hand, the long–term conditional variance of the exchange rate is positively affected by long–term conditional volatilities of the other two markets including itself ($h_{1,t}, h_{2,t}$, and $h_{3,t}$). As expected, the impact of their own market is higher ($h_{1,t}$), whilst the transmission from the hazelnut market is very negligible. In the same way, cross volatility interactions between markets ($h_{12,t}, h_{13,t}$, and $h_{23,t}$) affect the volatility of the exchange rate market at different degrees in varying directions. As expected, negative news on the gasoline market ($d_{2,t}$) and the gasoline market interacted with the exchange rate market ($d_{2,t}d_{3,t}$) increases the conditional variance of the exchange rate market. The two markets are initially dependent on world markets and the economic and non–economic events taking place directly affect these markets. Likewise, negative news occurs in its own market ($d_{3,t}$) increases long–term volatilities. In this context, the negative news in the exchange rate market rapidly increases the up–and–down swings determined by its market and has, therefore, a negative impact on the country's economy. In a country with a fragile economic structure, such as Turkey, quickly forming deterrent laws into practice against such sudden shocking news will undoubtedly bring about great amenities.

The conditional pairwise correlation volatilities derived in the VECM–BEKK–MGARCH model are given in Figures 2. While there seems a positive linear correlation between chubby hazelnut and gasoline markets and the negative correlation appeared between chubby hazelnut and exchange rate markets. On the other hand, the correlation relationship between the two macroeconomic markets (e.g., gasoline and exchange rate) has generally spread around zero over time, preserving its overall structure. In particular, the volatility transmission between the chubby hazelnut market and the exchange rate market was more pronounced than in the other two market pairs. The level of transitivity in this market volatility differs according to the transaction volume of the two markets (chubby hazelnut and exchange rate) and the degree of proximity to each other. When the uncertainty in the exchange rate increases, the uncertainties in the chubby hazelnut market increase, and when it decreases the uncertainty in the chubby hazelnut market also decreases. On the other hand, especially in recent years, the volatility spread between gasoline and exchange rate markets has been more pronounced than in previous years. This can be explained by the current economic situation the country has

experienced (several economic attacks in 2012-2016 and military coup in 2016). In recent years, the Dollar experienced a very large gain against TL is reflecting and this instability in these markets.

Please insert Figure 2

5. Conclusions

Agricultural commodity markets were exposed to relatively high price volatility especially in 2006 when biofuels started to appear in the markets. In this sense, the first decade of the 21st century in global agriculture has been exposed to higher price volatility compared to the previous two decades. Meanwhile, commodity prices are expected to show co-movement because their prices in question are generally affected by changes in macroeconomic indicators such as interest rates, industrial production, exchange rates, and inflation in the country. Of these, crude oil and exchange rates are perhaps among the most strategic commodities, as they affect a wide range of agricultural commodity markets.

In this study, we examined the volatility spread between hazelnut products, which is a very important source of income in foreign trade, and macroeconomic variables such as energy and exchange markets in Turkey covering the period of 21.07.2005-20.3.2018. In this context, the existence of a long–run relationship between these three markets was examined and as a result, such a relationship was found between the corresponding markets. Considering this relationship, the short–term shocks that diverge from the long–run equilibrium in the hazelnut and gasoline markets tend to move back to the long–run equilibria after a certain period, while a shock that will occur in the exchange rate gradually deviates from the long–run equilibrium. In this context, the fact that the establishment of a stable structure for the Turkish Lira especially against the dollar by the relevant units in the country will evolve to create an environment of confidence in these markets as in the whole economy.

While lagged changes in returns in gasoline and exchange rate and error correction factor shaped the hazelnut returns simultaneously, lagged returns of both hazelnut and exchange rate and error correction factor had no simultaneous effects on returns in gasoline. On the other hand, exchange rate returns were affected by the lagged returns of both hazelnut and gasoline markets and error correction factors. In this context, while hazelnut and exchange rate returns are generally affected by the country's internal dynamics, the returns in the gasoline market are more likely to be shaped by the worldwide dynamics.

As our results indicate that there is a mutual transmission between the markets, the long–term volatility in a market is comfortably determining the swings in other markets and has a lasting effect. An important finding is that the hazelnut market is affected by both the short and long–term volatility in both its own and the other two markets, while short– and long–term swings in the exchange rate market will affect the hazelnut market tremendously. In this context, a stable structure to be provided in the free exchange market in the country will create a more predictable atmosphere in the agricultural commodity markets for investors. Similarly, as the degree of correlation between exchange rate and agricultural commodities decreases, investors will be

protected from risk against uncertainties in various agricultural commodity markets. On the other hand, the driving force behind the spreads from the hazelnut market to the exchange rate market stems from the fact that hazelnuts are a prominent commodity in international trade and form raw materials for the growing chocolate sectors worldwide. At the same time, while there is an asymmetric pass–through of news among markets, the negative atmosphere in the exchange rate market has been found more pronounced in the hazelnut market. Similarly, the gasoline market is affected by its short–term shocks and long–term uncertainty, and the long–term volatilities in the hazelnut and foreign exchange market have long–term effects on the gasoline market. On the other hand, bilateral market interactions have permanent effects on the long–term volatilities of these three markets. In view of all of the above findings, we can say that news occurring in one market is easily transmitted to another market because the functioning of markets in Turkey exhibits many similarities to each other and is usually very high probability being affected by the same news or market fundamentals.

While there is more of a negative correlation relationship between hazelnut and the exchange rate, the opposite relationship is the case (e.g., a positive correlation) between hazelnut and gasoline market over time in the sample period (Figure 2). In addition, the gasoline and exchange rate market has initially provided a low tide around zero means, but the spread and the degree of the relationship has gradually increased over time especially after the end of 2012. This date coincides with the increasing spread of successive attacks on the economy of the country before the 2016 military coup in Turkey is not accidental. On the other hand, we can see that the swings between commodities increased especially after the 2008 world food and financial crisis, while the amplitude and frequency of these fluctuations became more evident after 2013. It is of great importance for the implementation of new economic measures and regulations that will minimize these fluctuations, which primarily concern all investors, including farmers engaged in agricultural production.

Volatility spreads between the markets can be considered as future studies by handling hazelnut and its close substitution pistachio markets while using both oil and exchange rates as exogenous variables in the conditional variances.

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Table 1. Descriptive Statistics

Statistics	Levels ($L_{j,t}$)		
	Level$_{h,t}$	**Level$_{g,t}$**	**Level$_{e,t}$**
Mean	12.025	6.663	1.525
Standard deviation	4.313	0.779	0.680**
t – statistic (Mean = 0)	60.956***	187.015***	48.993***
	(0.000)	(0.000)	(0.000)
Skewness	0.820***	-0.549***	1.266***
	(0.000)	(0.000)	(0.000)
Kurtosis	-0.231	-1.042***	0.824***
	(0.307)	(0.000)	(0.000)
Jarque-Bera for normality	54.581***	45.671***	141.212***
	(0.000)	(0.000)	(0.000)
Correlations (between Price Levels or Closing Levels (PL$_{j,t}$, j = hazelnut (h) and gasoline (g))):			
PL$_{h,t}$		0.916	0.926
PL$_{g,t}$			0.871
Autocorrelation Test (Levels of Series, L$_{j,t}$)			
Ljung-Box Q(10)	3886.110***	4200.578***	4642.255***
	(0.000)	(0.000)	(0.000)
HM-Q (10)	10216.774***		
	(0.000)		
ARCH Test (Levels of Series (L$_{j,t}$, j = hazelnut (h), gasoline (g), and exchange rate (e)))			
ARCH-LM(10)	1109.382***	1546.066***	5363.687***
	(0.000)	(0.000)	(0.000)
MARCH-LM(10)	90213.630***		
	(0.000)		
Unit root test for stationarity (L$_{j,t}$, j = hazelnut (h), gasoline (g), and exchange rate (e)))			
ADF	-2.681 (lags=7)	-2.392 (lags=3)	-0.137 (lags=7)
KPSS	0.609** (lags=3)	1.464** (lags=1)	1.033** (lags=0)

Note: ARCH-LM and MARCH-LM refer to Lagrange and multivariate Lagrange tests for ARCH effects, respectively. While Ljung-Box Q implements residual sequential dependency tests, HM-Q is Hosking's sequential dependency test in multivariate residuals. The zero hypothesis under the MARCH-LM test predicts that the mean of the return series is zero and a fixed covariance. The ADF refers to the Kwiatkowski-Phillips-Schmidt-Shin test, which is used to test the null hypothesis that the generalized Dick-Fuller test, taking fixed and trend variables into account, and the KPSS, are observable around a deterministic trend. The lag selection depends on the AIC, BIC and HQ values. Critical values vary with selected delays. Values in parentheses reflect p-values. *, ** and *** indicate the significance levels of the parameters at 10%, 5%, and 1% levels, respectively.

Table 2. Factors determining the average price level of the market

*Note: The parentheses indicate the significance levels of the t statistical values and the *, **, and *** levels at*

Vector Error Correction Model: $P_t^h + 10.167^{***} P^g + 9.006^{***} P^e - 90.257^{***}$

Short$-$run dynamic parameters:

$$
\begin{pmatrix} \Delta P_t^h \\ \Delta P_t^g \\ \Delta P_t^e \end{pmatrix} = \begin{pmatrix} \delta_h \\ \delta_g \\ \delta_e \end{pmatrix} + \begin{pmatrix} \alpha_h \\ \alpha_g \\ \alpha_e \end{pmatrix} z_{t-1} + \begin{pmatrix} \beta_{hh,1} & \beta_{hg,1} & \beta_{ge,1} \\ \beta_{gh,1} & \beta_{gg,1} & \beta_{ge,1} \\ \beta_{eh,1} & \beta_{eg,1} & \beta_{ee,1} \end{pmatrix} \begin{pmatrix} \Delta P_{t-1}^h \\ \Delta P_{t-1}^g \\ \Delta P_{t-1}^e \end{pmatrix} + \begin{pmatrix} \beta_{hh,2} & \beta_{hg,2} & \beta_{ge,2} \\ \beta_{gh,2} & \beta_{gg,2} & \beta_{ge,2} \\ \beta_{eh,2} & \beta_{eg,2} & \beta_{ee,2} \end{pmatrix} \begin{pmatrix} \Delta P_{t-2}^h \\ \Delta P_{t-2}^h \\ \Delta P_{t-2}^h \end{pmatrix}
$$

Variables	δ	z_{t-1}	ΔP_{t-1}^h	ΔP_{t-1}^g	ΔP_{t-1}^e	ΔP_{t-2}^h	ΔP_{t-2}^g	ΔP_{t-2}^e
ΔP_t^h	0.047*** (4.901)	-0.001*** (-11.539)	-0.032 (-1.131)	0.064 (0.467)	-0.419 (-1.133)	0.054** (1.684)	-0.282*** (-2.770)	-0.551** (-1.684)
ΔP_t^g	0.004 (0.960)	-0.0001** (-2.277)	-0.006 (-0.658)	0.038 (0.695)	-0.151 (-1.407)	-0.004 (-0.639)	-0.069** (-1.989)	-0.059 (-0.504)
ΔP_t^e	-0.011*** (-16.233)	0.0001*** (13.177)	-0.010*** (-3.861)	-0.003 (-0.371)	-0.031 (-0.595)	-0.009*** (-4.638)	-0.018** (-2.265)	-0.111*** (-4.066)

10%, 5%, and 1% levels, respectively.

Table 3. Parameter estimation of BEKK−MGARCH model

$$\text{BEKK−MGARCH:} \; C = \begin{pmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{pmatrix}, A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}, B = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{pmatrix}, D = \begin{pmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \end{pmatrix}$$

	H_t		G_t		E_t	
Log−likelihood Estimate:	Parameters	t-value	Parameters	t-value	Parameters	t-value
c_{1i}	0.038***	(3.843)				
c_{2i}	0.089***	(72.896)	0.000	(0.000)		
c_{3i}	-0.001	(-0.486)	-0.000	(-0.000)	-0.000	(-0.000)
a_{1i}	0.717***	(62.396)	0.004	(0.745)	0.028***	(18.225)
a_{2i}	0.267**	(2.505)	0.062	(1.194)	0.002	(0.131)
a_{3i}	-0.792***	(-3.012)	0.882***	(12.617)	0.591***	(38.062)
b_{1i}	0.798***	(280.341)	-0.014***	(-6.506)	-0.014***	(-37.264)
b_{2i}	-0.473***	(-7.044)	0.337***	(18.169)	0.130***	(37.046)
b_{3i}	1.758***	(17.250)	-0.380***	(-14.062)	0.730***	(142.165)
d_{1i}	0.688***	(23.159)	-0.035***	(-3.498)	-0.004	(-1.176)
d_{2i}	-0.172***	(-0.732)	0.284***	(7.037)	-0.079***	(-4.439)
d_{3i}	9.114***	(13.553)	2.798***	(15.321)	-0.390***	(-4.876)
Statistical Tests:						
LB-Q (6)	6.619	(0.358)	3.677	(0.720)	8.332	(0.215)
McLeod-Li (6)	2.431	(0.876)	8.815	(0.184)	2.482	(0.870)
MARCH-LM (6)	129.70	(1.000)				
MARCH-LM (10)	387.81	(0.150)				
MARCH-LM^2 (6)	45.84	(1.000)				
MARCH-LM^2 (10)	173.25	(1.000)				

Note: The parentheses indicate the significance levels of the t statistical values and the *, **, and *** levels at 10%, 5%, and 1% levels, respectively. The parentheses in the statistical testing section indicate the associated p-values.

Table 4. Marginal Effects of Variables in the Conditional Variance Equation in the BEKK−MGARCH Model

Parameters	$H_{h,t}$	$H_{g,t}$	$H_{e,t}$
$\varepsilon_{1,t}^2$	0.514*** (31.198)	0.000 (0.372)	0.001*** (9.113)
$\varepsilon_{1,t}\varepsilon_{2,t}$	0.383** (2.434)	0.0005 (0.583)	0.000 (0.130)
$\varepsilon_{1,t}\varepsilon_{3,t}$	-1.134*** (-3.034)	0.007 (0.729)	0.033*** (13.223)
$\varepsilon_{2,t}^2$	0.071 (1.253)	0.004 (0.597)	0.000 (0.065)
$\varepsilon_{2,t}\varepsilon_{3,t}$	-0.423** (-1.883)	0.110 (1.171)	0.002 (0.131)
$\varepsilon_{3,t}^2$	0.627 (1.506)	0.778*** (6.309)	0.350*** (19.031)
$h_{1,t}$	0.636*** (140.171)	0.0002*** (3.253)	0.0002*** (18.632)
$h_{12,t}$	-0.755*** (-6.938)	-0.009*** (-5.410)	-0.004*** (-24.153)
$h_{13,t}$	2.804*** (16.831)	0.010*** (5.642)	-0.021*** (-34.585)
$h_{2,t}$	0.224*** (3.522)	0.113*** (9.085)	0.017*** (18.523)
$h_{23,t}$	-1.663*** (-6.883)	-0.256*** (-12.157)	0.189*** (29.932)
$h_{3,t}$	3.090*** (8.625)	0.144*** (7.031)	0.533*** (71.082)
$d_{1,t}$	0.474*** (11.579)	0.001** (1.749)	0.000 (0.588)
$d_{1,t}d_{2,t}$	-0.236 (-0.739)	-0.020*** (-3.439)	0.001 (1.102)
$d_{1,t}d_{3,t}$	12.543*** (9.843)	-0.197*** (-3.619)	0.003 (1.048)
$d_{2,t}$	0.030 (0.366)	0.081*** (3.518)	0.006** (2.219)
$d_{2,t}d_{3,t}$	-3.131 (-0.754)	1.588*** (5.085)	0.062*** (2.709)
$d_{3,t}$	83.056*** (6.777)	7.828*** (7.660)	0.152** (2.438)

Note: The parentheses indicate the significance levels of the t statistical values and the *, **, and *** levels at 10%, 5%, and 1% levels, respectively.
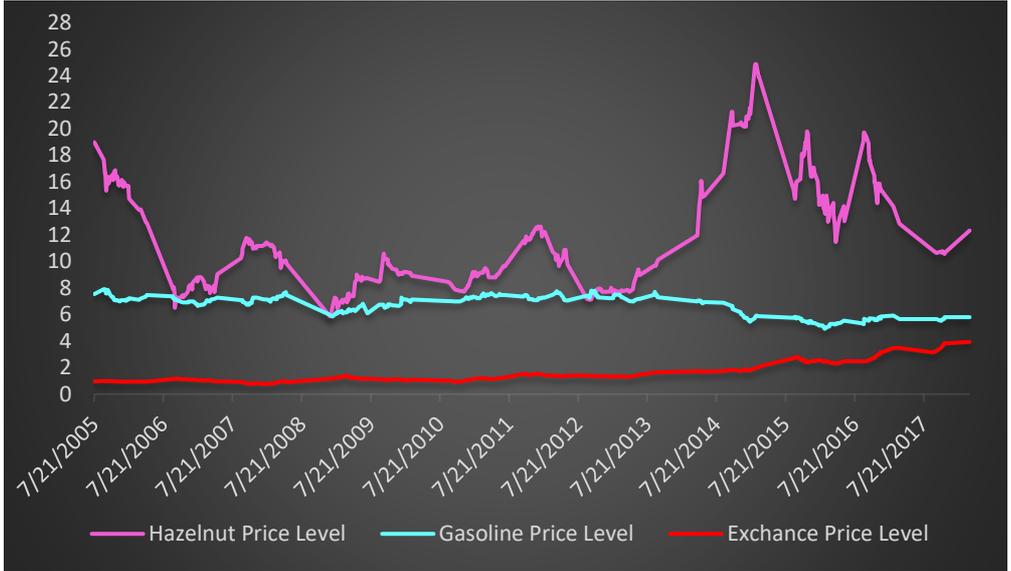
Figure 1. Hazelnut, gasoline real price and exchange rate levels.
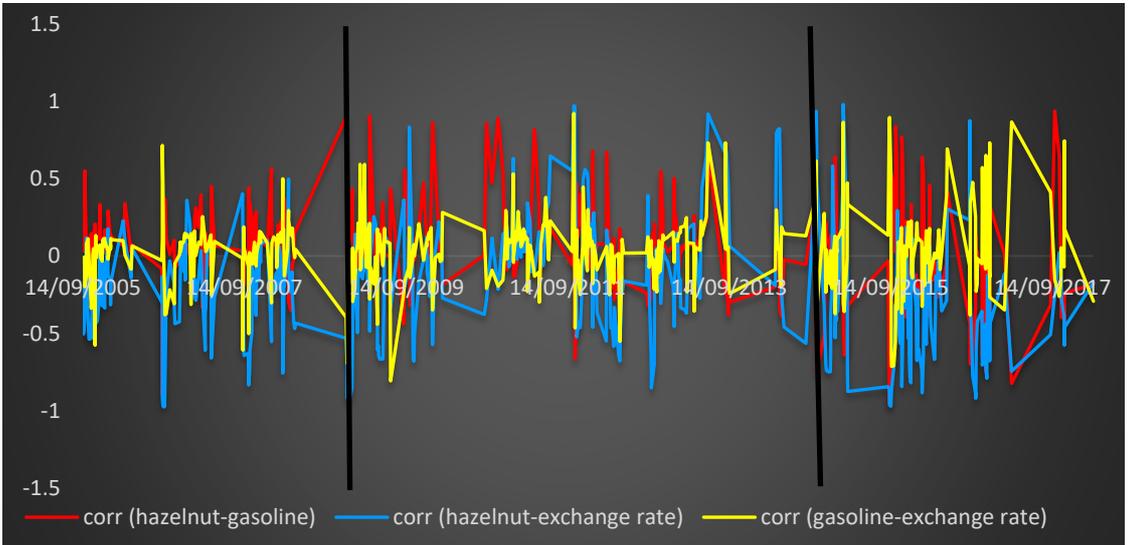
Figure 2. Pair correlations between commodities in question.