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Asymmetric Shock Transmission Between Artificial Intelligence Stocks and Carbon Markets: A Quantile-on-Quantile Connectedness Approach

Yapay Zekâ ve Karbon Piyasaları Arasındaki Asimetrik Şok Aktarımı: Kantil-Kantil Bağlantılılık Yaklaşımı

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ABSTRACT

The primary objective of this study is to examine the financial interaction between artificial intelligence (AI) indices and the carbon market and to reveal how shock transmission between the two markets varies according to market conditions. In this regard, the study analyzes the dynamics between two carbon indices, ICE EUA Carbon Futures Excess Return Index (ICEEUA) and S&P Global Carbon Credit Index (GLCARB), and two AI indices, Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO) and ROBO Global Artificial Intelligence Index (THNQ), using daily data covering the period from February 18, 2022 to June 27, 2025. Findings from the Quantile-on-Quantile Connectedness analysis reveal that the carbon market serves as a net shock transmitter across most quantile combinations; however, this role exhibits significant asymmetry, with transmission intensifying during extreme market conditions. Put differently, in certain periods characterized by heightened technological momentum, the AI indices also generate a meaningful feedback effect toward the carbon market. These interactions intensify in extreme quantile regimes, indicating stronger market integration during periods of stress. The results demonstrate that the financial structure of carbon pricing and the AI sector is becoming increasingly intertwined, and that sustainability policies need to be reconsidered in a manner that appropriately accounts for developments in technology markets.

Anahtar Kelimeler:
Yapay Zeka,
Karbon Piyasası,
Kantil-Kantil Bağlantılılık

Jel Kodları:
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ÖZET

Bu çalışmanın temel amacı, yapay zekâ (YZ) endeksleri ile karbon piyasası arasındaki finansal etkileşimi incelemek ve iki piyasa arasındaki şok geçişkenliğinin piyasa koşullarına göre nasıl değiştiğini ortaya koymaktır. Bu doğrultuda çalışma, 18 Şubat 2022 - 27 Haziran 2025 dönemini kapsayan günlük veriler kullanılarak iki karbon endeksi, ICE EUA Carbon Futures Excess Return Endeksi (ICEEUA) ve S&P Global Carbon Credit Endeksi (GLCARB), ile iki YZ endeksi, Nasdaq CTA Artificial Intelligence & Robotics Endeksi (NQROBO) ve ROBO Global Artificial Intelligence Endeksi (THNQ), arasındaki dinamikleri analiz etmektedir. Kantil-Kantil Bağlantılılık yöntemiyle elde edilen bulgular, karbon piyasasının büyük ölçüde YZ endekslerine doğru birincil şok yayıcı (shock transmitter) olarak hareket ettiğini göstermektedir. Bununla birlikte, teknolojik ivmenin arttığı belirli dönemlerde YZ endekslerinin de karbon piyasasına anlamlı düzeyde geri besleme etkisi oluşturduğu gözlemlenmektedir. Bu etkileşimlerin özellikle uç çeyrek (extreme quantile) rejimlerde belirginleşmesi, iki piyasa arasındaki entegrasyonun stres dönemlerinde daha da güçlendiğini ortaya koymaktadır. Sonuçlar, karbon fiyatlaması ile YZ sektörünün finansal yapılarının giderek daha fazla iç içe geçtiğini ve sürdürülebilirlik politikalarının, teknoloji piyasalarındaki gelişmeleri dikkate alacak şekilde yeniden değerlendirilmesi gerektiğini göstermektedir.

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1. INTRODUCTION

The growing centrality of artificial intelligence (AI) within the financial system makes it increasingly important to understand its relationship with carbon markets from a theoretical perspective. Carbon markets are data intensive, regulation driven, and highly sensitive to expectations, which means that the digital transformation driven by AI can have significant implications for their functioning. The integration of AI and blockchain systems into carbon credit trading (Adigun et al., 2024; Baklaga, 2024) illustrates that price formation in carbon markets is increasingly dependent on the quality and processing speed of information. As digital trading infrastructures expand, carbon pricing mechanisms may become more responsive to AI generated information flows, making the valuation of AI intensive firms and carbon assets more interlinked.

Beyond infrastructure effects, the interaction between AI and carbon markets also has a financial dimension. Evidence that market conditions create time varying linkages between AI activity and carbon price dynamics (Xu et al., 2024) suggests that AI is not merely a supportive technology but a factor that shapes how market signals are transmitted. The asymmetric influence of AI on carbon prices across different market regimes (Jiang et al., 2025) further implies that AI innovations can alter expectations and risk perceptions, particularly during periods of heightened uncertainty. Another theoretical channel strengthening this relationship is AI's role in carbon reduction technologies. The use of AI in carbon capture, energy efficiency, and process optimization (Priya et al., 2023; Gaur et al., 2023) can reshape long term supply demand expectations in carbon markets. As AI accelerates decarbonization in carbon intensive industries, projections of future carbon costs may shift accordingly. Studies showing that AI contributes to reduced emissions and improved emission efficiency (Ding et al., 2023; Wu et al., 2025) indicate that carbon markets increasingly internalize technological progress when pricing future carbon liabilities.

AI's role in the ongoing energy transition further enhances this theoretical linkage. Its applications in renewable energy production, demand forecasting, and smart grid management (Necula, 2023; Zhao et al., 2024) can create stronger synchronization between energy and carbon markets. Changes in expectations regarding the pace of energy transition may thus simultaneously influence the valuation of AI firms and the pricing of carbon credits. The presence of strong connectedness between AI and energy markets even in tail conditions (Tiwari et al., 2024; Raggad & Bouri, 2025) reinforces the view that these interactions intensify under market stress, suggesting a shared financial exposure to major technological and policy shocks.

Taken together, these mechanisms show that the relationship between AI indices and carbon markets cannot be explained by a single economic factor. Digital market infrastructures, enhanced information processing, carbon reducing technological innovations, and the financial effects of energy transition collectively shape a multi layered and dynamic interaction between the two markets. As such, the linkage is theoretically expected to be nonlinear, sensitive to market conditions, and prone to varying intensities across different periods. This conceptual understanding provides a strong justification for examining the connectedness between AI stock indices and carbon price indices using quantile based and asymmetry sensitive methodologies, which can capture the regime dependent nature of these interactions.

This theoretical framework necessitates the empirical examination of the multidimensional, asymmetric, and regime dependent interactions that may arise between AI indices and the carbon market. In this regard, the main objective of the study is to reveal the shock transmission mechanisms between the carbon market and the AI stock market under varying market conditions. The analysis employs two carbon price indices, ICE EUA Carbon Futures Excess Return Index (ICEEUA) and S&P Global Carbon Credit Index (GLCARB), and two AI stock market indices, Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO) and ROBO Global Artificial Intelligence Index (THNQ). These indices are selected because they reflect latest and comprehensive financial dynamics of both the global carbon market and the AI sector. The dataset consists of daily observations obtained from Refinitiv covering the period 18 February 2022 to 27 June 2025. The time span is determined by the continuity of trading activity and the availability of data across both markets. To examine how market interactions vary across different parts of the distribution, the study applies the Quantile-on-Quantile Connectedness (QQC) approach. Developed by Gabauer & Stenfors (2024), this method provides a suitable empirical framework for analyzing AI and carbon market interactions, as it captures the direction and magnitude of shocks with high sensitivity in tail regions, where volatility regimes tend to be most influential.

The relationship between artificial intelligence related financial indices and carbon markets has become increasingly pivotal as technological transformation exerts a growing influence on global financial systems. Despite this heightened relevance, empirical studies that directly examine the interaction between artificial intelligence driven financial markets and carbon markets within a unified financial connectedness framework remain notably scarce. The existing literature predominantly concentrates on the impact of artificial intelligence on carbon emissions, energy transition processes, or the institutional design and efficiency of carbon markets. However, the bidirectional shock transmission and dynamic comovement between artificial intelligence oriented financial indices and global carbon price dynamics have yet to be systematically investigated. This gap is particularly critical in an era characterized by the rapid convergence of technology driven and sustainability oriented markets. In response, the present study addresses this shortcoming by examining the interaction between artificial intelligence indices and carbon markets within a nonlinear, regime dependent, and distribution sensitive framework. Conventional empirical approaches, which rely largely on average effects, are insufficient to capture the underlying complexity of such relationships, especially in markets where volatility regimes play a central role in shaping price dynamics. By employing the Quantile-on-Quantile Connectedness methodology, this study enables a detailed assessment of how shock transmission mechanisms between artificial intelligence and carbon markets evolve across low, medium, and high volatility conditions. This approach provides a substantive methodological advancement by uncovering tail dependencies, asymmetric spillover effects, and state dependent inter market linkages that remain obscured under mean based analyses. Consequently, the study contributes to the literature by offering a more nuanced and comprehensive understanding of the financial interaction between artificial intelligence driven markets and global carbon pricing dynamics, particularly during periods of heightened market stress.

This study offers important strategic implications for a wide range of stakeholders operating at the intersection of artificial intelligence, carbon markets, and sustainable finance. From an investment perspective, identifying regime dependent shock transmission mechanisms between AI markets and carbon markets enables a more informed design of portfolio diversification and hedging strategies under varying market conditions. Incorporating these dynamics into risk management frameworks may enhance portfolio resilience, particularly during periods of heightened volatility. From a policy standpoint, the findings provide valuable insights into how developments originating in artificial intelligence driven financial markets may influence the stability and pricing dynamics of carbon markets. Such insights can assist policymakers and regulatory authorities in designing regulatory frameworks that more effectively account for the interconnected nature of technological advancement and sustainability oriented market structures. Recognizing these interactions is particularly relevant for ensuring the robustness of carbon pricing mechanisms in the context of rapid digital transformation. At the firm and industry levels, the results enable industrial firms and participants in carbon trading systems to better assess the indirect financial and cost related implications of artificial intelligence technologies on carbon management and compliance strategies. This improved understanding supports more effective long term strategic planning and investment decisions. Furthermore, institutions operating within the energy sector may utilize the observed comovement between AI and carbon markets to more accurately interpret risks and opportunities associated with energy transition processes. Overall, the study extends beyond its academic contribution by providing an integrated analytical framework that can support more informed decision making across technology, energy, and sustainable finance domains, particularly in environments characterized by increasing market interconnectedness and structural transformation.

This study consists of five sections. The first section presents the background and objectives of the research. The second section reviews existing studies on the relationship between AI indices and carbon markets, highlighting the gaps in the literature. The third section explains the data set, the selected indices, and the QQC method used in the analysis. The fourth section presents the empirical findings and discusses how market interactions vary across different regimes. The final section provides the main conclusions of the study, implications for policymakers and market participants, and suggestions for future research.

2. LITERATURE REVIEW

2.1. Interaction between Artificial Intelligence and Carbon Markets

Recent studies highlight that AI, blockchain, and fintech driven innovations have transformed the functioning of carbon markets. Adigun et al. (2024) emphasize that AI and blockchain applications enhance price discovery, transparency, and transaction efficiency in carbon markets through financial technologies, thereby strengthening market depth. Similarly, Baklaga (2024) demonstrates that the integration of AI and blockchain enables "smart carbon credit trading" based on smart contracts operating on distributed ledger technology, which reduces transaction costs and accelerates market integration.

Examining the relationship between carbon markets and AI directly through a time frequency spillover framework, Xu et al. (2024) identify both short and long term time varying connectedness among AI, the carbon market, and the energy sector. Their findings indicate that bidirectional shock transmission between AI and carbon prices intensifies particularly during crisis episodes and periods of high volatility. Jiang et al. (2025) analyze the linkage between AI indicators and carbon prices in China through the Quantile-on-Quantile Regression approach, revealing that the effect of AI activities on carbon prices is nonlinear and asymmetric across quantiles. Islam (2025) argues that AI supported carbon market intelligence and blockchain based governance mechanisms can enhance transparency in climate resilient infrastructure investments in the Global South. Overall, these findings suggest that AI is not only a tool that enhances operational efficiency in carbon markets, but also functions as a financial technology shock capable of reshaping price dynamics, volatility structures, and overall market connectedness.

2.2. Artificial Intelligence, Carbon Emissions, and Carbon Efficiency

The impact of AI technologies on carbon emissions is discussed in the literature through both mitigating and rebound mechanisms. Priya et al. (2023) show that AI supported carbon capture systems significantly increase capture efficiency through process optimization, forecasting, and real time control. Gaur et al. (2023) highlight that, AI can optimize carbon emissions in multiple subsystems, including energy, transportation, industry, and buildings, supporting a holistic carbon mitigation strategy.

Ding et al. (2023) find that AI development is associated with a significant reduction in carbon emissions in China, while Wang et al. (2024) show that AI can curb emissions by promoting the energy transition (from fossil fuels to renewables) and interacting with trade openness. Chen & Jin (2023) report that AI applications in manufacturing are insufficient alone, but yield stronger carbon reduction outcomes when combined with green innovation. Wu et al. (2025) further demonstrate that AI adoption increases carbon emission efficiency by enabling firms to produce the same output with lower carbon intensity.

This body of research suggests that AI has substantial potential to reduce carbon emissions through energy and resource efficiency, process optimization, and smart management systems. However, AI can also generate additional carbon and energy burdens through large data centers, high computational power requirements, and hardware demand, indicating that its net effect depends on the specific sectoral, technological, and policy context.

2.3. Artificial Intelligence and Corporate ESG Performance

AI’s impact on corporate environmental, social, and governance (ESG) performance and enviromental sustainability has become an increasingly prominent area of empirical focus (Balcı et al., 2025). Zhang & Yang (2024) find that AI applications enhance ESG performance by reducing environmental footprints, improving data processing capacity, and strengthening reporting transparency. Lim (2024) systematically examines the relationship between AI and ESG in finance, concluding that AI plays a critical role in risk management, measurement of climate and sustainability risks, ESG integration in portfolios, and the design of sustainable finance products.

Under the Industry 5.0 framework, Wang et al. (2025) position AI at the center of future production and management systems to strengthen corporate sustainability and ESG performance. Li & Bian (2025) and Xie & Wu (2025) show that AI adoption significantly and positively affects ESG scores among Chinese firms. Liu et al. (2025) highlight that AI applications generate particularly notable improvements in the environmental and governance dimensions, such as emission monitoring, corruption risk detection, and supply chain transparency. Tian et al. (2025) report that AI adoption has a positive and significant impact on ESG performance, which is closely linked to corporate strategy and managerial structures. Hamdouni (2025) finds similar results in Saudi Arabia, showing enhanced ESG outcomes through AI practices. Song et al. (2025) demonstrate that digital technological innovations create a “catching-up effect” in ESG performance, enabling laggard firms to rapidly approach higher ESG standards. Collectively, these studies indicate that AI functions as a general purpose technology that supports corporate sustainability, strengthens ESG reporting, and enhances transparency in identifying environmental and governance risks, implying that AI intensive sectors may exhibit relatively higher ESG performance.

2.4. Artificial Intelligence, Clean Energy, and Energy Markets

The literature on the interaction between AI and clean energy highlights AI’s strategic role in renewable energy development and the broader energy transition. Necula (2023) argues that AI is a critical complementary technology in the development of clean energy technologies in Europe, particularly through improvements in energy efficiency, smart grids, and demand management. Qin et al. (2024) find that the benefits of AI in renewable energy, including prediction accuracy, maintenance optimization, and system integration, outweigh potential drawbacks such as energy consumption and digital infrastructure costs, resulting in a net positive effect.

Zhao et al. (2024) claim that AI can accelerate the transition to renewable energy, especially by enhancing investment decisions, production and price forecasting, and risk management. Zhang et al. (2024) emphasize the rising role of AI in China's renewable energy development, showing that technology intensive investments accelerate the energy transition. Tian et al. (2024) demonstrate that the effect of AI on renewable energy is asymmetric under climate policy uncertainty, with investment responses varying depending on the level of uncertainty.

From the financial markets perspective, Tiwari et al. (2024) examine the connectedness between AI, clean energy, and conventional energy markets using CQ and WLMC techniques, finding significant shock transmission mechanisms between AI and both clean and conventional energy markets. Yang et al. (2024) argue that AI and blockchain technologies serve as key enablers that can unlock the potential of clean energy. Raggad & Bouri (2025) analyze tail based pairwise connectedness between AI and clean/dirty energy markets, providing important implications for portfolio diversification and risk management, particularly under extreme market conditions. These findings collectively indicate that AI influences not only corporate and production processes but also the spillover structure, volatility dynamics, and financial integration degree of energy and clean energy markets.

2.5. Research Gap

Although the existing literature extensively examines the effects of artificial intelligence technologies on carbon markets, carbon emissions, ESG performance, and the clean energy transition, the majority of these studies focus on macro level causality, linear relationships, firm level ESG outcomes, or renewable energy linkages. However, the direct financial interaction between AI stock market indices (such as NQROBO and THNQ) and global carbon price indices (ICEEUA and GLCARB), particularly the asymmetric shock transmission that emerges during periods of market stress, has been largely overlooked. Moreover, most existing studies rely on traditional approaches that capture only average effects, making them insufficient to reflect how extreme volatility, market stress, or tail events influence cross market dynamics. This gap is particularly significant because AI represents a technology intensive and volatility sensitive sector, whereas carbon markets are policy driven and highly responsive to external shocks, implying that their interaction may vary substantially across different quantile levels. Consequently, studies that reveal how the relationship between AI and carbon markets changes across distributional regimes, namely lower, median, and upper tails, are extremely limited. Therefore, the literature lacks a comprehensive empirical investigation that examines the structure, direction, and magnitude of the connectedness between the two markets using the Quantile-on-Quantile Connectedness (QQC) methodology, analyzes how shocks propagate in the tails, and interprets the findings within the broader context of sustainable finance, carbon pricing, and AI driven technological investments. The main contribution of this study is to fill this gap by uncovering the shock transmission mechanisms between AI and carbon markets through an asymmetric, distribution sensitive, and regime dependent analytical framework.

3. DATA AMD METHODOLOGY

3.1. Data

To evaluate the interaction between the carbon market and the AI stock market, the analysis investigates how shocks are transmitted between the two sectors. In this context, the study applies quantile connectedness methodology between two carbon price stock market indices and two artificial intelligence stock (AI) market indices, namely the ICE EUA Carbon Futures Excess Return Index (ICEEUA), S&P Global Carbon Credit Index (GLCARB), Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO), and ROBO Global Artificial Intelligence Index (THNQ). Daily data retrieved from Refinitiv for the period February 18, 2022, to June 27, 2025 form the basis of the analysis, with the analysis horizon constrained by data accessibility. To conform with the stationarity requirement of the empirical model, index values are converted into returns calculated as $\left(\frac{P_t}{P_{t-1}} - 1\right)$. Figure 1 displays the return series, while Table 1 provides the corresponding descriptive statistics.

Figure 1 illustrates that from 2024 to 2025, the carbon market indices display generally stable return behaviour, but a significant market shock occurs between 2022 and 2023. Similar movements occur in artificial intelligence indices (AI) between 2023 and 2025, but there are also significant shocks in 2025.

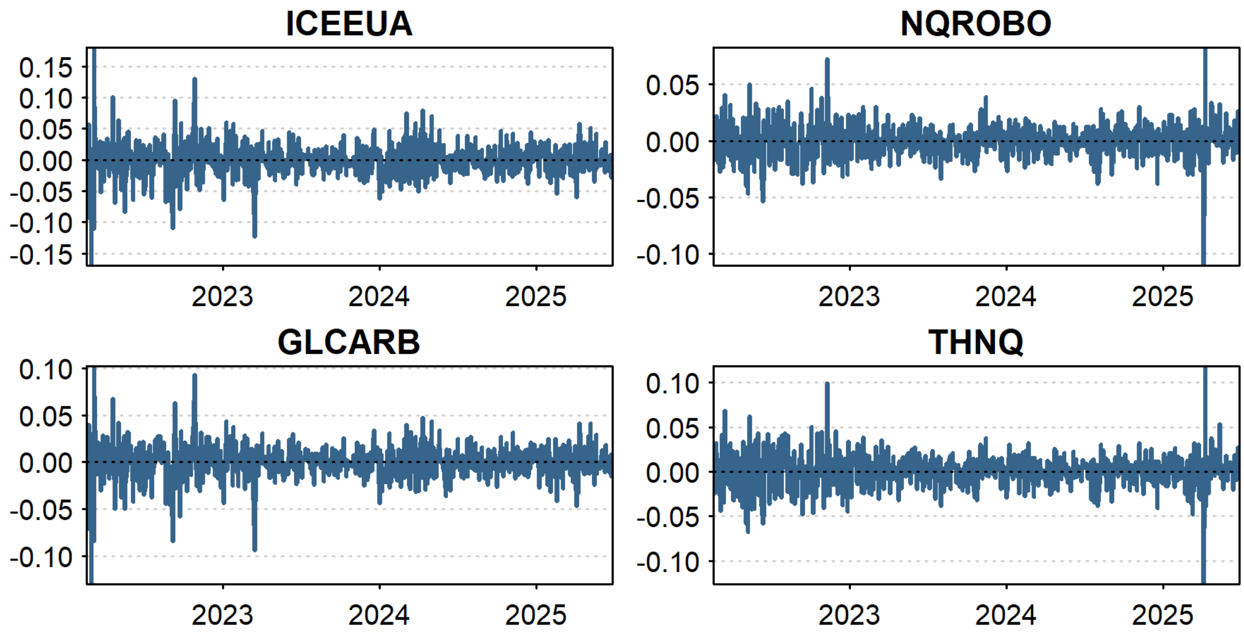

Figure 1. Return Series of Carbon and AI Indices

Table 1 illustares all mean values of indices positive and approximately zero. The ROBO Global Artificial Intelligence Index (THNQ) has the highest mean value (0.0007) and the second highest volatility (sd = 0.0193), which shows the index's growth potential and uncertainty risk. The Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO) has the second highest mean value (0.0001) and the lowest volatility (sd = 0.0154). Negative skewness in each index reflects heightened exposure to downside risks and external disturbances, and the leptokurtic nature (kurtosis > 3) indicates a greater probability of extreme market movements. The Jarque-Bera (1980) test results indicate that normality is rejected for each index, underscoring non-normal behaviour, whereas unit root tests affirm their stationarity. The correlation matrix additionally points to uniformly positive correlations. Additionally, the ERS test (Elliott et al., 1996) results indicate that the indices reject the unit root hypothesis at the 1% level, demonstrating stationarity.

Table 1. Descriptive Statistics

	ICEEUA	**GLCARB**	**NQROBO**	**THNQ**
Mean	0.0000	0.0000	0.0001	0.0007
Median	-0.0008	-0.0001	0.0003	0.0013
Maximum	0.1802	0.1020	0.0826	0.1181
Minimum	-0.1695	-0.1301	-0.1105	-0.1260
Std. Dev.	0.0270	0.0185	0.0154	0.0193
Skewness	0.0206	-0.4427	-0.2043	-0.0418
Kurtosis	8.9852	9.7334	7.4430	7.5486
Jarque-Bera	1207.58***	1554.69***	671.023***	697.654**
ERS	-2.094***	-2.086***	-3.415***	-2.076***
Q	21.34	26.54	39.72	31.27***
Q^2	150.39***	174.74***	88.071***	142.68V
		Correlation Matrix		
ICEEUA	1.0000			
GLCARB	0.9645	1.0000		
NQROBO	0.1468	0.1661	1.0000	
THNQ	0.0973	0.1036	0.9329	1.0000

Note: *** represents p < 0.001

3.2. Methodology

To assess how the carbon market interacts with the artificial intelligence (AI) stock market, the study utilizes the QQ methodology proposed by Gabauer & Stenfors (2024). This method enhances the quantile connectedness structures of Chatziantoniou et al. (2021) and Ando et al. (2022) by explicitly modelling variable interactions across different quantiles. The first stage of the methodology involves estimating the quantile level interdependencies through the Quantile Vector Autoregressive model of order p, as formulated in Equation 1.

$$x_t \;=\; \mu(\tau) \;+\; \sum_{j=1}^{p} B_j(\tau)\, x_{t-j} \;+\; u_t(\tau) \tag{1}$$

In Equation 1, x_t and x_{t-j} denote K-dimensional vectors of endogenous variables, where τ refers to the quantile level within the [0,1] interval and p indicates the lag order in the QVAR model. According to the QVAR model, $\mu(\tau)$ reflects the $K \times 1$ conditional mean component, $B_j(\tau)$ corresponds to the $K \times K$ matrix coefficients. Furthermore, $u_t(\tau)$ represents the $K \times 1$ innovation vector whose variability is characterized by a $K \times K$ covariance matrix. Subsequently, the QVAR specification is reexpressed in a QVMA form using the GFEVD methodology introduced by Koop et al. (1996) and further advanced by Gabauer & Stenfors (2024). In line with Wold's Decomposition Theorem, the QVAR process can be expressed as a moving average representation driven by past innovations.

$$x_t \;=\; \mu(\tau) + \sum_{j=1}^{p} B_j(\tau) x_{t-j} \;+\; u_t(\tau) \;= \mu(\tau) + \sum_{i=0}^{\infty} A_j(\tau)\, u_{t-1}(\tau) \tag{2}$$

As shown in Equation 2, shocks originating from j propagate to the behaviour of i over an F-step time span. Accordingly, $\mu(\tau)$ is specified as a $K \times 1$ indicator vector, equal to one in the I-th coordinate and zero for all remaining coordinates. The influence of a shock in series j on the behavior of series i is captured by the F-step ahead GFEVD, as presented in Equation (3).

$$\varphi^{g}_{i\leftarrow j,\tau}(F) = \frac{\sum_{f=0}^{F-1}\left(e_i' A_f(\tau) H(\tau) e_j\right)^2}{H_{ii}(\tau)\sum_{f=0}^{F-1}\left(e_i' A_f(\tau) H(\tau) A_f(\tau)' e_i\right)}, gSOT_{i\leftarrow j,\tau}(F) \;=\; \frac{\varphi^{g}_{i\leftarrow j,\tau}(F)}{\sum_{j=1}^{k}\varphi^{g}_{i\leftarrow j,\tau}(F)} \tag{3}$$

Following the normalization procedure of Diebold & Yilmaz (2012), the measure $\varphi^{gen}_{i\leftarrow j,\tau}(F)$, is scaled by the sum of its row to generate $gSOT_{i\leftarrow j,\tau}(F)$, which forms the core of the directional TO/FROM connectedness framework. As outlined in Equations (4) and (5), the FROM measure represents the connectedness directed toward series i, whereas the TO measure captures the influence that series i exerts on the remaining variables.

$$S^{gen,to}_{i\rightarrow\bullet,\tau} \;=\; \sum_{k=1, i\neq j}^{K} gSOT_{k\leftarrow i,\tau} \tag{4}$$

$$S^{gen,from}_{i\leftarrow\bullet,\tau} \;=\; \sum_{k=1, i\neq j}^{K} gSOT_{i\leftarrow k,\tau} \tag{5}$$

Equation (6) defines net aggregate connectedness as the TO measure minus the FROM measure for a given series.

$$S^{gen,net}_{i,\tau} \;=\; S^{gen,to}_{i\rightarrow\bullet,\tau} \;-\; S^{gen,from}_{i\leftarrow\bullet,\tau} \tag{6}$$

A positive $S^{gen,net}_{i,\tau}$ reflects net shock transmission from series i, whereas a negative value denotes that the series is predominantly a shock recipient. The last step involves calculating the adjusted TCI, bounded within [0,1] and proposed by Chatziantoniou et al. (2021), as specified in Equation (7).

$$TCI_\tau(F) \;=\; \frac{K}{K-1}\sum_{k=1}^{K} S^{gen,from}_{i\leftarrow\bullet,\tau} \;\equiv\; \sum_{k=1}^{K} S^{gen,to}_{i\rightarrow\bullet,\tau} \tag{7}$$

4. EMPIRICAL RESULTS

The study utilizes 60-month rolling window QVAR models with a six step forecast horizon for both the carbon and artificial intelligence (AI) indices to investigate their interconnected dynamics. Figure 2 presents the average dynamic connectedness between the carbon and artificial intelligence indices. Quantile levels for the average dynamic connectedness span from 0.05 to 0.95, increasing in increments of 0.225. The left panel visualizes the findings pertaining to the ICE EUA Carbon Futures Excess Return Index (ICEEUA) and artificial intelligence (AI) indices pair, while the right panel visualizes findings pertaining to the S&P Global Carbon Credit Index (GLCARB) and artificial intelligence (AI) indices pair.

The average dynamic connectiveness findings for the ICE EUA Carbon Futures Excess Return Index (ICEEUA) and Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO) are demonstrated in Figure 2, in the left panel. The findings indicate that one of the highest levels of average total connectedness (74%) between the ICE EUA Carbon Futures Excess Return Index (ICEEUA) and the Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO) is observed at the lower tail quantile combination, τ_1 = 0.05, τ_2 = 0.05. Likewise, for the other quantile intervals, the total connectedness estimates also display a peak at the same quantile point. For instance, the average total connectedness is 71.6% for the ICE EUA Carbon Futures Excess Return Index (ICEEUA) and Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO) at the 95th quartiles. Higher levels of total connectedness are observed at the directly related extreme quantiles τ_1 = 0.95, τ_2 = 0.95) and (τ_1 = 0.05, τ_2 = 0.05), situated in the northeast and southwest corners, and also at reversely related extremes (τ_1 = 0.95, τ_2 = 0.05) and (τ_1 = 0.05, τ_2 = 0.95) in the northwest and southeast corners.

The average dynamic connectiveness findings for the ICE EUA Carbon Futures Excess Return Index (ICEEUA) and ROBO Global Artificial Intelligence Index (THNQ) are shown in the left panel of Figure 2. The findings show that the peak average total connectedness (71.9%) for the ICE EUA Carbon Futures Excess Return Index (ICEEUA) and ROBO Global Artificial Intelligence Index (THNQ), observed at a point in the distribution where the relationship is directly extremely related to quantiles, τ_1 = 0.05, τ_2 = 0.05. Furthermore, the average total connectedness is 71.6% for the ICE EUA Carbon Futures Excess Return Index (ICEEUA) and the ROBO Global Artificial Intelligence Index (THNQ) at the 95th quartiles, indicating that the total connectedness estimates also display a peak at the same quantile. Total connectedness reaches relatively high values at both the directly related extreme quantiles (τ_1 = 0.95, τ_2 = 0.95) and (τ_1 = 0.05, τ_2 = 0.05), and the reversely related extremes (τ_1 = 0.95, τ_2 = 0.05) and (τ_1 = 0.05, τ_2 = 0.95) in the northwest and southeast corners, corresponding to the northeast and southwest corners and northwest and southeast corners, respectively

The average dynamic connectiveness findings for the S&P Global Carbon Credit Index (GLCARB) and Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO) are illustrated in Figure 2, in the right panel. The findings show that the peak average total connectedness (74%) for S&P Global Carbon Credit Index (GLCARB) and Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO), observed at a point in the distribution where the relationship is directly extremely related to quantiles, τ_1 = 0.05, τ_2 = 0.05. Similarly, across the remaining quantile intervals, the total connectedness measures also exhibit their highest values at the same quantile level. For instance, the average total connectedness is 70.8% for the S&P Global Carbon Credit Index (GLCARB) and Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO) at the 95th quartiles. High levels of total connectedness are evident at the same direction tail quantiles (northeast and southwest) as well as at the opposite direction extremes (northwest and southeast), namely (τ_1 = 0.95, τ_2 = 0.95), (τ_1 = 0.05, τ_2 = 0.05) and (τ_1 = 0.95, τ_2 = 0.05), (τ_1 = 0.05, τ_2 = 0.95).

The average dynamic connectiveness findings for the S&P Global Carbon Credit Index (GLCARB) and ROBO Global Artificial Intelligence Index (THNQ) are displayed in the right panel, Figure 2. The findings show that the peak average total connectedness (70.8%) for the ICE EUA Carbon Futures Excess Return Index (ICEEUA) and the ROBO Global Artificial Intelligence Index (THNQ), observed at a point in the distribution where the relationship is directly extremely related to quantiles, τ_1 = 0.05, τ_2 = 0.05. Consistently, for the additional quantile intervals, the total connectedness estimates reach their maximum at the same quantile. Furthermore, the average total connectedness is 72.5% for the S&P Global Carbon Credit Index (GLCARB) and the ROBO Global Artificial Intelligence Index (THNQ) at the 95th quartiles, indicating that the total connectedness estimates also display a peak at the same quantile. Elevated levels of total connectedness appear not only at the directly aligned extreme quantiles (τ_1 = 0.95, τ_2 = 0.95) and (τ_1 = 0.05, τ_2 = 0.05), in the northeast and southwest corners, but also at the cross extreme quantiles (τ_1 = 0.95, τ_2 = 0.05) and (τ_1 = 0.05, τ_2 = 0.95) located in the northwest and southeast corners.

Figure 2. Quantile Total Connectedness Indices between Carbon and AI Market Indices

As shown in Figure 3, the study charts the direct and inverse total connectedness indices and their differential (ΔTCI) to examine temporal patterns of aligned and counter, aligned connectedness between the carbon and artificial intelligence (AI) market indices. In Figure 3, the left panel displays results for the ICE EUA Carbon Futures Excess Return Index (ICEEUA), while the right panel presents outcomes for the S&P Global Carbon Credit Index (GLCARB). The evidence indicates that the direct TCI consistently exceeds the reverse TCI, reflecting a robust positive interconnectedness between the series.

The persistently negative ΔTCI values across the entire sample suggest a strong one-way transmission of shocks from the ICE EUA Carbon Futures Excess Return Index (ICEEUA) toward the Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO). The stronger direct TCI values imply that carbon market dynamics play a key role in shaping movements in the technology sector. This dynamic structure reveals the asymmetric and time varying connection between the two markets. Although both indices influence one another, the ICE EUA Carbon Futures Excess Return Index (ICEEUA) appears to serve as the more dominant transmitter of shocks, whereas the Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO) exhibits a comparatively more reactive role at certain times.

A mostly negative ΔTCI pattern signals that the ICE EUA Carbon Futures Excess Return Index (ICEEUA) serves as the primary transmitter of shocks, exerting a one directional impact on the ROBO Global Artificial Intelligence Index (THNQ). The leading position of the direct TCI demonstrates that shocks originating in the carbon sector significantly drive the behaviour of the technology sector. The results indicate reciprocal interactions; however, ICEEUA consistently emerges as the more influential source of shocks, whereas the ROBO Global Artificial Intelligence Index (THNQ) tends to react rather than initiate at various intervals.

The negative ΔTCI values observed throughout the dataset provide evidence of a stable unidirectional connectedness originating from the S&P Global Carbon Credit Index (GLCARB) and affecting the Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO). The direct TCI's dominance reveals that the sustainability sector acts as a major transmitter of effects to the digital technology sector. Although the relationship is bidirectional, the S&P Global Carbon Credit Index (GLCARB) demonstrates a stronger and more persistent transmission capacity, whereas the Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO) exhibits a more responsive behaviour at times.

The mostly negative ΔTCI values across the sample indicate a stable unidirectional spillover structure in which the S&P Global Carbon Credit Index (GLCARB) systematically transmits shocks to the ROBO Global Artificial Intelligence Index (THNQ). The dominance of the direct TCI further underscores the role of the sustainability sector as a key source of influence over the digital technology sector. Although the interaction between the two indices are formally bidirectional, the S&P Global Carbon Credit Index GLCARB displays a stronger and more persistent transmission capacity, whereas the ROBO Global Artificial Intelligence Index (THNQ) tends to exhibit a comparatively reactive response at certain points in time.

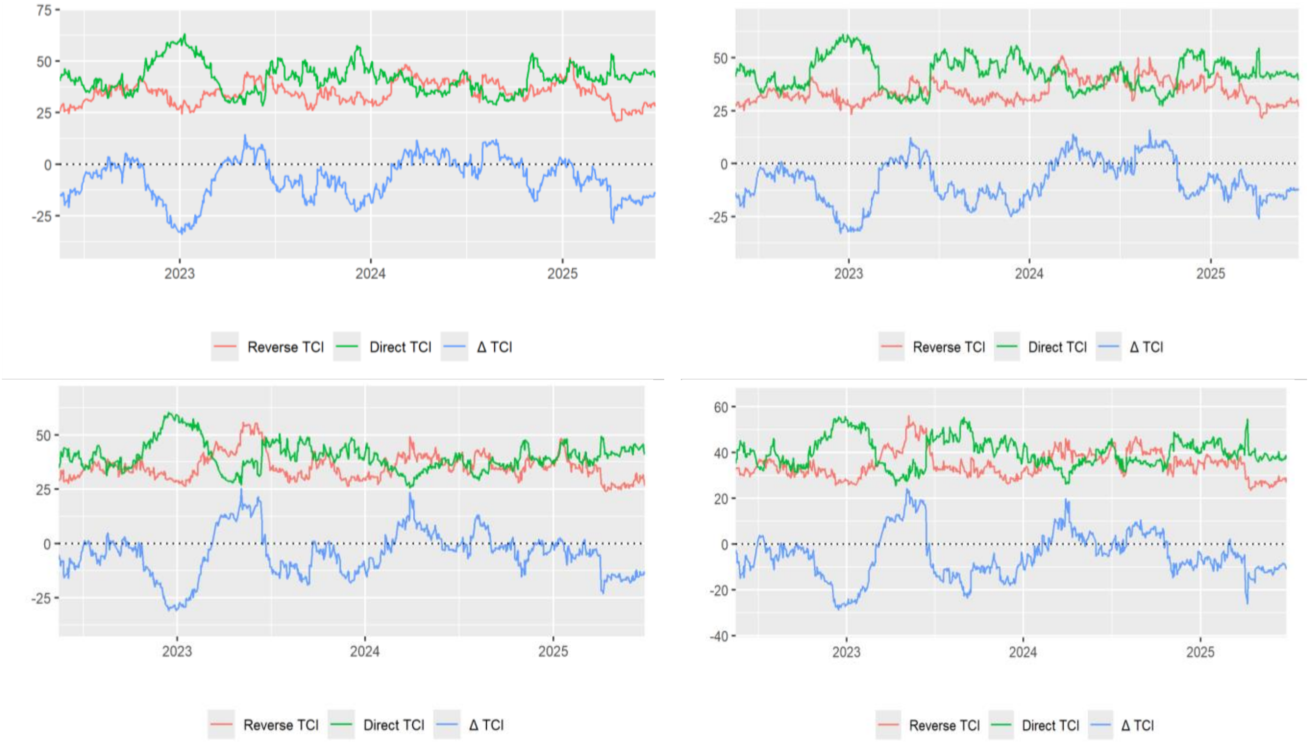

Figure 3. Direct and Reverse Total Connectedness Indices between Carbon and AI Market Indices

As a final component, quantile varying net directional connectedness is investigated, and Figure 4 visualizes the net interactions between the carbon and AI stock market indices. A three colour mapping is adopted in Figure 4, blue for strong negative outcomes, white for neutral or minimal values, and red for the most positive observations. This heatmap reports NET connectedness for the carbon market index, computed as TO minus FROM; hence, positive values indicate that the carbon market acts as a net shock transmitter, whereas negative values indicate that the carbon market becomes a net receiver and the artificial intelligence index emerges as the net transmitter in those regimes.

The quantile based net TCI heatmap highlights a nonuniform and asymmetric transmission of information between the ICE EUA Carbon Futures Excess Return Index (ICEEUA) and the Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO). The quantile based NET heatmap reveals a nonuniform and asymmetric transmission structure in which negative NET values indicate regimes where shocks are predominantly transmitted from the artificial intelligence index to the carbon market, while positive values reflect dominant shock transmission from the carbon market to the artificial intelligence index. The Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO) is identified as a net transmitter at extreme low the ICE EUA Carbon Futures Excess Return Index (ICEEUA) and extreme high quantiles, but it turns into a net receiver once the carbon sector moves into its middle performance ranges. The most pronounced impact is observed at the upper the ICE EUA Carbon Futures Excess Return Index (ICEEUA) quantile ($\tau = 0.95$), indicating that carbon markets are particularly vulnerable to disturbances originating in the technology sector.

Evidence from the quantile based net TCI heatmap points to an asymmetric information flow framework connecting the ICE EUA Carbon Futures Excess Return Index (ICEEUA) with the ROBO Global Artificial Intelligence Index (THNQ). The ROBO Global Artificial Intelligence Index (THNQ) exhibits net transmitting behaviour under conditions of very weak ESG outcomes and very high carbon market performance; however, it transitions into a net receiver when the carbon sector moves into middle tail. When the ICE EUA Carbon Futures Excess Return Index (ICEEUA) reaches its upper quantile level ($\tau = 0.95$), the influence is greatest, revealing the susceptibility of carbon market indices to technology sector shocks.

The heatmap of quantile specific net TCI values indicates an uneven structure of information flow linking the S&P Global Carbon Credit Index (GLCARB) to the Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO). During phases characterized by middle ESG values and mid range digital performance, the S&P

Global Carbon Credit Index (GLCARB) serves as a net transmitter, whereas it becomes a net receiver when AI technology sector performance lies at extreme low and high quantiles. The peak transmission occurs when the S&P Global Carbon Credit Index (GLCARB) is positioned at its upper quantile (τ = 0.95), highlighting the fragility of carbon market indices in the face of shocks from the technology domain.

Quantile level net TCI results reveal an asymmetric spillover mechanism between the S&P Global Carbon Credit Index (GLCARB) and the ROBO Global Artificial Intelligence Index (THNQ). the S&P Global Carbon Credit Index (GLCARB) is identified as a net transmitter at medium range quantiles, but it turns into a net receiver once the carbon sector moves into its extreme upper or lower performance ranges. The effect becomes most significant at the higher extreme of the S&P Global Carbon Credit Index (GLCARB) (τ = 0.95), demonstrating that carbon market equity indices are especially exposed to AI technology sector spillovers during high carbon states.

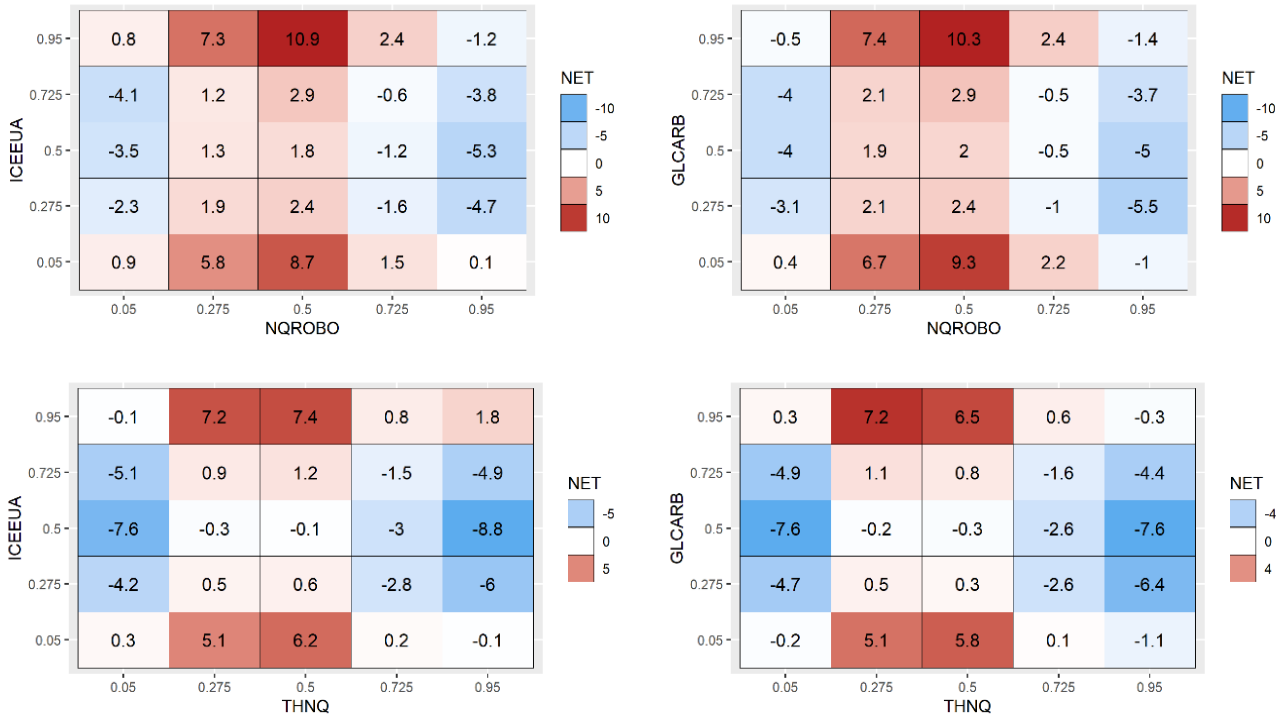

Figure 4. Net Quantile Connectedness between Carbon and AI Market Indices

5. CONCLUDING REMARKS AND POLICY SUGGESTIONS

The Quantile-on-Quantile Connectedness analysis conducted on the relationship between AI indices and the carbon market reveals a strong, time varying, and distinctly asymmetric interconnectedness between the two markets. The findings indicate that the interaction between the markets intensifies particularly during high and low market regimes, namely periods when market stress increases or when market conditions weaken. The analysis demonstrates that the carbon market most often assumes a dominant shock transmitting role toward artificial intelligence indices. This suggests that developments in carbon pricing exert a guiding influence on the market valuations of technology companies. In other words, fluctuations arising in the carbon market have become a significant external factor affecting the performance of AI firms.

On the other hand, the results show that artificial intelligence indices also play an effective shock transmitting role toward the carbon market under certain market conditions. Especially in periods when technology accelerates rapidly, innovation capacity increases, or digital transformation gains momentum, meaningful interactions emerge from AI stock markets toward carbon markets. This structure indicates that the relationship between the two markets is nonlinear and changes in a manner sensitive to market regimes and investor risk perception. The findings reveal that the carbon and AI markets are evolving into an increasingly integrated and mutually dependent financial structure. This integration has become an essential component of expectations concerning both sustainability policies and the future of the technology sector. Moreover, the results indicate that market interactions are not limited to movements in the same direction; reverse shock transmissions also occur at times. This suggests that investor behavior is shaped by a complex combination of sustainability related risk perceptions and expectations arising from innovations in the artificial intelligence sector. Therefore, AI and carbon markets exhibit a multilayered market relationship influenced simultaneously by economic, technological, and environmental factors.

The findings indicate that carbon markets and the artificial intelligence sector have become so closely intertwined that they can no longer be evaluated independently. Therefore, policy design must incorporate the mutual interactions between technology and sustainability domains. The fact that fluctuations in carbon markets exert a decisive influence on technology stocks shows that carbon pricing regulations should be formulated not only with environmental objectives in mind, but also with consideration of their potential repercussions on the digital economy and the innovation ecosystem. Such an approach may prevent carbon regulations from creating unintended vulnerabilities in the technology sector and contribute to a more balanced transition policy.

The capacity of the artificial intelligence sector to function as a significant transmitter of shocks to carbon markets under specific market conditions highlights the importance of strengthening policy coherence between technological development and climate finance. In this context, investments in digitalization, data processing capabilities, smart infrastructure, and energy efficiency enhancing technologies assume strategic relevance for the long term stability and effectiveness of carbon markets. Accordingly, public support instruments, incentive schemes, and regulatory initiatives targeting green technologies should be designed within an integrated policy framework that jointly considers digital transformation dynamics and carbon mitigation objectives. Moreover, the strong and regime dependent connectedness observed between artificial intelligence and carbon markets calls for a reassessment of existing financial stability frameworks. The potential for price shocks originating in carbon markets to generate spillover effects on technology oriented financial assets underscores the need for regulatory authorities to adopt integrated stress testing approaches that simultaneously account for both market segments. Enhancing early warning and monitoring mechanisms capable of capturing cross market vulnerabilities would facilitate the timely identification of emerging risks and contribute to mitigating systemic financial instability.

For industrial firms and participants in carbon trading systems, the findings indicate that investments in artificial intelligence technologies can play an important role in improving carbon cost management and mitigating exposure to market risks. The adoption of advanced carbon monitoring systems, AI driven forecasting tools, and digital sustainability platforms may enhance firms’ capacity to respond to volatility in carbon markets and to manage compliance more effectively. In a similar vein, organizations operating within the energy sector can reinforce their long term investment and transition strategies by explicitly considering the increasing comovement between artificial intelligence related markets and carbon markets, thereby anchoring energy transition decisions in a more comprehensive evaluation of risk and return dynamics. More broadly, the results suggest that technological development, sustainability objectives, and financial policy frameworks are becoming increasingly interconnected and can no longer be treated as independent domains. This interdependence underscores the importance of coordinated strategic approaches among regulatory authorities, technology developers, investors, and actors in the energy and industrial sectors. Operating within a shared and integrated policy framework has the potential to enhance market stability, improve risk management, and support a more efficient transition toward carbon neutral economic structures.

Although the findings of this study yield meaningful results, they also entail certain limitations. First, the analysis is conducted using a limited number of indices representing the artificial intelligence and carbon markets, and the inclusion of additional regional or sector specific indices could enhance the generalizability of the results. The relatively short data period has also made it difficult to fully capture long term regime shifts and the effects of structural transformations. Future research can move beyond these limitations and develop a more comprehensive analytical framework. In particular, conducting a disaggregated connectedness analysis between different artificial intelligence subsectors and the subcomponents of carbon markets would contribute to a more micro level understanding of these relationships. Moreover, incorporating factors such as policy shocks targeting AI technologies, carbon pricing reforms, green innovation investments, or macroeconomic risk indicators into the model may allow the causal direction of the relationships to be identified more clearly. Finally, as the global transition toward carbon neutral targets accelerates, exploring how artificial intelligence technologies integrate into this process and how they influence climate policies through financial markets offers a promising avenue for future research.

AUTHORS' DECLARATION:

This paper complies with Research and Publication Ethics, has no conflict of interest to declare, and has received no financial support.

AUTHORS' CONTRIBUTIONS:

The entire research is written by the author.

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