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The contagion effect of artificial intelligence across innovative industries: From blockchain and metaverse to cleantech and beyond

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ABSTRACT

Artificial Intelligence (AI) stands as a transformative force across business, technology, and science, yet its comprehensive impact on innovative industries remains relatively unexplored. This study delves into the interconnectedness between AI and pivotal sectors such as cryptocurrency, blockchain, metaverse, democratized banking, and Cleantech, among others. Employing the conditional autoregressive value-at-risk (CAViaR) and time-varying parameters vector autoregressions (TVP-VAR) methods, we scrutinize daily data spanning from June 1, 2018, to October 11, 2023, encompassing 12 stock indices representing each industry. Our findings unveil a strong contagion effect from AI to other innovative sectors, with the exception of Cleantech, which appears to have decoupled from the AI surge. Notably, democratized banking and the metaverse emerge as key recipients of this contagion. Examination of tail-risk spillovers highlights AI as one of the most influential risk transmitters during market tumult, while cryptocurrency and blockchain consistently function as net risk receivers throughout the sample period. The implications of these findings are multifaceted, offering substantive insights into the risk profiles of these critical innovative sectors. Investors and regulatory bodies stand to benefit significantly from this analysis, as it illuminates potential avenues for portfolio diversification and deepens understanding of contagion mechanisms within these evolving industries.

1. Introduction

The swift evolution of technological innovation and the emergence of new technology sectors in recent years have led to unprecedented advancements that fundamentally transform our way of life, work, and interaction with the world (Xu et al., 2024). Artificial Intelligence (AI) stands at the forefront of the 4th industrial revolution, playing a crucial role in reshaping our world. This technological advance is expected to erode the boundaries among physical, digital, and biological worlds, which could lead to a swift and profound change in our ways of life, work, and social interactions. Over the last four years, we recorded an increase of about 75 % in employment opportunities related to AI, and this upward trend is expected to persist in the next years.[1] The past few years were marked by a surge in activities and academic research related to AI and blockchain technologies, highlighting their significant role in shaping the 4th industrial revolution. While both technologies have been extensively studied and research evolves at an astonishing pace, there is a dearth in understanding of how such technological innovations are correlated and influence each other, as well as transforming other innovative industries.

The introduction of new technologies began with the rise of cryptocurrencies as a primary digital currency in 2009. The financial effects of this new blockchain-based asset class on broader financial systems have been quickly discovered, particularly, on part of risk-transmission to other part of the financial system (Corbet et al., 2018a). This milestone paved the way for subsequent transformative waves of technology, encompassing the integration of artificial intelligence (AI), robotics, machine learning, and the metaverse, among others (Choithani et al., 2023; Aysan et al., 2023), attracting wider range of investors. These technologies not only actively reshaped industries, improving firm performance through enhancing operational processes, increasing productivity, and reducing production costs, but also promptly exert a significant influence on financial markets, particularly in the stock market, where technological companies are indexed (Rajapathirana and

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[1] https://www.statistica.com/

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Hui, 2018). The interaction between these technologies plays a pivotal role in shaping the behavior of financial markets, especially during periods of economic downturns.

Another booming industry strongly associated with AI is robotics. According to the Global Industrial Robotics Market (2023)[2] report, the global market for industrial robotics held a valuation of approximately USD 16.5 Billion in 2022 and is expected to achieve around USD 20 Billion by 2027.[3] AI and robotics technologies have been embraced worldwide, extending beyond their use in manufacturing with industrial robots. These technologies are integrated in several economic sectors such as financial trading and analysis (Mhlanga, 2021).

Algorithmic trading, powered by advanced AI algorithms has revolutionized market dynamics by enabling automated execution of trades. In this spirit, the integration of AI and finance has reshaped the financial landscape. Specifically, employing the power of AI can boost the speed, security and efficiency of financial markets (Hussain and Al-Turjman, 2021). Automated trading bots endowed with machine learning (ML) prowess, can swiftly analyze past and large market data, news articles, social media posts, trading behaviors to predict price movements. AI driven predictive analytics could also recognize market trends and execute transactions at speed that exceeds traditional methods (El Hajji and Hammoud, 2023). This integration not only enhances the speed and accuracy of trading strategies but also contributes to increased liquidity and market efficiency (Martins, 2022). Through their ability to analyze extensive data swiftly and efficiently, AI could also identify patterns; pinpoint anomalies related to fraudulent activities that human analysts may overlook (Aljohani, 2023). AI algorithms boost security by constantly learning and adapting. As they analyze more transaction data, they get better at spotting risks and new types of fraud. This dynamic approach enables real time detection and prevention, reducing financial losses and safeguarding investors' assets (Yang and Li, 2018).

Blockchain technology has undergone significant development, evolving from its origins in cryptocurrency to applications across various industries. The global blockchain market size in banking and financial services has grown drastically and was valued at USD 4.61 billion in 2023 and is anticipated to reach about USD 7.12 billion by the end of 2024.[4] The surge in blockchain technology, augmented reality (AR), and virtual reality (VR) has led to the emergence of the metaverse in recent years (Iqbal and Campbell, 2023). The metaverse is a virtual space where people interact similarly to the real world (Nevelsteen, 2017). The metaverse is closely associated with the crypto-metaverse due to the strong integration of blockchain technology and cryptocurrencies into virtual environments (Vidal-Tomás, 2023). Recently, there has been a growing trend of interest in the Metaverse within the global financial market (Aysan et al., 2024b). On March 10, 2021, Roblox emerged as the first Metaverse share and was successfully listed on the New York Stock Exchange, symbolizing humanity's entry into the Metaverse. Later, Facebook CEO Mark Zuckerberg introduced the concept of Metaverse, revealing Facebook's venture into this virtual realm. Such a situation not only validates Metaverse as a viable business concept but also reveals its potential impact on the financial market (Wang et al., 2024). Specifically, in 2022, the global metaverse financial services market reaches a value of USD 67.26 billion and is anticipated to achieve a market size of USD 315.87 billion by the end of 2030.[5] It is worth noting that this market is projected to grow significantly by 40.6 % by the end of 2027.[6]

The convergence of the metaverse realm with the financial market denotes a significant paradigm shift, manifesting across various aspects of the financial sector (Gazuacik et al., 2023). Interestingly, the metaverse serves as an ideal environment for the creation, trading, and ownership of digital assets and cryptocurrencies. Examples of such assets including digital art, virtual real estate, and gaming tokens which can be purchased, sold, and traded within this virtual realm with the help of metaverse cryptocurrency coins (crypto asset with own blockchain) and token (traded on existing blockchains). There are several studies analyzed the metaverse from technology, theory and portfolio management perspective (Aysan et al., 2024a; Hajian et al., 2024; Wang et al., 2024).

Decentralized finance (DeFi) platforms are actively seeking opportunities within the metaverse. Users can engage in DeFi services like borrowing, lending, and gains yield without leaving the virtual world. This integration not only improves accessibility but also opens new avenues for earning and employing cryptocurrencies. The metaverse also transforms the nature of financial services (Ooi et al., 2023; Santana and Albareda, 2022). Virtual banks, insurance companies, and investment platforms can emerge within this digital world, offering users an alternative to traditional financial institutions (Chen et al., 2021). Smart contracts, powered by blockchain technology, can automate financial agreements, reducing the need for intermediaries and increasing the efficiency of transactions. Integrating the metaverse into finance enhance global financial system accessibility by removing traditional barriers (e.g., borders), encouraging innovation in financial services that could lead to new products and solutions, and promoting financial inclusion.

In the financial market, the transmission channels across innovative technological assets such as AI, robotics, Fintech and the metaverse among others are driven by their integrated functionalities and common digital frameworks. For instance, Fintech uses AI for sophisticated analytics and fraud detection, resulting in enhancing the security and efficiency of financial transactions, including those with cryptocurrencies (Cao et al., 2021; Tao et al., 2022). Cryptocurrencies employ blockchain technology, offering decentralized financial solutions that smoothly integrate with Fintech platforms (Kaniadakis and Foster, 2024; Uddin et al., 2024). Consequently, this integration with Fintech platforms enhances accessibility, security and efficiency across global markets (Chaudhry et al., 2022). Within the metaverse, a digital realm dependent on robust financial system, Fintech and cryptocurrency plays pivotal roles not in facilitating virtual commerce and transactions (Aysan et al., 2024b). They also drive innovation in how transactions are conducted and secured across virtual environments. Robotics and AI are instrumental in enhancing these interactions by automating process and improving user experiences. They boost efficiency and functionality within virtual environments, enabling seamless transactions and fostering innovative solutions in the metaverse. All these technologies collaborate through integrating data, platform interoperability, and advanced cybersecurity measures, resulting in creating an interconnected ecosystem where innovations or disruptions in one area can have significant effects across multiple domains (Hassan Polas et al., 2022; Bisht et al., 2022). For instance, a cybersecurity breach in a Fintech platform can cause ripple effects, leading promptly to affecting transactions involving cryptocurrencies within the metaverse and AI-driven analytics systems (Abbas Rivzi et al., 2024). Furthermore, regulatory shifts like updated guidelines for cryptocurrency trading can extend their influence on other innovative sectors, shaping compliance requirements for Fintech services and AI algorithms. Technological innovation, especially advancements in AI driven robo-advisors could influence how data analytics and decision-making processes are handled within Fintech platforms. Thus, could in turn influence the development and adoption of technologies such as cryptocurrency and blockchain within the financial sector (Aysan et al., 2024a). Moreover, advancements in AI could drive the advancements in cybersecurity protocols seeking to protect sensitive financial data, leading to improving the overall security framework for digital assets and transactions. As a result, shifts in AI-powered robot-advisors can spread across different sectors, influencing the evolution and integration of innovative

[2] https://www.marketsandmarkets.com/
[3] https://www.researchandmarkets.com/
[4] https://www.thebusinessresearchcompany.com/
[5] https://virtuemarketresearch.com/
[6] https://finance.yahoo.com/

technological assets. These shocks spread through interconnected channels of data integration such as platform interoperability, regulatory frameworks, and the adoption of innovations, highlighting the complex interdependencies within the financial technology ecosystem.

Analyzing the connectedness across innovative technological assets is essential for identifying synergies that drive innovation and progress. This understanding helps in making well informed investment decisions, managing risks, and developing strategic business models (Hoque et al., 2024; Naeem et al., 2024a,b; Rahman et al., 2024; Shafiullah et al., 2024; Younis et al., 2025; Zhang et al., 2024a,b; Naeem et al., 2024c). It helps also in establishing more effective regulatory frameworks and offers valuable insights into market participants and dynamics. By understanding these interconnections, financial institutions can manage more effectively market complexities, leverage synergies to enhance innovation, and anticipate regulatory shifts. Overall, this analysis promotes a holistic perspective that integrates several technological domains, enhancing cohesion and efficiency within the financial market ecosystem.

In this study, we analyze the transformative power of technology not only within each sector of the economy but also in their interactions with one another. Examining the linkages between technological innovations is particularly important from an investment perspective and is critical for society and policymakers who need to adapt to the high pace of technological advancement. To our knowledge, this study is the first to shed light on the dynamics of tail risk dependence across AI, blockchain, and cryptocurrency, as well as emerging technology markets such as democratized banking, space, nanotechnology, Cleantech, to name a few. Specifically, we utilize daily data for 12 stock indexes for the period from 01/06/2018 to 11/10/2023, covering the broadest set of innovative sectors influenced by AI and blockchain technologies. This comprehensive assessment of interconnectedness between the selected sectors helps to uncover important contagion patterns, especially around key periods of economic and political turbulence, such as the COVID-19 pandemic and the Russia-Ukraine conflict. Examining the connectedness across innovative technological assets during stressful periods is crucial for understanding the transmission of shocks and mitigating systemic risk. During periods of crisis, interconnected technology sectors can display a contagion effect, where disruption in a sector can swiftly spread to others (Yarovaya et al., 2021; Yarovaya et al., 2022a). For instance, a cyber-attack on Fintech system could disrupt financial transactions within the metaverse, affecting virtual economies and reducing user trust. By understanding these connections, stakeholders can identify potential vulnerabilities, and create robust risk management strategies to boost resilience against cascading failures. This proactive approach ensures stability and continuity across technological sectors, therefore mitigating the wider impact of market turmoil. Furthermore, analyzing these connections during crisis times could enhance decision-making and allow better strategic adjustments. Businesses can enhance their ability to predict how stress in one sector could affect others, enabling them to respond swiftly and by implementing adaptive measures. Investors can also enhance portfolio diversification by carefully considering interdependencies, therefore mitigating risks related to different sectors.

Building on the literature on financial market integration, contagion, and spillover effects, we hypothesize an increase in dependence across financial markets, especially during periods of market turmoil (Le et al., 2021a, 2021b; Patel et al., 2022; Shahzad et al., 2022). The rise in dependency indicates that higher exposure to losses in one market can easily spillover to other markets, manifesting a contagion phenomenon (Aloui et al., 2011). Financial contagion and spillover effects can often be asymmetric, where markets respond to positive and negative shocks in different manners and to different magnitudes (Khalfaoui et al., 2022; Yarovaya et al., 2017). Thus, it is important to assess the interdependence across selected markets during relatively tranquil periods and during unexpected events, including the COVID-19 outbreak and the ongoing Russia-Ukraine war, as well as industry specific events, such as withdrawal of Tesla's support for cryptocurrency and the Silicon Valley bank collapse. Some unexpected events can also be considered as 'black swan' events (Taleb, 2012), which can have more severe impacts on immature financial markets, such as cryptocurrency (Yarovaya et al., 2021). In this paper, we explore these unexpected events to identify whether the tail risk spillover across the considered markets is time varying and dependent on economic conditions.

We employ a combination of the Conditional Asymmetric-Slope Value-at-Risk (CAViaR) approach with the TVP-VAR technique advanced by Antonakakis et al. (2020) to explore tail-risk spillovers at 2.5 %, 5 %, and 10 % VaR measures. Interestingly, these two techniques offer several advantages. Starting with the CAViaR method which provides a significant advantage over traditional VaR based approaches in finance through its direct distribution-free methodology. Interestingly, this approach involves directly modeling the evolution of quantiles which evolves through time, instead of modeling and estimating the entire distribution of returns. Thus, by focusing on modeling the quantile, we can avoid the necessity to adopt the set of extreme assumptions adopted in other methodologies, such as the assumption that returns follow an independently and identically distributed *i.i.d* normal distribution. Additionally, the CAViaR method uncovers asymmetric trends at 2.5 %, 5 %, and 10 % VaR level, revealing various asymmetric and nonlinear patterns in the data. Concerning the TVP-VAR model, employing this technique offers several advantages, including its ability for analyzing low-frequency data, robust against outliers, and flexibility in selecting the rolling window (Naeem and Arfaoui, 2023).

Our findings reveal the strength of connectedness among the considered variables during crisis times, especially during the COVID-19 outbreak. Specifically, a pronounced tail-risk spillover is found between AI and democratized banking. Furthermore, we identify weak tail-risk spillovers between the cryptocurrency and blockchain index and the robotics index, suggesting the diversification benefits of integrating these assets into one portfolio.

Regarding the NET tail risk connectedness, findings demonstrate that democratized banking, cybersecurity, AI, robotics, and autonomous vehicles industries operate as net risk transmitters during the entire sample period. Another interesting finding reported in this study shows that cryptocurrency and blockchain and genetic engineering serve as net risk receivers, especially during times of crisis. It is important to highlight that nanotechnology, metaverse, and space industries act as diversifiers.

The rest of the paper is structured as follows: Section 2 presents a review of the related literature. Section 3 introduces the methodology and data. Section 4 reports and discusses the main empirical findings. Finally, section 5 concludes.

2. Background literature

The finance literature focusing on technology assets has garnered considerable attention during the last few years due to its remarkable and strong performance in the financial market. In this spirit, there is a recent body of research exploring the connectedness between Artificial Intelligence (AI) stocks and conventional financial assets. For instance, Demiralay et al. (2021) explore the connectedness between AI & Robotics stocks and several financial assets including stock, bond, cryptocurrencies, and commodities over the period ranging from December 19, 2017 to March 31, 2021. Using wavelet analysis technique, findings reveal the presence of strong (weak) connectedness between AI stocks and the rest of considered indices at low (high) frequencies. Results also show the leading role of AI equities for the rest of considered indices in this work amid COVID-19 outbreak.

More recently, Abakah et al. (2023) employ the nonparametric causality-in-quantiles method to explore the predictability across Fintech, Bitcoin, AI stocks, environmentally friendly assets (e.g., green bonds, clean energy) and others conventional financial markets. Using daily data ranging from March 2018 to January 2021, findings show evidence of strong asymmetry across the considered markets under different market circumstances. The authors also show that AI, Fintech, and Bitcoin act as weaker safe haven during periods of high volatility. Yadav et al. (2024) assess the dynamic connectedness between AI stocks (Meta, Microsoft, NVIDA, Google, and AMAZON) and commodity assets (soyabeans, wheat, rice, corn, and oats) in the USA market based on Diebold and Yilmaz (2012) and Baruník et al. (2016) approaches from December 2019 to February 2022. Findings reveal that AI stocks related to Microsoft and Google react promptly to shocks, both as recipients and transmitters. Rice and corn act as the weakest transmitters and receivers of shocks during the COVDI-19 outbreak. Nevertheless, Google and Amazon stocks are the highest receivers and transmitters of shocks during the ongoing Russia Ukraine conflict. The authors also unveil that the level of connectedness strength in the short-period especially during the COVID-19 outbreak and Russia-Ukraine conflict.

Abakah et al. (2022) document through a quantile VAR approach that Fintech stocks could predict the volatility of AI indices (e.g., KBW NASDAQ Financial Technology Index, NASDAQ AI Index) and Bitcoin returns during normal market condition. However, this predictive power diminishes as the market shifts towards extreme conditions. Furthermore, the authors indicate that the diversification benefits of technology-related assets face significant challenges, given the oscillatory predictability observed over time lags from Bitcoin to Fintech/AI. Le et al. (2021a, 2021b) explore the connectedness across financial technology assets, Bitcoin, and others traditional assets (e.g., MSCI world, green bonds, Oil, Gold, Bonds). Findings reveal the existence of strong connectedness across the examined markets. This empirical evidence suggests that during periods of market turmoil, AI assets (KBW NASDAQ Technology Index (KFTX), cryptocurrencies, green bonds and traditional assets exhibit a high probability of significant losses. Moreover, KFTX, Bitcoin, and MSCI world act as net transmitters, whereas Oil, Gold and Green bonds act as net receivers of spillovers. The authors also unveil that the connectedness across the examined markets strength in the short term. Another interesting finding shows that the 4th industrial asset plays the role of good hedgers compared to the rest of considered assets. Hanif et al. (2023a) report a strong connectedness between cryptocurrency and conventional markets (i.e., stock and commodity) in terms of volatility and its jump component. Nevertheless, their connectedness in terms of skewness and kurtosis is notably weaker. The authors also reveal that the connectedness in jump and volatility reveals greater persistence compared to those in skewness and kurtosis. Symitsi and Chalvatzis (2018) employ an asymmetric multivariate VAR-GARCH model to explore the connectedness between Bitcoin, technology, and energy companies. The authors argue the presence of significant return spillover from energy/technology stock. Moreover, we denote short-run fluctuations running from technology firms to Bitcoin, whereas Bitcoin has long-run volatility influences on energy companies. Recently, Younis et al. (2024) show through a TVP-VAR model the existence of strong connectedness across DeFi assets, banking indices and stock market across G7 during the COVID-19 outbreak and the Russia-Ukraine conflict. Pham et al. (2023) explore the time-varying and asymmetric spillovers among cryptocurrency, green and fossil fuel investments. Findings demonstrate the existence of time varying connectedness across the considered markets. The authors also show the existence of asymmetric spillovers among the considered variables, where negative return spillovers is more pronounced than positive return spillovers.

Cryptocurrency and blockchain take a prominent position in the burgeoning technology markets, catalyzing a substantial transformation and innovation in the financial sector (Li et al., 2020). Notably, the cryptocurrency market has emerged as a dynamic and swiftly evolving financial landscape, drawing the interest of investors, scholars, and policymakers alike. The emergence of this market is the result of the 2008 global financial crisis and the subsequent era of low-interest rates (Babaei et al., 2022). After the launch of the first cryptocurrency, bitcoin, numerous other crypto assets have emerged, characterized by advancements in the underlying technology (Chohan, 2022; Elsayed et al., 2022). The total market capitalization of cryptocurrency recorded a spectacular surge and move from USD 13.9 billion in 2013 to USD 1.75 trillion in 2023.[7] Bitcoin is the most traded cryptocurrency, and accounts for approximately 50 % of market capitalization, and it has been often considered as a highly speculative asset that is prone to bubble-like behavior (Corbet et al., 2018b,c; Hanif et al., 2023b).

There is a growing tendency among global companies to put their investments into business solutions built on blockchain technology. For instance, the use of Dogecoin for purchasing Tesla products depicts the pronounced advancement and progress in the cryptocurrency world. The popularity of cryptocurrencies has grown, and their integration with other financial assets seems increasingly inevitable (Yarovaya et al., 2022a). In recent years, cryptocurrencies have become one of the most interesting and attractive markets for investors due to their performance and diversification property (Arfaoui et al., 2023). In this spirit, numerous individual investors have amassed a large fortune by speculating on cryptocurrencies by analyzing news and following cryptocurrency market trends. Nevertheless, the high volatility nature of these markets makes it future uncertain, both from price perspective and policy perspective (Lucey et al., 2022). For instance, in April 2021, the market capitalization of Bitcoin plummeted from USD 1.18 trillion to USD 935 billion in ten days, then, it dropped again to 602 billion USD over the next three months, up to July 2021.[8]

Blockchain is the main technology supporting cryptocurrencies. Specifically, this technology is a distributed ledger or database used to record and verify transactions across a network of computers (Efanov and Roschin, 2018). It ensures transparency, security, and immutability, as each block of data is linked to the previous one, creating a chain of information (Corbet et al., 2020). The decentralized feature of blockchain removes the need for intermediaries, providing a trustless and efficient system. The integration of cryptocurrency and blockchain has the potential to revolutionize various industries, promoting financial inclusion, transparency, and efficiency in the swiftly advancing digital age (Kimani et al., 2020).

Another emerging trend in literature, with only a few studies, is beginning to focus on the analysis of metaverse and blockchain-related assets in the financial market. For instance, Zhao et al. (2023) explore the interconnection between Islamic and conventional technology stock indices with blockchain technology assets including Metaverse, High-Performance Blockchain, and Blocknet. Using the TVP-VAR model and the causality in quantiles methodology, the authors show that the connectivity between new generation blockchains including metaverse, conventional and Islamic markets is time-varying. They also show that the connectedness across the examined assets increases in the medium run and reaches its peak in the long run. Vidal-Tomás (2022) investigate the performance and dynamics of metaverse and play to earn games tokens between October 2017 and October 2021. The authors reveal that these tokens show a positive performance only in the long run. Moreover, findings underline the absence of high co-movement between metaverse/play to earn games tokens and cryptocurrency market. The authors also document the absence of financial bubbles in the new crypto niche (i.e., play to earn and metaverse tokens). Chen (2022) employed the Fama-French Model and showed that announcements related to metaverse positively influence the stock price of technology and real estate companies in the US market. Nevertheless, the emergence of metaverse does not show any significant effect on traditional industry assets. In the same vein, Xu et al. (2023) employ the event study methodology to investigate the reaction of 642 Chinese firms to metaverse-related announcements. Results show that metaverse coverage leads to a positive stock market reaction. Moreover, the authors' document that stakeholders consider metaverse announcements

[7] https://coinmarketcap.com/

[8] https://coinmarketcap.com/

as overhyped, and firms' stock price does not exhibit any significant reaction when listed companies are not adequately prepared to embrace the metaverse. Another study by Jian and Jain (2019) shows that companies modify their names to add the term "blockchain" recorded positive performance over the first two months. Nevertheless, this positive performance shifts to negative within five months following the company's name change. Similar findings on the impact of blockchain-related name changes were reported by Akyildirim et al. (2020), Corbet et al. (2020), among others.

During the last few years, financial markets have faced several episodes of market turmoil and extreme events such as the COVID-19 outbreak (Ajmi et al., 2021), the Russian-Ukrainian conflict (Yousaf et al., 2022), withdrawal of Tesla's support for vehicle purchases using cryptocurrency (Arfaoui et al., 2023), Silicon Valley bank collapse (Aharon et al., 2023), climate warming (Naeem and Arfaoui, 2023), international sanctions against Russia (Sun and Zhang, 2023) among others. Emerging economy sectors such as Cryptocurrency, AI and metaverse have been influenced by these unexpected events. For instance, the COVID-19 pandemic led to drastic increase of cryptocurrency market uncertainty as prices fluctuate significantly (Nguyen et al., 2022). According to Naeem et al. (2021), in early 2020, this pandemic affects the value of cryptocurrencies, particularly Bitcoin and Ethereum and then recovered faster in March 2020. By the end of 2020, the price of Bitcoin recorded a dramatic surge of 300 %, driven mostly by the rising of uncertainty and the speculations in the financial market (Sarkodie et al., 2022). Furthermore, the spectacular success of AI through ML in predicting the future trend of financial assets and the occurrence of financial crises or crashes such as the Silicon Valley bank collapse, leading to an exponential surge of this market which reach a value of about USD 11.76 Billion in 2023.[9] Moreover, we denote a rising of investments in emerging technologies including metaverse during the ongoing Russia-Ukraine conflict. Notably, spending related to the metaverse investments was estimated by more than USD 120 billion in 2022.[10] Specifically, during times of geopolitical uncertainty or military conflicts, investors may seek alternative investment opportunities. Emerging economy sectors such as Artificial intelligence and metaverse among others, appear as rapidly evolving and innovative sectors, capture the interest of investors seeking diversification or growth opportunities beyond traditional markets.

In the light of the discussion above, while a new trend of studies in the literature explores the connections across innovative emerging markets, to our knowledge no previous work have assess the tail-risk spillovers among AI and new emerging technology sectors during recent episodes of market turmoil. Interestingly, in the current work we explore the dynamic tail-risk spillovers among cryptocurrency, AI, metaverse and other emerging technology markets during episodes of extreme events, including the withdrawal of Tesla's support for cryptocurrency, the COVID-19 outbreak, the ongoing Russia-Ukraine conflict, and the Silicon Valley bank collapse. Methodologically, we employ a combination framework of the tail risk model of Engle and Manganelli (2004) using the conditional asymmetric-slope value-at-risk (CAViaR) method and the TVP-VAR connectedness approach of Antonakakis et al. (2020) to study tail-risk spillovers at 2.5 %, 5 %, and 10 % VaR measures.

3. Methodology and data

3.1. Conditional autoregressive value at risk (CAViaR)

In this paper, we employ the asymmetric slope for the Conditional Autoregressive Value-at-Risk (CAViaR) approach introduced by Engle and Manganelli (2004). The main advantage of this technique over traditional VaR based methods used in finance is its direct distribution-free approach. In particular this technique focuses on modeling the quantile directly, over time, rather than estimating the entire return distribution. By doing so, this technique avoids the need to rely on the set of extreme assumptions adopted by alternative methodologies which suggests that returns are independently and identically distributed (i.i.d.) under a normal distribution. Further, this technique out-performs the majority of indirect VaR methods especially when returns exhibit a fat-tailed distribution. This approach enables the direct estimation of VaR. We believe that this method is a superior version CAViaR since it accounts for asymmetric effects, that cannot be captured either by the symmetric absolute value or the indirect GARCH (1,1) approaches. The asymmetric slope CAViaR model suggests that the VaR of a particular quantile adheres to an autoregressive process, as depicted in Eq. (1):

$$f_{\alpha,t}(\beta) = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x_{t-1}^{+} + \beta_3 x_{t-1}^{-} \tag{1}$$

Where $f_{\alpha,t}$ stands for the Value-at-Risk (VaR) at the 5 % quantile level during period $t.\beta_0$ is the constant, β_1 is the weight for the lagged values. Moreover, β_2 and β_3 represent the positive and negative returns on VaR, respectively. $f_{\alpha,t-1}$ is the lagged terms for the VaRs.

3.2. TVP-VAR based connectedness approach

First, we employ CAViaR changes as the foundation for the TVP-VAR-based connectedness approach, with the aim to extract the information for the risk transmission mechanism. The TVP-VAR model offers several advantages, including the ability to use low-frequency data, the robustness against outliers, and its flexibility in selecting the rolling window (Naeem and Arfaoui, 2023). We estimate the TVP-VAR model using the *Bayesian Information Criterion (BIC)*, as given below:

$$\mathrm{z_t = B_t Z_{t-1} + \mu_t \mu_t \sim (0, S_t)} \tag{2}$$

$$\mathrm{Vec(B_t) = Vec(B_{t-1}) + v_t v_t \sim (0, R_t)} \tag{3}$$

Where Z_t and Z_{t-1} denote $k \times 1$ dimensional vectors that represent the tail risk series for period t and $t-1$, respectively. μ_t is the error term. β_t and S_t are $k \times K$ dimensional matrices illustrate the time-varying coefficients of the VAR model and the dynamic changes in variance-covariances over time. However, $vec\,(\beta_t)$ and v_t are vectors with dimensional $k2 \times 1$. Finally, R_t is the $k2 \times K2$ dimensional matrix.

Second, using the Generalized Forecast Error Variance Decomposition (GFEVD) formulated by Koop et al. (1996) and Pesaran and Shin (1998) in accordance with the World representation theorem, we transform a TVP-VAR model into a TVP-VMA model with equality processing, as outlined below:

$$\mathrm{z_t = \sum_{i=1}^{p} B_{it} Z_{t-i} + \mu_t = \sum_{j=0}^{\infty} A_{jt} \mu_{t-j}} \tag{4}$$

To further analyze the GFEVD, the (scaled) GFEVD normalizes the (unscaled) GFEVD $\Psi^g_{ij,t}(H)$, ensuring that the sum in each row equals unity. Thus, $\widetilde{\Psi}^g_{ij,t}(H)$ signifies the impact of variable j on variable i forecast error variance, measuring the pairwise directional connectedness from j to i. This indicator is specified as follows:

$$\Psi^g_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} (\tau_i' A_t S_t \tau_j) 2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (\tau_i A_t S_t A'_t \tau_i)} \tag{5}$$

$$\widetilde{\Psi}^g_{ij,t}(\mathrm{H}) = \frac{\Psi^g_{ij,t}(\mathrm{H})}{\sum_{j=1}^{k} \phi^g_{ij,t}(\mathrm{H})} \tag{6}$$

Where $\sum_{j=1}^{k} \widetilde{\Psi}^g_{ij,t}(H) = 1$, $\sum_{ij,t=1}^{k} \widetilde{\Psi}^g_{ij,t}(H) = K$. H corresponds to the forecast horizon, and τ_i serves as the selection vector, assigning unity to the *ith*

[9] https://www.statista.com/

[10] https://metav.rs/

position and zero otherwise.

We start by examining the case where variable i transmits the shock for other variables including j. This phenomenon referred to as total directional connectedness *TO* others:

$$C^{g}_{i\rightarrow j,t}(H) = \sum_{j=1,i\neq j}^{k} \widetilde{\Psi}^{g}_{ij,t}(H) \tag{7}$$

We continue with estimation of the shock that variable i receives from variable j, denoted as FROM others:

$$C^{g}_{i\leftarrow j,t}(H) = \sum_{j=1,i\neq j}^{k} \widetilde{\Psi}^{g}_{ij,t}(H) \tag{8}$$

Ultimately, the subtraction of Eq. (7) from Eq. (8) allows us to obtain the NET total directional connectedness. This measure can help in interpreting the influence of variable i on the analyzed network.

$$C^{g}_{i,t}(H) = C^{g}_{i\rightarrow j,t}(H) - C^{g}_{i\leftarrow j,t}(H) \tag{9}$$

Finally, the Total Connectedness Index (TCI) quantifies market interconnectedness and specified by the following equation:

$$C^{g}_{t}(H) = \frac{\sum_{j,i=1,i\neq j}^{k} \widetilde{\Psi}^{g}_{ij,t}(H)}{\sum_{j,i=1}^{k} \widetilde{\Psi}^{g}_{ij,t}(H)} = \frac{\sum_{j,i=1,i\neq j}^{k} \widetilde{\Psi}^{g}_{ij,t}(H)}{K} \tag{10}$$

3.3. Data and preliminary analysis

This study aims to explore the tail-risk spillovers among AI and the selected new emerging technology sectors during numerous episodes of market turmoil. In this regard, we collect daily data of 12 stock indices related to cryptocurrency and blockchain, robotics, cyber security, metaverse among others. Appendix A describes the variables. The data downloaded from DataStream and spanning from 1/06/2018 to 11/10/2023. Interestingly, in this work we choose to analyze the behavior of innovative technological assets during periods which characterized by the occurrence of recent episodes of black swans such as the COVID-19 outbreak (Yarovaya et al., 2022b), Tesla withdrawal, Russia-Ukraine conflict, and the Silicon Valley Bank collapse. We employ Log transformation returns for empirical analysis.

Table 1 reports the descriptive statistics of each return series considered in the current work. Results show that the mean tail risk changes are positive for all indices except for CRYPBLC, FIN, and DNA. Notably, CLEAN exhibits the highest mean with 6.4 %, whereas DNA shows the lowest mean with −3.6 %. Results also show that CRYPBLC (CYBER) is the most (least) risky as she exhibits the highest (lowest) volatility. Findings also reveal that all return series are negatively skewed, except for CRYPBLC and NANO. Moreover, all series are leptokurtic and reject the null hypothesis of normality for all return distribution. Meanwhile, results of the unit root test based on Stock et al. (1996) reveal that all series are stationary at the 1 % significance level. Results of ARCH and Q-stat values indicate the presence of the ARCH effect and non-randomness at lag 20 in all series, respectively.

Table 2 illustrates the Kendall rank correlations among the considered variables. Results show the presence of positive and significant correlation at the 1 % significance level across all variables. Specifically, the highest pairwise correlation is identified between AIGPT-META with 68.9 %. This empirical evidence underscores the presence of strong connection between these two emerging technology sectors, highlighting limited hedging and diversification opportunities for investors holding stocks within these sectors. Furthermore, we denote a high pairwise correlation between AIGPT-FIN with 66.4 %. This high correlation might limit the effectiveness of using both indices for diversification purposes in the same portfolio as they tend to move in tandem. By contrast, the weakest pairwise correlation is identified between CRYPBLC-MARS with 31.12 %, followed by CRYPBLC-DNA with 35.4 %.

4. Empirical findings

4.1. Tail risk

Fig. 1 reports the 5 % VaR tail risks (value-at-risk for 5 % quantile) showing the co-movements among artificial intelligence, blockchain, and other new technology sectors. We denote a distinguished pattern among the considered markets investigated in this study, such as the presence of diversification and hedging opportunities for portfolio managers who focusing especially on assets belonging to technology sectors (Huynth et al., 2020).

Specifically, we see that FIN, DNA, AIGPT, and GRIDS are the riskiest market indices between 2018 and 2019, with a level of volatility that does not exceed 6 %. This empirical evidence could be attributed to the prevailing uncertainty within these emerging markets. Specifically, the fast-paced and dynamic nature of technological advancements within these sectors led to rising levels of uncertainty (Zhao et al., 2023). For instance, in the case of companies focused on innovations within financial services (Democratized Banking Index), the integration of novel financial technologies, changes in regulatory environments, and evolving customer preferences may have created a climate of uncertainty for investors.

Regarding Genetic engineering and artificial intelligence sector, being at the forefront of technological innovation, could lead to raise uncertainties related to regulatory landscapes, ethical considerations, and the rapid pace of technological change. Similarly, the Smart Grids sector, driven by complex integration of technology in the energy infrastructure, could face challenges related to regulatory frameworks and the dynamic nature of the energy market (O'Dwyer et al., 2019). Thus, this uncertainty has made assets related to these indices sensitive to fluctuations and risks, as investors navigate the challenges associated with staying abreast of rapidly changing industry landscapes. Findings also show that the value of 5 % VaR based on the Asymmetric-slope CAViaR model reaches its maximum for FIN, AIGPT, and GRIDS during the first quarter of 2020, with about 19 % and 13 %, respectively. The evolving nature of technological assets and the rising attention of investors towards such assets are recorded during the COVID-19 outbreak and the implementation of quarantine to curb the spread of virus.

Notably, the COVID-19 outbreak accelerate digital transformation towards digital financial services and raise spectacularly the dependence on technology, making for instance assets of companies belonging to FIN performant and attractive as it encompasses sectors adapting to the changing dynamics of remote transactions and online banking services (Lee et al., 2021; Wang et al., 2021). Furthermore, the growing interest in AIGPT during the COVID-19 pandemic can be attributed to the increasing demand for automation, data analytics, predictions of financial asset trends, and AI-powered solutions. Investors and financial analysts are actively seeking efficiency and innovation amidst a turbulent and rapidly evolving financial landscape. It is important to notice that the adoption of AI in financial market is driven by the recognition of its potential to streamline operations, enhance data analysis capabilities, and offer innovative solutions to complex challenges, ultimately contributing to improved overall performance and adaptability in a highly dynamic market (Rahman et al., 2023; Wamba-Taguimdje et al., 2020).

Afterward, since mid-2020, the volatility of considered variables drops drastically before increasing again and reaching a high level around the first quarter of 2021. More precisely, CRYPBLC records a dramatic increase in volatility and reaches its maximum with about 16 % in early 2021. Specifically, with the rising of global uncertainty due to COVID-19 outbreak, digital assets witnessed a spectacular surge in volatility (Doumenis et al., 2021). As traditional markets experienced sharp declines, cryptocurrencies like Bitcoin, which is mainly considered as a potential hedge or safe-haven asset, faced a dramatic sell-off and leading to heightened volatility in prices. For instance, Bitcoin

Table 1
Descriptive statistics.

Name	Abbreviation	Mean	Std.Dev.	Skewness	Kurtosis	JB	ERS	Q(10)	$Q^2(10)$
Cryptocurrency & Blockchain Equity Index	CRYPBLC	−0.001	3.061	0.456	4.803	1396.628***	−15.630	24.026***	547.741***
Metaverse Index	META	0.033	1.982	−0.214	2.453	362.787***	−5.072	19.213***	515.083***
Artificial Intelligence Index	AIGPT	0.055	1.899	−0.435	4.488	1221.072***	−5.885	34.917***	599.409***
Democratized Banking Index	FIN	−0.003	1.996	−0.507	4.884	1453.964***	−9.168	28.432***	689.525***
Autonomous Vehicles Index	CARS	0.020	2.193	−0.381	3.708	837.565***	−10.815	24.950***	462.273***
Robotics Index	BOTS	0.022	1.588	−0.623	7.866	3703.442***	−6.606	53.477***	826.083***
Cyber Security Index	CYBER	0.037	1.549	−0.572	5.535	1866.031***	−9.996	36.291***	852.477***
Genetic Engineering Index	DNA	−0.036	2.280	−0.291	2.838	491.104***	−12.031	18.493***	404.460***
Smart Grids Index	GRIDS	0.012	1.854	−0.513	6.952	2884.313***	−11.864	54.262***	971.300***
Space Index	MARS	0.024	1.589	−0.920	12.655	9545.566***	−9.945	66.883***	1164.391***
Nanotechnology Index	NANO	0.007	2.114	0.118	3.010	533.387***	−9.550	19.509***	509.739***
Cleantech Index	CLEAN	0.064	2.784	−0.199	3.291	642.535***	−13.714	13.891***	397.742***

Notes: ***, **, * denote 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.

Table 2
Kendall rank correlation coefficients.

	AIGPT	CRYPBLC	META	FIN	CARS	BOTS	CYBER	DNA	GRIDS	MARS	NANO	CLEAN
AIGPT	1.000***											
CRYPBLC	0.433***	1.000***										
META	0.689***	0.442***	1.000***									
FIN	0.664***	0.552***	0.653***	1.000***								
CARS	0.640***	0.432***	0.585***	0.642***	1.000***							
BOTS	0.588***	0.371***	0.530***	0.610***	0.588***	1.000***						
CYBER	0.640***	0.383***	0.639***	0.609***	0.542***	0.602***	1.000***					
DNA	0.476***	0.354***	0.481***	0.486***	0.456***	0.488***	0.481***	1.000***				
GRIDS	0.576***	0.405***	0.538***	0.642***	0.643***	0.664***	0.580***	0.474***	1.000***			
MARS	0.477***	0.312***	0.423***	0.516***	0.486***	0.613***	0.544***	0.383***	0.609***	1.000***		
NANO	0.563***	0.419***	0.559***	0.592***	0.562***	0.590***	0.541***	0.527***	0.594***	0.474***	1.000***	
CLEAN	0.486***	0.377***	0.472***	0.523***	0.534***	0.485***	0.466***	0.429***	0.594***	0.434***	0.495***	1.000***

Notes: ***, **, * denote significance at 1 % significance level.

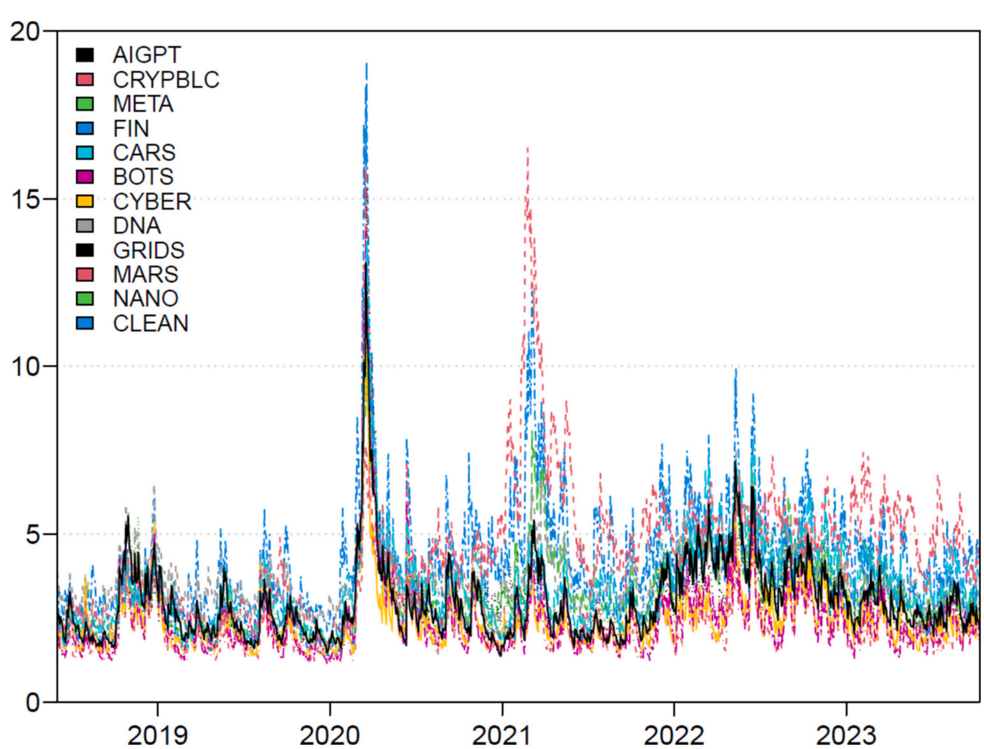

Fig. 1. Downside risk of artificial intelligence, blockchain, and other new economy sectors.
Notes: This figure represent the 5 % VaR using the asymmetric slope (AS) CAViaR model.

lost half of its value over two days and dropped below USD 4000 on March 2020.[11] Meanwhile, amid COVID-19, Blockchain technology plays a crucial role in financial markets by ensuring secure and transparent transactions during the surge in remote work and digital payments (Kordestani et al., 2021). Blockchain also gained prominence, by reducing the need for brokers and human traders, which might in turn increase speed, and reduce transaction costs (Corbet et al., 2019). Later, from mid-2021 until 2023, CRYPBLC and FIN appear as the riskiest indices without exceeding a VaR value of 10 %. Such empirical finding could be the results of the highest sensitivity of CRYPBLC and FIN to extreme events that dominate the period from 2021 and 2023 such as the geopolitical tensions between Russia and Saudi Arabia, the ongoing Russia-Ukraine conflict, and the Silicon Valley bank collapse. Interestingly, cryptocurrencies and blockchain-related assets are recognized for their significant volatility, accentuated during periods of geopolitical uncertainty. This heightened global uncertainty has led investors to increasingly consider cryptocurrencies as havens or speculative opportunities. Additionally, the indices of democratized banking, representing advancements in decentralized finance (DeFi), confront regulatory uncertainty and operational risks amid evolving global regulatory frameworks. As a result, the high risk related to CRYPBLC and FIN reveal that these two indices are perceived as high-risk assets, influenced by market dynamics and regulatory environments shaped especially by the ongoing geopolitical tensions between Russia and Ukraine.

4.2. Tail connectedness network

Fig. 2(a) visualizes the network of tail-risk spillover, highlighting the pairwise directional connectedness among all the considered variables over the full sample period. For clarity, the red color in the node reflects the contribution of the variable under examination to the other variables of the system, whereas green color denotes the contribution from the other variables to the variable under scrutiny. A wider edge indicates the strength of connectedness between a pair of variables.

From Fig. 2(a), we see that each variable in the network plays the role of transmitter and receiver of tail-risk spillover from and to the other variables of the network. Furthermore, the majority of tail-risk spillovers fall within 5 and 10 %, due to the prevalence of dotted green lines across the nodes. Findings show that the largest nodes correspond to AIGPT and FIN, revealing that these indices are the largest tail-risk transmitters and receivers of spillovers to/from other considered indices. This evidence corroborates the conclusion reported by Alshtater et al. (2022) and, Jareno and Yousaf (2023), highlighting the pivotal role of innovative technological assets in shaping the modern financial landscape. The predominance role of AIGPT and FIN as a main tail-risk transmitters and receivers of spillover may be due to their distinctive positions where technological innovation intersects with financial market (Polzin et al., 2016). Specifically, AIGPT, is highly sensitive to the rapid developments and uncertainties in AI technologies. As a result, any disruptions or fluctuations in the AI sector can significantly impact AIGPT, making it highly sensitive. Regarding FIN, assets related to this index are sensitive to any changes in regulatory policies or shifts in how consumers interact with financial services. These changes might significantly impact its performance, making it susceptible to easily contributing to or receiving shocks from other related segments.

Results also show that AIGPT exhibit the most tail-risk spillover transmission and reception, between 5 % and 10 %, with META, FIN, CARS, and CYBER. Specifically, AIGPT exerts the strongest tail-risk spillovers (greater than 10 %) on META, FIN, CARS, and CYBER. This empirical evidence reveals that META, FIN, CARS, and CYBER indices depend strongly on the performance and shocks occur to companies operated in AI and ML services. This evidence supports the conclusion advanced by Aysan et al. (2024b) and Zhang et al. (2023) highlighting the strong connections between Metaverse, robotics and AI/ML. On the other hand, we found that AIGPT receives the largest tail-risk spillovers (greater than 10 %) from META and FIN. This finding could be attributed to the fact that assets related to AIGPT are still in their early stages and are not yet mature. Consequently, the lack of maturity often implies a lower level of resilience and a higher sensitivity to external disruptions or unexpected events (Pagano and Zechner, 2023; Zhang et al., 2023).

When focusing our attention on the COVID-19 outbreak, Fig. 2(b) reveals different patterns compared to the findings reported during the full s ample. Interestingly, from this Figure we see that the connectedness across the considered variables strength drastically during the recent health crisis with greater predominance of tail-risk spillover effects greater than 10 %. Furthermore, results reveal that FIN acts as the largest transmitter and receiver of tail risk-spillovers in the network, followed by AIGPT and CYBER. The occurrence of the COVID-19 pandemic and the quarantine measure established by governments has accelerated the need for digital transformation and the adoption of advanced technology, particularly in the financial market (Fu and Mishra, 2022).

Notably, the integration of financial technology, AI, and robust cybersecurity measures has become more pronounced as a response to the evolving challenges posed by the ongoing health crisis. For instance, during the COVID-19 pandemic, companies record an increase in both internal and external cyber-attacks, mainly due to remote work and more use of video conferencing. Such a situation has lowered security standards (Amankwah-Amoah et al., 2021). Against this situation, companies have established cyber security solutions and use ML and AI to tackle cyber risks challenges and detect fraud attempts. Consequently, the rising popularity, use and investments in these technologies such as cyber-security solution, AI and ML during the recent health crisis reinforce the position of companies belonging to these sectors and elicit strong interest from investors worldwide (Demiralay et al., 2021). Nevertheless, findings indicate that CRYPBLC is the smallest transmitter and receivers of tail risk spillovers during the COVID-19 pandemic. This empirical finding indicates the resilience of CRYPBLC related assets to shocks due to COVID-19 outbreak. Specifically, cryptocurrencies are often associated with decentralized and secure blockchain technology and are always seen as an effective hedge during periods of market turmoil (Riahi et al., 2024; Vukovic et al., 2021). Such a situation leads investors to hold cryptocurrency instead of rushing to sell, which could in turn contribute to maintaining the stability of assets belonging to CRYPBLC.

When focusing on the Tesla withdrawal period, results depicted in Fig. 2 (c), are mostly consistent with the findings of the COVID-19 outbreak with a significant weakening of the degree of connectedness. At first glance, we report the predominance of tail-risk spillovers effects that exceed 10 %. Furthermore, results show that AIGPT and FIN maintain their dominants role as major transmitters and receivers of tail risk spillovers. Tesla is a prominent company with significant technological influence. In this regard, the sudden decision taken by Tesla to suspend vehicle purchases using Bitcoin could have a prompt effects on assets closely related to innovation and technology in the financial market (Sharma et al., 2023). Moreover, investors in the financial market could consider the sudden decision taken by Tesla as a signal for broader market changes, which influence their level of risk perceptions and their behaviors of decision making. Moreover, we notice that CRYPBLC maintains its position as a weak transmitter and receiver of tail-risk spillovers. Such empirical evidence underlines the effectiveness of CRYPBLC assets in providing diversification opportunities for portfolio managers during periods of market turmoil.

Dealing our attention to the Russia-Ukraine conflict period, results illustrated in Fig. 2(d), show the same patterns compared to the COVID-19 outbreak with a slight drop in the degree of connectedness across the considered variables. Notably, we see that the tail-risk spillovers effects greater than 10 % weakened during the ongoing Russia-Ukraine war. AIGPT and CARS appear as the largest transmitters and receivers of tail-

[11] https://www.cnbc.com/

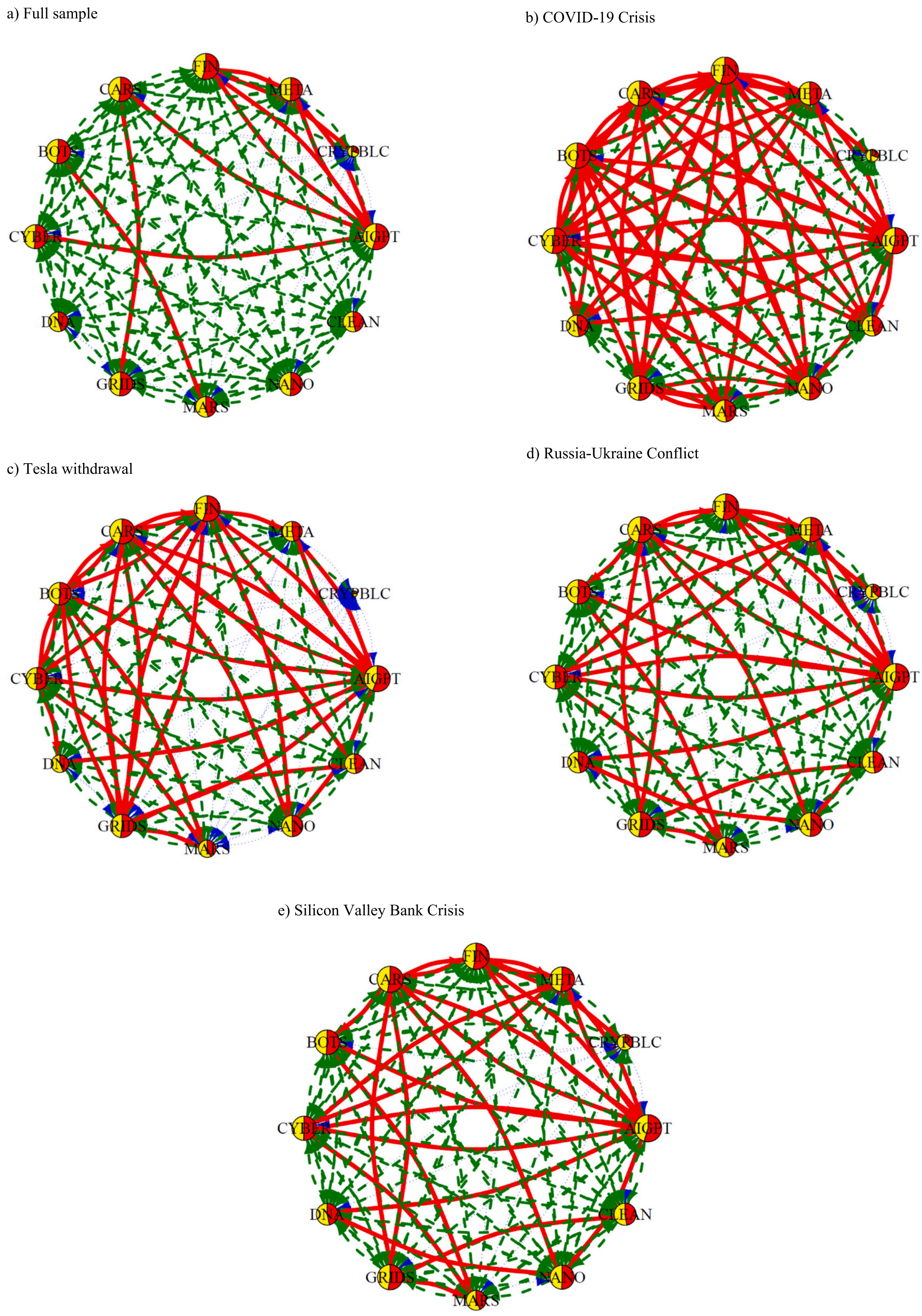

Fig. 2. Network spillovers of downside risk for artificial intelligence, blockchain, and other new economy sectors.
a) Full sample
b) COVID-19 Crisis
c) Tesla withdrawal
d) Russia-Ukraine Conflict
e) Silicon Valley Bank Crisis
Note: This figure showcases the spillovers of downside risk of artificial intelligence, blockchain, and other new economy sectors using a CAViaR-TVP-VAR model with lag 1 (SIC criteria) and a 10-step-ahead GFEVD. In the figures Red line indicates spillovers greater than 10, whereas, Green dashed and Blue dotted lines indicate spillovers between 5 and 10, and less than 5, respectively.

risk spillovers in the network. This finding is partially in line with the finding reported by Yadav et al. (2024), which underscores the role of AI during the ongoing Russia-Ukraine conflict. Specifically, the ongoing conflict between Russia and Ukraine illustrates the crucial need to use ML; a technology based on AI, algorithms, and advanced manufacturing methods to produce new military tools (Yadav et al., 2024). This situation could quickly boost demand of stocks related to AI and ML and therefore reinforce their performance and position in the financial market (Sonkavde et al., 2023). On the other hand, CRYPBLC maintains its role as the smallest tail-risk spillovers transmitter and receiver. This finding indicates the strong resilience of assets belonging to CRYPBLC during the conflict between Russia and Ukraine. Specifically, cryptocurrency is widely recognized as a safe and decentralized form of currency that exhibits strong resilience and even high-performance during times of crises. Consequently, this leads investors to position cryptocurrency as a reliable asset for the foreseeable future (Ustaoglu, 2023). It is also important to notice that AIGPT is the most index that exerts spillovers larger than 10 % on all considered variables except for CLEAN, MARS, and CRYPBLC. This empirical evidence could be due to the widespread impact of AI and technology sectors across multiple industries. AI and technology companies are crucial in modern economic infrastructure and innovation, influencing diverse sectors including finance and health care among others. In this spirit, during the Russia-Ukraine conflict, disruptions in global supply chains heightened cybersecurity concerns and increase dependence on digital and AI-driven solutions which could in turn strength the link between these companies and other market variables. Therefore, it is important to notice that the substantial spillover effect of AIGPT index illustrates how shift in AI and technology sectors across financial markets, affecting various economic activities and investor behavior.

The results for the Silicon Valley Bank collapse period are illustrated in Fig. 2(e) and are consistent with findings reported during the Russia-Ukraine conflict. Interestingly, we notice the predominance of tail-risk spillovers effects greater than 10 %. AIGPT maintains its leading position as major transmitter and receiver of shocks, followed by FIN and CARS. This empirical finding could be attributed to the fact that these technology sectors are not yet mature and highly volatile due to the swift technological development and changes. As result, the effect of the collapse of a prominent financial institution like the Silicon Valley Bank, known for its focus on providing financial services to start-ups, venture capital firms, and innovation-driven businesses in the technology and innovation sectors, can be more pronounced on assets related to companies operates in technological sector due to the limited resources available to absorb this shocks (e.g., liquidity, profitability, and regulatory compliance) in some sectors such as AI. Furthermore, we notice that CRYPBLC still exhibits the smallest node in the network compared to the previous crises' periods. This finding reveals that CRYPBLC keeps its role as the smallest transmitter and receiver of tail-risk spillovers. This empirical evidence proves the effectiveness of CRYPBLC in absorbing shocks related to unexpected events and its effectiveness in providing hedging and diversification benefits for portfolio managers and international investors. We notice also that only CRYPBLC and CLEAN receive the least tai-risk spillover greater than 10 %, especially from FIN and GRIDS, respectively. This resilience during the Silicon Valley Bank collapse period could be due to the decentralized and global attributes of blockchain technologies, which protect them from localized financial shocks and the long-term sustainability driving the Cleantech sector, ensuring stability amidst market uncertainties.

4.3. Averaged pairwise connectedness

Table 3 reports the average pairwise results derived from the pairwise connectedness index (PCI). In this context, the PCI table depicts the average co-movement among pairs of variables. It is worthy to note that all diagonal elements are identical and set to 1. Findings in Panel A of Table 3 show that the strongest connectedness is found between AIGPT-FIN with about 78.76 %. These findings could be the result of synergies between innovation related to AI and the innovative practices adopted by companies in their financial services. Investors could perceive this situation as a positive signal as innovations in financial services proposed by companies are aligning with advancements in AI. Consequently, this situation might lead to reinforcing the connectedness between AIGPT-FIN. Results also show the presence of strong connectedness between AIGPT-META with 77.37 %, which is in line with the study by Naeem et al. (2024d). The Metaverse depends strongly on AI as its main technology (Bojic, 2022). Thus, the connectedness between AIGPT and META could reflect the cross-industry applications of AI within the metaverse. We notice also that the pronounced connectedness between AIGPT-META reveals that investors' trust the strong growth potential of companies in the AI and metaverse sectors, leading to rising demand for their stocks. Nevertheless, we notice that the weakest connectedness is identified between CRYPBLC-DNA with 13.54 %. The weak connectedness between CRYPBLC-DNA could be probably the result of their distinct market dynamics and investor profiles. Cryptocurrency and blockchain assets attract traders looking for speculative opportunities amidst high volatility, whereas genetic engineering stocks tend to attract investors interested in long-term growth driven by advancements in biotechnology and healthcare. As a result, the distinct market dynamics and investor preferences could explain the weal connectedness observed between these two indices.

When focusing our attention on the COVID-19 outbreak period, results highlighted in Panel B of Table 3 are consistent with the findings of the full sample analysis. Specifically, we see that the connectedness between each market pairs strength slightly during the recent health crisis. This empirical evidence is in line with the idea suggesting the strength of connectedness across financial assets during periods of market tensions (Naeem and Arfaoui, 2023). Notably, the strongest connectedness is maintained between AIGPT-FIN (83.96 %), followed by AIGPT-META (81.78 %). On the other hand, the weakest average pairwise connectedness is found between CRYPBLC-BOTS with 18.06 %. This empirical finding proves the effectiveness of combining assets related to CRYPBLC and BOTS in the same portfolio with the aim to profit from diversification benefits.

Focusing on the Tesla withdrawal period the Tesla withdrawal period, findings seen in Panel C of Table 3 show a slight change in the behavior of connectedness across the considered variables. Interestingly, we notice a drop in the degree of co-movement across all market pairs. This finding reveals that the effect of the unexpected decision taken by Tesla to suspend vehicle purchases using Bitcoin has a more pronounced effect on market connectedness than the COVID-19 outbreak. This could be the result of investors' behaviors who are very sensitive to events related to major technology players and their involvement in emerging technology sectors. The strongest co-movement is found between AIGPT-FIN, followed by AIGPT-CARS, with 81.82 % and 75.57 %, respectively.

Investors aware of the swift evolution in technological advancements such as AI, ML, and CARS often recognize the potential for a substantial impact of these innovations on the financial market (Murinde et al., 2022). This recognition leads them to carefully structure their portfolios to take advantage of the growth potential in these evolving industries. The dynamic nature of these emerging sectors, coupled with investors' keen awareness of technological advancements, shapes their reactions to the ongoing developments. Consequently, this situation might, in turn, influence market trends and play a pivotal role in shaping and explaining the performance and connectedness among assets belonging to technology and innovation sectors.

Results also disclose significant changes regarding the weakest connectedness between market pairs compared to the COVID-19 outbreak. Notably, the weakest pairwise co-movement emerges between CRYPBLC-CYBER with 2.97 %, which corroborate the study by Caporale et al. (2021). This finding reveals that these two sectors are less synchronized between them compared to other pairs, due to their

Table 3
Averaged pairwise spillovers.

A) Full sample

	AIGPT	CRYPBLC	META	FIN	CARS	BOTS	CYBER	DNA	GRIDS	MARS	NANO	CLEAN
AIGPT	100	23.25	77.37	78.76	75.03	68.58	71.75	54.16	62.73	52.52	65.18	53.51
CRYPBLC	23.25	100	26.32	39.02	24.43	16.29	18.37	13.54	22.13	15.55	20.12	15.73
META	77.37	26.32	100	72.8	60.77	52.34	67.27	49.49	51.51	42.32	58.38	44.17
FIN	78.76	39.02	72.8	100	70.75	65.55	67.5	50.44	65.2	54.46	62.64	51.84
CARS	75.03	24.43	60.77	70.75	100	65.25	55.78	49.12	70.09	49.82	62.81	55.34
BOTS	68.58	16.29	52.34	65.55	65.25	100	68.07	53.76	65.06	65.33	64.93	51.24
CYBER	71.75	18.37	67.27	67.5	55.78	68.07	100	55.3	56.06	59.72	58.06	50.31
DNA	54.16	13.54	49.49	50.44	49.12	53.76	55.3	100	42.99	35.15	56.02	42.61
GRIDS	62.73	22.13	51.51	65.2	70.09	65.06	56.06	42.99	100	61.91	61.73	58.48
MARS	52.52	15.55	42.32	54.46	49.82	65.33	59.72	35.15	61.91	100	46.39	43.78
NANO	65.18	20.12	58.38	62.64	62.81	64.93	58.06	56.02	61.73	46.39	100	48.99
CLEAN	53.51	15.73	44.17	51.84	55.34	51.24	50.31	42.61	58.48	43.78	48.99	100

B) COVID-19

	AIGPT	CRYPBLC	META	FIN	CARS	BOTS	CYBER	DNA	GRIDS	MARS	NANO	CLEAN
AIGPT	100	29.01	81.78	83.96	77.21	72.79	79.73	66.5	65.97	59.83	70.6	57.02
CRYPBLC	29.01	100	28.1	42.05	28.13	18.06	24.25	21.74	25.88	21.84	24.84	23.74
META	81.78	28.1	100	75.59	67.04	55.35	72.79	60.03	55.62	46.59	58.66	49.4
FIN	83.96	42.05	75.59	100	78.57	74.86	77.45	63.67	76.83	66.03	72.78	58.25
CARS	77.21	28.13	67.04	78.57	100	72.64	69.11	59.86	73.88	59.01	67.87	59.63
BOTS	72.79	18.06	55.35	74.86	72.64	100	77.21	61.7	76.81	76.42	77	56.84
CYBER	79.73	24.25	72.79	77.45	69.11	77.21	100	68.48	66.41	66.51	70.81	59.06
DNA	66.5	21.74	60.03	63.67	59.86	61.7	68.48	100	53.69	46.18	56.13	53.24
GRIDS	65.97	25.88	55.62	76.83	73.88	76.81	66.41	53.69	100	72.04	69.15	56.04
MARS	59.83	21.84	46.59	66.03	59.01	76.42	66.51	46.18	72.04	100	57.53	43.85
NANO	70.6	24.84	58.66	72.78	67.87	77	70.81	56.13	69.15	57.53	100	50.98
CLEAN	57.02	23.74	49.4	58.25	59.63	56.84	59.06	53.24	56.04	43.85	50.98	100

C) Tesla Withdrawal

	AIGPT	CRYPBLC	META	FIN	CARS	BOTS	CYBER	DNA	GRIDS	MARS	NANO	CLEAN
AIGPT	100	7.14	66.56	81.82	75.57	60.08	58.12	45.08	58.3	37.9	57.37	47.36
CRYPBLC	7.14	100	7.58	14.29	12.46	3.52	2.97	4.88	9.58	3.3	7.86	7.69
META	66.56	7.58	100	60.15	48.86	32.03	49.17	34.91	37.16	24.56	45.46	33.89
FIN	81.82	14.29	60.15	100	74.29	55.81	56.98	37.88	63.82	41.29	55.33	47.6
CARS	75.57	12.46	48.86	74.29	100	62.98	43.78	34.15	63.72	41.7	58.11	52.83
BOTS	60.08	3.52	32.03	55.81	62.98	100	59.7	40.99	57.62	48.56	48.58	43.19
CYBER	58.12	2.97	49.17	56.98	43.78	59.7	100	49.6	45.27	50.23	45.55	39.44
DNA	45.08	4.88	34.91	37.88	34.15	40.99	49.6	100	35.19	21.97	37.21	35.56
GRIDS	58.3	9.58	37.16	63.82	63.72	57.62	45.27	35.19	100	50.71	50.72	55
MARS	37.9	3.3	24.56	41.29	41.7	48.56	50.23	21.97	50.71	100	26.63	27.3
NANO	57.37	7.86	45.46	55.33	58.11	48.58	45.55	37.21	50.72	26.63	100	47
CLEAN	47.36	7.69	33.89	47.6	52.83	43.19	39.44	35.56	55	27.3	47	100

D) Russia-Ukraine Conflict

	AIGPT	CRYPBLC	META	FIN	CARS	BOTS	CYBER	DNA	GRIDS	MARS	NANO	CLEAN
AIGPT	100	37.43	83.03	82.11	81.18	74.03	77.94	65.15	70.57	52.32	71.71	63.1
CRYPBLC	37.43	100	36.49	53.52	45.54	28.31	21.84	22.71	41.17	21.97	40.7	27.14
META	83.03	36.49	100	78.17	70.7	56.75	73.71	59.63	66.96	44.09	66.2	56.72
FIN	82.11	53.52	78.17	100	79.74	68.94	66.13	58.32	70.43	48.69	66.48	59.38
CARS	81.18	45.54	70.7	79.74	100	71.78	59.8	60.02	76.17	48.56	70.09	63.54
BOTS	74.03	28.31	56.75	68.94	71.78	100	69.58	58.31	67.99	69.29	65.19	53.88
CYBER	77.94	21.84	73.71	66.13	59.8	69.58	100	62.42	63.54	61.93	58.49	62.85
DNA	65.15	22.71	59.63	58.32	60.02	58.31	62.42	100	53.38	39.99	69.06	51.73
GRIDS	70.57	41.17	66.96	70.43	76.17	67.99	63.54	53.38	100	58.74	66.98	67.09
MARS	52.32	21.97	44.09	48.69	48.56	69.29	61.93	39.99	58.74	100	39.39	48.84
NANO	71.71	40.7	66.2	66.48	70.09	65.19	58.49	69.06	66.98	39.39	100	52.82
CLEAN	63.1	27.14	56.72	59.38	63.54	53.88	62.85	51.73	67.09	48.84	52.82	100

E) Silicon Valley Bank Crisis

	AIGPT	CRYPBLC	META	FIN	CARS	BOTS	CYBER	DNA	GRIDS	MARS	NANO	CLEAN
AIGPT	100	35.74	83.64	84.2	80.78	77.87	83.29	65.68	72.3	63.98	63.23	55.26
CRYPBLC	35.74	100	49.27	59.5	35.76	25.36	26.09	24.9	34.18	26.69	26.02	15.09

(*continued on next page*)

Table 3 (*continued*)

E) Silicon Valley Bank Crisis												
	AIGPT	CRYPBLC	META	FIN	CARS	BOTS	CYBER	DNA	GRIDS	MARS	NANO	CLEAN
META	83.64	49.27	100	83.82	71.66	61.62	71.84	64.41	64.12	58.94	59.25	51.2
FIN	84.2	59.5	83.82	100	75.09	70.62	75.53	63.55	69.57	64.14	58.72	51.61
CARS	80.78	35.76	71.66	75.09	100	69.66	65.49	64.95	76.61	63.22	65.06	58.55
BOTS	77.87	25.36	61.62	70.62	69.66	100	72.23	61.45	70.53	80.84	65.81	56.54
CYBER	83.29	26.09	71.84	75.53	65.49	72.23	100	61.44	65.44	62.82	48.85	58.99
DNA	65.68	24.9	64.41	63.55	64.95	61.45	61.44	100	55.8	57.47	68.14	49.37
GRIDS	72.3	34.18	64.12	69.57	76.61	70.53	65.44	55.8	100	71.67	61.04	73.63
MARS	63.98	26.69	58.94	64.14	63.22	80.84	62.82	57.47	71.67	100	57.58	62.48
NANO	63.23	26.02	59.25	58.72	65.06	65.81	48.85	68.14	61.04	57.58	100	48.91
CLEAN	55.26	15.09	51.2	51.61	58.55	56.54	58.99	49.37	73.63	62.48	48.91	100

Notes: Results are based on a CAViaR-TVP-VAR model with lag length of 1 (BIC) and a 10-step-ahead GFEVD.

fundamental differences in focus and operational aspects. Specifically, companies belonging to the Cryptocurrency & Blockchain sector are involved in developing and employing digital currencies and blockchain technology (Joo et al., 2020). This might include cryptocurrency platforms, creating and improving blockchain technology, and decentralized applications. On the other hand, companies operating in the cybersecurity sector focus mainly on providing solutions to safeguard computer systems, networks, and data from cyber threats. This includes services such as antivirus software and threat detection systems (Bendovschi, 2015).

Concerning the ongoing Russia-Ukraine conflict, results illustrated in Panel D of Table 3 record a slight change compared to the Tesla withdrawal period. Notably, at first glance, we see that the level of connectedness across variables increased drastically compared to the Tesla withdrawal period. This finding underlines the severity of the ongoing conflict between Russia and Ukraine on the considered variables in this study. Noticeably, AIGPT-META acts as the strongest co-movement with 83.03 %. The metaverse and AI markets consistently demonstrate positive growth trends, suggesting a promising perspective for these sectors. This upward trajectory is mostly driven by rising investors' demand on technology related stocks, driven by their higher performance, technological advancements, and evolving consumer preferences. As a result, investors might consider assets related to AI and Metaverse technologies as long-term trends resilient to geopolitical turmoil. For instance, the global AI market size increases by almost 47 % between 2021 and 2022 and reaches a market value by about USD 136.55 billion in 2022.[12]Further, the strong connectedness between AIGPT-CARS persists during Russia-Ukraine war. Results also disclose that the weakest averaged pairwise is maintained between CRYPBLC-CYBER, indicating the strongest resilience of these sectors to unexpected events.

"When focusing our attention on the Silicon Valley Bank collapse, we observe a noticeable change in the behavior of the considered variables compared to the findings obtained during the Russia-Ukraine conflict period. Interestingly, we see that the connectedness among the considered variables strengthened for some market pairs and weakened for others. The strongest average pairwise connectedness is found between AIGPT-FIN and AIGPT-META, with about 84.2 % and 83.64 %, respectively. This finding could be attributed to the fact that during the same period as the Silicon Valley Bank collapse, there were many notable positive AI announcements that contributed to strengthening the position of this new technology and enhancing its role as the primary technology, especially for the metaverse. For instance, Nvidia, one of the leading AI companies, announced in 2023 a range of new products designed for significantly faster and more scalable performance. These technological advancements empower applications to run much faster than they could a decade ago. Additionally, this progress simplifies the development of energy-efficient data centers, reducing energy consumption by orders of magnitude.

Furthermore, during 2023, OpenAI launched GPT-4, Google opened AI language models to developers, Anthropic unveiled AI assistant Claude, Microsoft integrated GPT-4 into Copilot 365, Google introduced Bard as ChatGPT's rival, and GitHub's CoPilot-X is transforming software development. Consequently, all these announcements are perceived as positive signals by investors in financial markets, leading to an increase drastically in the performance and the demand on AI related assets. For instance, by mid-2023, Nvidia's stock has risen by more than 80 %.[13] Moreover, OpenAI, the company that developed AI tools such as ChatGPT and DALL-E, recorded a drastic jump in its value and reaches a value that exceeds USD 80 billion in October 2023.[14] Results also document that the weakest pairwise co-movement is found between AIGPT-CLEAN. This finding is mostly the result of investors' behavior and perceptions which play a significant role in shaping this relationship. Investors may consider that AI companies have different growth drivers and risk factors compared to clean technology companies. Consequently, various investor attitudes and preferences in the financial market could contribute to weakening the connectedness between AIGPT-CLEAN assets.

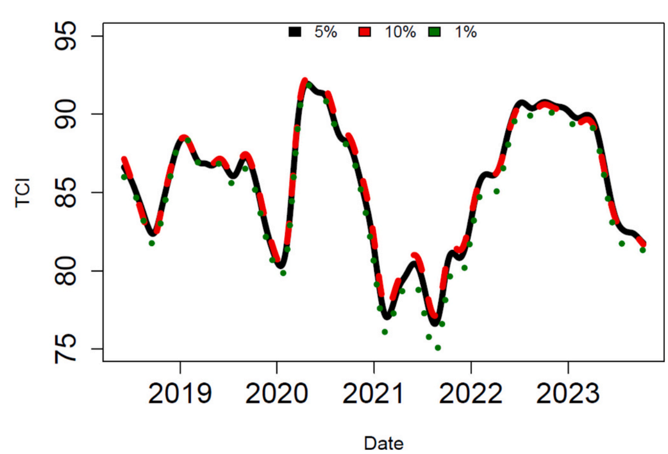

Fig. 3. Time-varying TOTAL downside risk transmission of artificial intelligence, blockchain, and other new economy sectors.
Notes: Results are based on a CAViaR-TVP-VAR model with lag 1 (SIC) and a 10-step-ahead GFEVD. Black line represents the 5 % VaR, while the red (dashed) and the green (dotted) lines represent the results of the 10 % and 1 % VaR, respectively.

12 https://www.forbes.com/

13 https://finance.yahoo.com

14 https://www.nasdaq.com/

4.4. Time-varying tail connectedness

Fig. 3 illustrates the evolution of total spillovers in tail risk at different levels of significance. At first glance, we see that the total spillovers in tail risk ranges from 75 % to 94 % over the whole sample period. The VaR computed based on the 2.5 %, 5 %, and 10 % metrics demonstrates synchronous movement, indicating the robustness of these measures. Findings reveal that the co-movement among the considered variables is strongly influenced by unexpected events occurred at specific points in time. Notably, since mid-2018, the total connectedness in the system has experienced a slight decline, reaching 83 % before undergoing a subsequent upward trend and recording about 89 % in early 2019.

This slight volatility in the total tail-risk spillovers can be attributed to the fact that the emerging technology sectors considered in the current work are still in the early phases of their development, which can lead to increase the level of uncertainties regarding their trajectory and development potential. These emerging sectors, often characterized by swift innovation and shifting market dynamics, lack established performance dynamics and benchmarks, making their growth and market behavior hard to predict. Furthermore, the regulatory environment and competitive landscape for these technologies are still evolving, resulting in increasing the level of uncertainties within this sector and leading to more pronounced risk spillovers. Afterward, the total connectedness follows a downward trend with a slight surge before decreasing and then increasing drastically by reaching its highest level during mid 2020 with approximately 94 %. The drastic rise of tail-risk spillovers could be the result of the COVID-19 outbreak which significantly influenced technology sectors. For instance, AI experiences a swift increase in adoption of AI technologies as companies actively use digital solutions to enhance efficiency and support virtual work environments. Further, the metaverse became increasingly popular as interests towards virtual collaboration spaces and experiences rose, leading promptly to a significant rise in investment related to this technology. Blockchain's transparent and decentralized features are used to enhance the resilience of supply chains. In this spirit, some countries have developed their own digital currencies which could serve as a medium for cross-border foreign exchange payments (e.g., yuan in China, e-krona in Swedeen). Overall, the recent health crisis served as a catalyst for innovation and dramatically increased exploration of these new technologies to address the challenges brought by the pandemic.

Afterwards, from mid-2020, we observe that the total tail-risk spillovers drop sharply and reach their lowest level at 77 % during February 2021. After that, it is followed by a small surge and then a slight decrease between September and October 2022. This empirical finding is mostly the results of several factors such as changes in interest rates taken by central banks to support their economies during the pandemic (Long et al., 2022), the inflations concerns (Armantier et al., 2021), and the geopolitical tension between Saudi Arabia and Russia concerning quota production (Yousaf et al., 2024). All these factors led investors to focus their attention on technology-related assets, which have demonstrated robust performance and resilience amid the COVID-19 (Abakah et al., 2023). Later, from the end of 2021, the trend of tail-risk connectedness increases sharply and reaches a high level with about 92 % in early

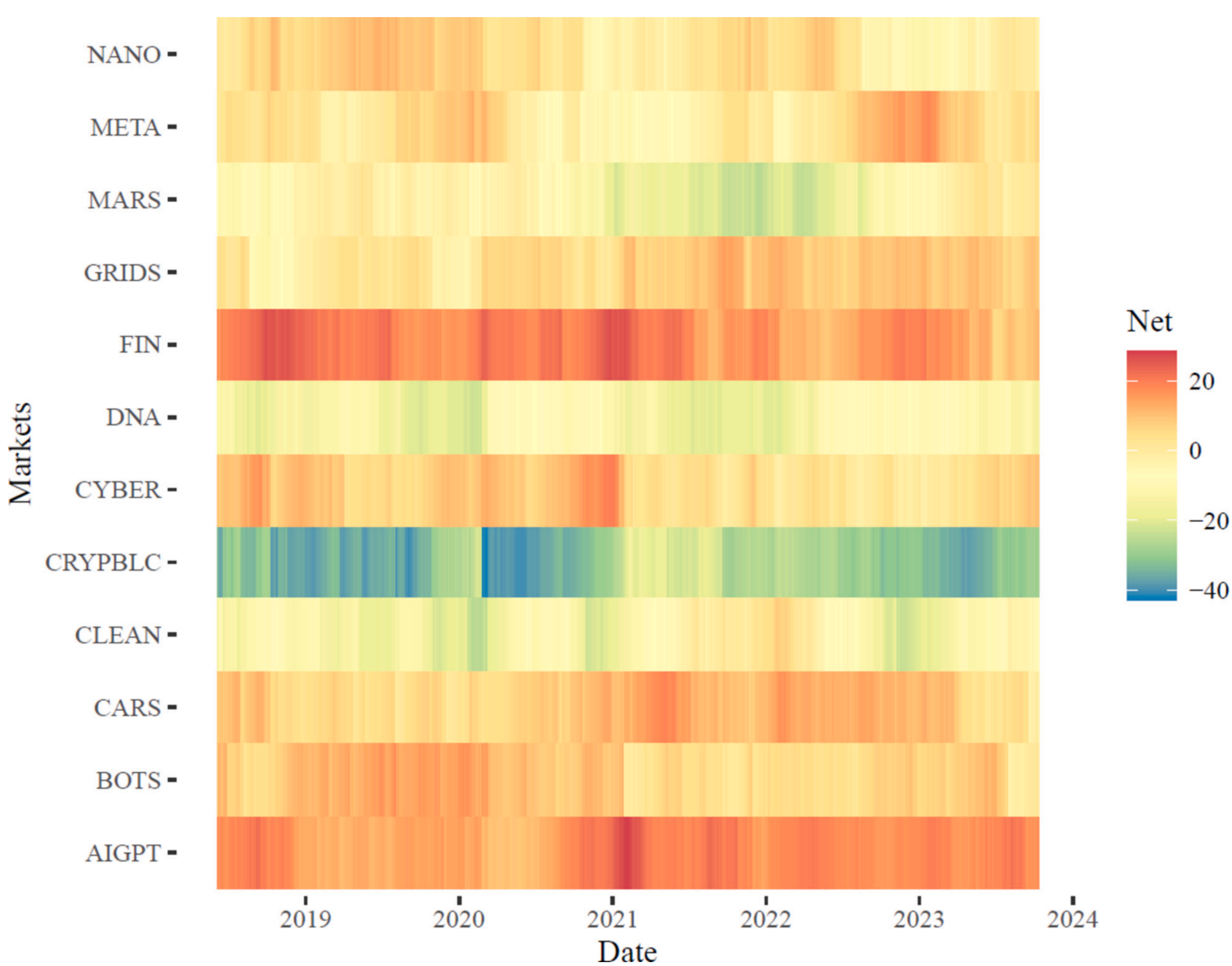

Fig. 4. Time-varying NET downside risk transmission of artificial intelligence, blockchain, and other new economy sectors.
Notes: Results are based on a CAViaR-TVP-VAR model with lag 1 (SIC) and a 10-step-ahead GFEVD.

2023, before undergoes a downturn trend until the end of our sample period. This could be the result of the ongoing Russia-Ukraine conflict which reinforces the dependence between assets belonging to technological sector including AI, Blockchain and metaverse among others (Yadav et al., 2024).

4.5. Time-varying NET tail connectedness

Fig. 4 displays the dynamic interconnectedness of total risk across the considered variables based on the TVP-VAR model. For clarity, blue color indicates that the variable is net risk receiver with negative value, whereas red color shows that the variable is net risk transmitter with positive value. Interestingly, FIN, CYBER, AIGPT, BOTS, and CARS are shown as net risk transmitter over the whole sample period. This evidence reveals that these variables exert a significant impact on the overall risk dynamics of the technological sector. We notice also that NANO, META, and MARS appear for most of the part a diversifiers. Such finding reveals that combining assets belonging to these indices in the same portfolio have the potential to reduce portfolio risk. Moreover, we notice that CRYPBLC and DNA act as net risk receivers for the most time during the whole sample period. This finding could be the result of weak liquidity, particularly as these sectors are still in their emerging stages (Abakah et al., 2023).

4.6. Robustness test

To check the accuracy of our findings, we performed a robustness test based on a TVP-VAR model. Fig. 5 illustrates the synchronized movement of SIC, AIC, and HQ trends throughout the entire sample period. Since the beginning of our sample period, the three measures shown a decreasing trend followed by a slight jump until early 2019. Next, from the first quarter of 2019, the trend of measures shows a gradual decrease until December 2019. From early 2020, we see that the trend of the three measures record a drastic fluctuation until the end of sample period where the highest increase was recorded during March 2020 and the first quarter of 2022, which coincides with the declaration of COVID-19 as a global pandemic and the Russian invasion of Ukraine. We notice also that the deepest decreases are found during the first and the second quarter of 2021 which is mostly the result of economic turmoil resulted from COVID-19.

Fig. 6 illustrates the time-varying NET tail connectedness within the considered indices. The analysis explores both incoming and outgoing co-movements, focusing on time-dependent patterns. Results depicted in Fig. 6 reveal that FIN, CYBER, AIGPT, BOTS, and CARS (CRYPBLC and DNA) maintain their role as net risk transmitter (receiver) over the whole sample period. It is important to highlight that NANO, MARS, and CLEAN exhibit mixed behavior between transmitter and receiver in response to shocks occurred throughout the entire sample period. Moreover, we notice that NANO and META keep their positive as a good diversifier as they show values closer to zero. To summary, findings of the time-varying total/Net tail connectedness reported in Figs. 5 and 6 are consistent with the primary findings shown in Figs. 3 and 4. This consistency reinforces the robustness and accuracy of our key findings.

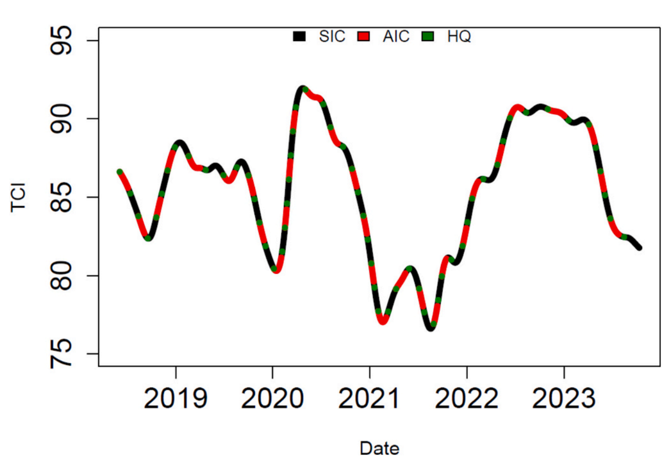

Fig. 5. Time-varying total downside risk transmission of artificial intelligence, blockchain, and other new economy sectors – Robustness.
Notes: Results are based on a TVP-VAR model with SIC, AIC, and HQ criteria and a 10-step-ahead GFEVD. Black line represents the SIC, while the red (dashed) and the green (dotted) lines represent the results of the AIC and HQ, respectively.

5. Conclusion

Emerging technology markets are closely intertwined, playing a pivotal role in shaping the future of digital interactions, virtual economies, and the financial market. Despite these connections across innovative technological assets, researchers have ignored to explore the dynamics of tail-risk connectedness from the AI industry to other innovative sectors, such as the metaverse, cryptocurrency, blockchain, and democratized banking during recent episodes of market tensions such as the COVID-19 outbreak, the Russia Ukraine war, and the Silicon Valley bank collapse among others. Employing tail-risk dependence analysis, as well as CAViaR and TVP-VAR methodologies, we assess the interconnectedness between 12 emerging sectors from January 6, 2018, to October 10, 2023. Our analysis measures the magnitude of spillover effects between these markets during various crisis episodes, highlighting which markets act as net transmitters and receivers of risk spillovers.

The results reveal that the AI industry serves as a primary transmitter of spillovers to other sectors, particularly exhibiting a strong contagion effect on the metaverse and democratized banking industries. While a high contagion effect typically implies negative outcomes and the transmission of risks from one market to another, in this case, we observe a phenomenon of '*positive contagion*,' wherein the thriving AI industry stimulates investments in other innovative sectors. Conversely, AI demonstrates only a marginal spillover effect on the Cleantech industry, suggesting that companies in clean technology have decoupled from the boom in AI companies. This presents diversification and hedging opportunities for investors.

Our findings illustrate that all selected industries exhibit robust interconnectedness during periods of market turmoil, such as the COVID-19 outbreak, Tesla withdrawal, Russia-Ukraine conflict, and Silicon Valley Bank collapse. Particularly, tail risk spillovers intensified significantly during the COVID-19 outbreak. The democratized banking index emerges as the primary transmitter and receiver of tail risk spillovers, surpassing 10 % within the network, followed closely by AI and cybersecurity indices. This trend can largely be attributed to the acceleration of digital transformation and the adoption of advanced technology, especially within the financial sector, driven by the COVID-19 pandemic.

However, the cryptocurrency and blockchain equity index appeared to be the least significant transmitter and receiver of tail risk spillovers amid the COVID-19 pandemic. While the DeFi boom occurred during the COVID-19 isolation period, where crypto assets gained popularity through online trading platforms, our results indicate an absence of positive contagion from the cryptocurrency and blockchain sector to other sectors. Furthermore, we identified the weakest connectedness in the entire sample between the crypto & blockchain industry and robotics. This empirical evidence highlights the diversification advantage offered by combining crypto and blockchain-based assets with stocks from the robotics sector within the same portfolio.

The time-varying trends reveal that the markets considered in this study experienced extreme risk spillovers at the 5 % Value at Risk (VaR), particularly during the COVID-19 outbreak and the Russia-Ukraine conflict. The analysis of net tail risk connectedness shows that AI,

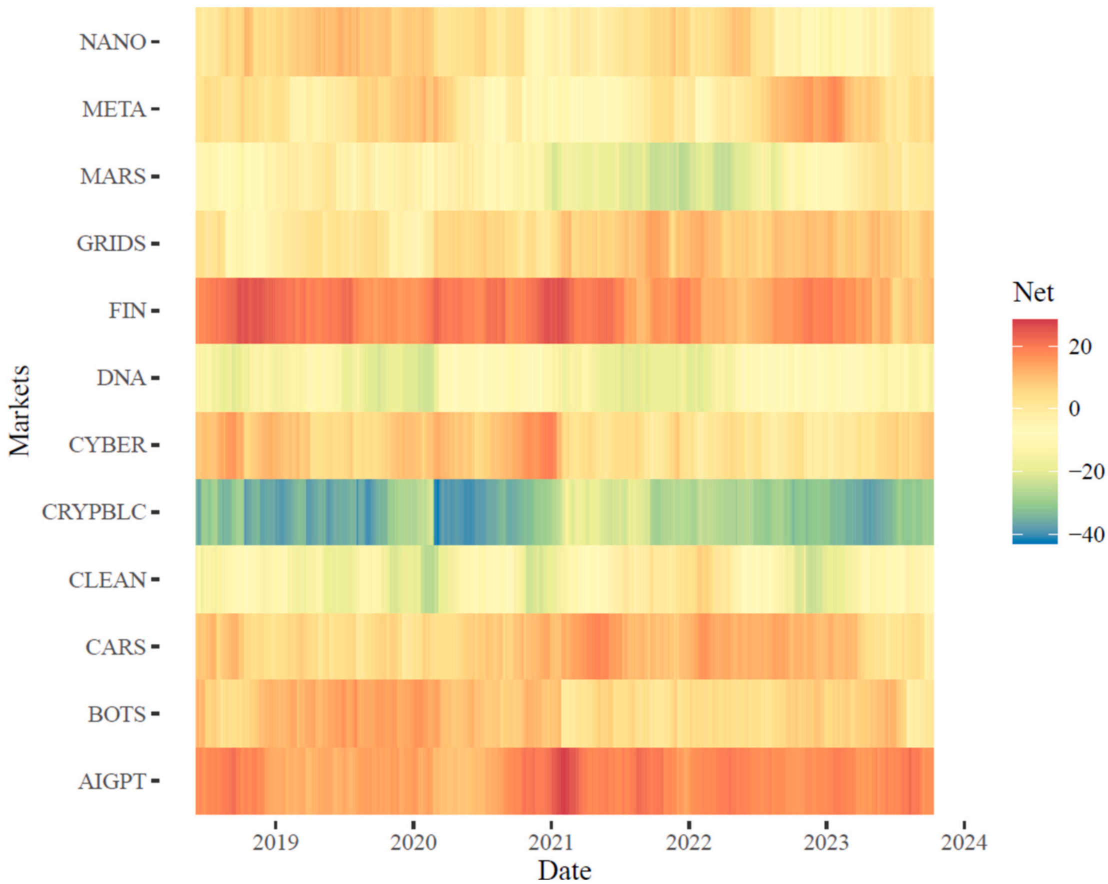

Fig. 6. Time-varying net downside risk transmission of artificial intelligence, blockchain, and other new economy sectors – Robustness.
Note: Results are based on a TVP-VAR model with SIC and a 10-step-ahead GFEVD.

democratized banking, cybersecurity, robotics, and autonomous vehicles act as net risk transmitters, while nanotechnology, metaverse, and space indices are net receivers. Cryptocurrency & blockchain, as well as genetic engineering, play the role of net risk receivers during most crisis periods.

5.1. Policy implications

Our research unveils crucial insights for international investors, portfolio managers, and policymakers. Specifically, it underscores the significance of integrating technology-related assets into investment portfolios. These assets not only bolster risk management and diversification but also potentially serve as safe havens, providing stability or positive returns during periods of market volatility or distress. For investors and portfolio managers, this emphasizes the importance of harnessing information from the technology sector to make more informed investment decisions and adjust risk strategies, especially during turbulent market phases. Such an approach proves essential in both favorable and adverse market conditions, prompting investors to meticulously consider the unique attributes of technology-related assets in their trading strategies. By using timely and accurate information from the technology sector in the financial market, investors could make informed decisions and adjust their risk strategies effectively, especially during heightened uncertainty. This allows investors to take advantage of emerging trends, mitigate risks related to potential downturns, and allocate investments across different phases of economic and technological development. Analyzing carefully technology-related assets ensures that portfolios are well for long-term growth and resilience amid market fluctuations. Further, investors and portfolio managers should stay vigilant about regulatory changes worldwide as these can significantly influence market access, compliance costs and how technology companies operate. Additionally, staying updated on technological developments enables investors to identify disruptive trends and innovative solutions that could enhance growth and competitive advantage in their portfolios. By establishing a forward-looking approach that considers both regulatory development and technological progress, investors can strategically position themselves to seize opportunities while managing effectively regulatory risks.

The intricate interplay among technology assets also bears substantial implications for policymakers. Recognizing the resilience and transformative power of these technologies is essential for effective crisis management and response. Policymakers should proactively participate in crafting policies that guide the ethical development and deployment of these technologies, especially during crises. This is crucial to prevent misuse and unforeseen negative outcomes. Achieving a balance in this regard is key to unlocking the full potential of these interconnected technologies, while simultaneously mitigating potential risks and addressing ethical concerns. These insights suggest a strategic approach to portfolio construction, emphasizing agility and informed decision-making. It advocates for a keen focus on technological trends and developments, leveraging these insights for portfolio optimization and risk management. For policymakers, it underscores the necessity of forward-thinking, responsible policy frameworks that not only foster technological advancement but also ensure its ethical application and societal benefit. Furthermore, as technology continues to evolve swiftly, policymakers are invited to address key concerns such as data privacy, cybersecurity, and the ethical use of emerging technologies. In this spirit, creating a supportive environment for technological progress and investment is essential to enhancing competitiveness and promote substantial economic growth. Therefore, policymakers should establish regulatory frameworks that encourage innovations, protect public interests, and ensure market stability in an increasing digital economy.

With the rising of investors' and portfolio managers' interests towards innovative technology assets, this study can be extended by exploring the role of these assets in improving the diversification of a portfolio including conventional and/or green assets during both normal and crisis times.

CRediT authorship contribution statement

Muhammad Abubakr Naeem: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Conceptualization. **Nadia Arfaoui:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Larisa Yarovaya:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Investigation, Conceptualization.

Appendix A. Variables definitions

Variable	Definition
Cryptocurrency & Blockchain Equity Index	The index measures the performance of companies focused on cryptocurrency and blockchain products and services.
Metaverse Index	The index captures the performance of companies involved in the metaverse.
Artificial Intelligence Index	The index measures the performance of companies involved in the artificial intelligence sector across technology, industrial, medical, and other economic domains.
Democratized Banking Index	The index assesses the performance of companies focusing on innovations within financial services such as direct lending, crowdfunding, automated wealth management demand insurance services, and digital currencies
Autonomous Vehicles Index	The index computes the performance of companies concentrates on autonomous and connected vehicles.
Robotics Index	The index gauges the performance of companies concentrating on the robotics sector and its key subsystems.
Cyber Security Index	The index evaluates the performance of companies specializing in safeguarding enterprises and devices against unauthorized access through electronic ways
Genetic Engineering Index	The index assesses the performance of companies engaged in the genetic engineering industries, encompassing those that provide tools to enhance the efficiency of research for other companies.
Smart Grids Index	The index tracked the performance of companies engaged in the smart power, intelligent water, and intelligent transportation systems industries.
Space Index	The index computes the performance of companies engaged in the space area, especially those whose main business strategy focus on space-related activities
Nano technology Index	The index is designed to evaluate the performance of companies engaged in the nanotechnologies sector. This encompasses companies producing nanoscale materials and those integrating nanotechnology into their production processes or developing machines able to computes information at the nanoscale.
Cleantech Index	The index assesses the performance of companies engaged in developing technologies or products that enable to generate clean energy

Data availability

Data will be made available on request.

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