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Cross-quantile risk assessment: The interplay of crude oil, artificial intelligence, clean tech, and other markets

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A R T I C L E I N F O

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A B S T R A C T

This paper explores the interconnections among oil, artificial intelligence (AI), clean technology, and traditional markets. We apply a novel generalized quantile-on-quantile connectedness method that assesses variable cross-quantile interdependencies, analyzing data from 2018 to 2023. Our study provides a detailed examination of risk transmission dynamics between oil, AI, clean technology, and major markets including equity, debt, and currency. Our findings indicate that tail risk spillovers are more pronounced than median quantiles. In contrast, the analysis shows negative spillovers across these tails in markets for U.S. government debt, the U.S. dollar, and gold. The dynamic risk transmission analysis reveals that while the stock and AI markets generally act as net transmitters of risk across all quantiles, the crude oil and USD index markets consistently receive net risk spillovers, particularly in the right tail of the distribution. Our results suggest that, on average, AI, and clean technology markets, along with the stock markets, are more likely to transfer risk spillovers compared to debt, currency, or other commodity markets. This positions the USD and crude oil as potential buffers against extreme risk transmissions emanating from the AI and clean technology sectors. This study highlights the complex risk dynamics and the pivotal role of oil in the interplay between emerging technologies and traditional financial markets.

1. Introduction

A recent expansion of Artificial Intelligence (AI) and its applications in diverse sectors of economic activity has become a new feature of the contemporaneous reality (Huynh et al., 2020; Demiralay et al., 2021; Urom et al., 2022; Teplova et al., 2023; Liu et al., 2024; Yousaf et al., 2024). The most important benefits catered by the use of AI are the improved effectiveness of production processes, bringing about reduced costs reduction and enhanced quality (Huynh et al., 2020; Demiralay et al., 2021), improvement of human workers interaction (Arslan et al., 2022); service automation (Webster and Ivanov, 2020), machine learning algorithms supporting efficient decision making in finance (Teplova et al., 2023), advanced investment opportunities and hedging strategies (Urom et al., 2022; Liu et al., 2024; Yousaf et al., 2024; Zeng et al., 2024).

In parallel with the AI advancements, during the last decade, there have been mounting public consciousness regarding environment, sustainability, and climate change (Savaresi, 2016; Gubareva and Gomes, 2019; Ghosh et al., 2023a, 2023b; Gubareva et al., 2023a; Hanif et al., 2023; Bossman et al., 2024; Esparcia and Gubareva, 2024; Esparcia et al., 2025). Following these environmental concerns and trying to withstand climate-related threats, several governmental and intergovernmental initiatives, e.g., the Paris Agreement on Climate Change, have upsurged on a global scale aiming at decarbonizing economies and mitigating global warning effects (Ghosh et al., 2023a, 2023b; Billah et al., 2024). In their turn, major national and international corporations are also gaining environmental consciousness at an institutional level; adopting sustainable business strategies, resorting to the renewable sources of energy, investing in green financial instruments, and employing clean technologies in their environment-friendly initiatives (Ghosh et al., 2023a, 2023b; Yang et al., 2023a; Billah et al., 2024).

In what concerns clean technologies, they represent the basilar foundations for enabling the expansion of the clean energy sources of

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geothermal, hydro, solar and wind origins (Harichandan et al., 2022). Therefore, clean technologies are those that allow producing more efficient solar photovoltaic elements and more powerful hydro and wind generators, turning this sector of economic activity into extremely important industry for a ubiquitous employment of renewable clean energies (Androniceanu and Sabie, 2022; Unuofin et al., 2023; Kosmopoulos, 2024). Clean technologies make affordable several critical facilities comprising enhanced health services, improved education, and increased connectivity to the populations around the globe, lacking electric load. These technologies also present an enormous potential in what concerns the creation of jobs, and, thus, reducing energy and economic precarity.

The worldwide clean technology scenery is in continuous development. Clean technologies help diminishing emissions of greenhouse gases, allow diversifying energy supply, and permit lessening reliance on fossil fuel characterized by highly volatile prices. Therefore, further perspectives for clean energies are extremely positive and promise growing capacities of renewable energy sources, helping to create feasible approaches to the energy crisis and reduce the reliance of the global economy on traditional highly polluting dirty energies. Globally, the world is experiencing an increasing environmental, social and governance (ESG) consciousness (Gubareva et al., 2023a). It is worth noting that the especial attention is paid to the environmental (E) pillar, which is revealed through a mounting climate change and global warning awareness and, henceforth, a generalized rapidly strengthening acceptance of renewable energies. This dynamic speed up the currently unfolding transition to clean energies and enabling them clean technologies (Yap et al., 2022; Alsharif et al., 2024). However, in spite of the encouraging path of advances in clean technologies, there remain several issues to be still resolved, such as excessive dependence on rare earth metals, which could delay clean energies transition (Hanif et al., 2023).

Moreover, an increasing employment of AI in clean technologies is intertwined with the contemporaneous worries regarding fossil fuel pollution and climate and environment changes (Urom et al., 2022). Overall, the energy sector is traditionally prone to resort to new technologies, and recently has become highly focused on clean energies supported by clean technological modernizations (Koroteev and Tekic, 2021). It is also worth noting that AI is one of the most rapidly advancing technologies, which has experienced several substantial alterations in the beginning of the 21st century (Boza and Evgeniou, 2021). Different researchers find that AI produces economically significant impacts upon total productivity and could result an accelerated productivity dynamics (Venturini, 2022; and the references therein). It is suggested that AI technologies may contribute to rapid productivity growth. Additionally, Czarnitzki et al. (2023) show that AI applications are associated with more elevated levels of firm's productivity. Given its effectiveness an added value potential, AI technologies have been extensively employed in several sectors of economic activity, such as robotics, manufacturing, healthcare, finance, etc. (Zhang and Lu, 2021; Urom et al., 2022; Liu et al., 2024; Yousaf et al., 2024; Zeng et al., 2024;). As a consequence, AI has become one of the technologies inherent to the contemporaneous technological development positively affecting the so-called green technologies, which support renewable energies.

Undertaking a brief survey of the findings of previous researches, we focus on the theoretical fundamentals of connectivity between artificial intelligence and clean technologies. Several aspects. The AI application is mostly centered at firm-level customers in supply chains and renewable energy production. Moreover, the AI applications also result in possible impacts for investors, who could opt to include the stocks of such firms in their equity holdings. In what concerns optimizing production of renewable energies, AI may have a substantial part in this field. E.g., machine learning may be employed to optimize the generation effectiveness of wind and solar energies. In addition, AI helps manage clean energy storage, enhancing in this manner the consistency of reliable energy production. On the other hand, AI may be employed for to monitoring environment and controlling renewable energy production chains. For instance, emissions of polluting substances and energy load may be followed-up in real time, assuring that renewable energy production is environmentally friendly. Moreover, AI may be used to analyze big amounts of data allowing to forecast energy consumption, and, hence, permitting to optimize the utilization and distribution of clean energies. In addition, AI-based algorithms could provide possibilities of monitoring the response of energy demand in real time allowing improved effectiveness of electric load utilization. In particular, AI-based systems may allow smart managing of clean technologies. In fact, AI could be successfully employed for the complete renewable energy value chain, comprising such facets of the process, as production of renewable energy, its storage, distribution, and consumption. The AI-based algorithms may be helpful to enhance the total effectiveness and resilience of renewable energies. And last but not least, AI can be especially useful in developing of clean technologies. The joint employment of AI and renewable energies may lead to upsurging of novel clean technologies, including data-driven models of energy production and AI-based energy storage technologies.

Bearing in mind the above-discussed aspects, it is expectable to have risk transmission between clean technologies and AI. Several aspects of such spillovers are still to be addressed by academic community (Zeng et al., 2024). From the theoretical point of view this risk transmission may be attributed to market expectations, risk appetite, contagion, asset substitution, hedging necessity, news interpretation, herding behavior, market sentiment, etc. (Philippas et al., 2021; Gaies et al., 2022; Ghosh et al., 2023a, 2023b; Zeng et al., 2023). Hence, our assumption is to uncover risk spillovers between clean technologies, AI, and other markets. It is also plausive to suppose that risk spillovers in question are asymmetric and heterogeneous depending on diverse market conditions.

A lot of research has been recently focused on clean technology markets and their interrelationship with traditional markets (Kuang, 2021; Gubareva et al., 2023b; Hanif et al., 2023; Mensi et al., 2024; Umar et al., 2024). However, the research including AI, and investigating interlinkages between AI and clean technologies are rather scant and insufficient, with very few exceptions (Zeng et al., 2024). Hence our motivation is to offer additional knowledge regarding the cross-market relationship, involving AI. We also cater relevant material evidence to investors and market regulators, thus contributing to the expansion of AI and clean technologies development.

At this point, it is worth addressing the validity of the proposed and developed analysis. We start by presenting the research questions of our study. As far as we know, several aspects of interconnectedness between AI, clean energies, and conventional asset classes remain overlooked in contemporary literature. In the next section, dedicated to the survey of recent publications relevant to our research endeavor, we provide a succinct discussion of the state-of-the-art in this field. Based on the identified lacuna, we aspire to answer the question of how and to which extent the above-mentioned markets are connected with each other. To provide more concrete facets of our investigation, it is worth mentioning that we are motivated to expand knowledge on AI, clean energy, and conventional financial instruments (stocks, bonds, currencies, and commodities) focusing on how extreme tail risks are transmitted between the concerned asset classes and how different types of extreme movements across markets influence one another.

Moreover, AI applications and clean energy technologies represent popular social issues as they affect productivity, sustainability, and welfare of societies. Hence, examining these issues from diverse perspectives has potential to contribute to financial and technological planning and forecasting as well as to be become a catalyst for social changes. Our research, employing advanced econometric methodologies and providing practical insights regarding portfolio management and financing activities, helps to continue developing clean and renewable technologies along with the AI-based solutions and paves the road for future studies, capable of interrelating technological, environmental, and social factors. Furthermore, our research adds to diversity of approaches and research topics, bearing in mind that diversity in research frameworks matters for accelerating social change (Janssens and Zanoni, 2021). Analyzing social problems from diverse points of view helps shaping public policies, including those targeting clean energy solutions and AI-based applications. Therefore, our research provides potential benefits also to the respective market regulations, portfolio allocation practices, risk management and financing of AI and clean energy technologies.

It is especially so as the topics of this study cover the two principal issues. First, we investigate whether AI and clean technology markets exhibit greater extreme tail risk in comparison with the traditional financial markets, namely, stocks, bonds, currencies, and commodities. Second, we assess how extreme movements in one market, especially AI or clean technologies, produce different effects on another market. We gauge the extent to which the upside risk in one market may be transmitted as downside risk in another and vice versa. In this manner, our study focuses on assessing the relative strengths of the 'reversely related' tails. Analyzing the obtained results, we link our findings with the formally stated hypotheses, which could be consulted in Subsection 2.2 dedicated to theoretical integration and hypotheses formulation. In its turn, Section 4, dedicated to our empirical findings, presents a fruitful discussion of several novel outcomes, delineating new avenues for future research and providing important clues for practical applications and social policies development.

In order to properly address the above-discussed issues, we resort to the quantile-on-quantile connectedness analysis approach, developed recently by Gabauer and Stenfors (2024), which is a generalization of the Chatziantoniou et al. (2021) quantile connectedness method using variable cross-quantile interdependencies. The Gabauer and Stenfors (2024) technique involves the computation of the quantile level dependencies using a Quantile Vector Autoregressive (QVAR) model. Our investigation adds to the existing state-of-the-art in the field because, to the best of our knowledge, our paper constitutes pioneering research, applying the advanced econometric technique, developed by Gabauer and Stenfors (2024) extensively study the interrelations between AI, clean technologies, and other markets under variable market conditions observed since June 2018 to October 2023. Among the major innovations of our paper, we highlight, first, the application of the novel generalized quantile-on-quantile connectedness method to both newly upsurging but still not sufficiently researched markets, namely AI technologies and clean renewable energies. Second, uncover that the spillovers across the 'reversely related' and 'directly related' tails are positive in AI, clean technology, and stock markets, while are negative for bonds, currencies, and commodities. Third, we report the observed asymmetry and dynamic effects and provide a thorough discussion of the respective implications. Wrapping up, we provide a timely alert on extremely complex and inherently intricate associations among the variables in the considered network. It is also worth mentioning as a novelty feature of our research the fact that we investigate the most recent turbulent historic period, which covers two major global stresses: the COVID-19 pandemic and the ongoing Russia-Ukraine military conflict. Our empirical analyses are based on the daily data, comprising the return indices related to Artificial Intelligence (S&P Kensho Artificial Intelligence index), Clean Technologies (S&P Kensho Cleantech Index), Global Financial Markets (FTSE World Government Bond and MSCI AC World indices), Currency Market (US Dollar), and Commodity Markets (Gold Bullion and Crude Oil-WTI prices).

Our results contribute to the literature along multiple strands. First, we provide a comprehensive analysis of risk transmission among clean technology, AI, and major equity, debt, currency, and commodity markets. Second, we show that tail risk spillovers in the are stronger than those at the median quantile. Third, we observe positive quantile-on-quantile net risk spillovers between the 'reversely related' and 'directly related' tails in clean technology, AI, and stock (MSCI AC World) markets. Spillovers across the 'reversely related' and 'directly related' tails are negative in the FTSE World Government Bond, US dollar, gold, and crude oil markets. Fourth, we demonstrate that risk spillovers at the tails plunge following the intensification of the Russia-Ukraine military conflict in mid- to late-2023 Fifth, the dynamic risk transmission analyses reveal that stock (MSCI AC World) and AI markets are, on average, net contributors of risk spillovers at the median as well as in the left and right tails. However, in the right tail, the crude oil (WTI) and the USD index are, on average, the only consistent net risk spillover recipients. Sixth, on average, AI, clean technology and stocks (MSCI AC World) markets transfer more quantile-on-quantile risk spillovers than debt, currency, or commodity markets. Therefore, USD and crude oil may act as cushions for the extreme risk transmission from the AI, clean energy and equity markets. Finally, to address all these issues we use a new quantile frequency connectedness method under heterogeneous market conditions and different investment horizons, thus contributing to the development of the applied econometric techniques, especially in what concerns such novel fields as AI and clean technology.

The rest of the manuscript is structured as follows. Sections 2 presents the review of the recent literature relevant to the study. Section 3 described the data and methodology. Section 4 provides empirical findings and discussion. Section 5 concludes.

2. Literature review

2.1. Review of the extant literature

Comprehending joint behavior of the clean energy and AI markets represents a crucial point in effective portfolio management and decision-making regarding the respective asset allocation. It may be extremely useful in articulating investment milestones in what concerns exposures to AI and clean technology stocks. Therefore, in our literature survey we discuss the principal research strands in the ASI and clean energy domains, focusing on the most recent publications in this field f knowledge. Herein, we target to address the time-varying interrelationships of AI, clean energy, and other assets, in general, as well as to shed additional light on interconnections of AI and green technology markets in particular.

AI provides a new niche for asset allocation strategies, presenting, however, diverse challenges inherent to investing in new technologies. Many papers in the past have addressed the associations between AI and other markets. Huynh et al. (2020) investigated the diversification attributes of exposures to AI, robotic stocks, green bonds and cryptos. The authors find, among others that the NASDAQ Composite Index, commonly considered as a main market proxy for technology investors, and general stock indices do not represent efficient hedge one to another. In their turn, Webster and Ivanov (2020) explored the effects of AI and robotics in light of the evolving nature of work. The authors showing how AI and robotics related technological advances change the very nature of economic activities. Moreover, they analyze how human beings could maintain their competitiveness the new economic order, improving those capabilities, which are demanded in the new economy, and how educational offering must alter to be aligned with the new AI-empowered economic order. Demiralay et al. (2021) studied the comovements between AI and robotics stocks and other digital and conventional assets. The authors report strengthening co-movements of AI and robotics equities with the commodities, corporate bonds, composite stock indices, indicating that exposure to these markets in AI portfolios may not improve risk-adjusted returns in the periods of crises. A more specific issue is addressed by Koroteev and Tekic (2021), investigated the impacts of AI on Oil & Gas upstream industry. Analyzing possible future applications of AI possibilities and reviewing the use-cases already in place, the authors delineate contemporaneous trends in enhancement of AI-supported instrumentarium and discuss their influence on de-risking and accelerating of processes in the upstream sector, making the industry potentially less capital intensive. In parallel, Zhang and Lu (2021) explored the state-of-the-art in the AI sector and outline the future perspectives. Their work presents a survey of AI advances resorting to the industry information. The authors outline the focus of AI discussing AI drivers, technologies, and applications, and discuss different points of view related to the AI future development.

In a more recent paper, Urom et al. (2022) investigated quantile comovements among AI and energy industries. The authors report strong dependence of energy sectors performance, particularly of renewable energies, on the returns of AI stocks. Moreover, it is found that, depending on the market conjuncture, the AI innovations affect in diverse manners the returns of energy companies from different sub-sectors. In his turn, Venturini (2022) studied the linkages between the development of AI technologies and the increases in productivity. Employing patent data at country-specific levels for a selection of developed markets, the authors quantified the AI-related spillover of productivity. It is also found that the aggregate productivity elasticity to the stock of knowledge related to AI technologies is economically relevant and statistically significant. Teplova et al. (2023) performed analysis of market sentiment at SPB stock exchange based on neural network. The authors designed diverse sentiment measures based on AI-empowered text analysis and use regression models to reject the selected hypotheses. It is also found that market sentiment of retail investors produces a statistically significant impact on price spikes. Furthermore, the authors report that the industries, most susceptible to market sentiment, are high tech and healthcare. Zeng et al. (2024) measured the tail linkages and the comovements in time-frequency domain between clean energy and AI indices. It is found that at bear markets, the NASDAQ CTA Artificial Intelligence and Robotics Index acts as a risk contributor. Moreover, at the bear and normal market trends, connectedness is mostly pronounced in a short-run. Wavelet local multiple correlations analysis implies that the NASDAQ CTA Artificial Intelligence and Robotics Index by large exhibits positive comovements with clean energies. Apart of the extreme bullish tail, the NASDAQ CTA Artificial Intelligence and Robotics Index Granger-causes of risk alternations in all clean energy indices.

At this point, we briefly survey the most recent papers addressing the challenges and perspectives of clean energies. Di Febo et al. (2021) investigated extreme interconnectivity of clean energies and oil prices. The authors study asymmetries in the reactions to bad and good events. It was found that the two considered markets affect one another more strongly at the occasions of extreme negative news in comparison to those of the positive events. Moreover, it is reported that the innovations transmission from crude oil to equity prices of clean energies is weaker than otherwise. Following the same strand of research, Kuang (2021) analyzed whether stocks and debt instruments of renewable energy companies represent safe-haven assets for major traditional stocks markets. It was found that renewable energy stocks and green debt securities diminish downside risks of carbon intensive energy stocks. The author also concluded that green bonds possess safe-haven attributes in what concerns major international stock indices, while alerting that the stocks of renewable energy companies may augment the risks of traditional stock portfolios. Foglia et al. (2022) explored tail interconnectedness of oil and clean energy markets. The tail-event driven networks risk model was used, allowing for gauging tail-risk spillovers for each sector and firm. The authors reveal a crucial role of oil prices in the risk dynamics of oil corporations. They also highlighted the importance of the self-inflicted sector-specific spillovers, when a sector transmits/receives innovation to/from itself.

Hanif et al. (2023) studied spillovers return and volatility between rare earth metals and clean energy stocks. It is found that the rare earths play the role of net receivers of return and volatility spillovers, whereas the renewable energy stock markets act as net spillover emitters in the domains of both return and volatility. The wind and solar stock are markets that behave as spillover transmitters/receivers before/during COVID-19. The rest of the markets change from net spillover recipients to emitters and vice-versa. The authors alert that the cross-market hedging may not perform efficiently throughout the times of financial turmoil. In parallel, Naeem et al. (2023) investigated the risk contagion of traditional, Islamic and sustainable debt and equity instruments. This research analyzed the extreme interconnectedness of the faith-based, sustainable, and traditional financial markets, resorting to a neural-network quantile regression. The neural-network algorithms revealed that both traditional and faith-based investments exhibit an elevated susceptibility to tail risks in the aftermaths of major global crises, recognizing that the green assets, at these episodes, are capable of providing substantial diversifying attributes to the investment portfolios. In addition, Zeng et al. (2023) investigated connectedness and spillover between clean energies and grain commodities. A TVP-VAR-based connectedness methodology was employed to uncover spillover features prior and after the coronavirus pandemic. The authors demonstrated that the pandemic substantially affects the time-frequency spillovers in the network, with the maximum of system connectedness observed during the initial expansion of the coronavirus outbreak. Their results imply that, in a short run, spillovers are stronger than in the intermedium and long run. This research was a pioneering work, which explore the time-frequency interconnectedness of returns in the green energy indices and the grain commodities. Billah et al. (2024) analyzed the transmission of downside risks across green bonds and Islamic sectoral stocks. The authors design a novel framework based on CAViaR and QVAR methodologies to design hedging and portfolio strategies. Their results demonstrated that connectedness in a short term is stronger than in the long term, whereas the transmission of downside risks varies along the time, being impacted by financial turmoil and crises. Green bonds of the US, the European Union, and China are the net recipients of innovations in low and medium downside risk episodes for diverse investment horizons. Conversely, the US and global green bond indices act as net emitters at elevated downside-risk conditions.

2.2. Theoretical integration and hypotheses

It is also worth noting that there exists an emerging strand focusing on the interlinkages between AI and clean technology markets: Hu et al. (2022), Liu et al. (2022); Entezari et al. (2023), and Zeng et al. (2024). In particular, Hu et al. (2022) addressed AI applications in clean energy systems. Liu et al. (2022) studied whether AI possesses the potential to enhance the energy effectiveness of Chinese manufacturing corporations. Entezari et al. (2023) provided a bibliographic perspective on AI and machine learning in the energy sector. Zeng et al., 2024 explore the tail connectivity and co-movements between AI and renewable energies in the time-frequency domain. AI is believed to serve as a tool for solving many of humanity's pressing needs, including climate change, energy and power, among other things. AI's role in developing and managing clean (especially renewable) energy is expected to be critical (Antonopoulos et al., 2020; Ahmad et al., 2021). However, AI requires copious amounts of energy/power itself (Edelman et al., 2023). As such, AI poses a double-edged sword with respect to energy and/or climate change. As such, its interplay with clean energy technologies, as well as conventional energy commodities, such as crude oil, remains crucial.

It is important to note that AI and clean energy technologies remain rapidly evolving — in the form of Advanced AI or Artificial General Intelligence (AGI) — and require substantial investments worldwide (Deng, 2018; Mou, 2019). Consequently, AI and clean technologies have the potential to positively transform (positively) the global economic landscape, especially in sectors such as industry, education, healthcare, finance, energy and power, transportation, law enforcement, and defense. However, AI is expected to pose risks such as job losses and global financial sector volatility. Accordingly, the financial markets for AI are expected to carry substantial variability and risk. A similar scenario exists for clean energy technologies. As such, these two sectors are expected to interplay, often extensively, with the international conventional financial markets.

The extant AI and Clean Tech literature strand, being still emergent and scant, overlooks the interconnectedness between AI, clean energies, and conventional asset classes. Our research paper is motivated to fill this gap. The present paper helps to understand the linkages between these domains better. We advance the knowledge frontier regarding the interactions among AI, clean energy, and conventional financial markets, including stock, bond, currency, and commodity markets. Based on the above literature survey, it is possible to infer that although some research has been done on the interconnectedness of the considered markets, the works mentioned above represent sizable limitations regarding the asset classes considered and the time span addressed. To address these shortcomings, our paper expands knowledge on AI, clean energy, and conventional financial markers by applying the advanced econometric quantile-on-quantile connectedness analysis technique to the most recent dataset. The quantile-on-quantile connectedness analyses, using the novel Gabauer and Stenfors (2024) approach, help decipher how extreme tail risks are transmitted between financial markets and how different types of extreme movements across markets affect each other. This is discussed in Section 3.2.

Following the discussions of theory and empirical literature hereabove, we propose the two following hypotheses:

H1. *AI and Clean Technology markets are expected to exhibit and/or impart greater extreme (tail) risk to conventional stock, bond, currency, and commodity markets.*

H2. *Extreme movements in one market, especially AI and/or Clean Technology, may impart differing impacts on another market. That is, the upside risk in one market may be transmitted as downside risk in another and* vice versa.

Both hypothesized scenarios may involve a 'cross-market rebalancing', a theoretically predicted and empirically observed scenario whereby investors adjust their optimal portfolio in response to a crisis in a particular financial market (Kodres and Pritsker, 2002).

3. Data and methodology

3.1. Data

Our empirical analysis employs daily data from various markets, including Artificial Intelligence, Clean Technology, global financial markets, currencies, and commodities. Specifically, we used the S&P Kensho Artificial Intelligence Enablers Index (USD) and the S&P Kensho Cleantech Index (USD) to represent the Artificial Intelligence and Clean Technology markets. The data for these two indices were downloaded from the official S&P Global website (https://www.spglobal.com/), ensuring the accuracy and reliability of the market information. For the global financial markets, we utilized the FTSE World Government Bond Index and MSCI AC World Index. Additionally, we examined the Currency Market using the US Dollar Index and commodity markets through the Gold Bullion Index and Crude Oil-WTI Index. The data for the global financial, currency, and commodity markets were downloaded from Refinitiv DataStream.

The time series spans from June 2018 to October 2023, providing a comprehensive view of market behaviors across different economic conditions, including key events like the COVID-19 pandemic and the Russia-Ukraine conflict. For estimation purposes, the data were transformed into logged differenced returns. This transformation ensures stationarity of the data, allowing us to accurately capture the dynamics and volatility across these diverse markets while eliminating potential non-stationarity issues commonly associated with raw financial time series data. This approach enhances the robustness of our econometric analysis and ensures the validity of the results derived from the Quantile-on-Quantile Connectedness method.

In Table 1, we can find the descriptive statistics of the seven returns series along with their symbols. The mean values of all markets are different to zero (0) — but remain close. The coefficient of variation $\left(\frac{\sqrt{\text{Variance}}}{\text{Mean}}\right)$ is, on average, very high for all seven indices—indicating high volatility. The highest magnitude of the coefficient of variation is observed in FTSE World Government Bond Index while the lowest is seen in Gold Bullion. As such, the sovereign bond index is the most volatile index in the sample while Gold Bullion — a commodity which is generally known as a 'safe haven' – is the least volatile index. Four out of the seven market returns are negatively skewed while all seven are leptokurtic. As observed by rejection of the Jarque and Bera (1980) null hypothesis, all seven time-series are not normally distributed. The Elliott et al. (1996), or ERS, test statistics find all market indices to be stationary in level form. Nevertheless, the returns indices are autocorrelated of order 10, as evidenced by the Ljung and Box (1978) Q(10) and $Q^2(10)$ test statistics except for Q(10) for Gold Bullion.

Fig. 1 displays the time plots of the seven market indices' returns. In concordance with Table 1, the plots are centered around a zero mean and oscillate at varying extents. However, in all the time series plots, large spikes can be observed with the advent of the COVID-19 pandemic in early 2020, as well as that of the Russia-Ukraine military conflict in early 2022. In terms of temporal fluctuations, the Clean Technology and Crude Oil-WTI indices are more vigorous, while the FTSE World Government Bond and US Dollar indices are the least.

Table 2 provides the correlation matrix for the seven sample returns series. The Artificial Intelligence and Clean Technology Indices are highly correlated with the MSCI AC World Index — with coefficient values of 0.706 and 0.828, respectively. The correlation between the FTSE World Government Bond and the other six market indices remains low — with the lowest (and insignificant) coefficients reported for Artificial Intelligence and Clean Technology. The correlation between the FTSE World Government Bond and Gold Bullion Indices is notable: at 0.320. The US Dollar Index is negatively correlated with all remaining six market returns. The only other (two) instances of negative correlation coefficients occur between the FTSE World Government Bond and Crude Oil-WTI Indices (at −0.070) and between the former and the MSCI AC World Index (at −0.052, but statistically insignificant).

3.2. Methodology

In this study, we resort to the quantile-on-quantile connectedness analysis, developed recently by Gabauer and Stenfors (2024). This

Table 1
Descriptive statistics of returns series.

Index	Symbol	Mean	Variance	Skewness	Kurtosis	JB	ERS	Q(10)	$Q^2(10)$
Artificial Intelligence Index	ARTIN	0.055	3.606	−0.435***	4.498***	1221.072***	−5.885	34.917***	599.409***
Cleantech Index	CLNT	0.064	7.75	−0.199***	3.300***	642.535***	−13.714	13.891***	397.742***
FTSE World Government Bond Index	BOND	−0.004	0.072	0.153**	2.835***	472.772***	−9.418	19.495***	506.743***
MSCI AC World Index	STOCK	0.019	1.132	−1.113***	15.766***	14,746.984***	−8.283	61.373***	862.760***
US Dollar Index	DXY	0.008	0.173	−0.115*	1.988***	232.848***	−11.072	11.074**	372.893***
Gold Bullion	GOLD	0.026	0.774	−0.379***	4.160***	1039.999***	−10.732	4.992	81.567***
Crude Oil-WTI	OIL	0.067	11.466	0.608***	22.158***	28,644.784***	−9.538	30.634***	567.245***

Notes: ***, **, * denote statistical significance at 1%, 5% and 10 % significance level; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; and ERS: Elliott et al. (1996) unit-root test.

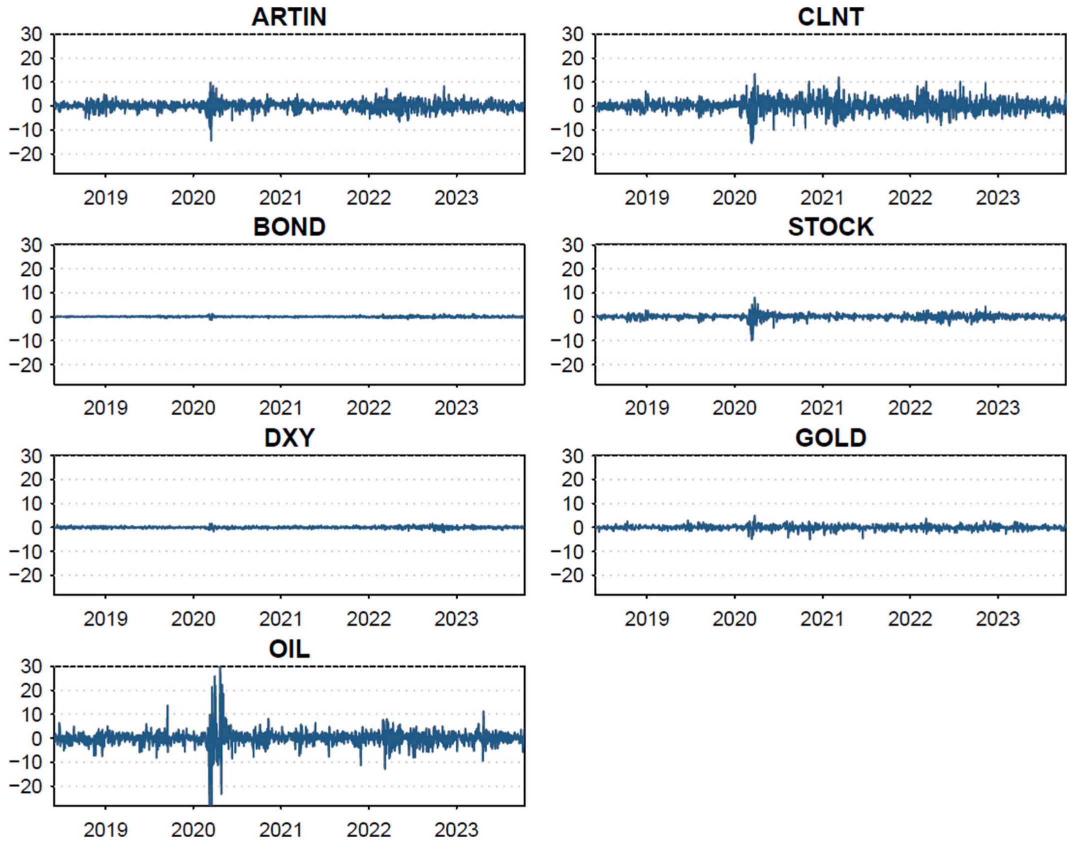

Fig. 1. Time series of returns.
Notes: This figure represents the time evolution of the returns series for the selected markets.

Table 2
Correlation matrix of the selected markets.

	ARTIN	CLNT	BOND	STOCK	DXY	GOLD	OIL
ARTIN	1.000***	0.706***	0.006	0.828***	−0.188***	0.096***	0.174***
CLNT	0.706***	1.000***	0.009	0.668***	−0.159***	0.139***	0.187***
BOND	0.006	0.009	1.000***	−0.052	−0.193***	0.320***	−0.070***
STOCK	0.828***	0.668***	−0.052	1.000***	−0.297***	0.155***	0.264***
DXY	−0.188***	−0.159***	−0.193***	−0.297***	1.000***	−0.377***	−0.036
GOLD	0.096***	0.139***	0.320***	0.155***	−0.377***	1.000***	0.093***
OIL	0.174***	0.187***	−0.070***	0.264***	−0.036	0.093***	1.000***

Note: This table showcases the Pearson correlation for the selected markets. *** represents statistical significance at 1 %.

approach is a generalization of the Chatziantoniou et al. (2021) and Ando et al. (2022) quantile connectedness methods using variable cross-quantile interdependencies. The Gabauer and Stenfors (2024) method helps detecting the surge in connectedness across financial markets frequently observed during extreme global events such as diverse crises (economic or otherwise) and other uncertainties. During such events, the financial markets connectedness networks face 'systemic shocks' that are greater in magnitude than the 'average shock' (Ando et al., 2022). The quantile connectedness analysis procedure exploits this attribute/assumption of extreme events where 'systemic shocks' represent a substantial deviation from the distribution's mean. This invariably results in 'systemic shocks' involving a change (or movement) that occurs in the distribution's extrema (or tails).

The quantile-on-quantile risk spillover analysis of Gabauer and Stenfors (2024) is useful in investigating whether (and to what extent) extreme risk (that manifests as tail risk) from one market (distribution) may culminate in extreme (tail) risk in another market (distribution). This novel technique also helps in gauging how the differing extrema of disparate distributions (markets) are interconnected: i.e., between the right tails of the distributions or between the right and left tails (upper and lower quantiles, respectively) of the distributions. The pioneering Gabauer and Stenfors (2024) quantile-on-quantile analysis of network connectedness remains, hitherto, the only method capable of enabling both the quantile-tail risk propagation analysis and the investigation of cross-quantile interdependencies. Past methods such as Chatziantoniou et al. (2021) and Ando et al. (2022) can only achieve the former, to a limited extent.

These attributes of the quantile-on-quantile connectedness analysis by Gabauer and Stenfors (2024), thus, make it indispensable for analyzing our sample of Artificial Intelligence, Clean Technology, and Global Financial Markets between mid-2018 and late-2023 and for verifying the rejection of hypotheses *H1* and *H2* (in Section 2.2). The sample includes markets that are nascent and/or have faced tumult during the sample timeframe, which was also characterized by troubling (and, perhaps unexpected) global events like the COVID-19 pandemic and the Russian invasion of Ukraine, among others.

The Gabauer and Stenfors (2024) technique involve the computation of the quantile level dependencies using a Quantile Vector

Autoregressive model (1) of order p or QVAR(p):

$$\boldsymbol{x}_t = \boldsymbol{\mu}(\boldsymbol{\tau}) + \sum_{j=1}^{p} \boldsymbol{B}_j(\boldsymbol{\tau})\boldsymbol{x}_{t-j} + \boldsymbol{u}_t(\boldsymbol{\tau}) \tag{1}$$

where, $\boldsymbol{x}_t$ and $\boldsymbol{x}_{i-j}$ denote $K \times 1$ vectors incorporating endogenous variables, $\boldsymbol{\tau}$ denotes the quantiles vector taking values within the range $[0, 1]$, p denotes the QVAR's lag order, $\boldsymbol{\mu}(\tau)$ denotes a $K \times 1$ vector incorporating conditional means, $\boldsymbol{B}_j(\tau)$ denotes a $K \times K$ matrix containing the coefficients of the QVAR model, and $\boldsymbol{u}_t(\tau)$ denotes a $K \times 1$ error vector incorporating a $K \times K$ variance-covariance matrix. Gabauer and Stenfors (2024) transform their QVAR model into a Quantile Vector Moving Average (QVMA) — to estimate the Koop et al. (1996) Generalized Forecast Error Variance Decomposition (GFEVD) — by way of Wold's Decomposition Theorem: $\boldsymbol{x}_t = \boldsymbol{\mu}(\boldsymbol{\tau}) + \sum_{j=1}^{p} \boldsymbol{B}_j(\boldsymbol{\tau})\boldsymbol{x}_{t-j} + \boldsymbol{u}_t(\boldsymbol{\tau}) = \boldsymbol{\mu}(\boldsymbol{\tau}) + \sum_{i=0}^{\infty} \boldsymbol{A}_i(\boldsymbol{\tau})\boldsymbol{u}_{t-i}(\boldsymbol{\tau})$. How a shock experienced by series j affects series i is accounted for by the F-step ahead GFEVD—as identified in eq. (2):

$$\phi^{g}_{i\leftarrow j,\tau}(F) = \frac{\sum_{f=0}^{F-1}\left(\boldsymbol{e}_i'\boldsymbol{A}_f(\boldsymbol{\tau})\boldsymbol{H}(\boldsymbol{\tau})\boldsymbol{e}_j\right)^2}{\boldsymbol{H}_{ii}(\boldsymbol{\tau})\sum_{f=0}^{F-1}\left(\boldsymbol{e}_i'\boldsymbol{A}_f(\boldsymbol{\tau})\boldsymbol{H}(\boldsymbol{\tau})\boldsymbol{A}_f(\boldsymbol{\tau})'\boldsymbol{e}_i\right)},$$

$$gSOT_{i\leftarrow j,\tau}(F) = \frac{\phi^{g}_{i\leftarrow j,\tau}(F)}{\sum_{j=1}^{k}\phi^{g}_{i\leftarrow j,\tau}(F)} \tag{2}$$

here, e_i denotes a $K \times 1$ zero vector incorporating unity as the ith element. The row sum of $\phi^{gen}_{i\leftarrow j,\tau}$ requires a normalization – as Diebold and Yilmaz (2012) argue since it is unequal to unity. The normalization involves a division of $\phi^{gen}_{i\leftarrow j,\tau}(H)$ using the row sum, culminating in the 'scaled GFEVD': $gSOT_{i\leftarrow j,\tau}(F)$. The scaled GFEVD estimates the total directional connectedness TO (FROM) others and is the bedrock of the Gabauer and Stenfors (2024) connectedness analysis technique. The TO total directional connectedness accounts for the impact of series i on other markets (in the sample) – i.e., eq. (3). In contrast, the FROM total directional connectedness calculates the impact of the other markets on series i – i.e., eq. (4).

$$S^{\text{gen,to}}_{i\rightarrow\bullet,\tau} = \sum_{k=1,i\neq j}^{K} gSOT_{k\leftarrow i,\tau} \tag{3}$$

$$S^{\text{gen,from}}_{i\leftarrow\bullet,\tau} = \sum\nolimits_{k=1,i\neq j}^{K} gSOT_{i\leftarrow k,\tau} \tag{4}$$

The series i's NET total directional connectedness is computed as the difference between its TO and FROM total directional connectedness, as identified in eq. (5):

$$S^{\text{gen,net}}_{i,\tau} = S^{\text{gen,to}}_{i\rightarrow\bullet,\tau} - S^{\text{gen,from}}_{i\leftarrow\bullet,\tau} \tag{5}$$

here, a positive magnitude of $S^{\text{gen,net}}_{i,\tau}$ implies that series i imparts more influence to all remaining series in the sample than the influence it receives from them. As such, series i can be identified as a 'net transmitter of shocks.' By contrast, a negative $S^{\text{gen,net}}_{i,\tau}$ reveals that series i receives more influence from others (in the sample) that it imparts to them. In such a situation, it is a 'NET receiver of shocks.'

Ultimately, eq. (6) estimates the Chatziantoniou et al. (2021) adjusted Total Connectedness Index (TCI). The (adjusted) TCI measures the extent of the interconnectedness of the network system—with magnitudes representing greater market risk.

$$TCI_\tau(F) = \frac{K}{K-1}\sum_{k=1}^{K} S^{\text{gen,from}}_{i\leftarrow\bullet,\tau} \equiv \sum_{k=1}^{K} S^{\text{gen,to}}_{i\rightarrow\bullet,\tau} \tag{6}$$

Additionally, the computed quantile-on-quantile risk transmission measures are used in assessing the pairwise risk transmission networks and time-varying NET risk spillovers across the seven sample markets. To this end, we avail the Diebold and Yılmaz (2014) connectedness analysis method. The Diebold and Yılmaz (2014) method incorporates a pth order generalized Vector Autoregressive model or VAR(p) that is covariance stationary and contains N number of variables. $x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$ specifies such a VAR(p), where $\varepsilon \sim (0, \Sigma)$ denotes a disturbance term which is identically and independently distributed (i.i.d.). The Diebold and Yılmaz (2014) connectedness approach also allows us to gauge the TO and FROM as well as NET total directional spillovers, over time, of series i vis-à-vis all remaining series (of the sample).

4. Empirical findings and discussion

Fig. 2 presents the estimated pairwise risk transmission networks across the seven sample markets at different quantiles. Part (a) of Fig. 2 displays the pairwise risk transmission network at the medians — i.e., at the 50th percentiles of the two market indices considered. As can be seen, the risk transmission network is dominated by Artificial Intelligence and MSCI AC World Indices. There are also considerable exchanges of risk between Artificial Intelligence and Clean Technology Indices, as well as between MSCI AC World and Clean Technology Indices. Accordingly, these three markets presided over the median risk propagation network.

The picture dramatically differs in the extreme lower quantiles (i.e., the left tails, or 5th–5th percentiles, of the distributions) of the market pair in question (Part b, Fig. 2.). The three above indices continue to dominate the risk transmission network but are supplemented by virtually all other sample markets. A similar observation can be made regarding the extreme upper quantiles of the respective market pair — i.e., the right tails, or 95th–95th percentiles, of their distributions (Part c, Fig. 2). However, the nodes and the arrows are slightly smaller and thinner in Part (c) than in Part (b), of Fig. 2. Additionally, in Fig. 2, the arrows in both Parts (b) & (c) are thinner than their counterparts in Part (a). Nevertheless, this highlights an important finding — the risk transmission network is more expansive and vigorous in the extrema (or tails) of a market pair's respective distributions than at the medians. As a result, a pairwise market risk transmission analysis may depict an unintentionally misleading picture and less insightful inferences relative to their counterparts at the tails. This finding, albeit novel, is similar to the extant, yet unrelated, studies that implement quantile econometric methods, especially the quantile-on-quantile technique(s) see, e.g., Shahbaz et al. (2018), Shafiullah et al. (2021), Naeem et al. (2022), Pham et al. (2022), among others. In sum, the greater risk connectedness at the tails of the distributions signifies the upside and downside risks faced by investors across AI, crude oil, clean technology, and other markets in the sample (see, e.g., Van Oordt and Zhou, 2016; Happersberger et al., 2020; Shafiullah et al., 2021; Xu and Lin, 2023). The above estimates and their corresponding inferences provide preliminary visual evidence for hypothesis ***H1****: AI and Clean Technology markets are expected to exhibit and/or impart greater extreme (tail) risk to legacy stock, bond, currency, and commodity markets*.

Fig. 3 exhibits the averaged TOTAL quantile-on-quantile risk transmission between its various quantiles. As can be seen, the tails of the distributions are highly and positively connected—i.e., 'reversely related' quantiles. The 'directly related' quantiles also remain well connected (in a positive direction), but their connectedness measure values are slightly lower than their 'reversely related' counterparts. In particular, the Total Connectedness Index (TCI) is the highest in value between the $[\tau_1 = 5\%, \tau_2 = 90\%]$ quantiles, i.e., the 'reversely related' left-tail and right-tails of the distributions. The lowest TCI value is observed between the $[\tau_1 = 90\%, \tau_2 = 90\%]$ quantiles: i.e., the 'directly related' right-tails of the distributions.

This novel finding highlights the dominance of the 'reversely related'

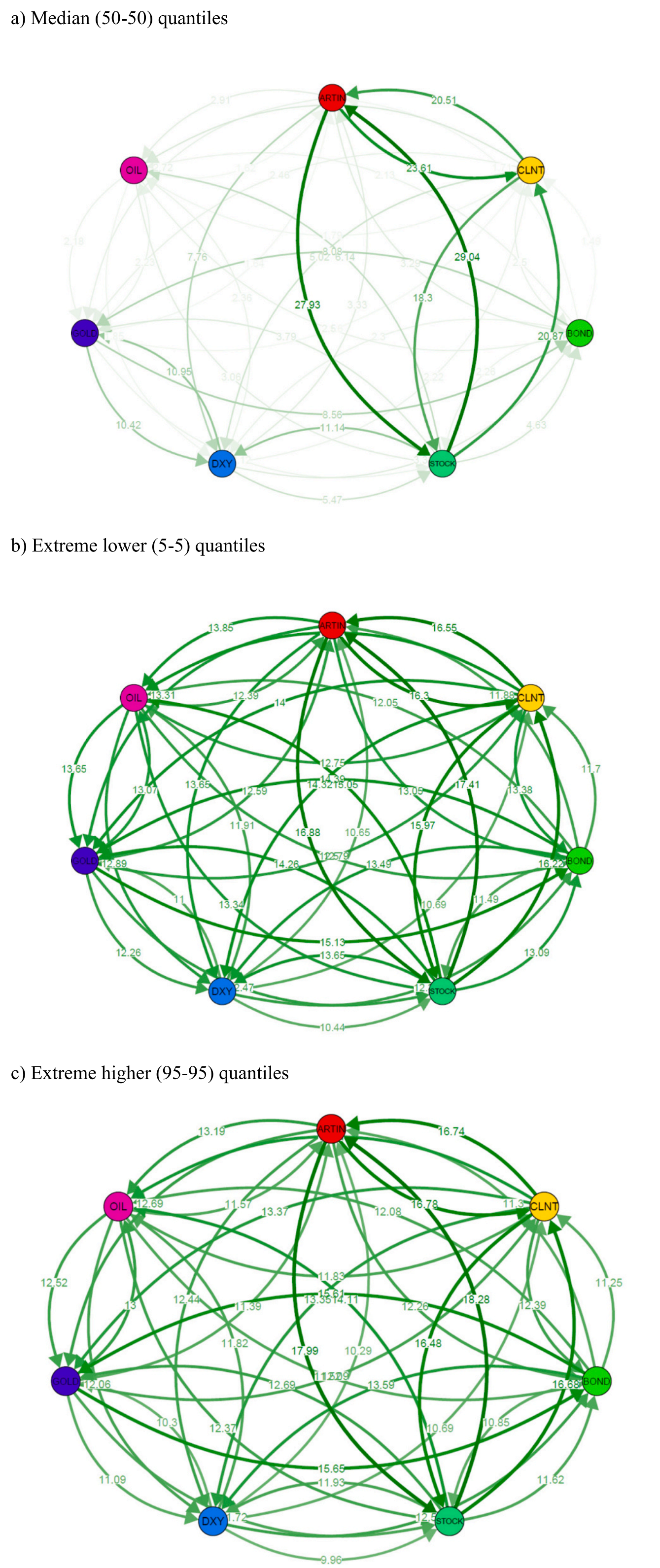

Fig. 2. Pairwise risk transmission networks of markets.
Note: This figure showcases the network spillovers between artificial intelligence, clean technology and other markets using a Quantile-Quantile connectedness model with lag 1 (SIC criteria) and a 20-step-ahead generalized forecast error variance decomposition.

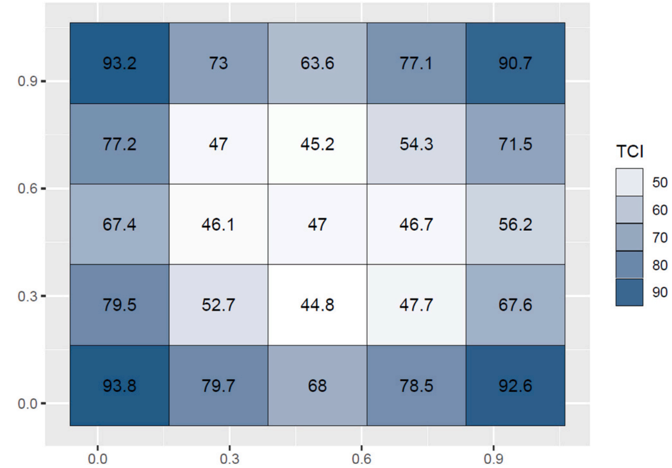

Fig. 3. Averaged TOTAL Quantile-Quantile risk transmission of markets.
Notes: Results are based on a Quantile-Quantile connectedness model with lag 1 (SIC criteria) and a 20-step-ahead generalized forecast error variance decomposition.

tails between crude oil, AI, clean technology, and conventional financial markets. This conclusion is in line with a recent quantile-on-quantile connectedness study of Gabauer and Stenfors (2024), who report a similar finding for the spillovers across the 2-year US Treasury yield (US2Y) and the yield curve spread between the 10-year and 2-year US Treasury yield (US2Y10Y). It is worth mentioning that risk transmission between oil price shocks and the term structure of the US yield curve (Umar et al., 2022) as well as between oil price shocks and technology markets (Umar et al., 2024) has recently attracted considerable attention. The results of Gabauer and Stenfors (2024) as well as the results of our study demonstrate that the average total connectedness between *reversely related* quantiles across certain markets is substantially higher than *directly related* quantiles, evidencing an important role of a 'negative correlation' between the distributions' tails at each end. The greater strength of the 'reversely related' tails (in Fig. 3) may also imply a 'cross-market rebalancing' across our seven sample markets — a scenario theoretically predicted and observed empirically in prior finance literature (Kodres and Pritsker, 2002). This finding may also highlight the differing (theoretically predicted and empirically observed) response of the tails at each end to fiscal and monetary policies — by governments and/or central banks — to stabilize the markets (and the macroeconomy at large) during these extreme, and unexpected, global events (Wheelock and Wohar, 2009; Chatziantoniou et al., 2021; Shafiullah et al., 2022; Ding et al., 2023). The findings from Fig. 3 help in non-rejecting hypothesis ***H2:*** *Extreme movements in one market, especially AI and/or Clean Technology, may impart differing impacts on another market. That is, the upside risk in one market may be transmitted as downside risk in another and* vice versa.

Fig. 4 then displays the averaged NET quantile on quantile risk transmission for individual markets. The averaged NET quantile on quantile risk transmission networks for each sample market (Fig. 4) is a contrast to the TOTAL counterparts (in Fig. 3). The Artificial Intelligence, Clean Technology, and Stock (MSCI AC World) markets generally exhibit positive NET quantile-on-quantile-on-quantile risk connectedness in the 'reversely related' as well as 'directly related' tails. For the remaining four markets (FTSE World Government Bond, US Dollar, Gold, and Crude Oil), the averaged NET connectedness values in the 'reversely related' and 'directly related' tails are negative but similar in magnitude to their positive counterparts.

For the middle quantiles, the NET connectedness measures for both 'reversely related' and 'directly related' quantiles are substantially greater in magnitude vis-à-vis their tail (extreme) quantiles. The largest magnitudes of averaged NET quantile-on-quantile connectedness can be

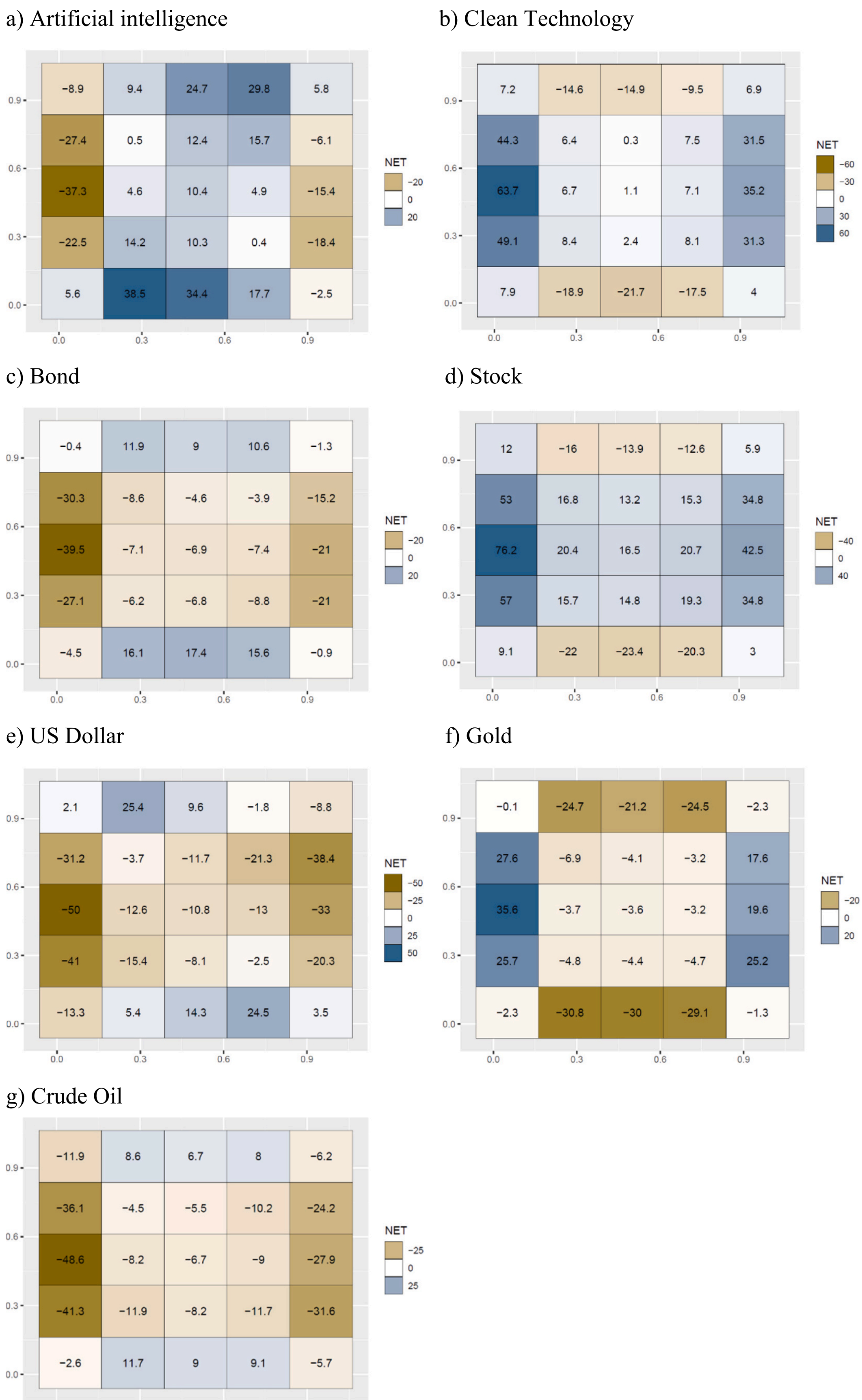

Fig. 4. Averaged NET Quantile-Quantile risk transmission of markets.
Notes: Results are based on a Quantile-Quantile connectedness model with lag 1 (SIC criteria) and a 20-step-ahead generalized forecast error variance decomposition.

observed in the Stock Market (MSCI AC World), while the lowest magnitudes are observed in the market for Artificial Intelligence. This demonstrates a contrasting picture of each market's (quantile-on-quantile) risk transmission. There is a greater TOTAL risk transmission in the extrema of the distribution (Fig. 3). In addition, Fig. 4 presents the quantile-on-quantile NET risk transmission for individual markets.

In Fig. 4 we also observe a substantial 'clustering' in risk spillovers within each sample market — vis-à-vis the 'cross-market rebalancing' in the 'reversely related' quantiles for the averaged TOTAL quantile-on-quantile risk transmissions (in Fig. 3). This clearly demonstrates the dynamics of the individual markets are not necessarily representative of the sample markets network as a whole. The 'clustered interconnectedness' within a larger cohort of financial markets is a novel finding for our sample of crude oil, AI, clean technology, and traditional markets. However, a similar finding of 'clustering' among certain market groups has been previously observed for 'Shanghai Oil and other markets' by Naeem et al. (2024a).

The TOTAL risk transmissions of our seven sample markets are presented in Fig. 5.[1] The 'directly related' right as well as left tails (of the distributions) remain highly and positively connected—similar to the observations in Fig. 3. The 'directly related' medians of the distribution are also positively connected, with their TCI ranging from slightly under 40 (in early-2019) to a little over 60 (in early-2023). However, TCI values peak following the onset of the COVID-19 pandemic in early 2020, the Russia-Ukraine military conflict intensifying, and worsening political uncertainty in the UK related to the austerity discussions and implementations). This demonstrates an increase in risk transmission during global and local crisis events. The finding of increased connectedness during global crises for our sample of AI, oil, clean technology, and other markets represents a novelty of our research. However, this outcome is in line with the extant literature such as Naeem et al. (2021), Hasan et al. (2022), Maher (2023), Naeem et al. (2024b), inter alia. The novel discoveries from Figs. 4–5 also provide evidence against rejecting hypotheses ***H1*** and ***H2***.

Fig. 6 illustrates the change in transmission of extreme upper and lower risk. The change in quantile-on-quantile TCI is negative for almost the entire sample time period, except for mid-2023, which is the wake of

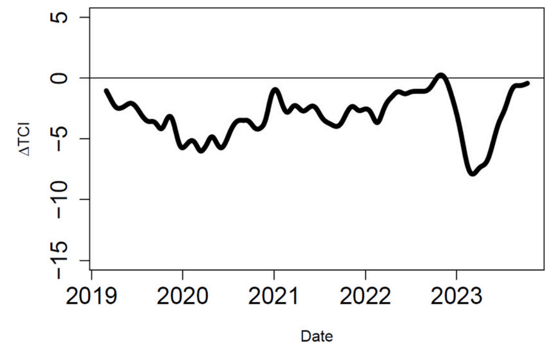

Fig. 6. Change in extreme upper and lower risk transmission.
Notes: Results are based on a 200-day Rolling Window Quantile-Quantile connectedness model with lag 1 (SIC criteria) and a 20-step-ahead generalized forecast error variance decomposition.

the intensifying Russia-Ukraine military conflict. In late 2023, we observe the largest decline in the change in the quantile-on-quantile TCI throughout the sample duration. This is likely due to the breakdown of the supply chains due to the Russia-Ukraine conflict as well as expansive economic sanctions imposed on Russia, including trade of its fuels and commodities (Naeem et al., 2024b). As a result, the total connectedness of the seven sample markets plummeted as geopolitical risks elevated, crude oil prices soared, and an inflation engulfed the globe (Yang et al., 2023b; Naeem et al., 2024a). This is also evident in Fig. 5, where the TOTAL risk transmission of the seven markets fell for all displayed quantiles — especially that in the left tail (5 % quantile). Overall, the findings in Fig. 6 provide further evidence against rejecting hypothesis ***H1***.

At this point it is worth noting that connectedness within the system of the analyzed markets is characterized by pronounced quantile-on-quantile asymmetries and substantial dynamic effects being a kind of asymmetry in the time domain. For instance, Fig. 3 presenting the averaged total quantile-on-quantile risk transmission within the considered networks of markets, reveals the maxima of in the corners, which correspond to the extreme tail associations, namely, lower-lower, lower-upper, upper-lower, and upper-upper quantile-quantile connectedness. We also observe an intuitively expected decay of the spillover strengths to the center of rows and columns. This behavior is consistent with the weakest strengths observed in the center of the square. In addition, Fig. 4 exhibits diverse types of similar asymmetries for each of the considered markets individually. An important implication of these results is that any decision based on mean or median quantile figures could be misleading and mistakenly support overoptimistic judgements regarding the risk present in the system. Therefore, we advise investors and portfolio managers to take their decisions based on a more detailed, quantile-on-quantile type of analysis.

In what concerns the dynamic effects, they are clearly observable in Figs. 5 and 6. E.g., Fig. 5 depicts the time-varying total risk transmission across the considered markets. One can clearly see the two peaks in connectedness; one in the beginning of 2020, which we ascribe to the outbreak of the coronavirus pandemic and another one in the first half of 2023, associated with the intensifying of the military hostilities between Russia and Ukraine. Interestingly, we also see quantile-related asymmetries coupled with asymmetries in the time domain. For example, we see that the extreme upper 95th quantile is the least sensitive along the time to the influence of uncertainties transversal to financial markets. The extreme lowest 5th quantile is more sensitive, while the medium 50th quantile is the most susceptible to global and local crisis occurrences. Furthermore, Fig. 6 presents changes in the extreme upper and lower risk transmission. One can neatly observe that anomalies once again coincide with the two above mentioned risk-generating events.

Finally, in Fig. 7, we present the NET risk transmission of each sample market over time. At the median quantiles (Fig. 7, Part a), the

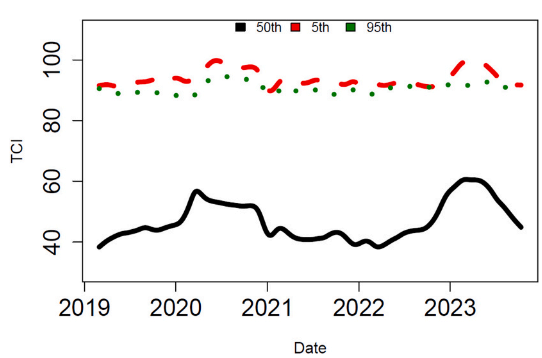

Fig. 5. Time-varying TOTAL risk transmission of markets.
Notes: Results are based on a 200-day Rolling Window Quantile-Quantile connectedness model with lag 1 (SIC criteria) and a 20-step-ahead generalized forecast error variance decomposition. The black line represents risk transmission at 50–50 quantiles, while the red (dashed) and the green (dotted) lines represent the results of the 5–5 and 95–95 quantiles, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

[1] In order to test the robustness of our results, we re-estimate our total time-varying connectedness using 250- and 300-day rolling window. The estimations are showcased in the Appendix, where is it clear that the results remain qualitatively similar.

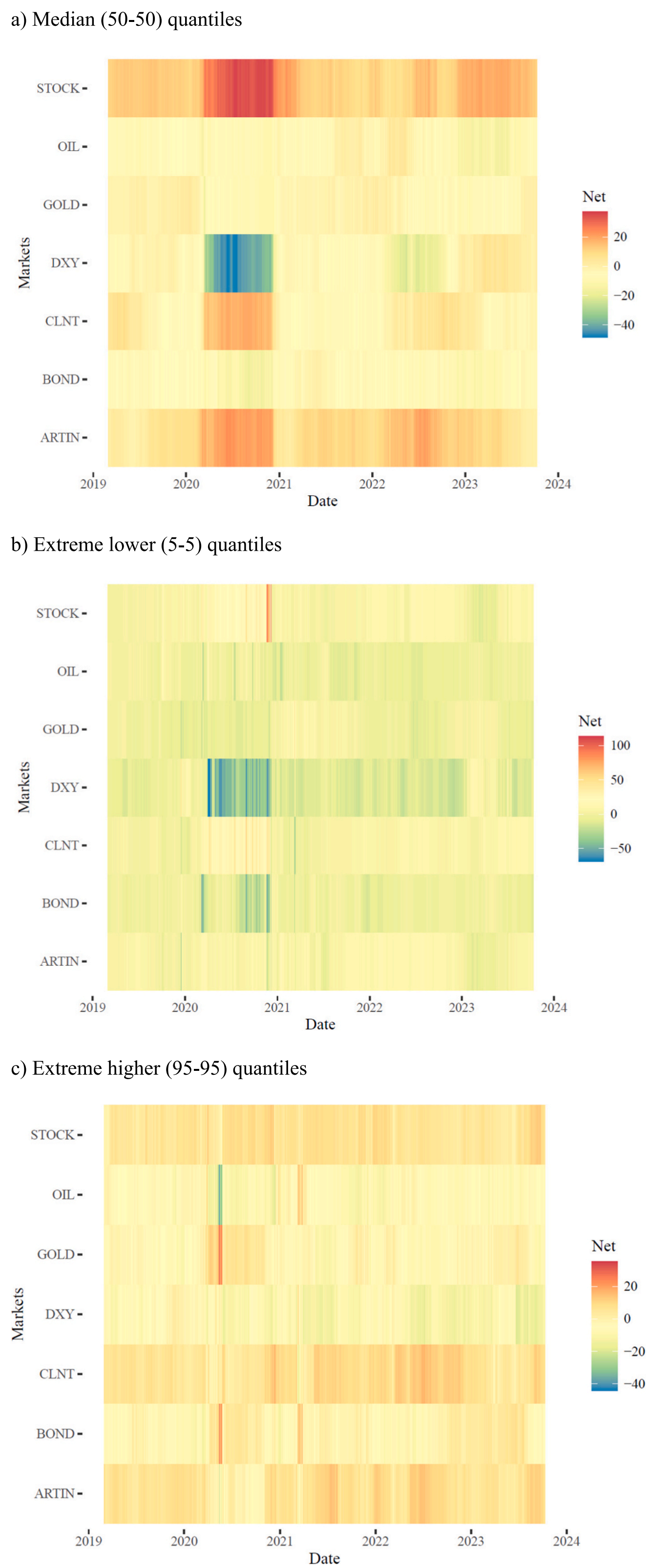

Fig. 7. Time-varying NET spillovers of the selected markets.
Notes: Results are based on a 200-day Rolling Window Quantile-Quantile connectedness model with lag 1 (SIC criteria) and a 20-step-ahead generalized forecast error variance decomposition.

Stock (MSCI AC World) and Artificial Intelligence Markets are, on average, NET transmitters of risk spillovers to the other five markets throughout the sample timeframe. The NET risk spillovers from the Stock and Artificial Intelligence are the highest following the onset of the COVID-19 Pandemic and ensuing travel restrictions (Shafiullah et al., 2022; Naeem et al., 2024b). A NET risk transmission from the Clean Technology Market is also observed in the wake of COVID-19. Similar upticks in NET risk spillovers are also found in the stock, artificial intelligence, and clean technology markets following the Russia-Ukraine military conflict. The US Dollar Index Market exhibits the largest receipts of NET risk spillovers during these (same) two extreme global events.

The time-varying NET risk spillovers at the extrema of the distributions (i.e., the left and right tails or 5th–5th and 95th–95th quantiles) illustrate contrasting pictures. In the left tails or 5th–5th quantiles (Fig. 7, part b), the markets are generally NET receivers of risk transmission, with the exception of Stock and Clean Technology Markets during the economic/financial crisis brought about by the COVID-19 pandemic (Hasan et al., 2022; Shafiullah et al., 2022). In contrast, the US Dollar Index and FTSE World Government Bond Index Markets are two of the biggest recipients of NET risk spillovers in the left tails (5th–5th quantiles). These two markets receive the largest amounts of NET risk spillovers following the onset of COVID-19.

By contrast, the right tails (95th–95th quantiles) in Fig. 7(c) indicate that only two markets—Crude Oil-WTI and US Dollar Index—are, on average, NET risk spillover receivers. In particular, the NET risk receipts by the Crude Oil-WTI Market are the greatest following the COVID-19 pandemic. The remaining five markets are, on average, NET transmitters of risk spillovers. Among the NET transmitters, Artificial Intelligence, Clean Technology, and Stock (MSCI AC World Index) Markets impart the greatest extent of risk spillovers. As such, there is some resemblance between the NET risk spillover patterns at the right tails and those at the medians.

In summary, the findings from Fig. 7 underscore the prominence of AI, Clean Technology, and Stock (MSCI AC World) markets in the spillover connectedness network. These markets generally impart more risk spillovers than they receive at the median as well as the left and right tails of their respective distributive. The NET risk transmission aggravates considerably during extreme global events like the COVID-19 pandemic and the Russian invasion of Ukraine. By contrast, the globally foremost currency, bond, and commodity markets (US Dollar Index, FTSE World Government Bond Index, and Crude Oil-WTI) are often some of the biggest NET receivers of risk transmissions, especially at the left and right tails. This is a novel finding of our study, but it remains in line with the global markets' focus on using clean (renewable) energy and AI to tackle climate change and other global problems (Filho et al., 2022; Kaack et al., 2022; Xu and Lin, 2023; Lin and Wang, 2024). As such, extreme movements in these markets are often contagious across global financial markets, especially those that are highly interconnected and/or dependent. The observations from Fig. 7 provide supplementary evidence against rejecting hypotheses ***H1*** and ***H2*** and vouch for the overall robustness of the above estimates and relevant inferences.

5. Conclusion

Our empirical analyses depict an interesting picture of the risk transmission among artificial intelligence, clean technology, and five major stock, bond, currency, and commodity markets. The risk transmission in the distribution tails (extrema) appears more extensive and forceful than at the median. Scrutinizing each market individually, there is stronger transmission of NET risk between the middle quantiles of the distribution for individual markets — highlighting the disparity between the aggregate and individual market-level transmission networks. In particular, positive NET quantile-on-quantile risk spillovers between the 'reversely related' and 'directly related' tails are observed in the Artificial Intelligence, Clean Technology, and Stock (MSCI AC World) markets. Spillovers across the 'reversely related' and 'directly related' tails are negative — albeit close in magnitude to their positive counterparts — in the FTSE World Government Bond, US Dollar, Gold, and Crude Oil Markets.

The total risk spillovers remain more vigorous at the tails than at the conditional means of the distribution. However, risk spillovers at the tails plunge following the intensification of the Russia-Ukraine military conflict (between mid- and late-2023). The time-varying NET risk transmission analyses reveal that Stock (MSCI AC World) and Artificial Intelligence Markets are, on average, NET transmitters of risk spillovers—at the median as well as in the left and right tails. This may demonstrate the disruptive effects of the Stock and Artificial Intelligence Markets on the 'new normal' of global economic reality induced by the COVID-19 pandemic and the Russian invasion of Ukraine. However, in the right tail, the Crude Oil-WTI and US Dollar Index are, on average, the only NET risk spillover receivers. The Artificial Intelligence, Clean Technology, and Stock (MSCI AC World) markets generally transfer more positive NET quantile-on-quantile risk spillovers than the Bond, Currency, or Commodity Markets. The latter four markets (especially the US Dollar Index and Crude Oil-WTI), thus, may act as cushions for the extreme (tail) risk transmission from the former three markets.

The above findings provide a valuable understanding of AI, Clean Technology, and (some) stock markets' risk-propagating roles. Emerging technologies like AI and Clean Technologies can potentially alter the global economic/financial landscape. AI can improve many sectors of the contemporary global economy, such as industry, education, healthcare, finance, energy and power, transportation, law enforcement, and defense. AI can potentially solve humanity's long-standing problems, such as low productivity growth and climate change. AI also poses potential hazards such as widespread job losses, privacy intrusion, misinformation and/or disinformation, military and warfare applications, centralizing political power and/or authoritarianism, etc. Similar to other/prior emerging markets/technologies/ventures, AI also poses localized and globalized risks to the financial sector. This paper provides novel empirical evidence of extreme/tail risk from AI markets, especially during crises such as COVID-19 and the Russia-Ukraine military conflict.

One of the biggest challenges faced by humanity globally is climate change. Climate change is expected to eventuate substantial disruptions to economies and human civilizations worldwide. Climate change will affect indispensable real sectors of the economy, such as agriculture, energy and power, industry, shipping, and transportation. Disruptions and/or uncertainties in these real sectors will aggravate market sentiments and, perhaps, an overreaction from the financial markets (as per the economic theory of real-financial duality). Clean (Energy) Technologies can reduce greenhouse gas emissions and other environmental damages in the global effort to mitigate climate change. However, Clean Technologies remain in continuous development/refinement, are often less mature technologically, and are in need of widespread adoption. As such, Clean Technology stocks represent risks to the real as well as financial sectors of the global and local economies. This study finds evidence of such an effect of extreme/tail risk propagation from Clean Technology markets. This finding is also novel, demonstrating cross-quantile risk spillovers from Clean Technologies, particularly during extreme events.

Our empirical analysis also finds that the U.S. Government Debt, the U.S. Dollar, and Gold absorb much of the risk transmission from the above two markets and the conventional stock markets. We argue that this finding offers a 'solution' to the 'problem' of the extreme/tail risk transmission from AI, Clean Technology, and conventional Stock markets. The U.S. Government Debt, the U.S. Dollar, Gold, and Oil can be used, as part of appropriate portfolios, to hedge against the risk posed by AI, Clean Technology, and conventional Stock markets. While the risk-buffering roles of the U.S. Government Debt, the U.S. Dollar, Gold, and Oil are observed in the extant literature, the extreme/tail and cross-quantile risk spillover absorbing tenets of such markets, detected in this study, are novel and unique. Wrapping up, the current study identifies novel problems and solutions concerning extreme/tail spillovers across the sample of AI, Clean Technologies, and other markets between mid-2018 and late-2023. These newly identified 'problems' and 'solutions' are expected to be helpful to academicians, investors, policymakers, regulators and alike.

CRediT authorship contribution statement

Mariya Gubareva: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Investigation, Formal analysis, Data curation, Conceptualization. **Muhammad Shafiullah:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tamara Teplova:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Conceptualization.

Declaration of competing interest

None.

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Appendix A. Appendix

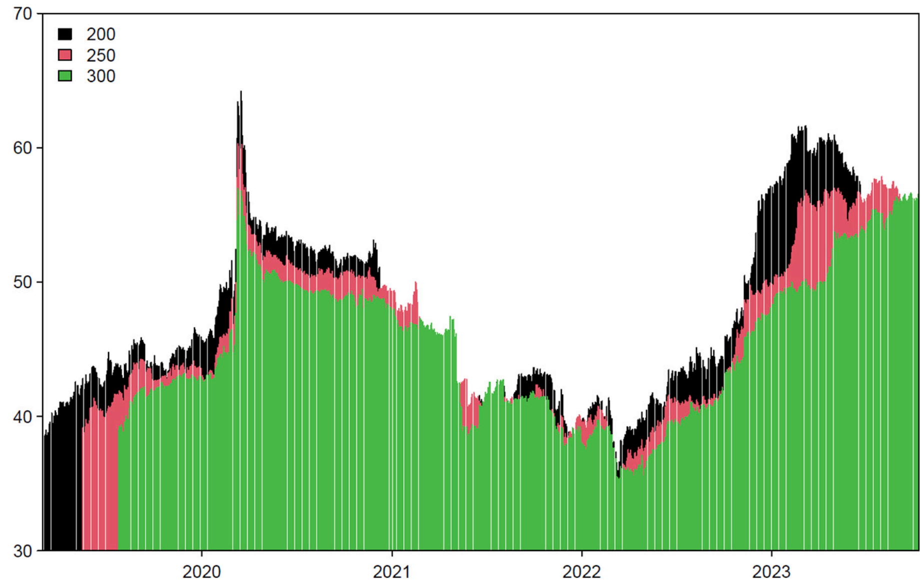

Fig. A1. Robustness – Time-varying risk transmission
Notes: Results are based on a Rolling Window Median (0.5) Quantile connectedness model with lag 1 (SIC criteria) and a 20-step-ahead generalized forecast error variance decomposition. The black line shows 200-day Rolling Window. Whereas the red and green lines show 250- and 300-day Rolling Window, respectively.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.108085.

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Corrigendum to “Cross-quantile risk assessment: The interplay of crude oil, artificial intelligence, clean tech, and other markets” [Energy Economics Volume 141, January 2025, 108085]

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