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RELATIONSHIP BETWEEN CLIMATE POLICY UNCERTAINTY AND AGRICULTURE AND FOOD MARKET INDICES: TVP VAR APPROACH

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ABSTRACT

Climate change significantly affects the availability, accessibility, quality and stability of food in the world. Climate change has the power to affect relevant companies, investors and policy-makers by putting pressure on agricultural production and practices. In this regard, the main purpose of this paper examines the dynamic connectivity nexus between the Climate Policy Uncertainty Index (CPU), FTSE 350 Food Producers Index (FTSE 350), S&P Commodity Producers Agriculture Net Return Index (S&P Commodity), FAO Food Price Index (FAO) and DAX Global Agricultural Index (DAX). In the paper time-varying parameter vector autoregressive (TVP-VAR) model was used in period of July 2007 to July 2022. It was observed that the FTSE 350 index spreads strong volatility to the CPU, S&P Commodity index and DAX index. In addition, it has been determined that S&P Commodity and DAX index emit weak volatility due to climate policy uncertainty.

Keywords: Climate Policy Uncertainty, FTSE 350, S&P Commodities, FAO, DAX.

Jel Codes: F30, F40

İKLİM POLİTİKASI BELİRSİZLİĞİ İLE TARIM VE GIDA PİYASASI ENDEKSLERİ ARASINDAKİ İLİŞKİ: TVP-VAR YAKLAŞIMI

ÖZ

İklim değişikliği, dünya genelinde gıdanın bulunabilirliği, erişilebilirliği, kalitesi ve istikrarı üzerinde önemli etkiler yaratmaktadır. Tarımsal üretim ve uygulamalar üzerinde baskı oluşturarak, ilgili şirketleri, yatırımcıları ve politika yapıcıları etkileyebilme gücüne sahiptir. Bu bağlamda, bu çalışmanın temel amacı, İklim Politikası Belirsizlik Endeksi (CPU), FTSE 350 Gıda Üreticileri Endeksi (FTSE 350), S&P Emtia Üreticileri Tarım Net Getiri Endeksi (S&P Commodity), FAO Gıda Fiyat Endeksi (FAO) ve DAX Küresel Tarım Endeksi (DAX) arasındaki dinamik bağlantıyı incelemektir. Çalışmada, Temmuz 2007 - Temmuz 2022 dönemine ait veriler kullanılarak zamana bağlı değişken parametreli vektör otoregresyon (TVP-VAR) modeli uygulanmıştır. Sonuçlar, FTSE 350 endeksinin CPU, S&P Commodity endeksi ve DAX endeksine güçlü oynaklık yaydığını göstermektedir. Ayrıca, S&P Commodity ve DAX endekslerinin iklim politikası belirsizliği nedeniyle zayıf oynaklık yaydığı belirlenmiştir.

Anahtar Kelimeler: İklim Politikası Belirsizliği, FTSE 350, S&P Emtiaları, FAO, DAX.

Jel Kodları: F30, F40

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INTRODUCTION

Climates around the world are changing rapidly and this change continues to be a common problem for all humanity. Due to the negative effects of climate change and the uncertainty that arises in this context, weather events may occur more frequently and pose risks that may cause serious problems for human health. In the Intergovernmental Panel on Climate Change (IPCC, 2018), held in 2018, it was determined that global temperatures will rise 1.5°C above pre-industrial revolution levels, sea levels will rise in the ozone layer, and Arctic ice will begin to melt. It may cause environmental impacts that may be possible as a result of its costs. Polar glaciers play an important role in protecting and balancing the world climate system, sea level and temperature, ocean currents, fresh water resources and all living spaces. As glaciers melt and oceans warm, ocean currents are disrupting weather patterns around the world. The significant increase in global carbon dioxide (CO2) emissions is the main cause of global warming and exacerbates climate change, which threatens the health of the planet. Measures that can be taken quickly and collectively in this regard are of strategic importance in reducing the negative effects of climate change and overcoming sustainability-related problems (IPCC, 2022). Climate change is an increase in global temperature as well as extreme weather events and floods, droughts, hurricanes, tsunamis, etc. Natural disasters such as increased frequency of heavy rainfall events and longer dry periods cause water acidification and sea level rise. The occurrence of unusual weather events in various countries of the world in recent years (such as the floods in Saudi Arabia9) is evidence of this situation. In addition, climate change pathways can affect agriculture, fisheries and animal husbandry and many other sectors (FAO, 2008). Food production is affected by all these different factors. Since it concerns sectors, it can be directly and/or indirectly affected by climate change worldwide. Therefore, the development of climate change and its effects on food safety and quality are of great importance (Misiou and Koutsoumanis, 2022).

Climate change leads to serious changes in the availability, quality, accessibility and stability of food in the world (Abbas et al. 2022). In other words, climate change and extreme climate events cause large food grain losses, which negatively affects food imports and other economic factors (Islam et al. 2022). For example, the agricultural sector is affected by changes in temperature and precipitation cycles. Changes in precipitation patterns, fluctuations such as seasonally changing and especially increasing temperatures in arable areas, increasing rainfall amounts in summer and sudden floods (such as food and drought) have negative effects on agricultural practices in arid and semi-arid regions (Chandio. et al. 2020; Chandio et al .2021a, b). Adnan et al. (2017) state that the vulnerability of climate change has negative impacts on agriculture sector. In addition, climate change puts pressure on agricultural practices and food supply increases food security-related problems (Ullah 2017; Nawaz et al. 2019). The Human Development report (2019) points outs that international policy is important to offset the shock to the livelihoods of rural people in low-income countries and sudden increases in food prices due to declines in global productivity. Additionally, food production contributes significantly to greenhouse gas emissions, which is considered a source of environmental degradation (Gomez-Zavaglia, et al. 2020).

Gavriilidis (2021) developed the US climate policy uncertainty index (CPU), which captures key events and articles related to climate policy in major US newspapers. CPU refers to the uncertainty caused by climate events or the uncertainty surrounding the U.S. government's policy decisions regarding climate risk reduction. This index was created following Baker et al., (2016) text-based approach. After the creation of the index in question, many studies have been conducted on climate policy uncertainty, clean energy, agriculture, commodity goods and sustainability.

Climate change creates some effects on the agricultural sector, and these effects are generally reflected directly or indirectly on the prices of agricultural products. First of all, climate change may cause temperature increases, extreme weather events such as droughts and floods, and the emergence of new disease and pest species. This situation causes agriculture to become more costly and production costs to increase. These rising costs could put pressure on food indices and the stock market values of agricultural companies. Additionally, impacts on water resources and changes in irrigation systems may cause agriculture to become more costly or difficult in certain regions, which may affect prices. In addition, climate changes often cause regulatory changes, and these changes can lead to fluctuations in agricultural and food indices. For example, policies that support sustainable agricultural practices can lead to changes in the industry, which in turn can have effects on stock market indices. Another factor is the impacts of climate change on trade routes. Increases in transportation and logistics costs affect the prices of agricultural products, which may cause food stock market indices to fluctuate. However, these effects are generally not limited to a specific region or product and can have a broad impact on global markets. Assessing the effects of climate change on agricultural and food stock market index returns requires an in-depth analysis and a broad perspective, given the complexity of the climate and the interaction of multiple factors.

With the impact of globalization, many country-specific situations also affected other countries. Recently, with the Russia-Ukraine war, the crisis related to energy and commodity goods has spread rapidly. In other words, the volatility spread between markets has increased in recent years. In this context, the purpose of this paper is the Climate Policy Uncertainty Index (CPU), FTSE 350 Food Producers Index (FTSE 350), S&P Commodity Producers Agriculture Net Return Index (S&P Commodities), FAO Food Price Index (FAO) and DAX Global Agriculture Index (DAX). The dynamic connectivity relationship between them was examined. Monthly data from July 2007 to July 2022 was used in the paper. TVP-VAR model was used in empirical analyses.

This study is expected to contribute to the literature in three different aspects. i) No research was found examining the nexus among climate policy uncertainty, agricultural indices and food indices. The nearest paper of this article is written by Wang et al. (2023). The difference of this paper from Wang et al. (2023) is that we focus only on agriculture and food. In this context, it will contribute to the literature by providing the first empirical findings. ii) Climate policy uncertainty and the complex relationships between agricultural indices and food indices reveal the need for further research. Using a newly launched index could provide new insights into the effects of uncertainty in climate policy pathways. iii) Climate policy uncertainty can increase carbon awareness and encourage countries to invest more in clean energy sources. In conclusion, understanding the relationship between the climate policy uncertainty index and agriculture and food indices will provide information to policy makers about evaluating the effects of climate policies on the agricultural sector and taking appropriate policy measures. It will also allow policy makers to provide guidance on how policy changes in a particular region or sector may affect agricultural and food indices. It can also provide strategic guidance for companies operating in the agriculture and food sector. In summary, the findings obtained in this research both contribute to the literature and can help create more effective strategies by providing concrete guidance to practitioners and policy makers operating in the sector.

This study consists of 5 chapters. Following the introduction, the first section presents previous research on the nexus between climate policy uncertainty and agriculture, food and commodity prices. In the third section, the variables, data set and method used in the research are introduced. Then, the results of the TVP-VAR method are included to determine then nexus among climate policy uncertainty, agricultural indices and food indices. In the last section, a general evaluation of the paper was made and suggestions were made for investors and policy makers.

1. Literature Review

Regarding the impact of climate change on agriculture, it is noted that the increase in atmospheric carbon dioxide concentration and temperature and extreme weather events will affect future agricultural production (Ren et al., 2021). In studies examining the impacts of climate policy uncertainty on agricultural products, the dominant findings are that the CPU affects the prices of agricultural products and the stock returns of companies that have markets in this sector. Wang, et al., (2023), which is close to this current paper in terms of variables and model preference, tested the effects of climate uncertainty on agricultural sector returns and crude oil prices using the quantile connectedness method. According to the findings of the paper, climate uncertainty has a strong connection on the agricultural sector. In this context, Laborde, et al., (2021), Mirzabaev and Tsegai (2012) found findings that climate uncertainty has a strong impact on agricultural outputs. Kim et al., (2019) stated that drought will reduce agricultural output, and Lobell, et al., 2013 argued that this situation will be further exacerbated by climate change.

Likewise, according to the World Bank (2007), it is stated that this situation will be even more effective in supported agriculture-based economies. Considering agriculture-based Asian countries, Brown and Kshirsagar (2015) argued that increases in climate change and adverse conditions caused negative price shocks on wheat prices. Chen et al. (2018) estimated that fluctuations in corn prices would increase agricultural income by 10%, while Nelson et al. (2014) argued that it was the reason for a 20% increase in global agricultural products. Considering that food products constitute a large part of the family budget in developing countries, it is inevitable that this situation will lead to even more negative consequences (Agyei et al., 2021). On the other hand, it is known that agriculture is almost the only method to combat poverty in these countries (Ullah et al., 2018). In the same direction, it has been observed that this situation also supports the results of ul Haq et al., 2008, Webb, 2010, Trostle et al., 2011, Bradbear and Friel, 2013.

It is emphasized in the literature that the interconnectedness between agricultural commodity markets is a result of financial development (Frimpong et al., 2021; Tang and Xiong, 2012). It is also known that agricultural commodity financialization reduces portfolio diversification advantages by increasing movement and shocks in its market and with traditional asset classes (Amrouk et al., 2019). However, climate uncertainty, extreme population growth, changes in food supply and demand, and environmental degradation have impacts on the food sector and the global food system (Janetos, et al., 2017, OECD/FAO, 2018). In addition, the effects of food price volatility on markets may vary depending on whether a household is a net buyer or net seller of a particular good (Stephens and Barrett, 2011). Global food prices and financial markets are greatly affected by external factors. Previous studies show that crude oil and agricultural commodity markets are cointegrated (Yahya et al., 2019). Many researchers have investigated the link between energy and agricultural commodities using a wide variety of econometric methods such as VECM and cointegration (Allen et al., 2018; Maadid et al., 2017; Algieri and Leccadito, 2017; Nazlıoğlu and Soytaş, 2012). A better understanding of the impacts of external shock on energy and agricultural commodity markets can help individuals and firms make more reasonable investment decisions in financial markets (Yip et al., 2020). In the studies conducted by He and Chen, (2011) and Ke et al., (2019) examining the relationship between agricultural commodity markets, findings were found that there is a long-run correlation between bond and agricultural markets. In fact, it is stated that this situation has reached its peak, especially in the dynamic spread between these markets, where the first and third phases of the Covid-19 period have strengthened (Deaton and Deaton, 2020, Adekoya and Oliyide 2021, Ömer et al. 2022).

It was observed that a significant part of the previous studies on the subject of this study focused on the relationship between the agriculture, food market index, crude oil and stock market indices. On the other hand, the relevant studies were carried out in terms of both developed markets and developing markets. However, no research has been found in the literature researchs the relation among the climate policy uncertainty index, agriculture and food market indices. It is thought that the study will make a significant contribution to the literature with this original aspect.

2.Methodology

2.1.Data

The paper investigated to examine the time-dependent dynamic connection between CPU and the global agricultural sector. For this purpose, it was reached data of the CPU and the FTSE 350 Food Producers Index (FTSE 350), the S&P Commodity Producers Agriculture Net Return Index (S&P Commodities), the FAO Food Price Index (FAO) and the DAX Global Agriculture Index (DAX). In the paper, monthly observations were used between the sample period of 01.07.2007-01.07. 2022.

One of the variables of the paper the CPU created by Gavrilidis (2021) is an indicator of the effectiveness and feasibility of measures taken to reduce the effects of climate change. For example; Increases in CPU were observed following events such as President Bush's rejection of the Kyoto Protocol, Volkswagen's admission of guilt regarding the emissions scandal, and Trump's decision to withdraw from the Paris Agreement.

The FTSE 350 Food Producers Index (FTSE 350) listed on the London Stock Exchange, the DAX Global Agricultural Index (DAX) listed on Germany's Düsseldorf Stock Exchange and the S&P Commodity Producers Agriculture Net Return Index (S&P Commodities) calculated by S&P Dow Jones Indices They are a stock market indices that track the performance of businesses. These indices provide investors with a reliable and publicly available reference for the performance of agricultural commodity markets. The FAO Food Price Index (FAO), calculated by the Food and Agriculture Organization of the United Nations, is a measure of the monthly change in international prices of a basket of food commodities. It consists of the average of commodity price indices consisting of grains, vegetable oils, sugar, meat and dairy products, which represent approximately 40 percent of agricultural production. The variables in question represent the global agricultural market. Table 1 provides information about the variables used in the paper.

Table 1. Variables

Variables	**Abrevation**	**Sources**
Climate policy uncertainty	CPU	www.policyuncertainty.com
FTSE 350 Food Producers Index	FTSE 350	www.investing.com
DAX Global Agriculture Index	DAX	
S&P Commodity Producers Agriculture Net Return Index	S&P Commodity	
FAO Food Price Index	FAO	

Price series graphs of the variables are given in Figure 1. According to the chart, CPU and FTSE 350 variables exhibit volatile movements; S&P Commodity and DAX variables had similar trends throughout the sample period and started to trend upward in the first quarter of 2020; It is seen that the FAO variable started to trend upward in 2020.05, following the S&P Commodity and DAX variables.

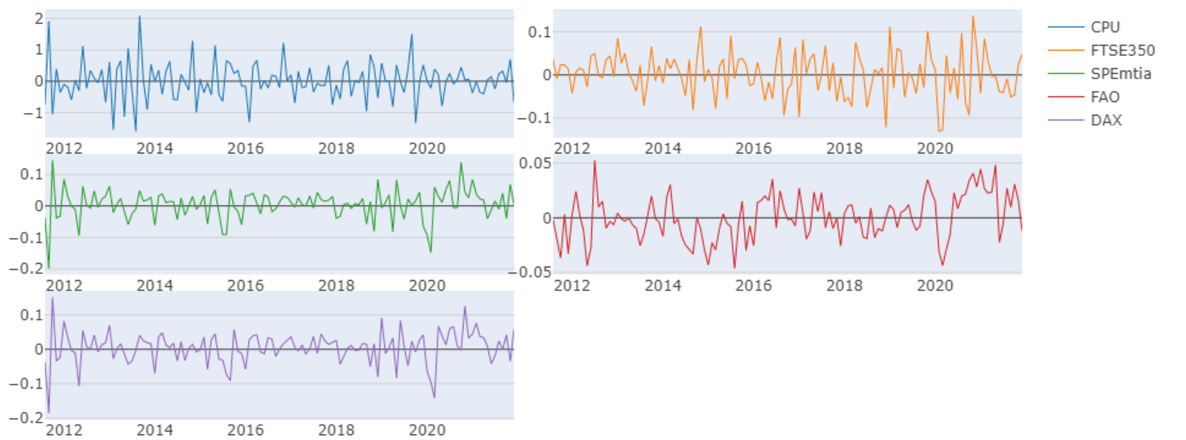

Figure 1. Price Series Graphs of Variables

In case of the level values of the variables were examined with the ERS unit root test (Stock et al. 1996), it was determined that they were not stationary and the logarithmic returns of the series were calculated with the formula *ln(Xt/Xt-1)* and the volatility series were calculated with the formula *ln(Xt/Xt-1)*^2 .The calculated volatility series are shown in Figure 2.

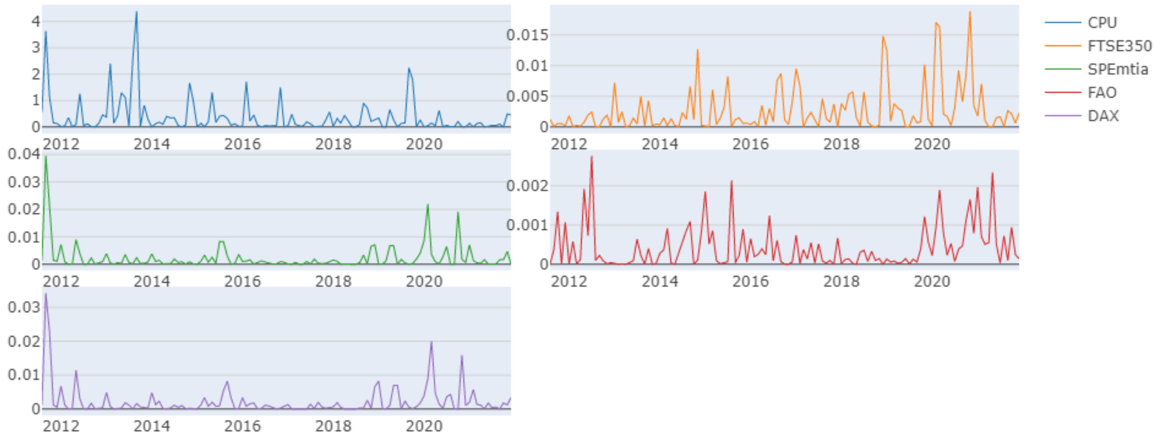

Figure 2. Volatility Series Graphs of Variables

Descriptive statistics for the variables used in the study are presented in Table 2. The table point outs that the observation distributions in all series were found to contain skewness and kurtosis and that the data deviated from the normal distribution according to the Jarque-Bera test statistics. This shows that stochastic models are more suitable for the data set instead of deterministic models based on the assumption of normal distribution. Because in time series that do not show normal distribution, stochastic models based on the assumption of randomness can give more accurate results. According to the ERS test developed by Elliot, Rothenberg and Stock (1996), the volatility of all variables is stationary in their returns. Additionally, Fisher and Gallagher's (2012) Ljung Box Q and Q2 test statistics show that the series contain various levels of autocorrelation. The fact that the series do not show normal distribution and contain autocorrelation shows that it is more appropriate to use a TVP-VAR model with time-varying parameters for this data set. The appropriate lag length for the model was determined as 1 according to the Schwarz information criterion.

Table 2.Descriptive Statistics

	CPU	**FTSE 350**	**S&P Commodity**	**FAO**	**DAX**
Mean	0,379	0.003	0.002	0	0.002
Skewnes	0,475	0	0	0	0
Kurtosis	3.310***	2.260***	4.760***	1.981***	4.359***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Excess	12.810***	5.197***	27.778***	3.969***	22.813***
Kurtosis	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Jarque-Bera	1082.917***	247.102***	4490.857***	163.780***	3106.322***

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-4.184***	-3.841***	-5.121***	-2.612***	-5.308***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(10)	9.321*	10.559*	15.564***	13.700**	20.058***
	(0.096)	(0.054)	(0.004)	(0.011)	(0.000)
Q^2(10)	5.696	13.915***	6.576	4.605	13.621**
	(0.406)	(0.010)	(0.297)	(0.568)	(0.012)

Notes: * p < 0.1; ** p < 0.05; *** p < 0.01. denote standard errors. the D'Agostino (1970) and Anscombe and Glynn (1983) statistics are used for skewness and kurtosis. JB (Jarque and Bera 1980) is the test for Normality, ERS unit root test (Elliot et al. 1996) tests for stationarity, Q(20) and Q2 (10) are the weighted Ljung-Box statistic for serial correlation in the returns and squared series (Fisher and Gallagher 2012), respectively

2.2. Method

Since the series used in the paper are not normally distributed and contain autocorrelation, TVP-VAR model was used to examine the time-dependent dynamic connection between climate policy uncertainty and the global agricultural sector. It was suggested by Antonakakis et al. (2020). In the TVP-VAR approach, Koop and Korobilis (2014) extends the connectivity approach proposed by Diebold and Yılmaz (2009, 2012, 2014) by allowing the variance-covariance matrix to change over time through a Kalman Filter estimate based on forgetting factors. In this way, the model prevents the loss of important observations that would affect the result (Antonakakis and Gabauer, 2017; Korobilis and Yılmaz, 2018; Gabauer and Gupta, 2018).

The TVP-VAR model is expressed as follows:

$$y_t = A_t z_{t-1} + \epsilon_t \qquad \epsilon_t|\Omega_{t-1} \sim N(0, \textstyle\sum_t) \tag{1}$$

$$vec(A_t) = vec(A_{t-1}) + \xi_t \qquad \xi_t|\Omega_{t-1} \sim N(0, \Xi_t) \tag{2}$$

and

$$z_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{pmatrix} \qquad A'_t = \begin{pmatrix} A_{1t} \\ A_{2t} \\ \cdots \\ A_{pt} \end{pmatrix} \tag{3}$$

Here, respectively, Ω_{t-1}, represents all the information available until t-1; Ω_{t-1}, and z_t are m × 1 and mp × 1 vectors; A_t and $A_{it}$are m × mp and m × m dimensional matrices; ϵ_t represents an m × 1 vector and $\xi_t$represents a m^2p × 1 dimensional matrix. The time-varying variance-covariance matrices $\sum_t$ and Ξ_t are m × m ve m^2p × m^2p dimensional matrix, respectively. Additionally $vec(A_t)$, m^2p × 1 is the vectorization of A_t, which is a m^2p × 1 -dimensional vector.

Prior estimation was used to initialize the Kalman filter. Accordingly, A_{OLS}, $\sum_{OLS}^{A}$ and $\sum_{OLS}$will be equal to the VAR estimate of the first 20 months:

$$vec(A_0) \sim N(vec(A_{OLS}), \textstyle\sum_{OLS}^{A} \sum_0 = \sum_{OLS}$$

To ensure numerical stability in the Kalman filter algorithm, the decay factors recommended by Koop and Korobilis (2014) were applied as k_1=0,99 and k_2=0,96

Time-varying coefficients and time-varying variance-covariance matrices, Koop et al. (1996) and the generalized connectivity procedure based on generalized impulse response functions (GIRF) and generalized prediction error variance decompositions (GFEVD) developed by Pesaran and Shin (1998) are used to estimate. To calculate GIRF and GFEVD, TVP-VAR must be converted to vector moving average (VMA) representation within the framework of Wold Decomposition theorem. The VMA representation is converted as follows:

$$y_t = J'(M_t(z_{t-2} + \eta_{t-1}) + \eta_t \tag{3}$$

$$= J'(M_t(M_t(z_{t-3} + \eta_{t-2}) + \eta_{t-1}) + \eta_t) \tag{4}$$

$$\vdots \tag{5}$$

$$= J'(M_t^{k-1} z_{t-k-1} + \sum_{j=0}^{k} M_t^j \eta_{t-j}) \tag{6}$$

M_t denotes an mp × mp dimensional matrix, η_t denotes an mp × 1 dimensional vector, and J denotes an mp × m dimensional matrix.

GIRFs (($\Psi_{ij,t}(H)$) express the response in all variables j to a shock in variable i. Since it is not a structural model, an H step ahead estimate is calculated where variable i is both a shock and a non-shock, and the difference between them is attributed to variable i. This is as follows:

$$GIRF_t(H, \delta_{j,t}, \Omega_{t-1}) = E(y_{t+H} | e_j = \delta_{j,t}, \Omega_{t-1}) - E(y_{t+j} | \Omega_{t-1}) \tag{7}$$

$$\Psi_{j,t}(H) = \frac{B_{H,t} \Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{\Sigma_{jj,t}}} \quad \delta_{j,t} = \sqrt{\Sigma_{jj,t}} \tag{8}$$

$$\Psi_{j,t}(H) = \Sigma_{jj,t}^{-\frac{1}{2}} B_{H,t} \Sigma_t e_j \tag{9}$$

GFEVD ($\tilde{\phi}_{ij,t}(H)$) which represents the bidirectional dependence from j to i, is calculated and the effect of variable j on variable i is explained in terms of prediction error variance shares. By normalizing the variance shares in question, all variables together explain 100% of the forecast error variance of variable i. Its mathematical expression is as follows:

$$\tilde{\phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi_{ij,t}^2}{\sum_{j=1}^{m} \sum_{t=1}^{H-1} \Psi_{ij,t}^2} \tag{10}$$

$\sum_{j=1}^{m} \tilde{\phi}_{ij,t}(H) = 1$ and $\sum_{i,j=1}^{m} \tilde{\phi}_{ij,t}(H) = m$. The denominator in the equation is the cumulative effect of all shocks; The numerator shows the cumulative effect of a shock in variable i. Using GFEVD, the Total Connectedness Index (TCI) is calculated as follows:

$$C_t(H) = \frac{\sum_{i,j=1, i\neq j}^{m} \tilde{\phi}_{ij,t}(H)}{\sum_{i,j=1}^{m} \tilde{\phi}_{ij,t}(H)} * 100 = \frac{\sum_{i,j=1, i\neq j}^{m} \tilde{\phi}_{ij,t}(H)}{m} * 100 \tag{11}$$

This connectivity approach shows the propagation of a shock in one variable to other variables. Based on this approach, Total Directional Connectedness To Others (TO), which shows the spread of the shock in variable j to all other j variables, is calculated as follows:

$$C_{i\rightarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{m} \tilde{\phi}_{ji,t}(H)}{\sum_{j=1}^{m} \tilde{\phi}_{ji,t}(H)} * 100 \qquad (12)$$

Total Directional Connectedness From Others (FROM), which shows the spread of the shock in all j variables to variable i, is calculated as follows:

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{m} \tilde{\phi}_{ij,t}(H)}{\sum_{i=1}^{m} \tilde{\phi}_{ij,t}(H)} * 100 \qquad (13)$$

The difference between Total Directional Connectedness To Others (TO) and Total Directional Connectedness From Others (FROM) is calculated to reveal Net Total Directional Connectedness (NTDC), which can be interpreted as the influence variable it has on the analyzed network:

$$C_{i,t} = C_{i\rightarrow j,t}(H) - C_{i\leftarrow j,t}(H) \qquad (14)$$

In this equation, if $C_{i,t}$ takes a positive value, it indicates that variable i directs the network by affecting other variables more than the effect it receives; If $C_{i,t}$ takes a negative value, it means that variable i is driven by the network under the influence of other variables.

Finally, to examine pairwise relationships, Net Pairwise Directional Connectedness (NPDC) is calculated by decomposing the Net Total Directional Connectedness (NTDC):

$$NPDC_{ij}(H) = \left(\tilde{\phi}_{jit}(H) - \tilde{\phi}_{ijt}(H)\right) * 100 \qquad (15)$$

NPDC defines the dominance of variable i over variable j or the dominance of variable j over variable i (Antonakakis et al., 2020: 4-7).

3.Empirical Findings

Here, the analysis results revealing average connectedness measurements, dynamic total connectedness findings and finally Net Total Directional Connectedness (NTDC) and Net Pairwise Directional Connectedness (NPDC) findings are presented respectively.

3.1. Average Connectedness Measures

First, we focus on the average connectedness measurement results, which are created independently of time by all variables in the network. These findings will help us form a general opinion about the connectivity relationship between variables. The average total connectivity results between the volatilities of the variables are given in Table 3. The FROM column in the table indicates the average of the total diffusion from other variables to the relevant variable, and the TO row indicates the average of the total diffusion from the relevant variable to other variables. The NET line obtained from the difference between TO and FROM shows the average of the net spread of the relevant variable in the network. Positive values in the NET line indicate that the spread from the relevant variable to other variables is higher compared to the spread from other variables to the relevant variable, and the role of this variable in the network is defined as a net transmitter. On the other hand, negative values in the NET line indicate that the spread from other variables to the relevant variable is higher than the spread from the relevant variable to other variables, and the role of this variable in the network is defined as a net receiver. The NPT line expresses the receiver/transmitter role of the variables in the network, respectively, depending on the values in the NET line. The variable with the highest negative value in the NET row is the net receiver in the network and is ranked zero in the NPT row. On the other hand, the variable with the highest positive value in the NET row is the net transmitter in the network and is ranked last in the NPT row. The Corrected Total Connected Index (cTCI) value in the lower right corner of the table shows the total connectivity within the network, regardless of time.

Table 3 shows that since the diagonal values are higher than the other values, the highest share in the variance of the variables is due to the spread in their own volatilities. This is due to the high volatility of the variables in the network. In variables that exhibit volatile movements, spreads from the variable's own values are more effective on the deviation from the mean compared to spreads from other variables. This indicates that the deviation from the average observed in the values of the variables in the network has a high impact on the spillovers from the variable's own values.

On the other hand, 71.68% of the changes in CPU variance are due to its own volatility, while 28.32% are due to other variables. Similarly, 73.47% of the changes in the FTSE 350 variance are caused by its own volatility, while 26.53% are caused by other variables. Within the network, FTSE 350 and S&P Commodity are net givers with 30.99 and 14.88 respectively; CPU, FAO and DAX are net buyers with 21.50, 21.24 and 3.14 respectively. According to the Corrected Total Connectedness Index (cTCI) value, the average impact of the volatilities of all other variables on the variance of a variable over time is 53.85%.

Table 3. Averaged Connectedness Table

	CPU	FTSE 350	S&P Commodity	FAO	DAX	**FROM**
CPU	71.68	12.18	5.48	4.93	5.73	28.32
FTSE 350	1.23	73.47	11.35	4.81	9.14	26.53
S&P Commodity	1.33	17.85	43.17	5.09	32.56	56.83
FAO	2.61	9.24	17.19	58.91	12.04	41.09
DAX	1.65	18.25	37.70	5.02	37.38	62.62
TO	6.82	57.53	71.72	19.85	59.48	**cTCI**
NET	-21.50	30.99	14.88	-21.24	-3.14	**53.85**
NPT	0.00	4.00	3.00	1.00	2.00	

Note: Results are based on a TVP-VAR model with a 1st-order lag length (BIC) and 20 step-ahead generalized forecast error variance decomposition.

3.2. Dynamic Total Connectedness

The average connectivity measures given above are time-independent. It expresses the average of the connectivity relationship within the network without any time point. Results that express average connectivity independently of time prevent observing the dynamic evolution of spreads between variables. Considering that various political and economic events that took place during the sample period may have positive or negative effects on the volatilities of the series, it would be more accurate to focus on dynamic measurements and the change in the spreads within the network over time.

The Total Connectedness Index (TCI) results presented in Figure 3 show the change in the dynamic total connectivity between the returns of the variables examined within the scope of the research throughout the sample period. When Figure 3 is examined, it can be seen that although the dynamic connection between the volatilities of the variables increases in some periods, it has a general downward trend over time.

Figure 3. Total Connectedness Index (TCI)

3.3. Net Total Directional and Net Pairwise Dynamic Connectedness

Finally, we present results from NTDC and NPDC analyzes to determine the evolution of the net donor or net acceptor roles of the variants over time and to reveal the bilateral interactions within the network.

Net Total Directional Connectivity (NTDC) analysis provides a dynamic view of the chronological evolution of a variable's net receiver or net donor role. Using NTDC, it is possible to classify variables in the data set as net donor or net receiver, further allowing to identify possible exchanges between the two roles. NTDC results are given in Figure 4. The zero point in the vertical section of the graph defines the role change of the relevant variable. Positive values above zero indicate that the spread from the relevant variable to other variables is more dominant and that this variable is a net transmitter in the network. Negative values below zero indicate that the spillovers from other variables to the relevant variable are more dominant and that this variable is a net receiver in the network.

According to Figure 4, it can be seen that FAO and CPU indices were mostly net spread receivers during the sample period, while FTSE 350 and S&P Commodity indices were mostly net spread transmitters. However, after December 2019, which corresponds to the coronavirus period, it is observed that the net donor effect of the S&P Commodity index increased and the FTSE 350 index switched from a giver position to a buyer position. However, the DAX index is mostly in a giving position at level values.

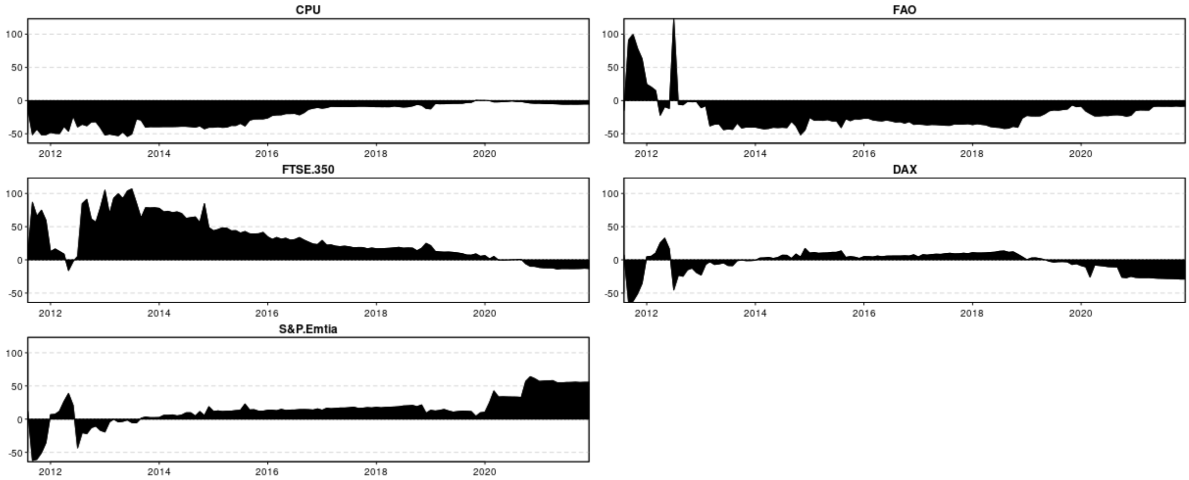

Figure 4. Net Total Directional Connectedness

Net Pairwise Dynamic Connectedness (NPDC) analysis provides a dynamic view of the chronological evolution of the net receiver or net transmitter role of variables, similar to NTDC analysis. Unlike NTDC, it refers to the mutual propagation of a variable with another variable, instead of the total propagation of a variable with all other variables in the network. The NPDC results presented below allow us to make more detailed inferences by showing the time-dependent change of bilateral relations between variables in the network. Each subgraph in the figure expresses the net receiver/transmitter role of the first-ranked variable relative to the second-ranked variable. For example, the black shaded area in the "CPU-FTSE 350" chart shows that CPU was a net receiver of spreads from the FTSE 350 over the entire sample period.

Figure 6 indicates that the CPU is the net receiver of all other variables. It was determined that, especially at the beginning of the sample period, volatility spillovers from other variables to the CPU were intense, but these spillovers gradually decreased. In addition, volatility spillovers from the FTSE 350 and S&P Commodity indices are the net transmitter of other variables in the network. These findings support our other findings and help us better understand the responses of variables within the network to volatility spillovers.

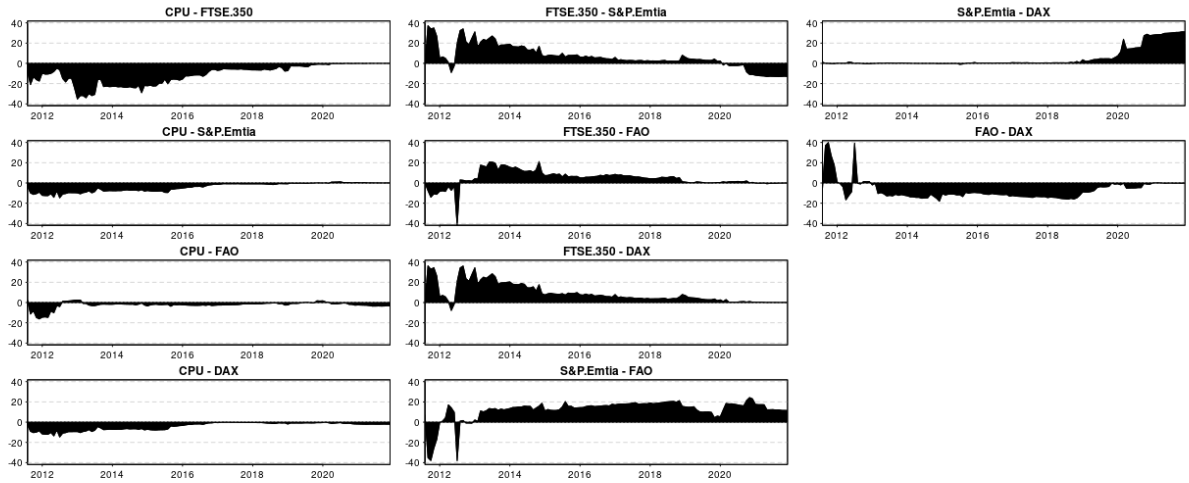

Figure 5. Net Pairwise Dynamic Connectedness

Figure 6 shows the propagation network of shocks. Yellow dots show the variables that receive the shock in the receiver position, while blue dots show the variables that spread the shock in the transmitter position to other variables. The size of the variable circles indicates the effect size of the variable transmitting or receiving the shock. Arrows drawn from circles show the direction of the relationship between variables. The thickness of these arrows shows the strength of the relationship. When the chart is examined, while FTSE 350 and S&P Commodity are the variables that carry out shock propagation, CPU, FAO and DAX are the variables that receive shock. There was a strong shock propagation from the FTSE 350 index to the CPU and DAX indices, and a weak shock spread to the FAO and S&P Commodity indices. Similarly, a strong shock propagation is observed from the S&P Commodity index to the FAO index and a weak shock propagation to the DAX and CPU index. However, there is a weak shock propagation from DAX to FAO and CPU indices, which relatively explains the interconnectedness relationship within the network.

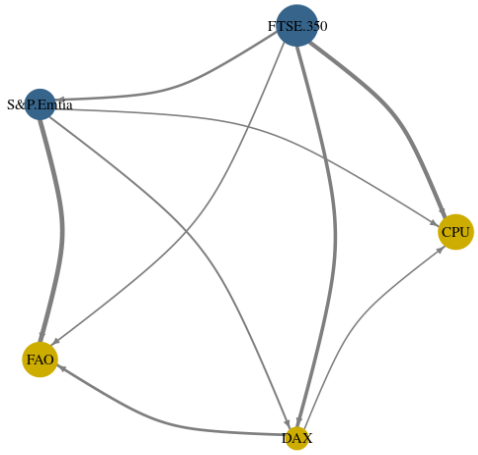

Figure 6. Shock spillover Network

CONCLUSION

This paper includes the Climate Policy Uncertainty Index (CPU), FTSE 350 Food Producers Index (FTSE 350), S&P Commodity Producers Agriculture Net Return Index (S&P Commodity), FAO Food Price Index (FAO) and DAX Global Agriculture Index (DAX). The dynamic connectivity between them has been investigated. In this context, TVP-VAR model was used in this paper.

According to the results of the first analysis, it has been observed that global agricultural markets are networked with each other at a high rate (54%). In the network evaluation made independently of the economic and political events during the period, FTSE 350 and S&P Commodity are net givers; It has been observed that CPU, FAO and DAX variables are also net receiver variables. Considering the impact of economic and political events in the examined period, it is considered a good development that the dynamic connectivity, which was high at the beginning of the examination period, decreased over time. When looking at the net receiver or transmitter characteristics of the variables in the network, the net spread receivers of the FAO and CPU variables during the sample period are; It has been observed that FTSE 350 and S&P Commodity indices are generally net spreaders. During the coronavirus period, the net giving feature of the S&P Commodity index increased; It has been observed that FTSE 350 has moved into a net buyer position. These structural changes can be associated with the effects of Coronavirus on international markets. Looking at the overall analysis, the shock absorbing properties of FTSE 350 and S&P Commodity indices; It has been observed that CPU, FAO and DAX indices are shock receivers. It is an interesting result that the production index (FTSE 350) revealed in the paper affects the uncertainty of climate policies (CPU) and the agricultural index (DAX).

DISCUSSION

According to the findings, it can be stated that investors and financial institutions should strengthen their risk management strategies and diversify their portfolios against the strong volatility arising from the FTSE 350 index. At the same time, companies should review their strategies for dealing with climate policy uncertainty and focus on sustainable practices. It is important to follow future changes in climate policies and be prepared in this context. Policy makers should take steps to make climate policies more predictable in order to reduce volatility in financial markets. Finally, investment strategies should be reviewed based on the obtained volatility results and more resilient portfolios should be created against potential risks in indices associated with climate policy uncertainty. These recommendations can be applied to prepare for volatility in financial markets, strengthen strategies to cope with sustainability and climate policy uncertainty, and create more effective policies.

When setting agricultural production targets, policy makers should take into account the uncertainty in climate policies and the impact of these figures on the agricultural index. On the other hand, it is important for investors that the return (S&P Commodity) affects the price (FAO). Investors should not neglect the impact of variables on each other when making investment decisions. In order for investors' decisions to be rational, attention should be paid to the effects of uncertainties in climate policy on price fluctuations. The dynamic relationship between policy uncertainty and agricultural commodity markets revealed in the findings of the paper also reveals that investors should collect as much information about the market as possible and that investors should use a dynamic portfolio management strategy for hedging purposes.

According to the quantitative-based linkage analyzes of this paper, climate policy-determining institutions should put in place ideal policy tools and monitoring mechanisms that will manage the extreme risk spillovers transmitted by agricultural production and price mechanisms. The findings of the paper can contribute to agricultural policy makers in terms of the potential effects of climate policy changes on grain production and prices. The findings of the paper reveal that agricultural production and prices become more evident, especially with global shocks that occur in certain periods, and that policy makers need to be more proactive in these periods.

On the other hand, in addition to the negative aspects in question, it should not be forgotten that the regulations and standards introduced to reduce the negative aspects in the agricultural food sector may present both difficulties and opportunities for companies and investors. The demand for organic and environmentally friendly products, as well as commitment to sustainable agricultural practices, also means different adjustments and investments for agri-food companies.

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EXTENDED ABSTRACT

GENİŞLETİLMİŞ ÖZET

İKLİM POLİTİKASI BELİRSİZLİĞİ İLE TARIM VE GIDA PİYASASI ENDEKSLERİ ARASINDAKİ İLİŞKİ: TVP-VAR YAKLAŞIMI

İklim değişikliği, dünya genelinde gıda üretiminin miktarını, kalitesini, fiyat istikrarını ve erişilebilirliğini tehdit eden önemli bir faktör olarak öne çıkmaktadır. Bu durum yalnızca tarım üreticilerini değil; aynı zamanda yatırımcıları, politika yapıcıları ve finansal piyasaları da doğrudan etkilemektedir. Bu bağlamda, bu çalışmanın temel amacı, İklim Politikası Belirsizlik Endeksi (CPU) ile küresel tarımsal piyasaları temsil eden FTSE 350 Gıda Üreticileri Endeksi (FTSE 350), S&P Tarım Net Getiri Endeksi (S&P Commodity), FAO Gıda Fiyat Endeksi (FAO) ve DAX Küresel Tarım Endeksi (DAX) arasındaki zamanla değişen dinamik etkileşimleri analiz etmektir. Çalışmada Temmuz 2007 – Temmuz 2022 dönemine ait aylık veriler kullanılarak Zamanla Değişen Parametreli Vektör Otoregresif (TVP-VAR) modeli uygulanmıştır.

Analiz bulgularına göre, küresel tarım piyasaları arasında yüksek düzeyde bir ağ bağlantısı (%54 oranında) mevcuttur. Ağ yapısı değerlendirildiğinde, FTSE 350 ve S&P Commodity endeksleri sistemde net volatilite yayarken; CPU, FAO ve DAX değişkenleri genellikle volatiliteyi absorbe eden yani net alıcı konumundadır. Bu bulgular, tarımsal üretim ve getiri göstergelerinin küresel belirsizlikler karşısında nasıl bir rol üstlendiğini ortaya koymaktadır. Özellikle FTSE 350 endeksinin hem CPU hem de DAX üzerinde belirgin etkiler yaratması, gıda üreticilerinin iklim politikalarına duyarlılığını ve bu politikaların tarım sektörüne olan yansımasını açıkça göstermektedir.

COVID-19 pandemisi gibi küresel şokların etkisi altında ağ yapısında yapısal değişimlerin meydana geldiği gözlemlenmiştir. Bu dönemde, S&P Commodity endeksi volatiliteyi daha yoğun bir şekilde yayarken, FTSE 350 endeksi net alıcı konumuna geçmiştir. Bu durum, küresel krizlerin piyasalar arası etkileşimleri nasıl yeniden şekillendirdiğini ortaya koymakta ve politika yapıcılar açısından kriz dönemlerine özgü politika senaryolarının hazırlanması gerektiğine işaret etmektedir.

Elde edilen bulgulara dayanarak birkaç önemli politika ve yatırım önerisi geliştirilmiştir. İlk olarak, yatırımcıların FTSE 350 gibi volatilite yayma potansiyeli yüksek endekslere karşı daha güçlü risk yönetim stratejileri geliştirmesi ve portföy çeşitlendirmesine öncelik vermesi gerekmektedir. Ayrıca, iklim politikalarındaki belirsizliklerin tarım piyasalarında oluşturduğu oynaklığı azaltmak amacıyla, politika yapıcıların daha öngörülebilir, şeffaf ve sürdürülebilir iklim politikaları geliştirmeleri önem arz etmektedir. Ayrıca, FAO gıda fiyat endeksinin CPU ve üretim endeksleriyle olan etkileşimi, fiyat dinamiklerinin yalnızca arz-talep değil, aynı zamanda politik belirsizlikler tarafından da şekillendiğini göstermektedir. Bu durum, yatırımcılar açısından rasyonel fiyat beklentileri oluşturulurken politik ve çevresel risk faktörlerinin dikkate alınması gerektiğine işaret etmektedir.

Bununla birlikte, çalışma, iklim politikası belirsizliğinin yalnızca risk oluşturmadığını; aynı zamanda sürdürülebilir tarım, çevre dostu üretim ve yeşil yatırım fırsatları açısından da yeni olanaklar sunduğunu göstermektedir. Organik ve çevreye duyarlı ürün talebinin artması, tarım-gıda şirketlerinin üretim süreçlerini yeniden yapılandırmasını ve çevreci yatırımları artırmasını gerektirmektedir. Bu bağlamda, sürdürülebilirlik odaklı dönüşümler, uzun vadede hem şirketler hem de yatırımcılar için stratejik avantajlar sağlayabilir. Sonuç olarak, bu çalışmanın bulguları, iklim politikası belirsizliğinin tarımsal piyasalar üzerindeki etkilerini anlamada önemli bir katkı sunmakta, finansal ve tarımsal karar alma süreçlerinde daha dinamik, bilgi temelli ve sürdürülebilir stratejilere yönelmenin gerekliliğini ortaya koymaktadır.

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