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ARAŞTIRMA MAKALESİ **RESEARCH ARTICLE**

Return and Volatility Connectedness in Electronic Warehouse Receipt Market of Turkey

Türkiye'nin Elektronik Ürün Senedi Piyasasında Getiri ve Volatilite Bağlantılılığı

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Abstract

Over the course of the last century, globalization and integration have increased significantly around the world. The rise in economic and financial globalization and integration has increased the connectedness between national economies and financial markets and secured an important place in the systemic risk spillover. It is important to analyze the issue in terms of different markets. Food prices around the world have increased significantly over the last 20 years. The price and volatility increase associated with food products lead to important socioeconomic and social problems. In this context, it will be important for decision-makers to assess the issue from the perspective of financial markets and to understand and reveal the dynamic structure of food commodity markets. This study aims to examine the connectedness of return and volatility in the Electronic Warehouse Receipt (EWR) market, where agricultural commodities are traded in Turkey, and to analyze its dynamic structure that changes over time. In this study, the Diebold-Yilmaz connectedness measurement method based on the forecast error variance decomposition after the VAR (p) model was used to analyze the connectedness between financial assets. According to the results of the static analysis performed, it was observed that while the return connectedness in the EWR market is very low, the volatility connectedness is at a higher level than the return connectedness. Based on the results of the dynamic analysis, no trend was observed in return connectedness; however, rapid increases and decreases were observed for certain periods. On the other hand, while an increasing trend was observed in the dynamic analysis of volatility connectedness, sudden increases and decreases were observed during periods of crisis. Of all agricultural commodities, it was observed that barley was the asset that sent the most net shock into the system. The EWR market in Turkey has come up recently. The market's structure, dynamics, and synchronization with other markets are still at a low level. The spillover effect of return and volatility shocks in the market are also low. The findings of this study can be used by producers, financial market participants and various decision makers for risk management, hedging and profit maximization purposes.

Keywords: Financial connectedness, Electronic warehouse receipts, Agricultural commodity market, Agricultural finance, Food prices volatility.

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Öz

Dünyada son yüzyıldan bu yana küreselleşme ve entegrasyon ciddi oranda yükselmiştir. Ekonomik ve finansal küreselleşme ve entegrasyondaki artış ülke ekonomileri ve finansal piyasalar arasındaki bağlantılılığı artırmakta ve sistematik riskin yayılmasında önemli bir yer tutmaktadır. Konunun farklı piyasalar özelinde incelenmesi önem arz etmektedir. Dünyada gıda fiyatları son 20 yılda önemli oranda artmıştır. Gıda ürünlerinde yaşanan fiyat ve volatilite artışları önemli sosyoekonomik ve toplumsal sorunları da beraberinde getirmektedir. Bu bağlamda konuya finansal piyasalar açısından bakmak ve gıda emtia piyasalarının dinamik yapısını anlamak ve ortaya koymak karar alıcılar açısından önemli olacaktır. Bu hedefle çalışmanın amacı Türkiye'de gıda emtialarının işlem gördüğü Elektronik Ürün Senedi (ELÜS) piyasasında getiri ve getiri volatilitesi bağlantılılığının incelenmesi ve zamanla değişen dinamik yapısının analizidir. Çalışmada finansal varlıklar arasındaki bağlantılılığın analizinde VAR (p) modeli sonrası tahmin hata varyans ayrıştırmasına dayalı Diebold-Yılmaz bağlantılılık ölçümü yöntemi kullanılmıştır. Gerçekleştirilen statik analiz sonuçlarına göre ELÜS piyasasında getiri bağlantılılığının oldukça düşük düzeyde iken volatilite bağlantılılığının getiri bağlantılılığına nazaran daha yüksek düzeyde var olduğu görülmüştür. Dinamik analiz sonucunda getiri bağlantılılığında herhangi bir trend görülmemiş, fakat belirli dönemlerde hızlı yükselişler ve düşüşler görülmektedir. Volatilite bağlantılılığının dinamik analizinde ise yükselen bir trend görülmekle birlikte kriz dönemlerinde ani yükseliş ve düşüşler görülmüştür. Tüm gıda emtiaları içerisinde sisteme en çok net şok yayan varlığın arpa olduğu görülmüştür. Türkiye'de ELÜS piyasası oldukça yakın bir geçmişe sahiptir. Piyasanın yapısı, dinamikleri ve diğer piyasalarla senkronizasyonu henüz düşük seviyededir. Piyasadaki getiri ve getiri volatilitesi şoklarının yayılma etkisi henüz düşük düzeydedir. Bu çalışmanın bulguları, üreticiler, finansal piyasa katılımcıları ve çeşitli karar alıcılar tarafından, risk yönetimi, hedge ve kar maksimizasyonu amaçlarıyla kullanılabilir.

Anahtar Kelimeler: Finansal bağlantılılık, Elektronik ürün senedi, Gıda emtia piyasası, Tarım finansmanı, Gıda Fiyatları volatilitesi

1. Introduction

The increase in the world population in the last century has reached inconceivable levels. The world population was 2.58 billion in 1951, and this figure has risen to 7.79 billion in 2020 (Worldometer, 2021). There has been a 200% increase in the world population within a period of only 70 years. This increase in the world population carries two important problems, namely, poverty and feeding the population. It is possible that the increase in the world population will support economic growth and development since the workforce will increase. However, in this case, it is necessary to solve the main problems brought along by population growth.

On the other hand, global food prices have been in an upward trend since the beginning of the 2000s. As of 2021, food prices in the world have increased by 126% in the last 20 years (FAO, 2021). Global warming and climate change, rise in oil prices, increase in population (Agizan ve Bayramoglu, 2021), and the consequent increase in demand (Negis et al., 2017) are among the most important reasons for the rise in global food prices (Chen et al., 2010).

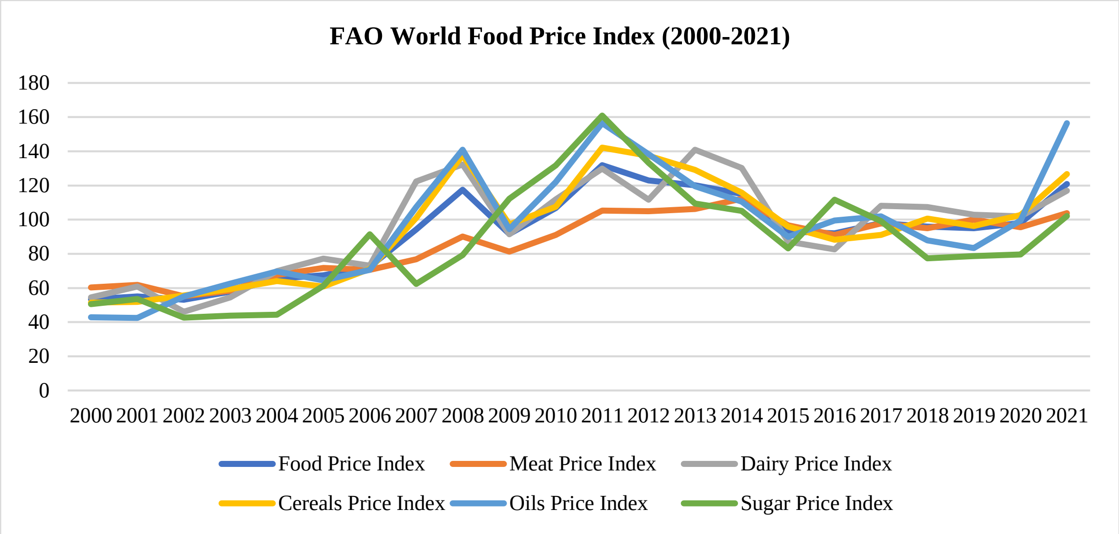

Figure 1. World food price index

The ongoing COVID-19 pandemic has led to a significant increase in global food prices. Since the beginning of the pandemic, many causes such as labor shortage and increase in demand due to reasons such as movement restrictions and pandemic measures, restrictions on global trade, and difficulty of people to access food products have led to serious increases and volatility in food prices (Laborde et al., 2020).

In this context, assessing the situation from the perspective of financial markets to understand the food prices that have increased since the beginning of 2000 and galloped during the COVID-19 period and the problems caused by the pandemic will contribute to the policy-making process of the stakeholders and decision-makers concerning this issue.

An important market where agricultural products are traded in Turkey is the Turkish Mercantile Exchange (TURIB). The TURIB, an organized market where securitized agricultural products are bought and sold in Turkey, was established in June 2018. The traded assets in TURIB are electronic warehouse receipts (EWRs), which is a new product for the Turkish financial markets and has emerged because of the securitization of agricultural products. The concept of warehouse receipts has been included in the literature for a long time. The warehouse receipts are defined as a valuable security that can be given as a guarantee, which is prepared by examining the class and standard of the products received by the warehouse in return for the agricultural products delivered to the licensed warehouses and represents product ownership (Cayir, 2019). These warehouse receipts can be issued and endorsed to name or order. On the other hand, EWRs refer to the electronic registration and storage transactions, which are created in accordance with the procedures and principles determined by the electronic registry agency and the Ministry of Commerce in return for agricultural products delivered to licensed warehouses (Cayir, 2019). EWRs are a type of securitized assets that enable the electronic recording of product securities and easy trading in financial markets.

The securitization of agricultural products as EWRs has several benefits. Some of these benefits can be listed as follows (Cayir, 2019):

- The classification of agricultural products as a financial asset increases their liquidity and turns them into a financial investment tool (Aydın, 2021). Thus, this classification creates an alternative investment tool and financing option within the scope of interest-free finance.
- EWRs are accepted as collateral by banks. Thus, it is possible for the farmer to access easy financing.
- The products are classified according to certain quality and standards by the markets where they are traded (TURIB). This classification makes important contributions to the buying and selling of products.
- Keeping the record of the product electronically and trading it in an organized market increases its liquidity and accelerates the financial transactions of agricultural products.
- Takasbank uses the international numbering system (ISIN – International Securities Identification Number) in the electronic classification of EWR products. Thus, EWRs issued by domestic licensed warehouses can be traded in financial markets around the worldwide.

It is important for developing agricultural commodity markets to understand and analyze the structure and dynamics of TURIB and EWRs. For this reason, in this study, the interactions of EWRs, whose underlying assets are wheat (durum wheat), barley, and corn, with return and volatility spillovers, are analyzed. These three products are chosen because they have been traded for the longest time without any interruption. For this purpose, we empirically investigate the connectedness and spillover effects of return and volatility shocks in the market.

Connectedness measurement and investigation of spillover effects are a type of analysis that has gained popularity in the literature on finance and economics recently. Developed by Diebold and Yilmaz (2009, 2012, 2014) and referred to by the same name, the Diebold-Yilmaz connectedness measurement (also known as the Diebold-Yilmaz spillover index) is mainly focused on measuring financial and macroeconomic connectedness. While the focus of financial connectedness is measuring the connectedness and spillover effects between different financial markets or financial products, macroeconomic connectedness generally concentrates on how shocks in different macroeconomic indicators, such as industrial production index, economic growth, unemployment, and inflation, expand through the countries and the spillover effects of international economic fluctuations.

Based on the studies of Diebold and Yilmaz (2009, 2012, 2014), the connectedness methodology is an econometric method that relies on a covariance-stationary Vector Autoregressive (VAR) model. The connectedness methodology basically uses the forecast error variance decomposition after a VAR model and exhibits that how shocks are transmitted in the system. With using the connectedness methodology, we can examine how the EWRs are connected to each other and how return and volatility shocks in the market are transmitted directionally (shocks from x_j to x_i and vice versa) and totally (shocks from x_j to all other x_i and vice versa). This study also uses the bootstrap rolling window approach, which enables us to analyze time-varying dynamics in these interactions.

There are many studies in the literature that investigate the connectedness of various financial assets, markets, or macroeconomic indicators. Being one of the pioneering studies in the literature, Diebold and Yilmaz (2009) measured the spillover effect of returns and volatility in 19 stock markets with a data set covering the period 1992–2007. The study shows that the effect of volatility spillovers among financial markets is higher than that of return spillovers. While return spillovers have an increasing trend, volatility spillovers do not follow any trend; however, bursts occur during crisis periods, followed by a rapid decline. In times of crisis, serious increases are observed in both return and volatility connectedness. Similar studies were performed by Yilmaz (2010) on the East Asian stock markets and by Diebold and Yilmaz (2011) on the stock markets of the countries in America, and corresponding results were obtained.

Diebold and Yilmaz (2012) measured the connectedness between different financial markets in the USA and the spillover effects of volatility shocks. In the study, volatility spreads between the stock market, debt market, foreign exchange market, and commodity market were analyzed, and it was observed that the main source of volatility shocks between the markets was the stock market. Additionally, the spillover effect of volatility shocks and the connectedness between the markets increased significantly during the periods of crisis. Similarly, In the study carried out by Diebold and Yilmaz (2014), the approach was combined with the network topology, and the connectedness between the 13 largest financial institutions of the USA was measured. As a result, they found a high level of volatility connectedness between the major financial institutions of the USA and showed that the connectedness reaches serious levels in times of crisis.

In the literature, many studies measure connectedness and spillover effects between financial markets and assets. Many of these researches on different markets, for instance; international equity markets (Barunik et al., 2016; Zhang, 2017; Demirer et al., 2018; Su, 2020; Diebold and Yilmaz, 2009; Polat, 2020), debt market (Alter and Beyer, 2014; Reboredo et al., 2020; Hussain Shahzad et al., 2019; Ferrer et al., 2021), commodity market (Antonakasis and Kizys, 2015; Balli et al., 2019; Uddin et al., 2019), cryptocurrency market (Corbet et al., 2018; Yi et al., 2018; Giudici and Pagnottoni, 2019; Ji et al., 2019; Li et al., 2020; Kliber and Wlosik, 2019), foreign exchange market (Antonakakis et al., 2020; Barunik and Kocenda, 2019; Bouri et al., 2020) and oil/energy market (Ferrer et al., 2018; Lovcha and Perez-Labardo, 2020; Toyoshima and Hamori, 2018; Hasan et al., 2021) detected high level of connectedness and spillover effects. On the other hand, some other studies have not found significant or low levels of connectedness and spillover effects in cryptocurrency markets (Trabelsi, 2018; Gillaizeau et al., 2019; Qarni et al., 2019; Balli et al., 2020) and oil/energy markets (Naeem et al., 2020; Zhang et al., 2020; Liu et al., 2020; Liu and Hamori, 2020; Balcilar and Usman, 2021).

In the literature review conducted, it was seen that the connectedness and spillover effects in the Electronic Warehouse Receipt market has not been investigated in any academic study yet. Within this context, the most important contribution of this study to the literature is the role of connectedness analysis in understanding the dynamics of the Electronic Warehouse Receipt market. Besides, the findings of this study have two important areas of usage for practitioners. First, producers can use the findings of this paper for operating risk management since this study exhibits how return and volatility shocks are transmitted between EWRs in the market, and stakeholders of TURIB can take action in this direction. Second, financial actors in the market can reap the benefit of this study for portfolio diversification and decision-making process since this study presents how return and volatility shocks are spread in the market and between assets.

2. Materials and Methods

In this section, first, the data of the study is introduced. Subsequently, the methods used in the measurement of return and volatility are explained, and finally, the connectedness analysis methodology, which is the main method used to achieve the aim of the study, is introduced. We conducted our analysis in two dimensions: return and volatility connectedness. Return connectedness exhibits that how return shocks are spread while volatility connectedness measures volatility shocks spills over the market.

2.1. Data

This study aims to measure the return and volatility connectedness of the Electronic Warehouse Receipt (EWR) market in Turkey and reveal the dynamics of the EWR market. In this context, commodities with underlying assets, such as wheat (durum), barley, and corn, which are traded for the longest time and have the highest trading volume in the Turkish Mercantile Exchange (TURIB), are used as the data set in the study. The return series and the volatility of the dataset are calculated over the closing prices of these three products for the 499 trading days between 30.07.2019 and 30.07.2021, and the analysis of connectedness between the commodities are performed. The data covers the period from the day that the market is first opened for trading to the day the analysis is completed.

2.2. Methods of measuring return and volatility

In return connectedness analysis, logarithmic return series of the data are used as the input of the VAR model. The calculation of the logarithmic return series is performed as follows in equation 1. In equation 1, $P_{i,t}$ stands for the price of i^{th} product at time *t* and $r_{i,t}$ stands for return of product *i* at time *t*.

$$r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{Eq.1}$$

For volatility connectedness, we use realized conditional volatilities in the VAR system. To measure the EWR volatilities, a stochastic volatility model GARCH is applied. The GARCH (p,q) model is a method developed by Bollerslev (1986) and Taylor (1986) based on the work of Engle (1982), and it is used to measure volatility in financial markets. The GARCH (p,q) model is calculated by modeling the volatility (σ_t^2) of a series by using the past deviations (u_{t-i}^2), and the past conditional variance (σ_{t-i}^2). The GARCH (p,q) process is addressed in equation 2.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} a_i u_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \qquad \text{(Eq.2)}$$

GARCH (p,q) can be performed using different p and q values. However, empirical studies in the literature have demonstrated that the GARCH (1,1) method is usually the best model (Hansen and Lunde, 2005; Brooks, 2019). In this study, different GARCH (p,q) rankings were tried, and the best fit model to the volatility measurement of the return series is found to be GARCH (1,1). In the literature, different volatility measurement methods, such as those proposed by Garman and Klass (1980), Parkinson (1980), and Alizadeh et al. (2002) are recommended. However, these methods require the opening, closing, intraday high, and intraday low prices of the assets. In our study, instead of these methods, volatility measurement is applied using the GARCH (p, q) model due to the low trading volume of the EWR market and the observation that the intraday price movements are quite stagnant and in the form of sudden increases with large buy orders.

2.3. Diebold-Yilmaz connectedness measurement

Diebold-Yilmaz connectedness analysis is a method based on the forecast error variance decomposition after constructing a Vector Autoregressive (p) model, and it is used to measure how shocks spill over through the system. The method is based on studies conducted by Diebold and Yilmaz in 2009, 2012, and 2014. The method operates as follows:

A Vector Autoregressive model with constant covariance and N variables is as in equation 3.

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t \,;\, \varepsilon_t \sim (0, \Sigma) \qquad \text{(Eq.3)}$$

Since the VAR (p) model has fixed covariance, it complies with the invertibility rule, which is frequently used in time series, and can be written as an infinite-order moving average (MA) process. The infinite-order MA representation of the series is as follows.

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-1} \qquad \text{(Eq.4)}$$

The expression A_i in equation 4 represents the square coefficient matrix with a size of $N*N$ and has the $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$ recursion formula. On the other hand, A_0 corresponds to the unit matrix with $N*N$ dimensions, and when $i<0$, $A_i=0$. The MA coefficients and their variance decompositions in equation 4 play an important role in understanding the structure of the system. The connectedness method is based on variance decompositions, which helps in the decomposition of the forecast error variances at the H-step ahead of each variable in the system into parts that can be attributed to various system shocks.

Different methods are used for the variance decomposition. The most frequently used variance decomposition methods in the literature are Cholesky Decomposition and Generalized Impulse Response Function (GIRF). However, Cholesky Decomposition cannot give robust results as it gives varying results depending on the order of the variables. For this reason, in this study, the variance decomposition is performed using the GIRF algorithm, which is invariant to the order of the variables and based on the studies by Koop et al. (1996) and Pesaran and Shin (1998). In the variance decomposition using GIRF based on the VAR model, the share of the *j* in the H-step ahead forecast error variance decomposition of variable *i* for each H=1,2,3…, is as shown in equation 5.

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)^2} \qquad \text{(Eq.5)}$$

In equation 5, Σ represents the variance matrix of the error vector, the symbol σ_{ii} represents the standard deviation of the i^{th} error term, while e_i represents the selection vector in which the i^{th} element is 1 and the others take the value 0. Although equation 5 performs the forecast error variance decomposition, the row sum does not yield 1 as the shocks directed to each variable are not orthogonal. Thus, normalization is required. The normalization process is described in equation 6.

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \qquad \text{(Eq.6)}$$

The total connectedness calculation can be performed with the results of the normalized variance decomposition. The total connectedness calculation is shown in equation 7. The total connectedness index (C(H)) shows the extent to which the shocks experienced in the returns or volatility of the assets spillover through the system.

$$C(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \quad \text{(Eq.7)}$$

Shocks from all other *j* variables to *i* variable are called "Contributions from Others (FROM)" and are calculated as in equation 8.

$$C_{i\leftarrow\blacksquare}(H) = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} * 100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} * 100 \quad \text{(Eq.8)}$$

Similarly, shocks directed from variable *i* to all other variables *j* are called "Contribution to Others (TO)" and are calculated as in equation 9.

$$C_{\blacksquare\leftarrow i}(H) = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} * 100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} * 100 \quad \text{(Eq.9)}$$

The net total directional connectedness is measured as in equation 10. Net total directional connectedness (net spillovers) is calculated by netting the shocks from all other *j* variables to the *i* variable and the shocks from the *i* variable to all the other *j* variables. In short, it is the difference between the value calculated in equation 9 and the value calculated in equation 8.

$$C_i(H) = C_{\blacksquare\leftarrow i}(H) - C_{i\leftarrow\blacksquare}(H) \quad \text{(Eq.10)}$$

The final value calculated with the connectedness method is the measurement of net pairwise directional connectedness. Net pairwise directional connectedness is used to measure the net pairwise spillovers between the two variables. Net pairwise directional connectedness (net pairwise spillovers) is calculated as in equation 11.

$$C_{ij}(H) = C_{i\leftarrow j}(H) - C_{j\leftarrow i}(H) \quad \text{(Eq.11)}$$

3. Results and Discussion

When investigating return and volatility connectedness, the analyses are carried out as both static analysis and dynamic analysis. In static analysis, we run the model using a full-sample series. This full-sample connectedness provides a good perspective on average connectedness during the whole sample period. But it lacks to exhibit time-varying dynamics of spillovers. On the other hand, financial markets are dynamic. The relationships in the markets are stochastically determined and change over time. For this reason, we also model the dynamic structure of connectedness.

For dynamic analysis, we apply the bootstrap rolling-window approach to calculate time-varying (dynamic) connectedness. The bootstrap rolling-window approach is a statistical application used to overcome parameter non-constancy by running the econometric model with partitions of full-sample via setting sub-sample windows. By selecting a sub-sample rolling window with *K* observations, the full sample with *T* observations can be altered to a series of *T-K* sub-samples, in other words, *ψ-K+1, ψ-K, …, T* for *ψ=K, K+1, …, T* (Li et al., 2019). In the dynamic analysis, the window size (*K*) is set as 100 trading days, and the window sliding is performed by shifting one trading day in each analysis. As Kang et al. (2019) state, the harvest period for most of the agricultural crops, especially cereals, is about four months. Therefore, to allow the effect of harvest periods in price shocks, we set the window size as 100 trading days, which is nearly four months. Since the window size is set as 100 days when applying the rolling windows method, the first 100 days of the data set are lost in the dynamic analysis results. Therefore, dynamic analysis results show the dates between 25.12.2019-30.07.2021.

In the connectedness analysis, first, it is necessary to build the most optimum VAR (p) model. The analysis show that the VAR (9) model in return connectedness and the VAR (10) model in volatility connectedness are the best models according to the AIC and FPE information criteria. The forecast error variance decomposition is performed up to *H*=15 steps ahead in both return and volatility connectedness. After the *H*=15, no significant change is observed in the connectedness measurements.

3.1. Static return connectedness

The results of the static analysis of return connectedness are presented in *Table 1*.

Table 1. Return connectedness

	Barley	Wheat	Corn	Contribution From Others (FROM Spillovers)
Barley	92.3	3.12	4.54	7.65
Wheat	6.57	91.05	2.38	8.94
Corn	7.75	1.72	90.5	9.48
Contribution To Others (TO Spillovers)	14.3	4.86	6.93	
Net Spillovers	6.69	-4.08	-2.55	**Total Connectedness Index**=8.70%

In the connectedness table, the diagonal elements show to what extent the shocks experienced in the return of the Electronic Warehouse Receipt (EWR) asset in the row they correspond to are caused by internal shocks, and the last column of the table shows to what extent they are affected by external shocks. The "Contribution to Others" row shows the extent to which each EWR asset transmits shocks to other assets, while the "Net Connectedness" row demonstrates the difference between shocks to others and shocks from others. Finally, the Total Connectedness Index, located at the bottom right of the table, is an indicator that measures the extent to which return shocks are spread through the system.

In the EWR market, the return connectedness between assets is quite low. Shock spillovers within the system are about 8.70%. It is seen that the majority of the shocks in the returns of assets in the EWR market are due to the innovations experienced in the internal shocks of each asset, and the spillover of the return shocks between the assets is at a very low level. When the net spillovers are analyzed, all assets except barley EWRs have negative net spillovers, and the shocks they spread to others are more than the shocks from others. In terms of return connectedness, it can be said that the main product that causes a net shock in the market is barley.

3.2. Dynamic return connectedness

In the dynamic analysis of return connectedness, the measure of total connectedness is shown in *Figure 2*, net total connectedness in *Figure 3*, and net pairwise connectedness in *Figure 4*.

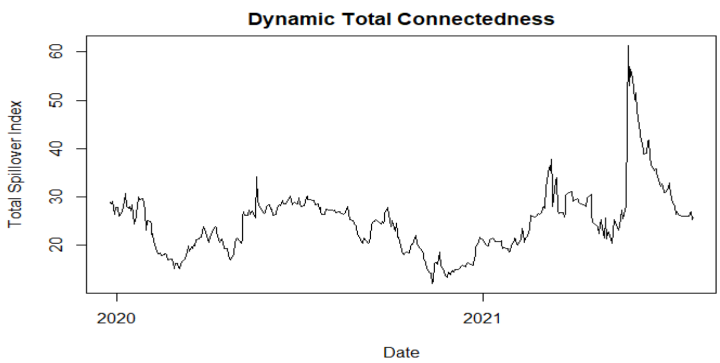

Figure 2. Dynamic total connectedness (return connectedness)

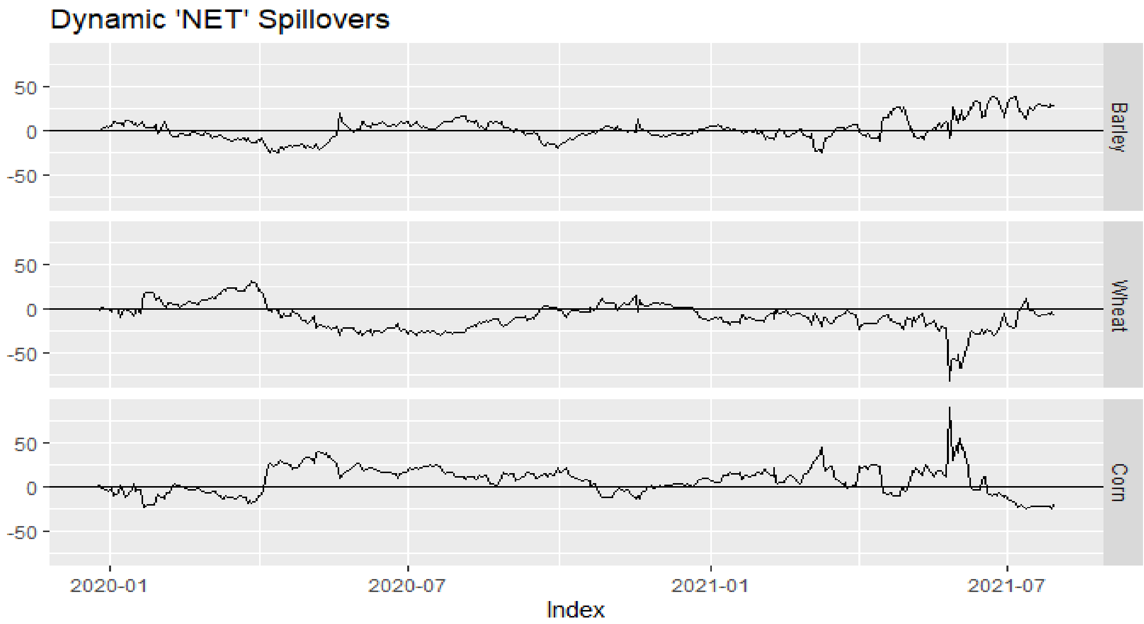

Figure 3. Dynamic net total connectedness (return connectedness)

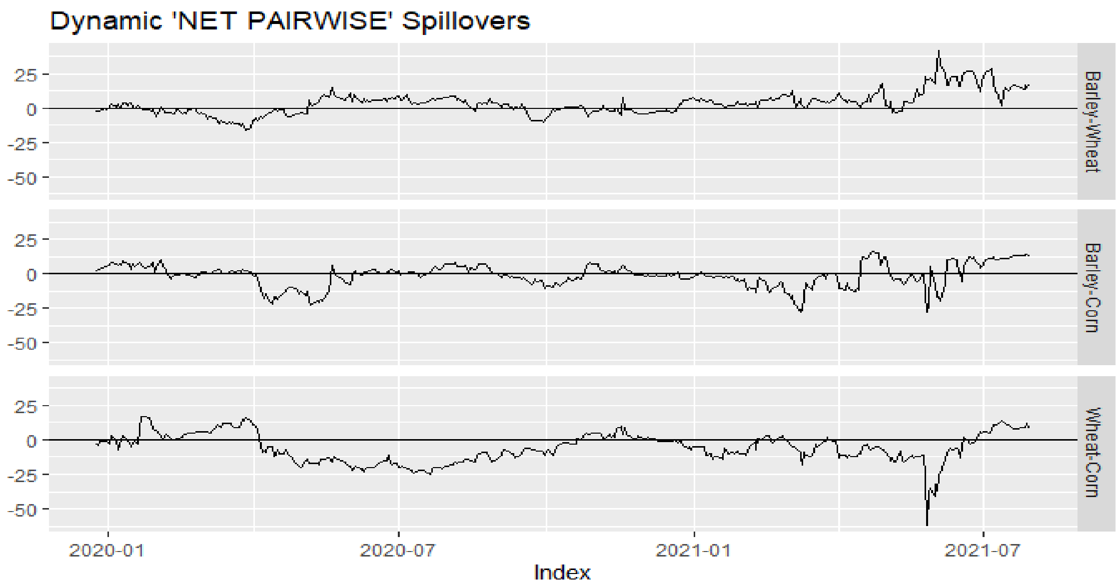

Figure 4. Dynamic net pairwise directional connectedness (return connectedness)

When the dynamic total connectedness analysis is examined, no trend is observed in the return connectedness. There was an abnormal increase in total connectedness between 25.05.2021 and 04.06.2021, but it decreased rapidly in the following days. In the EWR market, the connectedness between assets do not have an increasing trend. On the other hand, the spillovers increase in certain periods due to shocks. However, it is subsequently returning to its previous levels. Although it was experienced at a lower intensity, there were decreases after sudden increases in total connectedness during the period between the beginning of February 2021 to mid-April 2021. No significant impact from COVID-19 was observed on the measurements of total dynamic connectedness.

The net spillover of assets in *Figure 3* is very close to zero. Unlike the others, the net spillovers of corn EWRs are generally positive, but quite low. The effect of important innovations experienced in the period between the end of May 2021 and June 2021, also observed on the total connectedness, was seen, and the net positive spillover of corn and the negative spillover of wheat increased significantly during this period, and these two products exhibited an inverse correlation.

Net pairwise spillovers are shown in *Figure 4*. The net pairwise connectedness between all assets is very low except for the period of abnormal increase defined above. In net pairwise connectedness between barley-wheat, the net pairwise shock transmission is usually from barley to wheat. The opposite can be said for the relationship between barley-corn. Finally, when the relationship between wheat and corn is analyzed, it is seen that corn is in a position that transmits the net shock to wheat, especially in the periods when there are sudden shocks to the system.

3.3. Static volatility connectedness analysis

When measuring volatility connectedness in the Electronic Warehouse Receipts (EWR) market, volatility must be measured first. Barley, wheat, and corn EWR volatilities are measured by GARCH (1,1), and the comparison between them is given in *Figure 5*. Although the dynamic volatility is low in barley EWRs, there are sudden increases in volatility in the period between mid-May 2021 and the first week of June 2021. The volatility of corn EWRs follows a similar course. Although there was a slight increase in wheat EWRs during the same periods, high volatility increases were not observed as in other assets. Unlike the others, in wheat EWRs, increases and decreases were observed on certain dates during the analysis period.

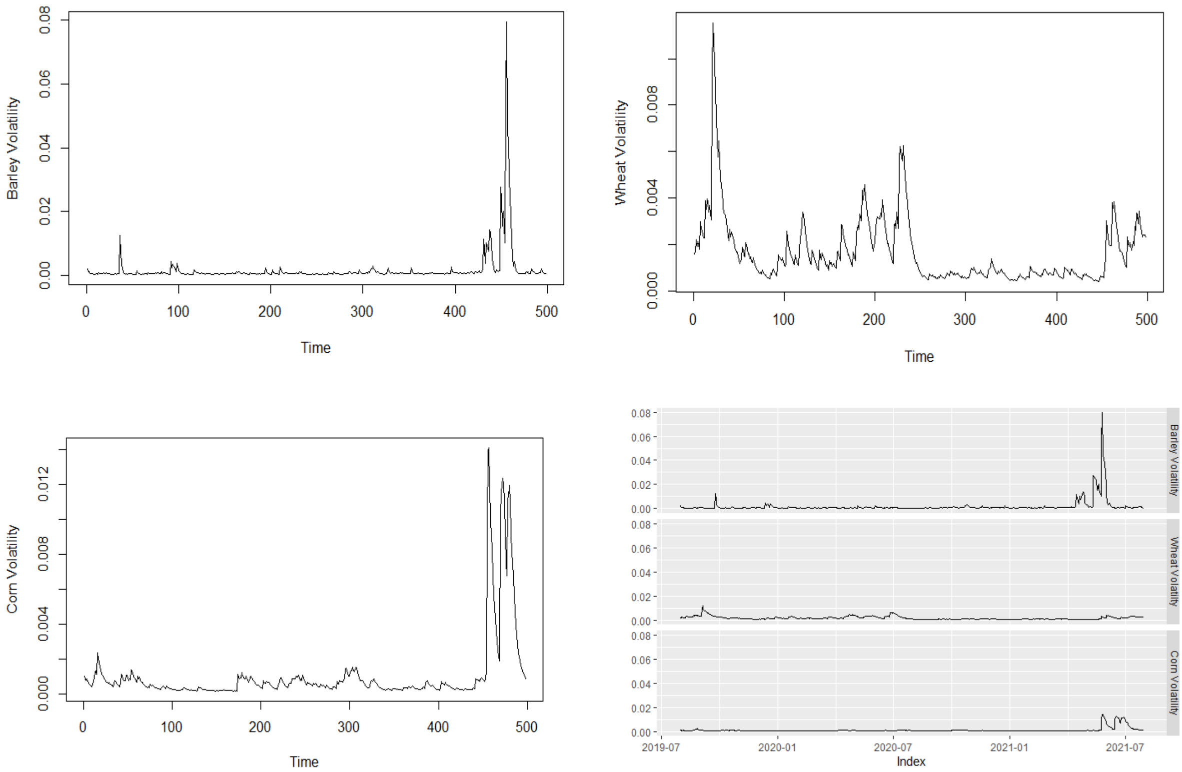

Figure 5. EWR volatilities

The results of the volatility measurements carried out using the results of GARCH (1,1) model. Static volatility connectedness measurements are given in *Table 2*.

Table 2. Volatility connectedness table

	Barley	**Wheat**	**Corn**	**Contribution From Others (FROM Spillovers)**
Barley	78.2	1.19	20.7	21.84
Wheat	3.15	92.8	4.05	7.2
Corn	30.5	0.31	69.2	30.84
Contribution To Others (TO Spillovers)	33.7	1.5	24.7	
Net Spillovers	11.9	-5.7	-6.12	**Total Connectedness Index**=19.97%

As seen in *Table 2*, the Total Connectedness Index is 19.97%. This figure indicates that 80.03% of the volatility shocks experienced in the EWR market are caused by the internal shocks of the assets, and 19.97% are due to the volatility shocks (external shocks, spillover effects) experienced in the market due to the volatility shocks experienced in other assets. Compared to return connectedness, volatility connectedness is relatively high in the EWR market, while 78.2% of the volatility shocks experienced in barley EWRs are due to their own internal shocks. 21.84% of the volatility shocks to barley EWRs are due to the volatility shocks experienced in wheat and corn EWRs. Similarly, 92.8% of volatility shocks in wheat EWRs and 69.2% of volatility shocks in corn EWRs are caused by the assets' own internal shocks, while 7.2% and 30.84%, respectively, are due to volatility shocks to other assets. When the net connectedness is analyzed, barley has the highest net spillover, while other assets have negative net spillovers. In the EWR market, it is seen that the asset in the position of the net shock-transmitter in the system is barley, while the other assets are in the net shock-receiver position.

3.4. Dynamic volatility connectedness

The results of dynamic analysis of total volatility connectedness are given in *Figure 6*, the net total connectedness in *Figure 7*, and the net pairwise connectedness in *Figure 8*.

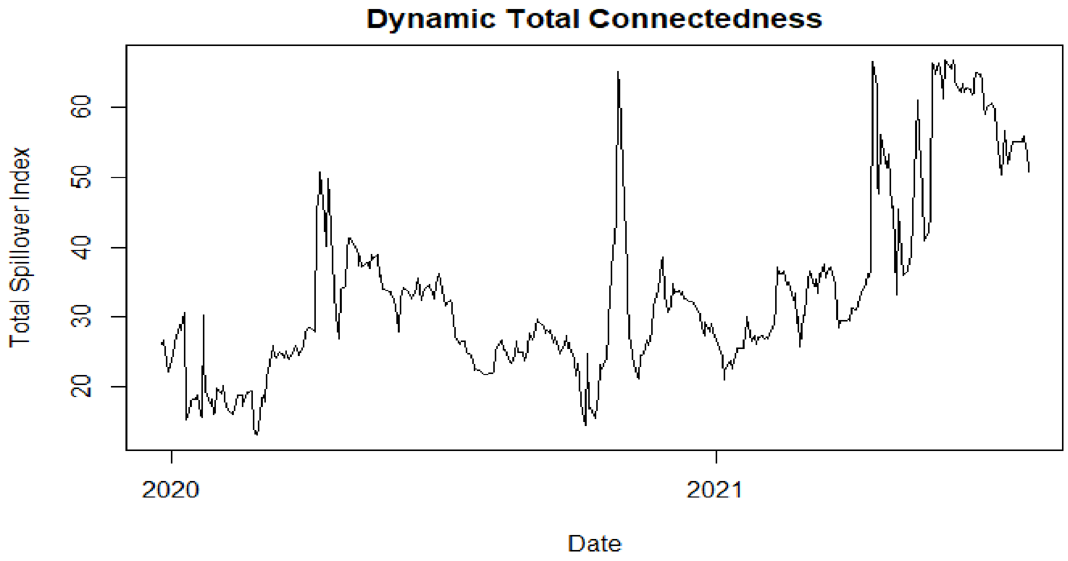

Figure 6. Dynamic total connectedness (volatility connectedness)

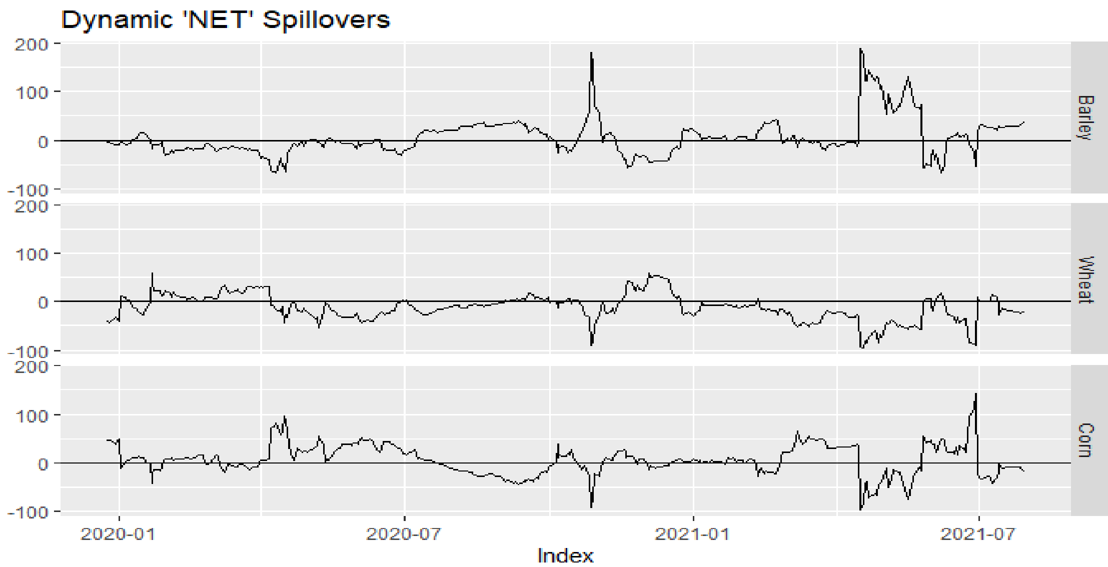

Figure 7. Dynamic net total connectedness (volatility connectedness)

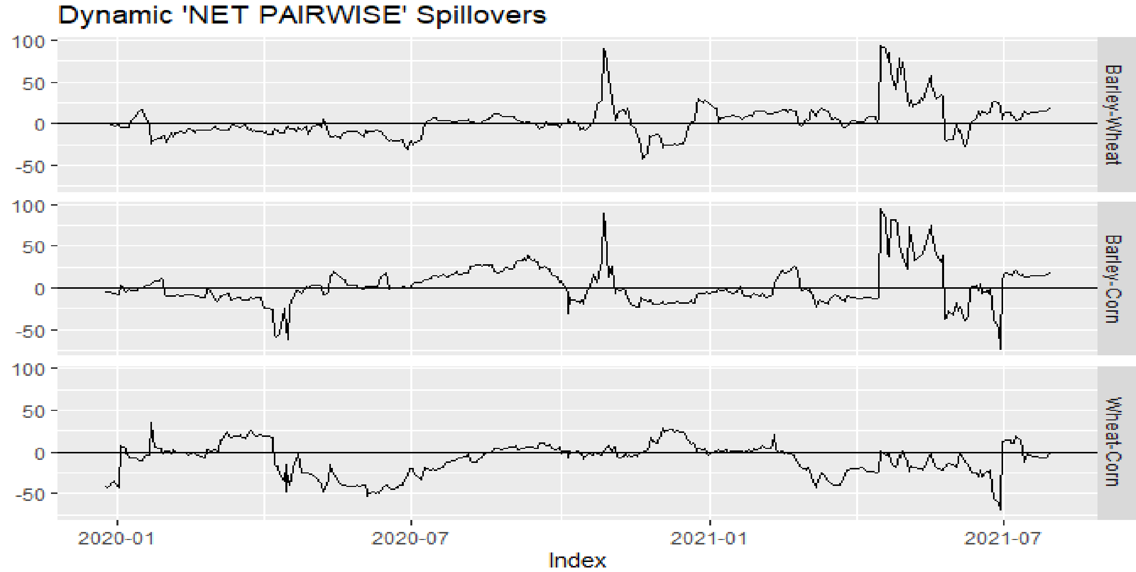

Figure 8. Dynamic net pairwise directional connectedness (volatility connectedness)

As shown in *Figure 6*, the dynamic analysis results of volatility connectedness are at a higher level compared to return connectedness. Compared to return connectedness, there is an exponential upward trend in volatility connectedness that starts in early October 2020. These periods coincide with the periods when there was a significant increase in cereal prices worldwide, and the increasing trend in prices started (See *Figure 1*). In addition to the spillovers of volatility shocks through the system, the trend includes sudden increases and decreases. Between 07/04/2020-17/04/2020 and 26/10/2020-30/10/2020, and 16/04/2021-07/05/2021, the volatility connectedness suddenly increased with a rapid decrease afterward. However, volatility connectedness, the process in which shocks propagated through the system increase as bursts and then transition to a sudden decline, demonstrates very short time intervals. The characteristic of the three-movement periods is that they are in the form of short-term sudden increase and decreases. The reasons for these were investigated and it is thought that they may be associated with Turkey's import of cereal products. It was observed that there were no significant movements in the Turkish financial markets (stock market, debt market, commodity, foreign exchange markets) during the aforementioned dates. It is believed that global food price fluctuations also do not have a significant effect, as a global effect would be expected to have longer-term effects, not such short-term effects. This is only the case with the increase in volatility spillovers in October 2020. This is because these periods coincide with the times when food prices in the world increased significantly, and they also create a significant upward trend in the following periods.

Finally, unlike other volatility bursts, serious increases were experienced in volatility connectedness on 17/05/2021 and the high level of connectedness continued. Contrary to return connectedness, the volatility connectedness analysis shows the effect of the periods when COVID-19 first appeared in Turkey. These periods coincide with the period of price shocks caused by the increase in demand on the dates when the curfews due to COVID-19 were announced both in Turkey and in the world.

The results of the dynamic net connectedness analysis are depicted in *Figure 7*. In the analysis of net spillovers, it is seen that there is a moderate negative correlation between barley and wheat and a high level of negative correlation between barley and corn. In the dynamic analysis, short but high-impact sudden increases seen in certain date ranges are also seen in net spillovers. In these periods, the main source of the spillover of volatility shocks in the system is the shocks in barley EWRs. Similar results are also observed in the net pairwise connectedness analysis. Net pairwise spillovers, which usually have a horizontal course, show sudden increases in certain periods due to shocks to the market. The volatility shocks experienced in barley EWRs during these periods significantly affect wheat and maize EWRs.

3.5. Discussions on findings

In the study, it is observed that the return connectedness in the EWR market is quite low, and although it has some upward movements in certain periods, it does not have any upward or downward trend. In this respect, our study found various results from the pioneer studies of Diebold and Yilmaz (2009), Yilmaz (2010), and Diebold and Yilmaz (2011) on other financial markets. On the other hand, in the analysis of volatility connectedness, it is observed that an exponentially increasing trend has started in the connectedness of EWR assets in the market as of October 2020. While the effect of COVID-19 on the return connectedness is not observed, the effect of COVID-19 on the volatility connectedness can be seen in the April 2020 period when the first cases emerged in Turkey and the first full lockdown was imposed. However, contrary to return connectedness, there were sudden increases in volatility connectedness when there were shocks to the market, followed by rapid decreases. Similar types of behavior are not observed in volatilities. In this context, our study is in concordance with those studies in the literature (Diebold and Yilmaz, 2009; Yilmaz, 2010; Diebold and Yilmaz, 2011; Antonakakis and Kizys, 2015; Yi et al., 2018; Ji et al., 2019). The findings exhibit low return connectedness and high volatility connectedness in the market. These results could be arisen because EWR is a newly introduced concept and TURIB is a relatively a new and small market compared to other peers.

Previous studies (Diebold and Yilmaz, 2009; Yilmaz, 2010; Diebold and Yilmaz, 2011; Diebold and Yilmaz, 2012) showed that global risks and volatility shocks spread quickly in different markets or assets around the worldwide. However, return shocks and bull markets are more endogenous and occur domestically, either country-specific or market-specific. So, return connectedness is more domestic and lower than volatility connectedness, which are more influenced by global risks. Since TURIB is a small market yet, it may be more sensitive to external risks and volatilities occur in other national or global markets. Such external risks have increased enormously at the beginning of the COVID-19 pandemic. This could be the main reason for high volatility connectedness in the market. On the other hand, when we discuss low return connectedness, this finding could be due to the same fact that the EWR market is a small and quite new concept. Thus, agricultural-based financial assets and the actors in the EWR market have not significantly integrated in other global or national markets. This may be the reason why high return connectedness and the bull market movements in the global markets are not experienced in the TURIB market.

The result of the connectedness between the assets in the EWR market displayed that the main product in the market that transmits net shocks is barley EWRs. It is concluded that the main source of both return and volatility shocks in the TURIB market is barley EWRs. It is not surprising when Turkey's production data for cereals are investigated. According to Turkstat (2021), Turkey's barley production decreased over 30% while wheat decreased 13.9% and corn production increased 3.8% in 2021. Most of the data in our analysis cover years 2020 and 2021. Evaluating net and pairwise connectedness results with agricultural production changes in Turkey, we may comment that return and volatility shock-transmitter products are directly related with current and/or producers' and investors' expected future production amount. We may also comment that since these results first started in 2020, producers and actors in the market may have foresight about the future changes in production and take actions before. In the future periods, net total and net pairwise return and volatility shocks in the EWR market may be shaped in line with the current and/or expected future production amount.

4. Conclusions

In today's world, which has been globalizing and becoming highly integrated, the relations and synchronization between national economies, financial markets, and assets have significantly increased. This situation has created a highly connected economic and financial environment in which systematic risk and global economic/financial shocks are transmitted rapidly through different countries, financial markets, and assets. Understanding the connectedness of financial assets and markets has an important place in understanding the dynamics of financial markets, measuring the effects of these dynamics, managing risk, and foreseeing the future. Within this context, in this study, a connectedness analysis based on return and volatility series are performed using Diebold-Yilmaz connectedness analysis to understand the dynamics of Electronic Warehouse Receipts (EWR), a new asset in Turkish financial markets, and the Turkish Mercantile Exchange (TURIB). We conduct connectedness analysis on two-dimensions; return and volatility series. According to the findings of this study, there is a low level of connectedness in the returns of EWR assets. On the other hand, we detect that volatility shocks are highly spread across the market. Besides, there is an increasing trend in volatility connectedness. We believe that the above findings are related to the fact that both EWR assets and TURIB have a very recent history compared to other financial assets and markets in Turkey. Thus, EWR assets are significantly affected by external volatility shocks, whereas returns are more endogenous and market-specific. Another important finding of this study is that barley EWRs are the main source of return and volatility shock in the market. This could be because most recent statistics on Turkey's cereal production indicate enormous falls in barley production. Therefore, we believe that the dynamics of the EWR market are related to agricultural production amount of Turkey. Of course, this hypothesis requires to be tested in future studies.

In addition to enriching literature by investigating connectedness and spillover effects in the EWR market, this study makes important contributions to practitioners in two perspectives. For producers, operational risk can be hedged using EWRs whose net pairwise spillovers are negatively correlated with producer’s main crops. Such a wheat producer who wants to minimize its risk against price volatility can use corn EWRs and of course, vice versa is also true. Investors in the market can also apply the same strategy. Besides hedging price volatility risk, a similar perspective is also true for fixing profit according to return connectedness results. A barley producer who wants to minimize loss from its expected return can purchase wheat or corn EWRs since they have negative return spillovers. From the perspective of investors who seeks profit with lower risk can use the EWR market since return shocks spills over low-degree in the market, which is a great opportunity for portfolio optimization with other assets.

The EWRs and TURIB market is a new concept for Turkish financial markets. Additionally, the fact that TURIB is a new, low-recognized market where the trading of EWR assets does not have as large transaction volumes as other financial products and that is still a young market makes it difficult to understand the dynamics of this market. In the following periods, if the transaction volume expands and more investors turn to these products, the structure of the market will become clear, and changes in its dynamics will occur.

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