The Risk Spillover Effect Between the EUA Carbon Market and Carbon-intensive Sectors in European Stock Markets

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Abstract

This study examines the risk spillover effect between European emission allowance (EUA) carbon price and the indices of energy-intensive industries in the stock market in the European countries. To achieve this, we employ the Diebold and Yilmaz model to investigate both the static and dynamic risk spillover effect and discuss the impact of the economic conditions and policy changes on the carbon market. The findings reveal that the carbon market primarily acts as a risk receiver, with the main transmission of risk occurring from the electricity and energy sectors. Notably, these effects are more pronounced during periods marked by significant events. The results of our research can offer valuable insights to policymakers and investors, facilitating market stabilization and effective management of investment risks.

Keywords: Risk spillover, EUA carbon market, Carbon-intensive sectors, European stock markets, Diebold and Yilmaz model.

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1. Introduction

This paper presents a quantitative research study that investigates the risk connectedness between the EUA (European Union Allowance) carbon market and five prominent stock indices representing the electricity, conventional energy, new energy, material, and consumer staples sectors. By examining the impact of carbon market fluctuations on sector-specific stock performance, as well as the reverse relationship, we provide valuable insights to support informed decision-making within an environmentally conscious society.

The continued emission of greenhouse gases into the atmosphere is causing the Earth's temperature to rise, leading to severe environmental consequences. With the increasing public awareness of global warming, many countries and international organizations have implemented policies and regulations aimed at reducing greenhouse gas (GHG) emissions in response. The United Nations Framework Convention on Climate Change (UNFCCC), for instance, is the most influential international binding agreement established by the United Nations in 1992 with the clear purpose to stabilize greenhouse gas concentration in the atmosphere. Kyoto Protocol (1997), as an extension of the UNFCCC, further stipulates the objectives of reduction of greenhouse gas concentration.

The carbon trading system, first introduced in the Kyoto Protocol, is considered an important method to mitigate carbon emissions. Such a market enables companies to purchase additional carbon emissions permits if they fall short of meeting their emission obligations or sell their excess permits to those who have a shortfall. In 2005, the European Union implemented the world's first carbon trading system, known as the EU Emission Trading System (EU ETS). It has since become the largest carbon trading market globally.

The EU ETS operates on the principle of "cap and trade" where companies in certain sectors, such as power generation and energy-intensive industries involved in greenhouse gas capture and storage, are required to participate in the system. A cap is the total amount of greenhouse gas that can be emitted by companies covered by the system, and it is reduced over time to achieve the objective of emission reduction. Currently, the goal is to cut greenhouse gas emissions by at least 55% by 2030 as proposed in the 2030 Climate Target Plan (European Commission, 2020).

The EU ETS has undergone three phases to date: phase 1 (2005-2007), phase 2 (2008-2012), and phase 3 (2013-2020). It is currently during the 4th phase (2021-2030). Each phase has brought about stricter regulations and improvements to the system. For example, the cap is reduced annually by a linear reduction factor of 1.74% in phase 3 and 2.2% in phase 4 as a target. Additionally, the Market Stability Reserve (MSR) was implemented in 2019 to resolve the oversupply issue caused from phase 1 and 2.

Due to the novelty of carbon trading, there has been ongoing debate and research on carbon prices, the effects of the carbon market, and its associated risks. As a new financial market and instrument, its relationship with other financial markets has attracted extensive attention. Many scholars have found correlation between the carbon market and other financial markets, including the energy and stock markets (Emilie Alberola et al., 2008; Anna Creti et al., 2012; Nicolas Koch et al., 2014). Moreover, existing literature demonstrates how these markets interact with each other and how financial risk can be transferred across different markets, which is known as risk spillover.

Risk spillover occurs when a risk or shock originating from one sector or area of the economy spreads to other areas or sectors. This phenomenon is facilitated by interlinkages between different parts of the economy, enabling risks to amplify and propagate across various regions, markets, and institutions.

As the economy shifts towards a low-carbon future, the carbon market and its associated policies will play a critical role in driving this transition. The impact of changes in carbon prices and policies is expected to be particularly significant for energy-intensive companies, making it crucial to examine the risk spillover between the carbon market and equity market. Understanding the interdependence and potential contagion effects can provide valuable insights for both investors and policymakers, helping them to gauge the extent of risk transmission between the two markets.

Investors in the carbon market can use this knowledge to effectively manage their portfolios and mitigate potential losses, while policymakers can identify areas where regulations may need to be adjusted to manage systemic risk. Additionally, understanding the risk spillover between the two markets has implications for financial stability and can promote the stable development of the carbon market. Therefore, analyzing risk spillover is crucial for investment decision-making, risk detection and management, and promoting financial stability.

In practicality, numerous scholars have conducted studies on the risk spillover between the carbon market and the energy market (Mehmet Balcılar et al., 2016; Dayong Zhang et al., 2018; Julien Chevallier et al., 2019; Yuqin Zhou et al., 2022), and results indicate the presence of interdependence across these markets. However, there is a relatively scarcity of research focusing on the carbon and stock markets in European markets. Furthermore, most of the existing studies tend to concentrate on a specific index (Anupam Dutta et al., 2018; Waqas Hanif et al., 2021; Qiang Ji et al., 2019). Given the findings that the stock market influences the EU carbon prices in a complex way (Creti et al., 2012; Nicolas Koch et al., 2014), investigating the movement of shocks and interactions within these markets becomes a valuable area of study. Hence, we build upon the research conducted by Waqas Hanif et al. (2021), which solely examined the risk spillover between the carbon price and the clean energy index. In our paper, we expand the scope by including five stock indices, namely electricity, conventional energy, new energy, material, and consumer staples, where the equities have a substantial contribution to carbon emissions, as stated in the Inventory Report (2023) from the European Environment Agency, to investigate the risk spillover effect against the carbon allowance market. Additionally, we adopt Diebold and Yilmaz (2012) model, which offers a more comprehensive approach by considering both the magnitude and direction of risk spillover. By taking into account the joint distribution of asset returns, the DY model provides valuable insights into the intensity and directionality of risk transmission between different markets. One of the key advantages of the DY model is its ability to capture the interconnectedness among multiple assets or markets. This allows for a more comprehensive understanding of risk transmission channels and interdependencies. Financial systems are inherently complex, and the DY model helps us to grasp the intricate relationships and dynamics at play, which allows us to uncover the intricate relationships and dependencies within the financial system, contributing to a more comprehensive assessment of risk transmission dynamics.

This research contributes from three perspectives. First, this paper investigates the risk spillover effect between carbon price returns and returns of five stock indices which represent sectors that account for over 90% of annual greenhouse emissions within EU countries. Second, this paper introduces the risk spillover model proposed by Diebold and Yilmaz (2012) to examine the risk spillovers, enabling the assessment of directional spillover effects. Meanwhile, a rolling window technique is implemented in the DY (2012) model to investigate the time-varying risk transmission over time. Third, the research primarily focuses on phase 3 and phase 4 of EU ETS, incorporating the latest available data. By updating previous research with up-to-date information, this study offers novel evidence and insights into the risk spillover dynamics between the carbon market and the selected stock indices, showing evidence of the risk transmission to the EUA carbon market.

The remainder of the paper is organized as follows: Section 2 summarizes the related literature reviews. Section 3 introduces the methodology of the risk spillover and connectedness approaches; Section 4 describes the data; Section 5 demonstrates and analyzes the empirical results; and Section 6 discusses the conclusions based on the results.

2. Literature

The literature on carbon markets has received significant attention in recent years, with numerous scholars dedicating their research efforts to exploring different aspects of the carbon market. In this section, we provide a comprehensive summary of the key findings and contributions from these scholarly works.

2.1. Carbon Price Determinant

The carbon price is determined through the interaction between government supply and enterprise demand within emission trading schemes. Several studies have analyzed the factors influencing carbon prices. For example, Chang-Jing Ji et al. (2018) discuss and summarize the carbon market price mechanism in different countries based on price theories and its influencing factors. From the enterprises' perspective which affects the product demand in the carbon market, Julien Chevallier (2015) verifies that industrial production and economic activities have a significant effect on the carbon price. Keen N (2014) finds that except for the economic conditions, the development of renewable energy source and the growth of wind and solar electricity production is an important price determinant of EUA prices. Gernot Wagner et al. (2015) further demonstrate the energy use structure by enterprises, including wind and solar power, showing it has influence on building an effective carbon prices. From the government's perspective, policies such as price limits, carbon permit reserves, and supervision affect carbon prices directly. Government actions such as quota allocation, taxes, subsidies, and other mandatory measures indirectly impact carbon prices. Yue-Jun Zhang et al. (2015) specifically highlight that the carbon price is influenced by the allocation rules within the Emissions Trading Scheme (ETS), stricter allocation rules within the ETS lead to higher carbon prices, potentially incentivizing greater emission reduction efforts by covered enterprises. Alberola et al. (2008) identify the oversupplied allowance affects the carbon price during phase 1 of EU ETS. Dallas Burtraw et al. (2001) and Rong-Gang Cong et al. (2010) analyze the potential impact of different allocation options of allowance, showing the design has a different impact on the carbon price.

In addition to the factors mentioned earlier, other studies have examined various factors influencing carbon prices within ETS. Anna Creti et al. (2012) investigate the determinants of carbon prices of EU ETS in phases 1 and 2, highlighting the equilibrium relationships that exist for both phases. Piia Aatola et al. (2013), Christiansen A.C. et al. (2005), and Emilie Alberola et al. (2008) discover a strong relationship between carbon prices and energy prices, including fuel prices, electricity prices, economic growth, and even weather conditions, suggesting their significance as determinants of carbon prices. Julien Chevallier (2011) analyzes the volatility of carbon prices based on three measures from distinct datasets and detects periods of instability. Frank J. Convery et al. (2007) focus on the legal framework and policies that have influenced carbon prices and the development of the EUA market, showing the scheme has effectively established a transnational price signal while showcasing strong political support and institutional capacity. These studies contribute to a comprehensive understanding of the factors shaping carbon prices and their dynamics within ETS.

2.2. Risk Spillover across Carbon Market and Financial Markets

The interrelationship and linkages between carbon prices and energy prices have been established as carbon price determinants. Based on the above articles, the dynamics of volatility transmission between carbon markets and energy markets, including its risk management, have been explored by many scholars, indicating there exist closed links. From the methodological viewpoint, the multivariate GARCH model, copula-CoVaR model, and Diebold and Yilmaz (DY 2009, 2012, 2014) model are largely used in the research of risk spillover. Early studies, such as Mehmet Balcılar et al. (2016) examine the risk spillover between Europe-based carbon futures contracts and energy future prices by using Markov regime-switching dynamic correlation, generalized autoregressive conditional heteroscedasticity (MS-DCC-GARCH) model, investigating significant dynamic risk spillover from the energy to carbon market and develop hedging strategies for EUA market and CER market respectively. Dayong Zhang et al. (2018) study the carbon-energy system, including electricity and clean energy prices, with the VAR model and DY (2014) model, revealing that the electricity market is the main net information receiver in terms of both returns and volatility. Bangzhu Zhu et al. (2020) examine positive risk spillover effects from carbon to electricity market and negative spillover effects from electricity to carbon market by using the conditional Value-at-Risk (CoVaR) model. While Juan C. Reboredo (2014) find there are no significant risk spillovers between EUA and oil markets by using a multivariate conditional autoregressive range model, Qian Ding et al. (2022) have obtained contrasting findings, indicating that the carbon market is the net receiver of spillovers from the oil market and clean energy markets. Ruirui Wu et al. (2022) adopt CoVaR model to measure the extreme risk spillovers to carbon markets from energy markets, showing that extreme events cause large shocks.

However, the risk of the carbon market is not solely dependent on the energy market but is also interconnected with other financial markets. The research about risk spillover and connectedness between the carbon market and other sectors of the stock market is less explored. Waqas Hanif et al. (2021) use the spillover index method proposed by Diebold and Yilmaz (2012, 2014) and Baruník and Křehlík's (2018), and copula model to investigate the time-varying frequency spillovers and connectedness between EUA prices and renewable energy indices, indicating that the carbon market is the risk receiver. Qiang Ji et al. (2019) investigate the carbon price return and electricity stock returns based on firm-level, showing the spillover effect is relatively high.

Given this background, this research aims to analyze the risk spillover between the carbon market and related sectors in the stock markets, namely the electricity, material, conventional energy, new energy, and consumer staples sectors, which expand the previous studies to a variety of sectors. We adopt the VAR, Diebold and Yilmaz (DY) model, and rolling window to get both the static and dynamic spillover index. Unlike previous studies, this research focuses on the spot carbon price of phase 3 and phase 4 of the EU ETS, investigating changes in spillover in response to policy and regulatory changes aimed at increased emissions cuts.

3. Methodology

This paper is investigated with the Diebold and Yilmaz (DY) risk spillover model statically and dynamically. The DY model starts with the construction of a vector autoregressive (VAR) model, the computation of the forecast error variance decompositions (FEVD), and the calculation of spillover index measures.

In this section, we will provide a comprehensive explanation of the DY model construction, and the approach of the dynamic analysis. This section is divided by 3 subsections: Spillover Models, Spillover Measures, and Dynamic Approaches.

3.1. Spillover Models

To determine the Diebold and Yilmaz spillover indices, we start with constructing an N-variable vector autoregressive (VAR) model:

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t \tag{1}$$

where x_t is the vector of returns of each market, Φ_i is a coefficient matrix, and $\varepsilon \sim (0, \Sigma)$ is the error vector which is independently and identically distributed. To determine the lag p, the VAR model is fitted with lags ranging from 1 to 12, and the AIC scores for each model with different lag values are computed. The model with the lowest AIC score is considered optimum.

Following that, the VAR model is transformed into a vector moving average (VMA) representation, which is:

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{2}$$

where A_i is a $N \times N$ coefficient matrix that follows the recursion of $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$, with A_0 being an $N \times N$ identity matrix, and with $A_i = 0$ for $i < 0$. The Σ and A_i derived from the VAR model and the VMA model are required for the following computation of the spillover measures.

The spillover indices are defined based on the KPPS H-step-ahead forecast error variance decomposition (FEVD). H is the forecast horizon. The estimator of spillovers from x_j to x_i, is defined as the fraction of the H-step-ahead forecast error variances in x_i that are due to the shocks to x_j, denoted as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \tag{3}$$

where Σ is the variance matrix of the error vector ε, σ_{jj} is the standard deviation of the error term of the jth equation. e_i is the selection vector, with one as the ith item and zero otherwise. If $i \neq j$, we can get the variance shares across two different markets, which is considered the risk transition in between. Accordingly, if $i = j$, we will obtain the variance shares of the market on itself. After the construction of the FEVD, we further generalize the estimators by the row sum, denoted as $\tilde{\theta}_{ij}^{g}(H)$, such that the row sum $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H)$ equals to unity, and the total forecast error variance $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)$ equals to N.

3.2. Spillover Measures

Based on the generalized FEVD, we can acquire four types of spillover indices, which are Total Spillover (TS), Directional Spillover (DS), Net Directional Spillover (NDS), and Net Pairwise Directional Spillover (NPDS). The definitions are revealed in the following subsections.

Total Spillover (TS)

The Total Spillover measures the contribution of spillovers of the cross-market volatility shocks to the total forecast error variance:

$$S^{g}(H) = \frac{\sum_{i,j=1\, i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{\mathrm{N}} \times 100 \tag{4}$$

Directional Spillover (DS)

The Directional Spillover provides the directional risk transmission for each market. A FROM DS of market i means the volatility spillovers come FROM all other market j to market i, denoted as:

$$S_{i \leftarrow j}^{g}(H) = \frac{\sum_{j=1\, j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{\mathrm{N}} \times 100 \tag{5}$$

A TO DS of market i is regarded as the volatility spillovers that come from market i TO all other market j. The equation is similar to Equation 5 but switches the notation of i and j.

Net Directional Spillover (NDS)

The Net Directional Spillover provides a net spillover measurement between two markets including the net direction and amount. The NDS from market i to all other market j is defined as:

$$S_i^g(H) = S_{j\leftarrow i}^g(H) - S_{i\leftarrow j}^g(H) \tag{6}$$

which is the difference between the volatility shocks of market i transferred to and received from all other market j.

Net Pairwise Spillover (NPDS)

The Net Pairwise Spillover offers a more detailed view, where we can see the interconnectedness between two specific markets. Similar to NDS, a NPDS is the difference between the volatility spillovers transmitted from market i to a specific market j and those transmitted from the specific market j to market i, which is defined as:

$$S_{ij}^g(H) = \left(\frac{\tilde{\theta}_{ji}^g(H) - \tilde{\theta}_{ij}^g(H)}{\mathrm{N}}\right) \times 100 \tag{7}$$

3.3. Dynamic Approaches

The dynamic analysis is performed by implementing the rolling window technique on the DY spillover model, which originally yields static results for the dataset. By employing the rolling window technique, we can compute spillover measures for various data windows. For instance, let us consider a rolling window of 200 days. The spillover indices will be calculated at regular intervals of every 200 observations. The first calculation will cover the period from the 1st to the 200th observation, the second calculation will encompass the period from the 2nd to the 201st observation, and so forth. By adopting this approach, we gain visibility into the time-varying trends of spillovers, enabling us to capture the changes and fluctuations that occur over time. This enhances our ability to analyze and interpret the spillover phenomena in a more nuanced and accurate manner.

4. Data

For the carbon market, we utilize the spot prices from the European Energy Exchange (EEX) for both phase 3 (2013-2020) and phase 4 (2021-2023). While for the stock markets, five indices are selected: The STOXX Europe 600 Utilities index, The STOXX Europe 600 Basic Resources index, The STOXX Europe 600 Oil & Gas index, NASDAQ OMX Clean Energy Focused Europe index, The STOXX Europe 600 Industry Consumer Staples EUR Price index. These indices can be representative index that are linked to the European carbon market. These datasets are obtained through Refinitiv Eikon, with daily granularity.

According to the data availability, it covers a range from October 31, 2012, to December 31, 2020, for phase 3 (2046 observations) and from January 5, 2021, to March 13, 2023, for phase 4 (565 observations), consisting 2611 observations in total.

We compute the daily return by $(p_t - p_{t-1})/p_{t-1}$. Table1 presents the descriptive statistics of the daily return series. It is observed that all the returns have positive means, with the carbon market exhibiting the highest mean. Similarly, it has the largest standard deviation at the same time. To assess the normality of the data, we conduct the Jarque-Bera normality test (JB). The results indicate that none of the series follow a normal distribution. Furthermore, Augmented Dickey–Fuller test (ADF) shows that all the series are stationary.

Table 1

Summary statistics of returns.

	EUA	Electricity	Material	Conventional energy	New energy	Consumer staples
mean	0.15	0.02	0.03	0.01	0.05	0.02
std	3.25	1.11	1.85	1.56	1.22	0.90
min	-33.62	-14.24	-14.40	-16.83	-12.80	-8.23
max	22.37	6.11	15.87	15.78	8.78	3.91
Skewness	-0.34	-1.14	-0.05	-0.41	-0.61	-0.49
Kurtosis	11.67	16.95	8.44	17.43	10.57	8.68
Jarque-Bera	8224.63***	21740.10***	3223.88***	22702.60***	6398.55***	3610.09***
ADF	-14.90***	-15.68***	-14.43***	-16.01***	-11.96***	-50.70***

Note: *The table shows mean, the standard deviation (SD), minimum (min), maximum (max), skewness, and kurtosis statistics. It also reports the Jarque-Bera normality test (JB) and ADF stationary test. The asterisks ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively.*

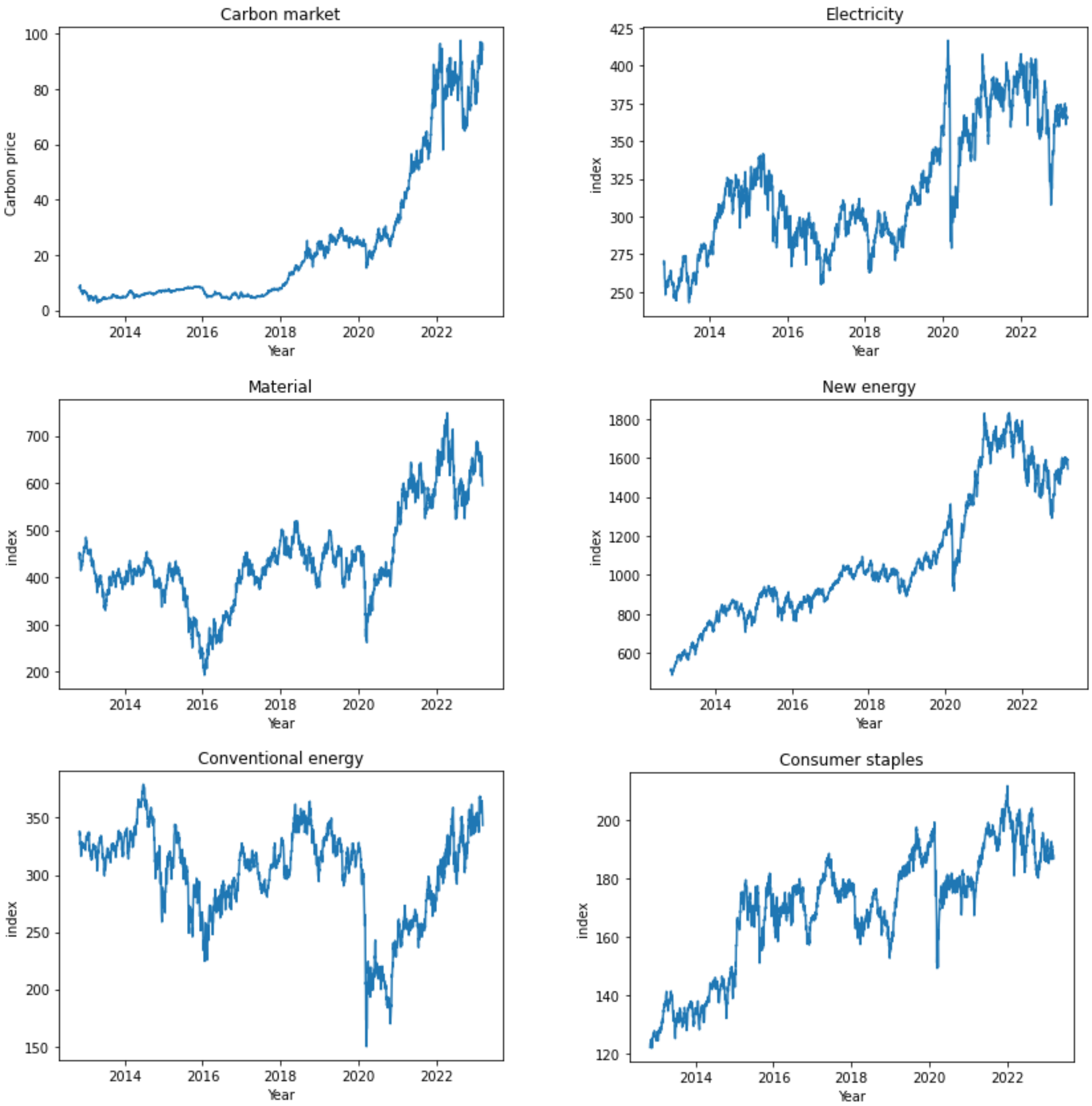
Fig.1 plots the carbon price and the five stock market indices, and their returns are shown in Appendix Fig. A1. The plot reveals that the carbon prices were relatively low before 2018 but started to increase in 2020, reaching a new high of around 100 euros per metric ton of carbon in 2022. Since then, they have fluctuated around 90 euros. The low prices before 2018 were mainly due to the oversupply of carbon permits in the EU ETS, combined with the lack of strong policies and the 2008 financial crisis, which further contributed to the oversupply of permits due to low demand and decreased industrial activities.

To address the oversupply of carbon permits and strengthen the ETS's effectiveness in reducing greenhouse gas emissions, the EU implemented a series of reforms in 2018, such as adjusting the cap on emissions reduction and reducing the number of allowances. Furthermore, Market Stability Reserve (MSR) is introduced in 2019. This measure helped to create a more balanced supply and demand for permits, resulting a higher carbon prices, and reflecting the EU's commitment to improving the functionality of the ETS and ensuring its effectiveness in driving emissions reductions.

In early 2020, the outbreak of the COVID-19 pandemic had a significant impact on global financial markets, particularly on the stock markets. This unprecedented crisis led to a sharp decline in both the stock market and the carbon prices, albeit with a relatively smaller impact on the latter. However, since then, the EU stock market has largely recovered, with certain industries, such as materials and new energy, even reaching new highs.

The implementation of Phase 4 of the EU ETS in January 2021 marked a significant milestone in carbon market reforms. As the global economy began to recover, carbon prices started to climb and reached new highs. This upward trend reflected the growing recognition of the importance of reducing greenhouse gas emissions and the increased demand for carbon permits. However, the Russia-Ukraine war in early 2022 led to a steep fall in carbon prices. The conflict had a profound impact on financial markets, resulting in fluctuations in both the carbon and stock markets.

Fig.1. Dynamics of prices for EUA carbon market and five indices in the stock market



5. Empirical Results and Analyses

In this section, we will present and analyze the empirical results of both static and dynamic risk spillover separately, considering the data and methodology employed in our study.

5.1. Static Risk Spillovers

We explore the static risk spillover between the carbon market and five indices in the stock market. To determine the most appropriate Vector Autoregression (VAR) model and lag order, we compute and compare the Akaike information criterion (AIC) value. The lag is identified as 1 since it corresponds to the lowest AIC value. The results of the static spillover matrix, including the sum of FROM, TO and NET for each variable are displayed in Table 2.

To further examine the direction of spillover effects, we calculate the directional spillover index by selecting the row sums FROM and column sums TO, indicating the spillover effect FROM all other markets to one market, and the spillover effect from one market TO all other markets, respectively. The net spillover index is the difference of FROM and TO, and the market is the net-recipient if the value is expressed as negative, while the market is net-transmitter if the value is expressed as positive.

Table 2

The table shows the static spillover across the carbon market and stock market.

	EUA	Electricity	Material	Conventional energy	New energy	Consumer staples	FROM
Carbon price	88.56	1.89	2.26	4.07	2.26	0.97	11.44
Electricity	0.80	37.67	8.55	12.33	21.44	19.21	62.33
Material	1.03	9.81	43.20	22.27	15.29	8.41	56.80
Conventional energy	1.69	12.99	20.51	39.90	15.06	9.86	60.10
New energy	0.90	20.93	13.06	13.96	36.85	14.29	63.15
Consumer staples	0.44	21.70	8.24	10.55	16.55	42.53	57.47
Directional TO Others	4.85	67.31	52.62	63.19	70.59	52.73	311.28
Directional Including Own	93.41	104.98	95.82	103.08	107.44	95.26	TCI
NET Directional Connectedness	-6.59	4.98	-4.18	3.08	7.44	-4.74	51.88

Within each market, the self-contribution is the largest, but the magnitude varies across the markets. The carbon market exhibits the highest self-explanatory power, accounting for 88.56% of its own variability. In contrast, the other sectors in the stock market have less than 50% self-explanatory power, with the material index having the largest self-contribution at 43.2%, and the new energy index having the lowest at 36.85%.

Based on the data presented in Table 2, the total risk spillover is 51.88%, suggesting the presence of a risk spillover effect between the EUA market and the selected stock indices. Among the sectors, the new energy sector shows the highest contribution and reception of spillover, with 70.59% and 63.15%, respectively, followed by the electricity sector with 67.31% and 62.33%.

Specifically, 11.44% of carbon return can be attributed to the stock market indices. The conventional energy and the material sectors have the largest spillovers on the carbon market, with 4.07% and 2.26% respectively. The smallest spillover is consumer staples, which is only 0.97%. Meanwhile, the carbon market itself demonstrates the largest spillover effects on the same indices, with a value of 1.69% in the conventional energy sector and 1.03% in the material sector. The index of conventional energy involved various aspects of the oil and gas sector, where the companies engaged in activities related to crude oil, natural gas, and petroleum products. Similarly, the index of material include in the extraction and production of basic resources such as metals, mining, and forestry products. Obviously, as the carbon price fluctuates, companies in the conventional energy sector, such as fossil fuel-based power generation or oil and gas extraction, may face increased costs and reduced competitiveness compared to cleaner, low-carbon alternatives, which can impact their profitability and overall financial performance. Similarly, the material industries, which include sectors like cement, steel, and chemicals, may experience higher costs due to the stricter carbon policy. These industries often have energy-intensive production processes and may rely on fossil fuels as raw materials or for energy generation. As the carbon price increases, their production costs may rise, affecting their profitability and competitiveness in the market.

In terms of information flow, the EUA market, along with the material and consumer staples sectors, act as net information receivers from the system, indicating that it is influenced by factors such as policy changes and market dynamics originating from the other sectors. Notably, the EUA market stands out as the highest receiver of shocks in the system, indicating its susceptibility to various influences from the other three indices.

On one hand, investors' awareness of sustainable and low-carbon investments, coupled with the increasing focus on renewable energy sources, such as solar, wind, and hydroelectric power, has propelled the growth and importance of the new energy sector. The sector's advancements and contributions towards reducing carbon emissions make it a key driver of change in the broader energy landscape. On the other hand, stringent climate policies and regulations, including carbon pricing mechanisms like the EU ETS, have a direct impact on the EUA carbon market. The EUA carbon market acts as a receiver as it responds to changes in emissions caps, trading regulations, and market dynamics.

This highlights that the developments of new energy sectors and the related policies have a significant impact on the EUA carbon market, however, the results of the static spillovers only provide the general information for the entire investigated period. They are unable to reflect time-varying changes that occur at different time points resulting due to policy changes and market movements. Therefore, we perform a dynamic analysis for a more in-depth examination.

5.2. Dynamic Risk Spillovers

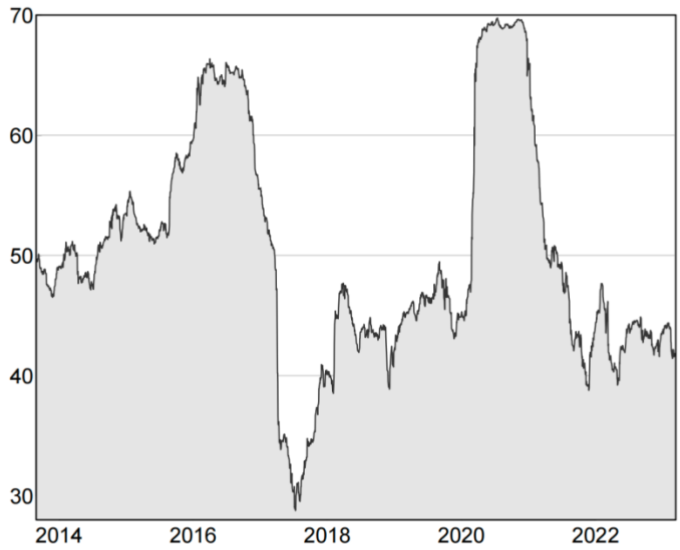
5.2.1. Dynamic Total Risk Spillovers

The rolling window technique is leveraged to further investigate the dynamic trends of risk spillover effects over the past decade. A rolling window is a statistical tool that allows us to analyze data over a fixed period and move it forward in time, resulting in a dynamic analysis of trends. In this case, we use a 200-day rolling window and 10-day forecast horizon, which means we analyze the data over a 200-day period along, estimating the values of the variable for the next 10 consecutive days, to observe the changes in risk spillover effects.

Fig. 2 displays the time-varying total spillover index within the sample period. The spillover index starts at approximately 50% and undergoes a steady rise until the middle of 2015. Then, it encounters a drastic increase, reaching over 65% in the middle of 2016. From the beginning of 2017 to 2017Q2, the total spillovers decline by more than half, from 65% to under 30%.

The total spillovers experience another uptrend from 2017Q3 to the middle of 2018, hitting 48%. The total risk spillovers hover between 40% to 50% until the end of 2019. Thereafter, the total spillovers skyrocket from 45% to approximately 70%, reaching the highest peak in 2020 and 2021 during the sample period. The last peak is around 48% at the beginning of 2022, and then falls back to the level of 40% to 45%.

Fig.2. Dynamic Total Spillover Index among the investigated markets



The empirical results of the dynamic total risk spillovers can be linked to contemporary regional and global events. The elevated initial level of total spillovers observed in 2014 appears to be indicative of the impact of the struggling EU economy following the euro debt crisis. The upward trend during 2014 and 2015 coincides with the adoption of the European Central Bank's (ECB) quantitative easing policy, aimed at stimulating the EU economy and fostering market recovery (ECB, 2015). The large increase during 2016 is closely related to the United Kingdom European Union membership referendum. The considerable uncertainty surrounding the future economic performance caused by Brexit led to a decline in both the UK and EU economies in 2016, and led to broad fluctuations in financial markets both regionally and globally (Qiu, L. et al., 2023).

The notable decline in the first half of 2017 can be attributed to two possible factors. Firstly, the ECB's quantitative easing policy until 2017Q3 successfully revived the weak EU economy (ECB, 2018). Secondly, the relief of the intense situation, along with the resolution of the Brexit vote, alleviated the uncertainty in the financial markets.

The substantial rise from Q3 2017 to mid-2018 indicates the political impacts of the 2017 German federal election and the 2018 Italian general election on the investigated markets. In the latter half of 2018, when total risk spillovers were approximately 45%, a pressing concern emerged regarding the Italian budget deal. The European Commission's rejection of the Italian budget plan resulted in a continued rise in the Italian 10-year bond yield, exposing investor apprehension regarding credit contraction in the European financial markets. This circumstance caused significant turbulence and raised concerns within the market.

Following the suspension of the Quantitative Easing (QE) policy at the end of 2018, the economy of the European Union experienced a period of sluggish performance throughout 2019. As a result, the European Central Bank (ECB) was compelled to reintroduce its loose monetary policy in September of that year, as documented in the ECB's annual report (2019). This policy shift corresponded with a rise in the total risk spillover index from 40% to just under 50%.

The spike in cases during 2020 and 2021 is evidently caused by the COVID-19 outbreaks. Since the beginning of 2021, there has been a drastic decline in cases, returning to pre-pandemic levels due to the easing of lockdowns and restrictions in EU countries. The last peak, at around 48% during 2022, aligns with the Russian invasion of Ukraine. The influence of warfare on the EU economy persists until the end of the sample period, at a level of around 45%.

5.2.2. Dynamic Directional Risk Spillovers

Fig. 3 and Fig. 4 demonstrate the directional (FROM and TO) risk spillovers over time at an aggregate level. It is notable that each pair of FROM and TO spillovers of each market exhibits similar trends to the dynamic total spillover index, with the highest values occurring during 2016 and 2021. However, the volume differences between each market's FROM and TO determine its reception or transmission characteristics at different time points, which will be explored further in the analysis of the Net Directional Spillover Index.

The case of the EUA carbon market has the most obvious difference between the FROM and TO graphic results. The reception from others ranges from close to zero to around 9%, and the transmission to other markets ranges from close to zero to 5%. Its highest received spillover is almost 1 time the transmitted value, which is the largest discrepancy compared to the figures in other pairs of FROM and TO graphs of each market. The electricity market has a reception ranging from around 6 to 12 percents, and the transmission value ranging from approximately 7 to 14 percents. The conventional energy market has similar figures to the electricity market. The new energy market has the highest values of reception and transmission, which is the same as the static risk spillovers result. The low points are the same as the electricity and conventional energy markets, but the peaks for FROM and TO are reaching 15 and 12.5 percents, respectively. The material market receives 3 to 12.5 percents from other markets and transmits 3 to 13 percents to others. The reception values of the consumer staple market range from 6 to 12 percents, the same as the electricity and conventional energy markets. The transmission values, however, are slightly lower than those markets, ranging from around 5 to 12 percents.

Fig.3. Dynamic Directional Spillover Index FROM

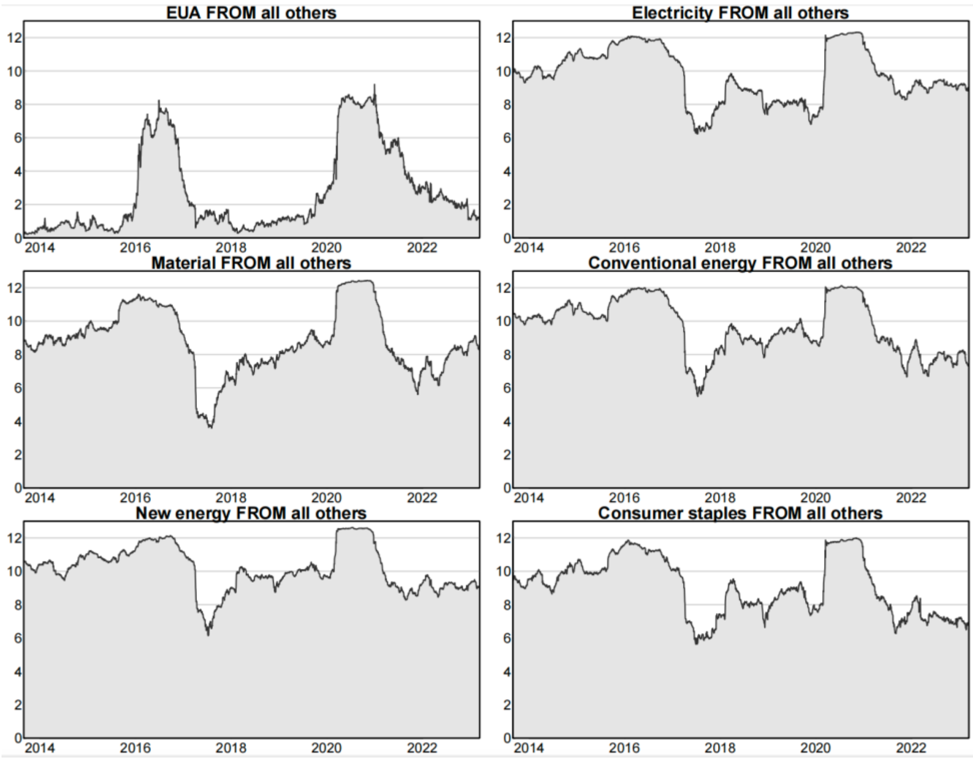
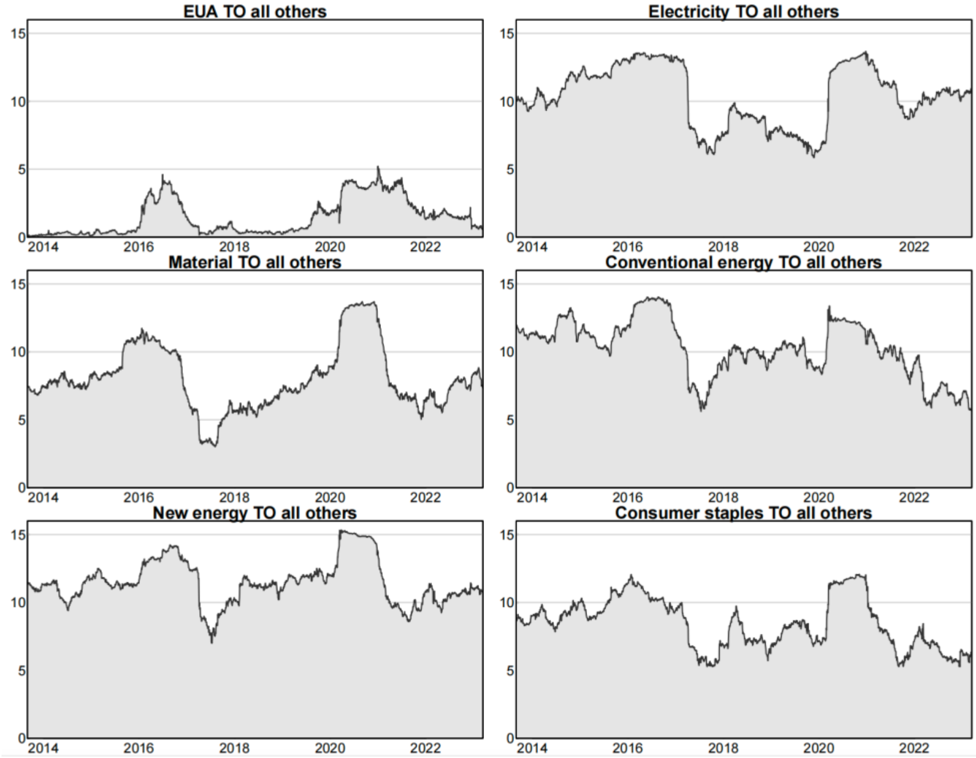


Fig.4. Dynamic Directional Spillover Index TO



Upon examining the graphical results of the spillovers FROM and TO each market, it becomes evident that substantial events like the Brexit vote and the outbreak of COVID-19 had a profound impact on all markets. Also, it is noteworthy that all other markets, apart from the carbon market, consistently exhibit a minimum level of risk spillovers at approximately 5% throughout the examined period. The carbon market exhibits pronounced reactions primarily during significant events, with risks during the remaining periods typically below 2% and occasionally even approaching zero. This suggests that the other five sectors are more interconnected with each other than with the EUA market, and there exists a baseline level of interconnectedness and transmission of risks among these markets, highlighting their relative stability in terms of spillover effects. Furthermore, a comparison of the EUA market's FROM and TO figures reveals that the carbon market receives a greater amount of risk than it transfers to other markets. This observation underscores the role of the carbon market as a recipient of risk from external sources rather than being a significant transmitter of risk to other markets.

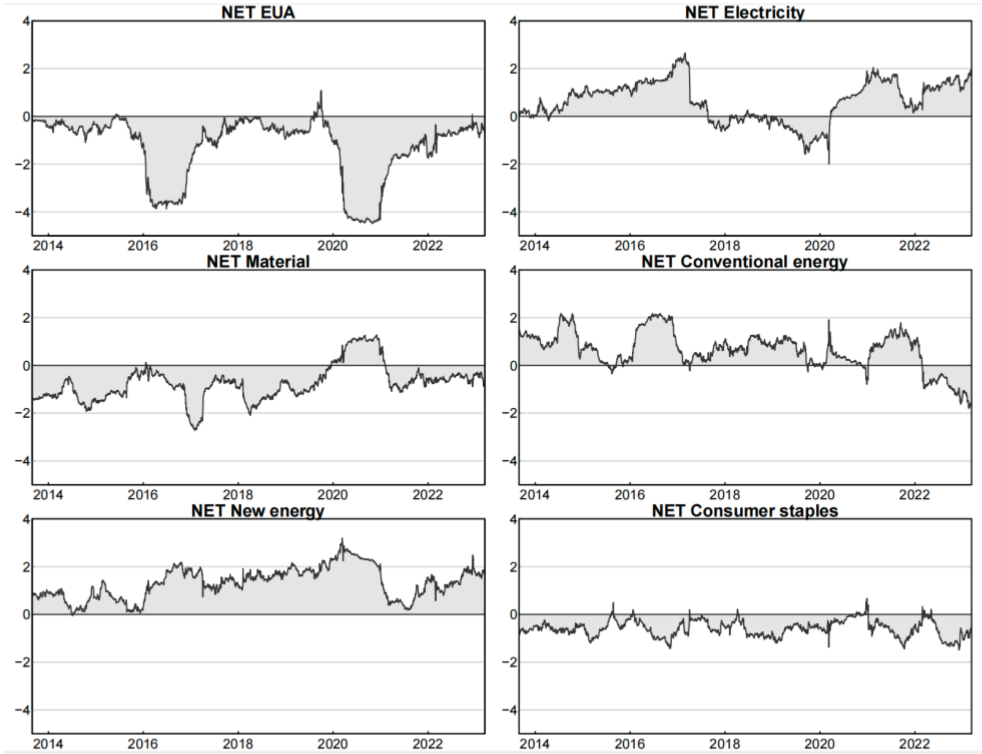
During the beginning of 2021, a distinct spike is observed in the directional index from EUA to all other indices, signaling a significant rise of approximately 5% in the risk spillover from the carbon market to the stock market. This spike coincides with the transition period from phase 3 to phase 4 of the EU ETS. The adjustments made to the framework and the implementation of new policies during this phase transition likely play a role in influencing the dynamics and interactions between the carbon market and other markets, ultimately leading to an intensified risk spillover.

5.2.3. Dynamic Net Directional Risk Spillovers

The Net Directional Spillover Index of each market is illustrated at an aggregate level in Fig. 5. It is one of the essentials of the DY risk spillover model that allows us to distinguish the pure risk connectedness between a specific market and the rest within our investigated system. The equivalent contribution of directional risk spillovers is canceled out during the netting of FROM and TO spillovers. A market is considered a net receiver of spillovers if its net directional spillover value is negative, while it is considered a net transmitter if its value is positive.

The EUA carbon market is the net risk receiver for most of the sample period, as indicated by the graph. The largest net spillover received from other markets occurs between 2020 and 2021, reaching almost -4.5%. The second largest net spillover occurs in 2016, at a slightly higher level than -4%. During the remaining time, net risk reception remains at a low level, between 0 and -1 percents. The only noticeable net spillover transmitted appears briefly during 2019Q3, with the highest figure at approximately 1%. The electricity market acts as the risk transmitter for two-thirds of the sample period, except for the duration between 2017Q4 and 2020Q1. The largest net transmission occurs at around 2.5% in 2017Q2, and the largest net reception is -2% in 2020Q1. During most of the sample period, the conventional energy market transmitted risk. However, since 2022, this has not been the case. The transmission value fluctuates between 1 and 2 percents, and at the beginning of 2022, it becomes reception, ranging between -1 and -2 percents. During the sample period, it is apparent that the new energy market is the primary transmitter of risk. The transmission rate typically hovers around 1 to 2 percents, but reaches a peak of 3% in 2020Q1. The material market typically acts as a risk receiver, except for the year 2020. Prior to 2020, the receiving values are higher, ranging from -1 to almost -3 percents. However, after 2020, these values become smaller, hovering around -1%. The transmission during 2020 remains steady at a level of 1%. The consumer staples market is also at obvious risk. The reception values range slightly above or below -1%. All in all, the empirical analysis reveals that the EUA carbon market, along with the material and consumer staples markets, primarily act as risk receivers, with the EUA market being the largest receiver. In contrast, the electricity, conventional energy, and new energy markets predominantly function as risk transmitters throughout most periods, which aligns with the findings from the static spillover analysis.

Fig.5. Dynamic Net Directional Spillover Index



The graphical results of Fig. 5 indicate that the highest risk-received periods of the EUA occurred during 2016-2017 and 2020-2021, which coincided with the Brexit vote and the Covid-19 outbreak. A possible cause of risks spill in the carbon market during 2016-2017 is regarding the UK's withdrawal from the EU, which created immense uncertainties in the financial markets due to the UK's significant role in the EU's economic activities. The UK economy contributed more than 17% of the EU's GDP and over 10% of its import and export activities. The UK was also a vital player in capital and financial markets. In fact, the UK capital market comprised 80% of the EU capital market, and most of the EU’s derivative transactions and hedge activities were conducted there. The exclusion of the UK from the EU region resulted in a significant market shrink and market instability for stakeholders. On the other hand, for carbon market investors, the UK's withdrawal from the EU ETS would reduce the total cap of carbon allowances due to the removal of UK installations, which could increase future EUA carbon prices. However, the offload of carbon allocations from UK installations before the withdrawal might also create downward pressure on the carbon market (BURKE, 2017). Overall, the political risks associated with the Brexit issue make the carbon market a risk receiver during 2016 and 2017. The obvious drop in carbon emissions during the 2020-2021 period can be attributed to the global economic recession caused by reduced production and business activities. This led to decreased consumption of utilities, oil, and raw materials, resulting in lower carbon emissions. The reduced production could not only lower the demand for carbon allowances but also encourage installations to sell additional permits, leading to a glut in the carbon market.

During 2019Q3, conspicuous positive values are observed, with the highest figure at around 1%. This coincides with the implementation of the MSR in the EU ETS. This reserve enables the European Commission to control the supply of carbon allowances circulated in the market, which can impact the level of carbon prices. The influence of the MSR can be clearly seen in Fig.1, as carbon prices have skyrocketed since the it became effective.

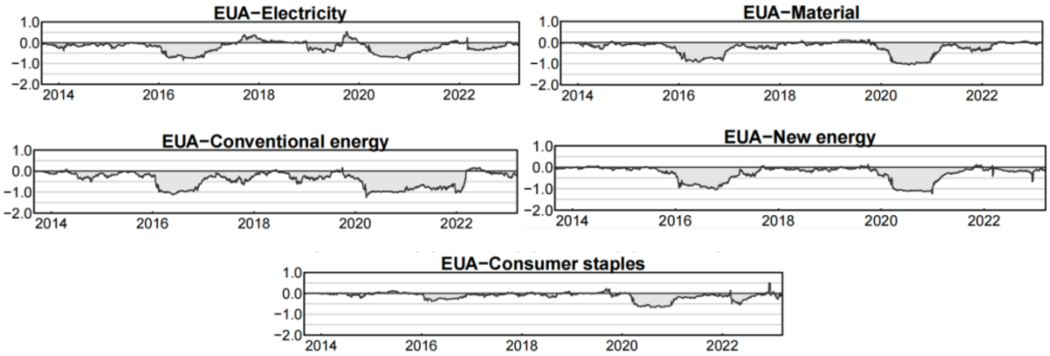
5.2.4. Dynamic Net Pairwise Directional Risk Spillovers

Based on the Net Pairwise Direction Spillovers graphs for the EUA carbon market, we can observe that the carbon market is affected by all other markets in the system for most of the sample period. Notably, the reception periods in 2016-2017 and 2020-2021 for all pairwise results coincide with the two main peak periods in the dynamic total spillover index figure. Upon closer examination of each pairwise graph, we can see that the risks that the carbon market faces from conventional energy, new energy, and material markets reach approximately -1% at their peaks, while those transmitted from electricity and consumer staple markets are around -0.5%, which is half the size of the former.

When examining the graph of the carbon and electricity markets, it becomes apparent that, aside from the majority of the time when risk reception occurs, there are two distinct periods where the carbon market serves as a transmitter to the electricity market, with a maximum of 0.5%. On the other hand, during the majority of the sample period, the carbon market receives risks from the conventional energy market. Notable periods of risk reception are observed in 2014-2015, 2017-2018, and 2018-2019, where the carbon market experienced a risk reception level of approximately -0.5%. In 2020, negative figures continue and extend into 2022, reaching -1%, before turning positive at nearly 0.2% in the middle of 2022. However, the figures become negative again since the end of 2022 onwards.

Except for the notable periods of 2016-2017 and 2020-2021, the new energy market generally transmits risks within the range of -0.1 and -0.2 percents. However, there are two irregular spikes in 2022Q1 and 2022Q4, where the risk transmission reaches -0.5%. The material market experiences minor reception during 2014-2015, 2017-2018, and 2021-2022, ranging from 0 to -0.5 percents, with the highest reception observed in 2021. Lastly, compared to other pairwise graphs, the figures in the carbon and consumer staple markets are smaller during 2016-2017 and 2021-2022. There is a notable peak in the first half of 2022, with a receiving value of -0.5%, followed by a transmitted value of 0.5% in 2022Q4.

Fig.6. Dynamic Net Pairwise Directional Spillover Index



The pairwise graphs provide a breakdown of spillovers received and transmitted from and to different markets. It is evident that the greatest portion of risks is received from the new energy and conventional energy markets, followed by those from the material and electricity markets, and lastly from the consumer staple market. This result clearly demonstrates the risk-connectedness relationship between carbon and each investigated market. In most cases, the EUA carbon market is affected by other markets more than it affects them. The result of this study not only confirms the findings of Waqas Hanif et al. (2021), which showed that the EUA market acts as a net-receiver from clean energy indices, but also extends these findings to include conventional energy, electricity, and material indices.

As carbon-intensive industries heavily rely on energy sources, any fluctuations or shocks in the energy sectors can have a significant risk transmission to the carbon market. On the other hand, the weaker relationship between the EUA carbon market and consumer staples indices can be attributed to the nature of consumer staple industries. These industries, such as food, beverages, and household products, are generally less carbon-intensive compared to the energy sector. As a result, they may be less susceptible to carbon price fluctuations and have limited direct exposure to carbon market dynamics. Consequently, the risk spillover effects from the EUA market to the consumer staples sector are relatively weaker compared to the energy sector.

There are two noticeable transmissions from carbon to the electricity market at 0.5%. One is in 2017-2018, and the other is in 2019-2020. The former where the carbon market serves as a transmitter for the electricity market can be attributed to the impact of declining volumes of auctioned credits, which subsequently drove the carbon price to rise (EEA, 2019). The European Commission implemented the Market Stability Reserve in January 2019 to address the problem of oversupply of carbon allowances, which is considered the cause of the second transmission period in 2019-2020. The transmission to the rest of investigated markets is present but relatively mild. This is reasonable since utility production contributes over two-thirds of carbon emissions annually within the EU, according to the statistics from EEA (2023). The volatility in carbon prices can have a direct impact on the cost of production, which, in turn, can influence the price of utilities.

The net pairwise index between EUA and other indices is clearly decreased in the beginning of 2021, apart from the conventional energy. On one hand, this is the period of economic recovery and stabilization following the impact of the COVID-19 pandemic. As economic conditions improved, market participants become more focused on sector-specific factors and fundamentals, which could have reduced the overall level of risk spillover between different asset classes. On the other hand, the transition to phase 4 could have influenced the risk transmission mechanisms between the EUA and other indices, reducing the spillover to other indices. However, the conventional energy index which includes fossil fuel-based industries exhibit different dynamics compared to other indices. The decreased in Russia's production levels, and the changes in the export policies in 2021 influenced the oil and gas prices and supply dynamics, causing uncertainties on the conventional energy sectors and contributing to a higher level of risk spillover from the conventional energy index to the carbon market.

5.3. Robustness Test

The robustness test for total risk spillover is conducted by assessing different lags and forecasting horizons. Fig. 7 and Fig. 8 illustrate the sensitivity of the index to the VAR orders ranging from 2 to 6, and forecasting horizons over 2 to 10 days.

The figures reveal that the total spillovers follow similar trajectories, indicating that the total spillovers are independent and consistent despite the variations of lags and forecast horizons. The presence of consistent trajectories in the total spillovers provides compelling evidence to support the reliability of the results obtained and validates the appropriate use of the spillover index method employed in the study. This robustness in the findings enhances the confidence in the derived implications, highlighting the significance and practical relevance of the study's conclusions. Researchers and policymakers can have greater assurance in the reliability of the obtained results and the potential applicability of the study's findings to real-world policy decisions.

Fig.7. Sensitivity of the index to the VAR lag structure

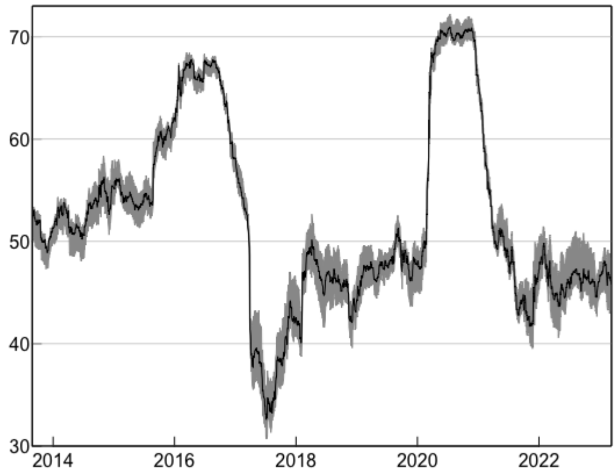
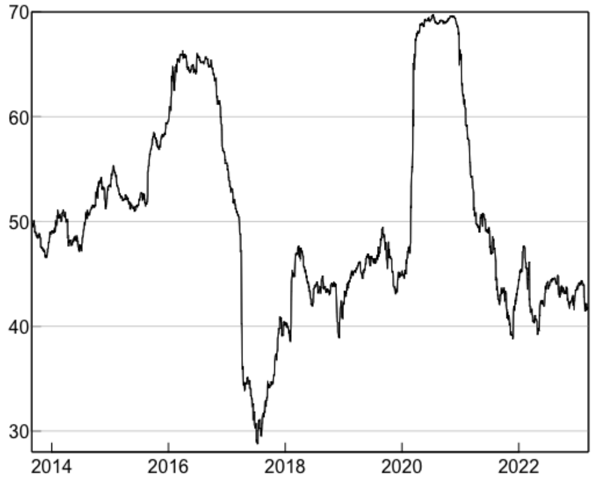


Fig.8. Sensitivity of the index to the forecast horizon



6. Conclusion

This paper investigates the interconnectedness and risk spillover effect between EUA carbon and carbon-intensive stock markets. Five stock indices from EU stock markets, including those for electricity, conventional energy, new energy, materials, and consumer staples sectors, are selected to represent the objective carbon-intensive markets. A VAR model is utilized to construct the KPPS H-step ahead FEVD, and the DY risk spillover indices are derived according to the FEVD estimators.

The following conclusions can be drawn from the empirical results. First of all, the results demonstrate the EUA carbon market is the predominant risk receiver during the examined period. Secondly, the risk spillover effects for the carbon market are more significant during the period of substantial events, such as the Brexit Vote (2016-2017) and COVID-19 (2020-2021) in the sample period. These events typically have broad impacts on the macroeconomy, causing economic recession or negative public expectations towards future economic performances at regional, national, or global levels. Thirdly, the risk spillover effects to the EUA market are not only significant from electricity, conventional energy and new energy sectors, but also from the material sector. Last but not least, instances of risk transmission from the EUA market to other markets are also observed, particularly during periods when there were disruptions in the carbon market caused by adjustments to the ETS policy. However, it is important to note that these instances involved relatively small amounts. Consequently, as the transition from phase 3 to phase 4 took place, the impact of this transition was mitigated by the simultaneous effects of the recovery from the COVID-19 pandemic.

These findings carry significant implications for both policy makers and carbon market traders. For policy makers, it is crucial to comprehend the patterns of linkage and spillovers between carbon-intensive markets and the carbon market to design effective market mechanisms and policy responses to extreme events. This understanding ensures the healthy development of both markets. Similarly, traders need to carefully assess the level of interconnectedness during substantial economic events and dynamic linkages across markets to formulate improved hedging strategies. Recognizing that carbon-intensive markets and the carbon market may move in tandem, particularly during periods of market disruptions, is particularly important for risk management and portfolio formation. In summary, our research provides a fresh and comprehensive perspective on comprehending risk spillovers across carbon and carbon-intensive markets.

These findings hold significance not only for the development of emissions trading systems in the EU but also for similar markets worldwide.

Despite the valuable insights provided by our study, it is important to acknowledge its limitations. Firstly, our analysis focuses solely on the spot prices of the EUA carbon market, which restricts the generalizability of our findings to other countries or regions with different carbon market structures and dynamics. Future research could expand the scope to include a broader range of carbon markets to gain a more comprehensive understanding of risk spillover effects in a global context. Secondly, we have limited our examination to five specific indices in the stock market, which may not fully capture the diversity of energy-intensive industries and their potential impact on the carbon market. To enhance the robustness of our study, future investigations could consider a wider selection of indices or explore alternative methodologies to identify the most relevant and representative indicators of energy-intensive sectors. Furthermore, incorporating futures prices in addition to spot prices could provide a more comprehensive analysis of risk spillover effects, as futures markets often reflect market expectations and forward-looking information. This would allow for a better understanding of how anticipated developments in carbon pricing impact risk transmission. To address these limitations and further advance our understanding of risk spillover dynamics, future studies can expand the dataset, consider additional indices or variables, and incorporate futures prices to capture a more comprehensive view of risk transmission in the carbon market.

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Appendix

Fig. A1. Returns of EUA carbon market and stock market