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ARAŞTIRMA MAKALESİ RESEARCH ARTICLE

The Analysis of the Relationship Among Climate Policy Uncertainty, Logistic Firm Stock Returns and ESG Scores: Evidence from the TVP-VAR Model

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Abstract

This study examines the relationship between climate policy uncertainty (CPU), China's environmental impact, social responsibility and corporate governance practices (ESG) leader scores and logistics stocks. China Ocean Shipping Company (COSCO), one of the pioneers in global markets, was chosen to represent the logistics industry. The variables were analyzed with the Time-Varying Parameter Vector Autoregressive Model (TVP-VAR) using monthly data from October 2007 to July 2022. As a result of the analysis, it was determined that the COSCO logistics sector variable spreads the volatility to the Chinese ESG Leaders and CPU variables. This indicates that COSCO, one of the leading companies in the global markets, has an impact on the sustainability scores of the CHINA Stock Exchange. In other words, it has been observed that shock transfer occurs from the COSCO variable to the China ESG Leader and CPU variables. Finally, it proves that the sustainability scores of companies operating in the Logistics sector, especially for China, are dominant among all other sector scores.

Keywords: Climate Policy Uncertainty, ESG, Logistics Sector, COSCO

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İklim Politikası Belirsizliği, Lojistik Firma Hisse Getirileri ve ESG Puanları Arasındaki İlişkisinin Analizi: TVP-VAR Modelinden Kanıtlar

Özet

Bu çalışma iklim politikası belirsizliği (CPU), ESG skorları ve lojistik hisse getirileri arasındaki ilişkiyi incelemektedir. Lojistik sektörünü temsilen China Ocean Shipping Company (COSCO) seçilmiştir. Ekim 2007-Temmuz 2022 döneminin aylık verileri kullanılarak Zamanla Değişen Parametre Vektörü Otoregresif Modeli (TVP-VAR) uygulanmıştır. Analiz sonucunda COSCO`nun volatiliteyi Çin ESG ve CPU`ya yaydığı tespit edilmiştir. Bu durum küresel piyasalarda öncü firmalardan olan COSCO`nun Çin Borsasının sürdürülebilirlik skorları üzerinde etkili olduğunu işaret etmektedir. Başka bir ifadeyle, COSCO değişkeninden Çin ESG skorları ve CPU değişkenlerine şok aktarımı gerçekleştirdiği görülmüştür. Son olarak, özellikle Çin için Lojistik sektöründe faaliyet gösteren firmaların sürdürülebilirlik skorlarının tüm diğer sektör skorları içinde de baskın olduğunu kanıtlar niteliktedir.

Anahtar sözcükler: İklim Politika Belirsizliği, ESG, Lojistik Sektörü, COSCO

1. Introduction

Global warming and climate change are not only one of the most important problems facing humanity in the 21st century, but also a problem that changes the future plans of companies (Chen et al. 2023). On the other hand, policies aimed at combating climate change bring along the efforts of countries around the world to reduce greenhouse gas emissions for a more sustainable future (Gavriilidis, 2021). Therefore, how to regulate environmental protection along with economic growth in the face of climate change has become an important issue all over the world (Ren et al. 2022). The Paris Agreement has brought a new perspective to climate policy, such as promoting the use of clean energy, carbon emission permits and green bonds. However, there are concerns about the uncertainties in the implementation of these policies and the macroeconomic effects of these uncertainties (Li, 2022).

Logistics has become a rapidly growing and developing industry around the world, playing a very important role in global trade and economic growth (Yingfei et al., 2022). The primary purpose for companies is to organize logistics activities in a way that maximizes profitability. However, in recent times, as a result of growing public and governmental emphasis on ecological matters, company have faced mounting demands to diminish the ecological footprint arising from their logistical activities (McKinnon, 2015). The growing trend of globalization, coupled with the rising prominence of outsourcing and commercial interactions within the logistics industry, underscores the critical significance of effective supply chain management. However, this heightened connectivity and economic activity also contribute to environmental challenges. Greenhouse gas emissions stemming from fuel consumption, escalating use of natural resources, and the mounting volume of packaging and other waste types present substantial issues, impacting sustainability across environmental, economic, and social dimensions (Yontar, 2022).

Logistics pertains to the systematic administration of procurement, conveyance, and warehousing of resources, components, and finalized goods across companies and distribution networks, encompassing the associated streams of information to meet order requirements (Christopher, 2011). Green logistics is the main sustainability trend of modern logistics. The notion of eco-friendly logistics pertains to a collection of supply chain management practices concentrated on the handling of materials, waste disposal, packaging, and transportation. Its objective is to minimize the environmental and energy impacts associated with the distribution of goods (Seroka-Stolka & Ociepa-Kubicka, 2019). Maritime transport accounts for more than 80% of world trade, which constitutes a large area for global logistics applications (Pang et al., 2021:423). Although this situation offers shipping companies new opportunities in the global economy, it has caused the maritime industry to cope with some new challenges. The globalization of commercial practices has brought with it climate change and environmental problems caused by maritime transport (Felicio et al. 2021).

Supply chain practices, especially logistics practices, are part of the critical practices of companies that consume more energy and release dangerous gases and wastes into the environment (Agyabeng-Mensah et al., 2020:1). Logistics is the most dependent on fossil fuels of all sectors. In addition, 37% of CO2 emissions in 2021 originate from the logistics sector. Although logistics is one of the sectors most affected by the Covid-19 epidemic, this rate is increasing day by day due to global trade (IEA, 2021). In 2021, global CO2 emissions from the logistics sector rose 8% to around 7.7 Gt CO2, as pandemic restrictions were lifted and passenger and goods movements resumed after the big drop in 2020 (IEA Transport Report, 2022). Figure 1 shows the global CO_2 emission rates in transport by mode for 2020. In Figure 1, "shipping" CO_2 emissions rank third after "passenger cars" and "medium and heavy trucks".

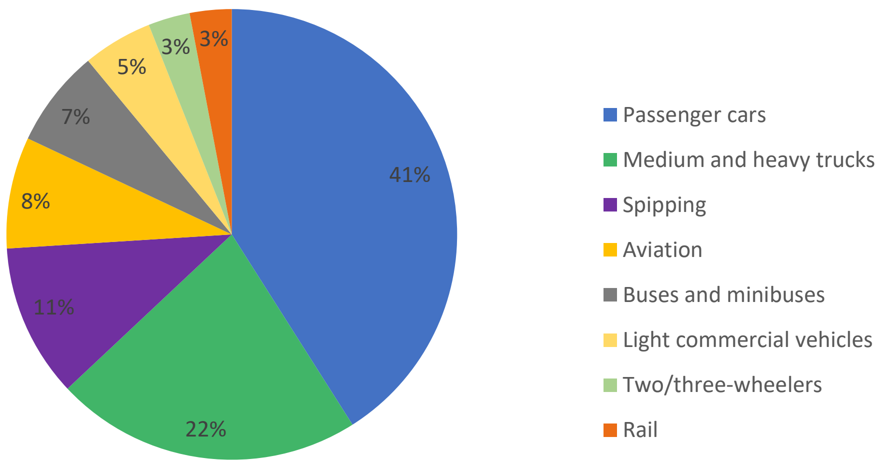

Figure 1. Global CO_2 emissions in transport by mode of 2020

Source: IEA, 2022

The possible stagnation of economies in an environment of uncertainty is supported by academic literature. On the other hand, it is seen that many prediction and calculation methods have been developed for the uncertainties in global markets. Apart from the known methods, an indexing that has been trying to find a place in the academic literature in recent years has come to the fore. These indexes, in which economic and political uncertainties are calculated, appear as a form of calculation that includes political discourses along with financial risk. The climate policy uncertainty index(CPU) is also an index created using this method (Gürsoy, 2021). Combating environmental degradation worldwide is of great importance for both developed and developing countries. The fact that the issue has global as well as local effects forces countries to cooperate in improving environmental quality in this field. Researchers examine numerous determinants of environmental quality that can help reduce the growing ecological footprint and achieve sustainable development and make recommendations on how environmental quality can be improved worldwide. Financial and economic variables can influence environmental dynamics in various ways, ultimately causing environmental degradation or contributing to environmental recovery. As a result of both situations, there is an expectation that environmental sustainability has a two-way interaction, especially with logistics (Shahbaz et al. (2023)

This study explores the correlation spread between CPU, ESG and COSCO stock returns. Previous studies have shown that CPU index and sustainability were examined together. In particular, the relationship between climate policy uncertainty and variables such as sustainable financial assets (stock market, bonds), fossil fuel prices, geopolitical risk, EPU, exchange rate is frequently investigated. The number of studies investigating the relationship between CPU, ESG and stock market is quite limited. In the study, the share prices of China Ocean Shipping Company (COSCO) were taken to represent the logistics sector. COSCO is one of the world's leading conglomerates for container shipping. On the other hand, it is the largest company in China. COSCO is the world's fourth largest container shipping company in 2022, with operations spread over 40 countries with a fleet of approximately 480 container ships with a container carrying capacity of 2,932,779 TEU (Marine Insight, 2023). On the other hand, it is still the fourth largest company in the world with a container transport capacity of 2,888,256 TEU and a market share of 10.8% as of May 19, 2023 (Alphaliner, 2023). In addition, the results of the study are important for investors and company managers. The results obtained will allow policy makers to develop more realistic and accurate sustainable environmental policies.

The rest of this study is created as follows: In the subsequent section a brief literature review is given. In section 3, detailed explanations are given about the time-varying parameter vector autoregressive (TVP-VAR) model. In Chapter 4, after giving information about the variables and data set, analyses are made to determine the asymmetric dynamic spillover relationship and empirical findings are discussed. Finally, the results are evaluated and suggestions for next studies are presented.

2. Literatür Review

In the last few years, the Climate Policy Uncertainty (CPU) Index, MSCI China ESG Leaders Index (China ESG Leaders) and the shipping market have been evaluated from different perspectives in the literature using the time-varying parameter vector autoregressive (TVP-VAR) model. Below is a three-dimensional literature review. First of all, studies on CPU and TVP-VAR model, and secondly, studies on MSCI Index and TVP-VAR model were examined. Finally, studies focusing on the shipping market and TVP-VAR model were examined.

- CPU Index and TVP-VAR Model

Yan and Cheung (2023) explored the changing impacts of Central Processing Unit (CPU) and coal price on the carbon price in China through the implementation of the TVP-VAR model. The research involved the development of a CPU index specifically for China. The findings of the analysis revealed that both CPU and coal price exhibited noteworthy time-varying influences on the carbon price. Yu et al. (2023) examined the time-varying effects of CPU on green bond market volatility using the TVP-VAR model. With short-term overreactions or underreactions as well as medium and long-term inversions were found from the analyses.

Xiao and Liu (2023) evaluated the effect of uncertainty measures of CPU, geopolitical risk (GPR), economic policy uncertainty (EPU), and equity market volatility (EMV) on the oil implied volatility index (OVX) using TVP-VAR model. Empirical results have shown that the CPU is more important to trigger oil market fears since the last Paris Agreement. During the COVID-19 pandemic, CPU, EPU and EMV instead of GPR play an important role in increasing the fear of the oil market.

Zhou et al. (2023) investigated a model known as the time-varying parameter vector autoregressive model with stochastic volatility (TVP-VAR-SV) to ascertain the changing association between CPU, oil prices, and renewable energy consumption. The outcomes of their examination revealed that the relationship between these variables fluctuates over time. In a separate study, Guo et al. (2022) examined the nonlinear impacts of CPU, financial speculation, economic activity, and the US dollar exchange rate on global prices of crude oil and natural gas by employing TVP-VAR-SV models. The findings underscored the existence of significant nonlinear effects in how energy prices respond to various shocks.

- MSCI Index and TVP-VAR Model

Polat et al. (2023) investigated the influence of the media coverage index (MCI) related to COVID-19 on the interconnectedness of return and volatility among five MSCI Climate Changes Indices, namely the USA, Emerging Markets (EMU), Japan, Europe, and the Asia Pacific. The research employed the TVP-VAR model and the frequency-dependent connectedness network approach for analysis. Empirical results underscore that the MCI acts as a recipient of net shocks across all waves, with the highest level of interconnectedness observed in the initial wave. Similar patterns were observed regarding volatility in the findings. Cepni et al. (2023) assessed the influence of climate-related uncertainty on the transmission of effects among conventional and environmental, social, and governance (ESG) financial markets in Europe. The study examined the spillover effects stemming from climate uncertainty within these markets. TVP-VAR and asymmetric dynamic conditional correlation (ADCC) models and portfolio analysis were used in the analyses. The results show substantial evidence of climate uncertainty, important insights into managing climate risk exposures, and the driver of information spillovers across conventional and ESG assets.

Liu et al. (2023) examined the effect of ESG investment on return and volatility spillover effects in major Chinese financial markets such as stock, bond, interbank and foreign exchange markets using the TVP-VAR method. In the study, it was found that sustainability and stability are positively related. Akhtaruzzaman et al. (2022) investigated the dynamic connectedness between the COVID-19 MCI and the ESG leader indices. The results of the analysis showed that MCI facilitated the contagion during the pandemic to the developed and emerging equity markets.

- Shipping Market and TVP-VAR Model

Xie et al. (2023) analyzed risk spillovers in China's financial and maritime markets using dynamic spillover measures based on TVP-VAR and generalized forecast error variance decompositions (GFEVD). Unexpectedly, the study found that bonds, gold, and shipping were safe tools that facilitate portfolio optimization. Samitas et al. (2022-a) evaluated the dynamic interconnections between fine wine, equities, bonds, crude oil, commodities, gold, copper, shipping, and real estate markets using the TVP-VAR model. The research investigated the presence of positive spillovers in terms of volatility among these markets. However, the study revealed that the overall connectedness is susceptible to external shocks, which reach their highest levels during periods of stress.

Samitas et al. (2022-b) analyzed the transmission of volatility between natural alternative investments (such as timber and water) and a range of traditional financial instruments (including bonds, crude oil, gold, real estate, shipping, and currency) using a time-varying spillover methodology. The results indicate that these markets demonstrate a moderate level of integration, and the overall interconnectedness amplifies during periods of heightened stress. In a separate study, Chen et al. (2021) explored the nonlinear and dynamic relationship between the global oil market, the global shipping market, the Chinese stock market, and GDP using the TVP-VAR-SV model. The findings suggest that the impact intensity of the Baltic Dry Index (BDI) on China's economy triggers diverse changes, ranging from positive to negative, across various lag periods.

In Table 1, the author, variable, period information and methodology of the studies in the literature are summarized, respectively.

Table 1. Literature Summary

CPU Index and TVP-VAR Model			
Yan and Cheung (2023)	- CPU Index - Coal Price - Carbon Emission	02.01.2019- 05.05.2022 (daily)	- TVP-VAR Model
Yu, Zhang, Liu and Wang (2023)	- CPU Index - Green Bond Index - Green bond volatility	01.01.2010 - 31.12.2021 (monthly)	- TVP-VAR Model
Xiao and Liu (2023)	- CPU Index - OVX Index - GPR Index - EPU Index - EMV Index	01.05.2007 - 31.10.2021 (monthly)	- TVP-VAR Model
Zhou, Siddik, Guo and Li (2023)	- CPU Index - Oil Prices - Renewable Energy Consumption	01.01.2005 - 30.04.2021 (monthly)	- TVP-VAR-SV Model
Guo, Long and Luo (2022)	- CPU Index - Oil Prices - Natural Gas Prices - Baltic Dry Index - US dollar exchange rate - T-index (WT)	01.01.2000 - 31.03.2021 (monthly)	- TVP-VAR-SV Model

Table 1. Literature Summary (Continuing)

MSCI Index and TVP-VAR Model			
Polat, Khoury, Alshater and Yoon (2023)	- MSCI Climate Change Index - Media Coverage Index	11.03.2020 - 19.01.2023 (daily)	- TVP-VAR Model - Frequency-based TVP-VAR Network Connectedness
Cepni, Demirer, Pham and Rognone (2023)	- MSCI Europe ESG Various Euro-based Leaders Index - ESG Bond Indexes	03.01.2014 - 30.09.2021 (daily)	- TVP-VAR Model - ADCC Model - Portfolio analysis
Liu, Guo, Ping and Luo (2023)	- ESG Stock - General Stock - Interbank Market - Bond Market - FX Market	01.09.2010 - 31.08.2022 (monthly)	- TVP-VAR Model
Akhtaruzzaman, Boubaker and Umar (2022)	- Media Coverage Index - ESG leader Index (EMU, China, Brazil, Russia, India, and South Africa, UK and US)	01.01.2020- 21.04.2021 (daily)	- TVP-VAR Model
Shipping Market and TVP-VAR- (SV) Model			
Xie, Cheng, Liu, Zheng and Li (2023)	- Stock, - Fund - Bond, - Interbank - Forex, - Futures - Gold, - Shipping	20.01.2020 - 26.05.2022 (daily)	- TVP-VAR Model - GFEVD
Samitas, Papathanasiou, Koutsokostas and Kampouris (2022-a)	- Fine wine, Bonds - Equities, Gold - Bonds, - Crude oil, - Commodities, -, Shipping - Copper, -, - Real estate	01.01.2010- 31.05.2021 (monthly)	- TVP-VAR Model
Samitas, Papathanasiou, Koutsokostas and Kampouris (2022-b)	- Timber, - Water - Equities, - Bonds - Crude oil, - Gold - Real estate, - Shipping - Currency	01.01.2010 - 30.09.2021 (monthly)	- TVP-VAR Model
Chen, Zhang and Chai (2021)	- World oil market - Global bulk shipping market - Stock market - Economic growth	01.01.1998 - 31.12.2020 (quarterly)	- TVP-VAR-SV Model

3. Research Methodology

This section provides an elaborate description of the time-varying parameter vector autoregressive (TVP-VAR) model, elucidating its conceptual framework. Figure 2 below illustrates the methodological structure employed in the study.

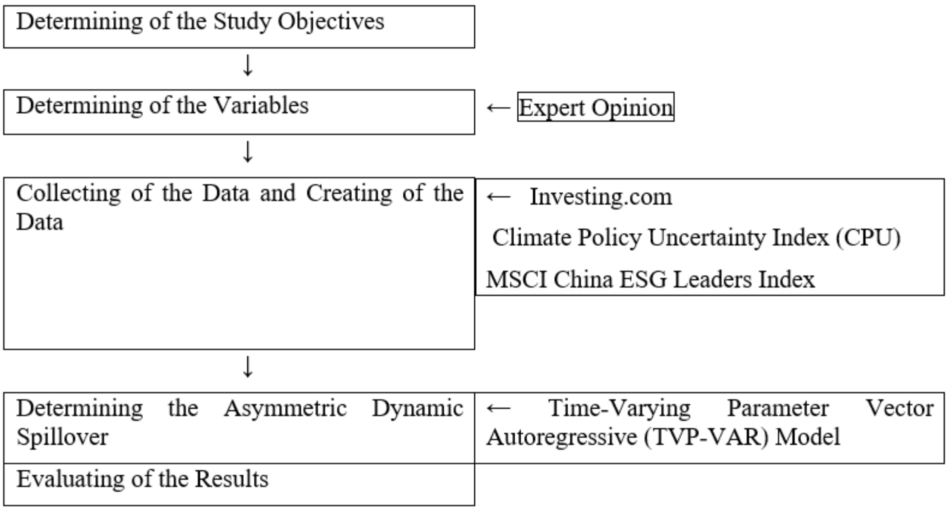

Figure 2. Methodological Framework

In this study, time-varying parameter vector autoregressive (TVP-VAR) model was used to investigate the time-dependent dynamic relationship between the returns of the series, proposed by Antonakakis et al. (2020). The TVP-VAR approach proposed by Antonakakis et al. (2020) allows variation of the variance-covariance matrix over time through a Kalman Filter estimation based on Koop and Korobilis (2014) forgetting factors. In fact, it extends the connectedness approach proposed by Diebold and Yılmaz (2009, 2012, 2014). In this way, the model avoids the possibility that the rolling-windows technique, which has no consensus in the literature about the selection criteria and which is usually chosen arbitrarily, leads to irregular or flattened parameters and the loss of valuable observations (Antonakakis & Gabauer, 2017; Gabauer & Gupta, 2018; Korobilis & Yilmaz, 2018). Accordingly, the model can be used to examine dynamic connectivity measures for both low-frequency data and limited time-series data. The lag length of the series was determined as 1 according to the Bayes information criterion (BIC) and the TVP-VAR (1) estimation was performed.

The TVP-VAR model is expressed as follows:

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

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

with

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

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

Prior prediction is used to initialize the Kalman filter. Based on equations, with A_{OLS}, $\sum_{OLS}^{A}$ and $\sum_{OLS}$ equal to the VAR estimate for the first 20 months:

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

$$\textstyle\sum_0 = \sum_{OLS}$$

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

Time-varying coefficients and time-varying variance-covariance matrices, Koop et al. (1996) and Pesaran and Shin (1998), based on generalized impulse response functions (GIRF) and generalized prediction error variance decompositions (GFEVD) to estimate the generalized connectivity procedure. For the calculation of GIRF and GFEVD, TVP-VAR needs to be converted to a vector moving average (VMA) representation within the framework of the Wold Decomposition theorem. The VMA representation is converted as follows (Dogan et al., 2023; Akkus and Dogan, 2023):

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

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

$$\vdots \tag{5}$$

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

M_t indicate a dimension matrix of the mp × mp, η_t is dimention vector of a mp × 1, J indicate a dimension matrix of the mp × m

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

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

$$\Psi_{j,t}(H) = \frac{B_{H,t} \sum_t e_j}{\sqrt{\sum_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{\sum_{jj,t}}} \qquad \delta_{j,t} = \sqrt{\textstyle\sum_{jj,t}} \tag{8}$$

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

Calculating GFEVD ($\tilde{\phi}_{ij,t}(H)$) which represents bidirectional dependency from j to i. The effect of variable j ' on variable i is explained in terms of estimation error variance shares. The said variance shares are normalized and all variables together explain 100% of the estimation error variance of the variable i. Its mathematical expression is as follows:

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

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

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

This connectedness approach shows the spread of the 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 i to all other variables j, is calculated as follows:

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

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

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

To unveil the Net Total Directional Connectedness, which signifies the impact a variable exerts on the examined network, the disparity between Total Directional Connectedness to Other Variables (TO) and Total Directional Connectedness from Other Variables (FROM) is computed:

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

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 it has; 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, Net Pairwise Directional Connectedness is calculated by decomposing Net Total Directional Connectedness to examine bidirectional relationships:

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

NPDC indicate the situation where variable i dominates variable j or variable j dominates variable i (Antonakakis et al., 2020, pp. 4–7).

4. Analysis

In this section, firstly, information about the variables and data set used in the study was given. Then, explanations were made regarding the findings obtained in the analyses.

4.1. Data Set

This study examined the asymmetric dynamic spillover relationship between China Ocean Shipping Company (COSCO) stock returns, Climate Policy Uncertainty (CPU) and MSCI China ESG Leaders Index (China ESG Leaders). This index is a publicly adjusted, market capitalization weighted index. It was created by taking into account the performance of companies selected from a core index based on Environmental, Social and Governance (ESG). Factor Groups (e.g. Value, Size, Momentum, Quality, Return and Volatility) that have been extensively documented in academic literature. Calculated by taking into account data in the literature and confirmed by MSCI Research as the main drivers of risks and returns in stock portfolios.

A dataset containing monthly data was used for the sampling period from October 2007 to July 2022. First of all, it was determined that the series were not stationary according to the ERS unit root test (Elliott et al., 1996), which takes into account an unknown mean or trend in the series. and the logarithmic return of the series was calculated with the formula $ln\ (y_t/y_{t-1})$ .The graph expressing the logarithmic return of the series is given in Figure 3. Adekoya et al. (2022)'s approach was followed to observe the asymmetric spread in the series and monthly returns were decomposed into positive and negative as follows;

$$y_t^+ = \begin{cases} y_t, & eğer\ y_t > 0 \\ 0, & eğer\ y_t < 0 \end{cases}$$
$$y_t^- = \begin{cases} y_t, & eğer\ y_t < 0 \\ 0, & eğer\ y_t > 0 \end{cases}$$

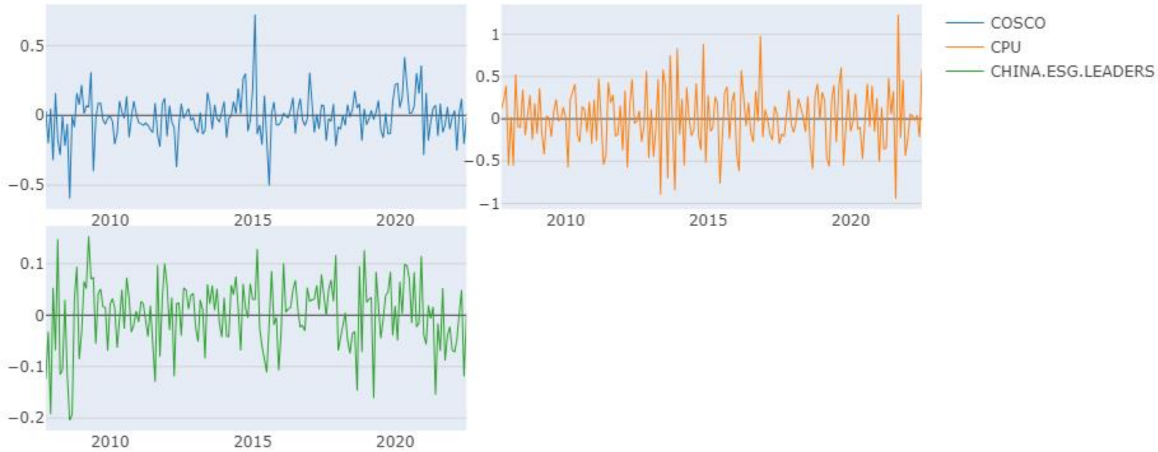

Figure 3. Logarithmic Return of Series

Descriptive statistics of the return series are given in Table 2. According to the ERS unit root test, it was determined that each series has a unit root, that is, the null hypothesis was rejected for all series at 1% or 5% significance level. Fisher and Gallagher's weighted Ljung-Box results show that the returns of all series have significant autocorrelation in their squares. This means that each series has time-varying variances and it is appropriate to use the TVP-VAR model in the study.

Table 2. Descriptive Statistics

	COSCO	CPU	CHINA.ESG.LEADERS
Mean	-0.008	0.008	0.001
Varyans	0.024	0.132	0.004
Skewness	0.185	0.089	-0.524***
	-0.298	-0.616	-0.005
Ex.Kurtosis	3.586***	0.326	0.365
	0	-0.285	-0.248
JB	96.372***	1.022	9.142***
	0	-0.6	-0.01
ERS	-4.231***	-5.208***	-1.479*
	0	0	-0.141
Q(10)	9.523*	27.712***	4.025
	-0.087	0	-0.661
Q2(10)	5.24	13.443**	24.735***
	-0.47	-0.013	0

Note: *, ** and *** represent significance level at 1, 5 and 10% respectively

Within Table 2, you will find an overview of the descriptive statistics pertaining to the variables utilized in this research. The results show that the variables are not normally distributed and do not include unit root. In addition, Q and Q2 test statistics show that it contains autocorrelation.

4.2. Findings

4.2.1. Average connectedness

Average connectivity results are given in Table 3. The upper section of Table 3 displays the comprehensive outcomes, disregarding any asymmetry. The lower sections, however, focus on assessing measures of asymmetric interconnectedness concerning both positive and negative returns. The values along the diagonal represent the impact of past shocks from the variables on their respective error variance. Conversely, off-diagonal values indicate the binary correlation between variables within the network. It is evident that the diagonal values surpass other values within the network, highlighting the significant contribution of variables' own shocks to the estimation error variance. For example, the largest value in the COSCO column is 87.49, which represents an 87% contribution to its own forecast error variance. A value of 22.77 in the column indicates a 23% return spillover from COSCO to China ESG Leaders.

The Corrected Total Connected Index (cTCI) value shows the total connectivity within the network regardless of time. The cTCI value at the top of the table is 29%, implying that the interdependence of the variables within the network is partially high. The “From” column represents the connectedness to a variable that is passed from all other variables in the network; The “To” line indicates the transfer of connectivity from one variable to all other variables in the network. When the relationship between “From” and “To” is examined for each variable, the correlation of COSCO stock returns to other variables in the network; It is observed that the China ESG Leaders index is the variable that is transferred from the other variables in the network. However, looking at the average net donors and net buyers, the main net giver within the network is COSCO stock returns. China ESG Leaders and CPU indices are net buyers in the network.

The middle and bottom of Table 3 represent positive and negative returns, respectively. It shows that both the main findings and the findings from positive and negative returns are similar in terms of ranking of network transmitters and network receivers. It should be noted, however, that cTCI is greater in connectivity based on negative returns (31%) compared to that based on positive returns (ie 16%). Negative returns have higher overall network connectivity, implying evidence for asymmetric effects.

Table 3. Average Connectivity

	COSCO	CPU	CHINA.ESG.LEADERS	FROM
COSCO	87.49	1.74	10.77	12.51
CPU	4.4	85.42	10.18	14.58
CHINA.ESG.LEADERS	22.77	8.4	68.82	31.18
TO	27.17	10.14	20.95	58.27
Inc.Own	114.66	95.56	89.78	cTCI/TCI
NET	14.66	-4.44	-10.22	29.13/19.42
NPT	2	0	1	
+	**COSCO**	**CPU**	**CHINA.ESG.LEADERS**	**FROM**
COSCO	91.94	4.15	3.91	8.06
CPU	5.12	88.32	6.56	11.68
CHINA.ESG.LEADERS	7.04	6.14	86.82	13.18
TO	12.16	10.29	10.47	32.92
Inc.Own	104.1	98.61	97.29	cTCI/TCI
NET	4.1	-1.39	-2.71	16.46/10.97
NPT	2	0	1	

Table 3. Average Connectivity (Continuing)

-	COSCO	CPU	CHINA.ESG.LEADERS	FROM
COSCO	77.17	2.1	20.73	22.83
CPU	4.83	92.29	2.89	7.71
CHINA.ESG.LEADERS	29.5	2.21	68.29	31.71
TO	34.33	4.31	23.61	62.25
Inc.Own	111.5	96.6	91.9	cTCI/TCI
NET	11.5	-3.4	-8.1	31.12/20.75
NPT	2	0	1	

Note: The outcomes are derived from an analysis utilizing a TVP-VAR model with a lag length determined by the Bayesian Information Criterion (BIC) and a generalized prediction error variance decomposition conducted up to 20 steps ahead.

4.2.2. Dynamic total connectivity

The above-mentioned measures of mean connectivity are time-independent and, therefore, it is not possible to observe the dynamic evolution of spillovers between variables. Considering that various economic and political events occurred during the sample period that could affect the returns of the series positively or negatively, it would be more accurate to focus on dynamic measurements. From this perspective, the Total Connectedness Index (TCI) results, which show the change in the dynamic total interconnectedness between the returns of the variables during the sample period, are given in Figure 4. The black shaded area shows the evolution of the TCI, which includes both positive and negative values. With this, the green line on the Chart represents the TCI consisting of only positive returns, while the red line represents only negative returns.

Focusing on the black shaded area to observe the evolution of connectivity within the network throughout the sample period, it is seen that the connectivity between the variables exhibits a decreasing trend over time. Despite the downtrend from 80% to 20%, the correlation between the variables is relatively strong. Also, although the three different series exhibit a qualitatively downward trend, the correlation between positive returns is very low, while the correlation between negative returns is much higher, supporting previous findings. The fact that the correlation between negative returns is relatively higher and volatile compared to positive returns reveals that negative news is more effective on stability in the network.

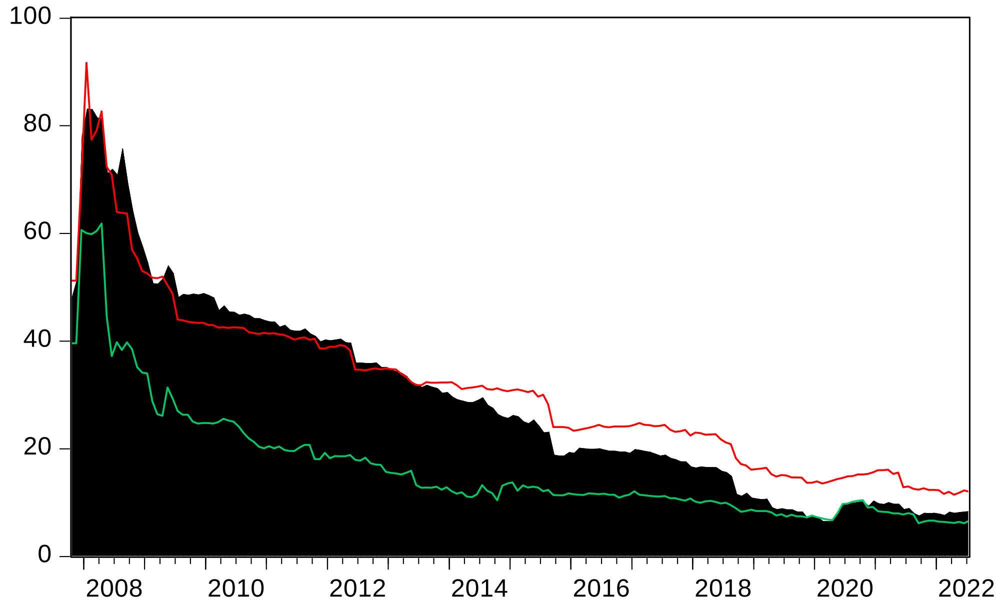

Figure 4. Total Connectedness Index (TCI)

Notes: Results presented herein are derived from a TVP-VAR model utilizing a lag length of one (selected based on the Bayesian Information Criterion) and a generalized prediction error variance decomposition conducted up to 20 steps ahead. In the visual representation, the black region corresponds to the symmetrical total interconnectedness, while the green and red lines signify positive and negative total interconnectedness, respectively.

4.2.3. Net total and net bidirectional connectivity

Net Total Directional Connectivity provides a dynamic view of the net-receiving or net-transmitting role of a variable. The results are given in Figure 5. A positive value in Figure 5 indicates that the variable is a net transmitter in the network, and a negative value indicates that it is a net receiver. It should be noted that the role of a variable in the network may change over time.

In Figure 5, according to the total returns without considering the asymmetric relations; During the entire sample period, China ESG Leaders are net receiver and COSCO is net transmitters. However, the role of the CPU index changes over time, but is usually in the receiver position.

According to the results of asymmetrical interconnectedness relations, a role change occurs between the positive returns of all variables. In terms of negative returns; There is no role change in the negative returns of COSCO and China ESG Leaders. Unlike general findings, especially in some periods, COSCO is the receiver of positive returns from China ESG Leaders.

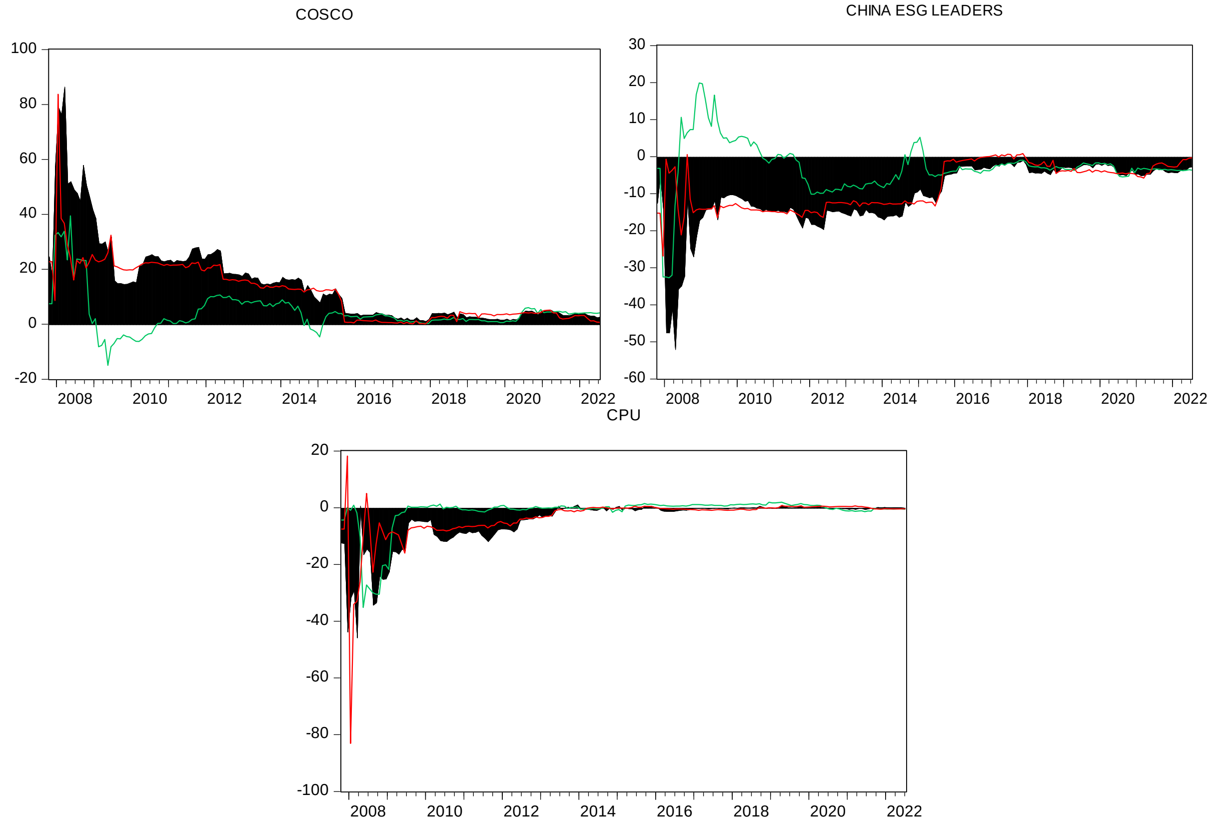

Figure 5. Net Total Directional Connectivity

Notes: The outcomes stem from an analysis employing a TVP-VAR model with a lag length determined by the Bayesian Information Criterion (BIC) and a generalized prediction error variance decomposition extending up to 20 steps ahead. The shaded region depicted in black signifies the overall balanced interconnectedness, while the presence of green and red lines denotes positive and negative interconnectedness, respectively.

For more detailed inferences, we focus on Net Bidirectional Connectivity results. The Net Bidirectional Connectivity results given in Figure 6 show the dynamic interconnectedness between two variables in the network. Each graph represents the net transmitter/receiver role of the variable named in the first row with respect to the variable named in the second row. For example, when we examine the black shaded area in the "COSCO-CHINA ESG LEADERS" graph, we can say that China ESG Leaders were net recipients of emissions from COSCO during the entire sample period. Findings from both general and positive and negative returns support previous findings.

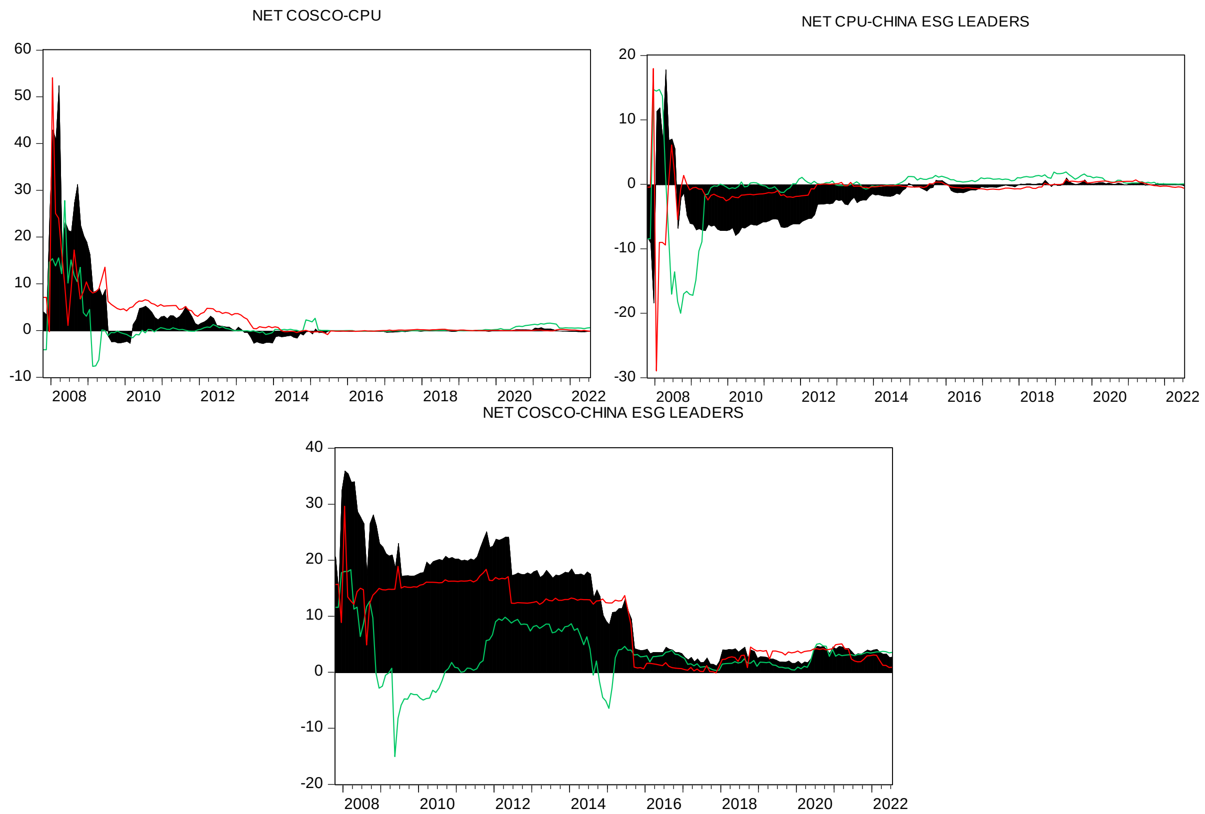

Figure 6. Net Bidirectional Connectivity

Notes: The findings presented in this study are derived from an analysis conducted using a TVP-VAR model, employing a lag length determined by the Bayesian Information Criterion (BIC), and a generalized prediction error variance decomposition carried out up to 20 steps ahead. The shaded region in black illustrates the comprehensive interconnectedness, while the presence of green and red lines indicates positive and negative connectivity, respectively.

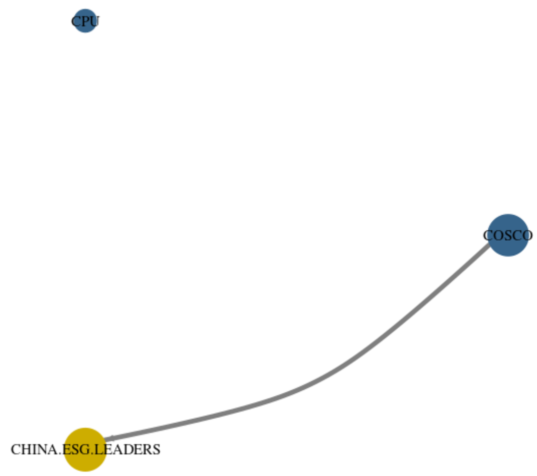

Figure 7. Network graph representation of volatility spillover of variables.

In Figure 7, the connectivity transfer network between the variables is presented. The blue dots represent the transmitter variables that conduct connectivity to other variables, and the yellow dots represent the receiver variables that are linked from other variables. The size of the variable circles indicates the effect size of the transmitter or receiver variable. The arrows drawn from the circles show the direction of the relationship between the variables, while the thickness of these arrows shows the strength of the relationship. When the graph is examined, COSCO is the variable that transmits the shock, while the China ESG Leaders and the CPU are the variables that receive the shock. Shock transfer takes place from the COSCO variable to the China ESG Leaders variable.

5. Conclusion

This study explored the link between CPU, ESG and COSCO stock return spread. An autoregressive model with time-varying parameter vector was used in monthly data covering the period October 2007-July 2022. As a result of the analysis, it was seen that the volatility spread to the COSCO variable, China ESG Leaders and CPU variables. In other words, shock transfer occurred from the COSCO variable to the China ESG Leader and CPU variables.

As a result of industrialization, environmental degradation increases significantly with the developing economic development. Countries need to realize their management and strategies within the framework of sustainability. Since the logistics sector acts as a bridge in trade, it is important to take measures to prevent environmental degradation. In addition, determining the leading criteria in the realization of green logistics activities and ensuring the selection of areas according to these criteria is one of the steps that should be taken in order to prevent environmental degradation caused by the logistics sector. Based on the findings obtained as a result of the study, the evaluation of the logistics sector in terms of green transformation and the centralization of the sector with this awareness will make a great contribution to solving the greenhouse gas problem in the world.

There are a number of limitations to this research, which examines the correlation spread between CPU, ESG and COSCO stock returns. First of all, the results should be evaluated in terms of COSCO share returns, which represent the logistics industry. Future studies on green logistics activities will help environmental sustainability policy makers. In addition, examining the relationship between the logistics sector index and sustainability indices, clean energy indices and carbon emission indices will contribute to the literature.

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