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Engagement of true intelligence in financial forecasting: interactions of blockchained sectors and artificial intelligence

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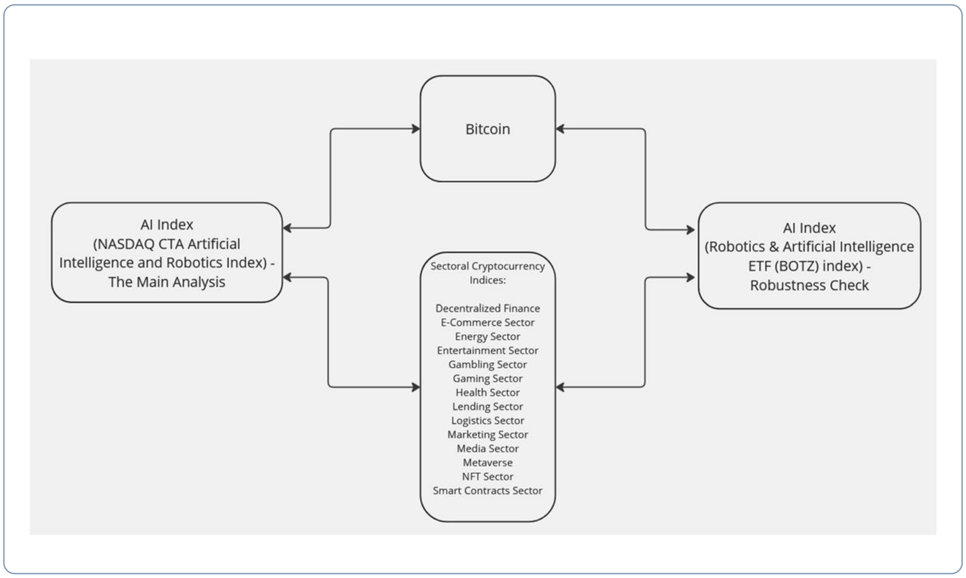
Abstract

In this study, we examine the connectedness between the NASDAQ artificial intelligence index and sectoral cryptocurrency indices. Empirical analyses were conducted via the quantile–quantile methodology and cross-multiquantilogram tests across 15 cryptocurrency sectors from June 1, 2021, to May 28, 2024. The results show that dynamic total spillovers primarily occur in extremely low and high quantiles, corresponding to the left and right tails of the return distributions. Net directional spillovers indicate the dominance of the AI sector over the cryptocurrency market, which intensifies during significant crashes or booms. The most substantial effect of AI is observed in the DeFi, NFT, and Smart Contracts sectors, highlighting the prominence of financial operation-based blockchain applications in their interaction with artificial intelligence. The cross-multiquantilogram results also suggest that developments in artificial intelligence dominate the cryptocurrency market and have high predictability in its price movements. On the basis of our findings, we recommend using the AI market as an early indicator for the cryptocurrency market and advise against combining these two asset groups in the same portfolio to maintain diversification benefits.

Keywords: Blockchained sectors, Artificial intelligence, Forecasting, Quantile-on-quantile, Cross-multiquantilogram

Graphical Abstract



Introduction

Although in its initial phase, blockchain technology exhibited a revolution, specifically in financial transactions, today, its usage has extended from international money remittance to supply chain management, logistics, healthcare media, etc. Integrating blockchain technology with artificial intelligence (AI) could further accelerate this transformation, enabling a seamless transition from traditional business practices to their digital counterparts. This study aims to uncover patterns in the relationship between AI developments and blockchain-based business models, focusing on token markets that have already embraced this transformation across various sectors.

With the rapid advancement of technology, data-driven activities pose risks for individuals and businesses. Various solutions are available to safeguard digital information to address this, with blockchain technology standing out. By utilizing distributed ledgers and smart contract-based billing systems, blockchain enhances security, reduces data manipulation risk, and offers an efficient, transparent alternative to traditional double-entry bookkeeping. Accounting scandals in history, such as Enron in 2001, Freddie Mac in 2003, and Madoff in 2008, show that financial data processing and fraud may induce a disaster for an institution, its stakeholders, and investors. The traceable mechanism of the system significantly lessens the burden for auditors. This process overcomes human errors in the system and provides completely accurate and compliant records. Andersen (2016) considers the blockchain as the next step in accounting and financial operations and states that this revolution results in the establishment of a connected and long-lasting record system and project that, at the end of the road, we may end up fully automated audits, not only traceable audit trails. However, as discussed by Centobelli et al. (2022), the knowledge gap between blockchain developers and accounting experts is one of the reasons for the delay of this technology's employment in adaptation in accounting and financial operations. Blockchain technology can streamline the processes involved in accounting and finance for business operations. However, its implementation often requires a third party to manage the system, which adds an extra layer of costs that may not be efficient. To improve efficiency, blockchain can be automated with AI, offering case-specific solutions and a human-like learning process to address various challenges. Thus, integrating AI with blockchain technology can accelerate the transition to fully digitalized business models. As AI systems require increasing amounts of data, the growing number of network participants will enable faster improvements, potentially leading to a swift transition from traditional finance and accounting models to a completely digitized financial world.

Excluding either blockchain technology or AI could create a significant gap in the effectiveness of future business models. Blockchain-supported intelligence has the potential to enhance business operations, making the exploration of their interconnectedness highly valuable. This study aims to provide evidence of their interactions to deepen our understanding of the relationship between these two rapidly growing yet nascent technologies. Our primary objective is to inform investors and policymakers about the direction and magnitude of the interactions between blockchain-based cryptocurrency sectors and global AI developments while also providing insights into their mutual price discovery dynamics. Although these markets are significantly less mature than their traditional counterparts are, evidence gathered at this early stage can help policymakers develop appropriate regulatory measures and incentive programs. Accordingly, we aim to provide comprehensive market evidence from 15 blockchain-related sectors to identify their relationships with AI advancements and support the development of tailored policies. To that end, we analyze the relationship between sectoral cryptocurrency indices, which employ blockchain technology rather than the conventional way of doing business, and the NASDAQ CTA Artificial Intelligence and Robotics Index, which proxies for global AI performance. The cryptocurrency sectors utilized in the empirical investigation are as follows: DeFi, e-commerce, energy, entertainment, gambling, gaming, healthcare, lending, logistics, marketing, media, metaverse, NFT, smart contracts, and tourism. The interactions between sectoral cryptocurrency indices and AI are analyzed via the quantile-on-quantile spillover method (Gabauer And Stenfors 2024) and the cross-multiquantilogram test (Han et al. 2016). The rapid advancements in blockchain and AI technologies indicate dynamic relationships that evolve alongside market developments and economic cycles, necessitating analysis under diverse conditions, as addressed by the abovementioned models. These methodologies offer significant advantages over traditional approaches. Unlike the mean-based spillover analysis of Diebold and Yilmaz (2012) or the quantile-specific method of Chatziantoniou et al. (2021), quantile-on-quantile analysis examines return transmission across different quantiles, eliminating the need for positive correlations. The cross-multiquantilogram further captures correlations at specific quantiles without relying on moment conditions, effectively addressing heavy tails resulting from extreme market movements. This enables analysis of tail risk and nonlinear, quantile-dependent relationships. These models provide valuable insights into lead–lag dynamics between assets by incorporating multiple lags, enhancing the price discovery process. Overall, combining these two models deepens our understanding of the predictive relationships between variables.

Although the current literature argues for these two groups of technologies in various channels of research, namely, portfolio management (Briere et al. 2015; Guesmi et al. 2019; Qarni And Gulzar 2021), risk management (Naeem et al. 2021; Okorie and Lin 2020; Bouri et al. 2020), fiat-money engagement (Gunay et al. 2021; Shahzad et al. 2022;

Levulytė and Šapkauskienė, 2021), sustainability (Erdogan et al. 2022; Gunay et al. 2023; Fadeyi et al. 2019), and entrepreneurship (Phillips et al. 2023; Skrypnyk et al. 2019), the focus is either on blockchain technology or independently evaluating the revolution and opportunities presented by AI in finance (Lin 2019; Goodell et al. 2021; Bahrammirzaee 2010; Giudici And Raffinetti 2023). However, the future association of these two technologies may expedite the process and shorten the distance to reach. As mentioned above, at the beginning of this journey, presenting evidence regarding the current status of this relationship may offer opportunities for investors, entrepreneurs, and policymakers.

The econometric framework we construct offers several advantages. First, using various quantiles provides crucial insights into specific market conditions, such as tail risks arising from extreme positive or negative price movements. For example, evidence obtained from lower quantiles, representing left-tail conditions, can offer valuable insights for portfolio managers seeking to understand the direction of interactions between blockchain-based sectors and AI market developments under such scenarios. Similarly, incorporating multiple lags benefits both portfolio managers and policymakers by visualizing the sequence of interactions and uncovering lead–lag relationships. For example, if AI demonstrates causal dominance over blockchain markets, this insight could guide investors and entrepreneurs to focus on AI advancements before making financial or business decisions in cryptocurrency markets influenced by AI. Furthermore, the framework provides policymakers with actionable sector-based evidence by examining sector-specific associations between blockchain technology and global AI developments. Identifying closely or weakly related pairs can help guide policy actions, such as implementing incentive plans to strengthen beneficial connections or introducing regulations to mitigate risks associated with problematic relationships during extreme market conditions. This contributes to the safety and stability of markets, offering a more predictable environment for investors and entrepreneurs. Finally, the identified spillovers and lead–lag relationships provide critical information for market participants. By recognizing assets that serve as early warning signals within a pair, investors can adjust portfolio allocations promptly, potentially avoiding significant losses during market crashes. This proactive approach ensures a more resilient investment strategy and enhances market stability. The lead–lag relationship reflects the behavior of one asset moving ahead or lagging behind another, making it a useful tool for price discovery. This allows investors to make more efficient forecasts by identifying patterns in the empirical section. In this context, our findings suggest that AI markets may provide valuable insights for predicting the prices of specific cryptocurrency sector indices.

In the following section, we present a comprehensive literature review of studies on blockchain and AI. Section "Econometric methodology" outlines the econometric framework of the models used in the empirical analysis. Section "Data and empirical results" discusses the findings and offers insights into the interactions between blockchain-based sectoral indices and AI. Finally, section "Robustness check" concludes by providing key arguments and implications for various market stakeholders.

Literature review

Blockchain technology has significant potential to be employed in various business fields, enhancing efficiency and transforming business operations. AI further accelerates this transition. The collaboration between these two groundbreaking technologies is poised to revolutionize many aspects of business and shape the future. However, the connectedness of these studies in the literature has not been sufficiently analyzed.

While there is extensive literature on the cryptocurrency market and a growing body of research on AI-related developments, the intersection of these two fields remains largely unexplored. The existing attempts in the literature seem insufficient to address this gap comprehensively. For example, Zeng et al. (2024) incorporated the NASDAQ CTA artificial intelligence & robotics index in their empirical investigation. Nevertheless, their focus is limited to the connectedness between AI and the clean energy market. Similarly, Gunay et al. (2023) examine various cryptocurrency sectors, but their analysis is confined to the interactions between global sustainability and the cryptocurrency market. Closer attempts also fall short of addressing the evidence revealed in our study. For instance, Huynh et al. (2020) analyzed the relative contributions of AI and robotics stocks, green bonds, and Bitcoin to portfolio diversification. Abakah et al. (2023a) also investigated the dynamic impact of Bitcoin, fintech, and AI stocks on environmentally friendly assets, Islamic stocks, and traditional financial markets. However, their study did not explore the causal relationship between the returns of Bitcoin, KFTX, and the NASDAQ AI index. In a related study, Abakah et al. (2023b) identified a Granger causality-in-variance from AI to Bitcoin, specifically for the middle quantile distribution. Building on this prior research, our study expands the scope by incorporating data from an additional 15 cryptocurrency sector indices, offering significantly broader data coverage and more comprehensive insights into the dynamic interactions between cryptocurrencies and AI technologies.

While the studies mentioned above are at least tangentially related to our approach, the rest of the literature focuses primarily on either blockchain or AI-related data rather than examining the intersection of both. For example, using a data sample of 366 banks and 300 nonbanks focused on financial services and applying both principal component and regression analysis, Rajnak and Puschmann (2021) reported that blockchain technology impacts all the elements of banks' business models. Additionally, Garg et al. (2023), using structural equation modeling and a survey of 289 respondents, provided empirical evidence of a direct relationship between blockchain capabilities and organizational performance, which was partially mediated by competitive advantages in the Indian banking sector. Siddik et al. (2021) show that blockchain technology positively influences international trade by enhancing security, trust, and transparency while minimizing trade-related costs. Furthermore, Jiang et al. (2023) compared the effects of blockchain technology with those of traditional supportive policies, such as fiscal subsidies, using a dynamic stochastic general equilibrium (DSGE) model framework. Their results indicate that a blockchain-based green finance platform can more effectively reduce green credit interest rates, increase the scale of green credit, promote total output and green sector employment, and decrease pollutant emissions under a positive one-unit shock.

The application of blockchain technology in various fields has demonstrated its efficiency beyond financial transactions. For example, integrating blockchain into smart healthcare systems secures electronic health records. As shown by Hajian et al. (2023), blockchain-based information systems can empower patients by providing them with a sense of control over their health records. Zarour et al. (2020), using feedback from 56 healthcare management experts and an integrated fuzzy-ANP-TOPSIS method, concluded that a private blockchain model is the most effective and robust solution for healthcare blockchain technology. The insurance sector has also seen blockchain applications. Grima et al. (2020) examined factors influencing blockchain adoption and found that societal receptiveness to new technologies, although the general population may still be reluctant due to the complexity of the technology. Lanfranchi and Grassi (2021), focusing on the U.S. public P&C insurance sector, used both nonparametric (two-stage DEA) and parametric (SFA) approaches and reported that, on average, insurance companies have not yet leveraged technological innovations to improve efficiency. In logistics and supply chain management, Wamba et al. (2020), through structural equation modeling (SEM) and surveys in India and the USA, reported that blockchain applications improve supply chain performance. Using hierarchical regression analysis, Dubey et al. (2020) provided evidence that blockchain technology positively influences operational supply chain transparency, which fosters swift trust, collaboration, and supply chain resilience. Choi (2023) developed analytical models for traditional and blockchain-supported supply chains, deriving optimal contracting and quantity decisions between manufacturers and retailers via Nash bargaining. Because blockchain technology offers security, accuracy, trust, transparency, and immutability, it may also improve the political process. Cheema et al. (2020) proposed a stable and efficient e-voting system architecture that relies on blockchain and machine learning principles, offering transparency, trust, and security. Khan et al. (2021) presented an empirical analysis of the transaction malleability threat to blockchain, highlighting the role of factors such as network delay, the block generation rate, and software-induced delays. In addition, blockchain technology has been deployed in energy applications because of its desirable attributes, such as anonymity, decentralization, and transparency. Focusing on two fully commissioned offshore wind farms in the UK, they found that utilizing blockchain technology in strategic management reduces costs. Strepparava et al. (2022) analyzed issues related to deploying blockchain-based local energy markets on devices and investigated the sustainability of the application. Their results show that the developed application uses minimal resources from the embedded device, implying that deployment at the data concentrator level is feasible. Ullah et al. (2024) examined critical factors affecting users' intention to accept blockchain technology for smart grids. Using a structural equation modeling framework, they reported that relative advantage is the most significant factor in adopting blockchain technology for the smart grid, with innovativeness, cost savings, and regulatory support also playing important roles. The distributed ledger attributes of blockchain technology also offer potential educational benefits, such as easier transfer of academic records, traceability of learning data, inclusion, privacy, and information security for learners. Using a sequential mixed methods design involving quantitative survey data, Alshahrani et al. (2020) provided empirical evidence that four blockchain attributes positively influence students' and employers' acceptance of a blockchain-based certification process in higher education. Furthermore, blockchain is considered an appropriate technology for eliminating intermediaries from the tourism industry's supply chain and preventing new intermediaries from gaining access to this industry. Sharma et al. (2021) used a hybrid research methodology to assess the causal relationship between blockchain technology and the hospitality and tourism sectors and reported that low cost and risk management are key drivers for adopting blockchain technology. In the real estate industry, intermediaries traditionally play an important role in connecting potential buyers and sellers. Swinkels (2023) examined the financial and economic consequences of tokenizing 58 residential rental properties in the U.S. They found that tokenization fulfills its promises by dispersing ownership of properties of modest value, leading to substantial risk sharing across households. With respect to identify management, centralized servers and cloud storage are vulnerable to data theft and hacking. Mulaji and Roodt (2021) conducted a meta-synthesis of 69 papers and reported that while blockchain shows promise, it remains immature. Similarly, blockchain can simplify and secure intellectual property rights management. Using a bargaining model, Cai et al. (2023) reported that an idealized application of blockchain can yield a Pareto optimal solution to IP transfer from research to developer firms. In the transportation industry, Gong and Liao (2019) showed that blockchain technology can facilitate data sharing in urban intelligent transportation and address data loss issues in traditional network architectures. Li et al. (2021), using a two-step structural equation modeling approach, confirmed with empirical evidence from Korea that tracking and tracing, digitalized management, air traffic management, regulatory governance and industry standards, and technological improvements positively influence the intention to use blockchain.

Kim et al. (2022) noted that, similar to blockchain technology, AI is rapidly advancing, aiming to equip machines with the cognitive capacity to understand, infer, and adapt to the collected information. The potential integration of blockchain and AI offers numerous prospects. Hussain and Al-Turjman (2021) concluded that the synergy between blockchain and AI applications is still in its early stages, with challenges yet to be addressed in various domains. They also discussed how cloud technology can be utilized alongside blockchain and AI to enhance security, reliability, trust, transparency, information management, and computations in AI applications. In the healthcare sector, Tagde et al. (2021) explored the possibility of creating reliable AI models in e-health via blockchain, which could improve service efficiency, reduce costs, and democratize healthcare. Similarly, Wang et al. (2021) discussed how blockchain could facilitate AI applications in secure data sharing (for model training), preserving data privacy, and supporting trusted AI decision-making and decentralized AI. From a different perspective, Hua et al. (2022) concluded that incorporating blockchain and AI into smart grids could support the integration of prosumers with trading, control, and policy functions.

The joint application of blockchain technology and AI in the financial services industry promises a new era of enhanced security and transparency by leveraging the unique strengths of each technology to complement and augment the capabilities of the other (An et al. 2021; Rane et al. 2023). Gwala (2025) provides a comprehensive review of the integration of blockchain and artificial intelligence (AI) within the fields of cryptocurrency and medical technology, highlighting their transformative potential. The study underscores how these technologies contribute to enhanced transparency, security, and efficiency, driving innovation and socioeconomic growth across both sectors. According to Ouyang et al. (2022), AI-driven blockchain intelligence can enhance smart contracts—self-executing agreements with predefined rules—by streamlining processes and reducing human intervention, thereby improving the accuracy and efficiency of financial transactions. Identity verification plays a crucial role in financial transactions. Khare and Srivastava (2023) introduced an advanced E-KYC (Know Your Customer) authentication system that combines blockchain technology with AI-driven facial recognition to overcome the inefficiencies and security vulnerabilities of traditional KYC processes. Blockchain trust, security, and reliability largely depend on consensus mechanisms, which govern several vital network functions. Integration with AI has shown potential for addressing challenges such as energy inefficiency, scalability, and susceptibility to cyberattacks, thereby increasing security within the financial sector (El Hessaini et al. 2024). Soundararajan and Shenbagaraman (2024) argued that the fusion of explainable artificial intelligence (XAI) with blockchain technology creates a powerful synergy that directly addresses interpretability issues often associated with AI models in finance. This combination provides stakeholders valuable insights into the factors influencing critical financial decisions, offering transparent, human-interpretable explanations for AI predictions on an immutable distributed ledger.

Chowdhury (2024) discussed the synergies among AI, ML, and blockchain and provided a case study in which the HSBC uses blockchain for secure and transparent trade finance transactions. By integrating AI and ML, HSBC automates document checking processes, reducing the time and cost associated with trade financing and ensuring compliance with regulatory standards.

Mikhaylov and Bhatti (2024) demonstrated that AI-driven financial management can increase efficiency and reduce mismanagement in digital financial assets (DFAs). By applying AI to postmodern portfolio theory, they showed that AI-managed DFA portfolios outperformed short-term DFA investments in financial performance between February 2022 and February 2023.

As outlined in the arguments above, the current literature focuses primarily on blockchain or AI independently, without establishing a connection between them. Additionally, efforts to link the cryptocurrency market with AI have focused mostly on specific assets, such as Bitcoin. The literature lacks comprehensive, market-wide evidence on this topic, particularly in the context of the transformation from traditional business models to digitalized ones. In light of these gaps, this study provides extensive evidence from 15 sectors that have already undergone this transformation in terms of blockchain utilization and their interactions with global AI developments.

Econometric methodology

We investigate the dynamic link between the returns of the AI and cryptocurrency sectors by concentrating on different quantiles of the variables in addition to time-varying characteristics. Recently, a unique approach called quantile-to-quantile spillover analysis was proposed by Gabauer and Stenfors (2024) to study the process of spillover between a collection of variables at different quantiles. The method introduced by Gabauer and Stenfors (2024) is a generalized framework based on Chatziantoniou et al. (2021)

quantile connectedness methodology. This new approach captures interrelated interactions across different quantiles of interest, analyzing how the τ_1-quantile of variable X impacts the τ_2-quantile of variable Y and vice versa. While this approach resembles the methodology of Sim and Zhou (2015), as it operates on received and transmitted spillovers, it also allows us to ascertain the network among the variables on the basis of the methodology proposed by Diebold and Yilmaz (2012). Gabauer and Stenfors (2024) highlight that the key advantage of this approach over quantile spillover analysis is its ability to capture relationships between variables at the same level of quantiles and across different quantile levels. Hence, this new method enables the examination of spillovers across different quantiles, which is impossible with the quantile connectedness approach, which tests only spillovers through selected tau values, assuming that all series are positively correlated. In contrast, we can account for the possible negative correlations between variables by employing the quantile-on-quantile methodology. This is particularly important in the context of the variables studied because Wang et al. (2022) emphasize the distinct dynamics between cryptocurrency markets and stock markets. While Tarchella et al. (2024) reported that Bitcoin provides a good hedging opportunity for the G7 stock market during tranquil periods, Stensas et al. (2019) reached similar conclusions for stock markets in developing countries, emphasizing the importance of examining relationships across different quantile levels. Similarly, Al Rahahleh et al. (2017) provide empirical evidence of left-tail dependence among the stock markets of the UK, the USA, and Taiwan, suggesting stronger comovement during market downturns. Even when focusing on the tail dependence between AI and cryptocurrencies, it is essential to note that the index representing AI is traded in traditional stock markets. Consequently, bull and bear market periods in the stock and cryptocurrency markets do not always align or synchronize. Therefore, to account for the asymmetry between the business cycles of the two markets, it is essential to analyze the relationships between variables not only at the same quantile levels but also across different quantile levels.

Using this method, the following quantile vector autoregression (QVAR) models are estimated over various quantiles:

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

where $\boldsymbol{x}_t$ and $\boldsymbol{x}_{t-j}$ represent $K \times 1$ dimensional vectors of endogenous variables, with $\boldsymbol{\tau}$ denoting quantiles within the range [0, 1]. The parameter p corresponds to the lag order of the QVAR model, $\boldsymbol{\mu}(\boldsymbol{\tau})$ represents an $K \times 1$-dimensional conditional mean vector, $\boldsymbol{B}_{\boldsymbol{j}}(\boldsymbol{\tau})$ denotes an $K \times K$-dimensional QVAR coefficient matrix, and $\boldsymbol{u}_{\boldsymbol{t}}$ is an $K \times 1$ -dimensional error vector characterized by an $K \times K$-dimensional variance–covariance matrix, $\boldsymbol{H}(\boldsymbol{\tau})$. Transforming the QVAR model into a quantile VAR moving average representation is essential for calculating the generalized forecast error variance decomposition (GFEVD), as outlined by Koop et al. (1996): $\boldsymbol{x}_{\boldsymbol{t}} = \boldsymbol{\mu}(\tau) + \sum_{i=0}^{\infty} \mathbf{A}_{\boldsymbol{i}}(\tau)\boldsymbol{u}_{t-i}(\tau)$. The F-step-ahead GFEVD measures the influence of a shock in series j on series i, as described by:

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

$$gSOT_{i\leftarrow j,\tau}(F) = \frac{\phi^{g}_{i\leftarrow j,\tau}(F)}{\sum_{j=1}^{k}\phi^{g}_{i\leftarrow j,\tau}(F)} \tag{3}$$

where the zero vector $\boldsymbol{e}_{\boldsymbol{i}}$, which has unity at its ith location, is an $K \times 1$-dimensional vector. The total directional spillover to (FROM) others is determined via scaled GFEVD, which is a key component of the spillover approach. While the total directional spillover FROM displays the aggregate effect of all series-on-series i, the TO total directional spillover illustrates the influence series i has on all other series. These spillover measures can be calculated as follows:

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

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

By deducting the FROM from the TO, one can determine the NET total directional spillover for variables i:

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

Variable i is a net transmitter (receiver) of shocks when $S^{gen,net}_{i,\tau}$ is greater than 0 ($S^{gen,net}_{i,\tau}$ is less than 0). This means that variable i has a greater (less) impact on all other variables than it does on them. The following formula may be used to obtain the adjusted total spillover index (TSI):

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

This indicator reflects the degree of network dependency. A greater connection is implied by an increase in the TSI.

To conduct the quantile–on-quantile spillover analysis, we first employ the bivariate quantile VAR model and the Bayesian Schwarz information criterion to find the optimal lag length. To accommodate the dynamic relationship, we employ a rolling window strategy that spans 365 days or one year. As in Yip et al. (2017, 2024), we employ a 7-day forecasting horizon (one week) for variance decompositions to capture short-term dynamics effectively.[1]

[1] Gabauer and Stenfors (2024) suggest that a one-month (20-day) forecast horizon may be adequate for investors to rebalance their portfolios, while shorter periods (3, 5, and 10 days) could also be more aligned with investor preferences. To ensure robustness, we also employ spillover analysis using a 20-day forecast horizon.

Data and empirical results

This paper aims to examine the relationship between the global AI index and 15 cryptocurrency sectors using daily closing prices from June 1, 2021, to May 28, 2024, encompassing 1,093 observations. The emergence of blockchain technology was closely linked to the rise of Bitcoin in 2008. However, the introduction of other cryptocurrencies and tokens has accelerated, as they offer utility tools for decentralized applications that use blockchain technology in conventional markets. This has led to the introduction of numerous tokens in recent years, and the growing diversity of tokens has allowed us to group the cryptocurrency market in parallel with its conventional counterpart. Despite this progress, the market remains nascent, meaning that there is still an insufficient number of tokens in each group and that the data length does not align across tokens within the same group. This presents a significant constraint for empirical analysis, limiting us from extending the analysis prior to 2021 while aiming to cover as many cryptocurrency sectors as possible. To maximize the coverage of asset numbers and sectors, we focus on the 2021–2024 period, which offers the best representation of industries and tokens. Extending prior to 2021 either requires dropping sectors due to insufficient tokens or removing specific tokens because of unavailable data. Therefore, this time range maximizes our sample size. We present the data description and data source in Table 1.

The cryptocurrency sectors utilized in this investigation are as follows: DeFi, e-commerce, energy, entertainment, gambling, gaming, healthcare, lending, logistics, marketing, media, metaverse, NFT, smart contracts, and tourism. To represent the performance of each sector, we construct indices that accommodate five tokens as constituents from each sector (except for the Tourism sector, which has three tokens due to data unavailability). The tokens are selected on the basis of the highest market caps in the respective

Table 1 Data description and sources

Abbreviation	Explanation
NQROBO	NASDAQ CTA Artificial Intelligence and Robotics Index
BOTZ	Robotics & Artificial Intelligence ETF (BOTZ) index
BTC	Bitcoin
DEFI	Decentralized Finance
E-COMMERCE	Electronic Commerce Sector
ENERGY	Energy Sector
ENTERTAINMENT	Entertainment Sector
GAMBLING	Gambling Sector
GAMING	Gaming Sector
HEALTH	Health Sector
LENDING	Lending Sector
LOGISTICS	Logistics Sector
MARKETING	Marketing Sector
MEDIA	Media Sector
META	Metaverse
NFT	NFT Sector
SMART CONTRACTS	Smart Contracts Sector
TOURISM	Tourism Sector

The data sources for the variables are LSEG Workspace for NQROBO and BOTZ and coinmarketcap.com for the remaining variables sector. We also consider Bitcoin to represent broader developments in the cryptocurrency market. As in Huynh et al. (2020) and Abakah et al. (2023a), our global AI index of choice is the NASDAQ CTA artificial intelligence and robotics index (NQROBO), which was introduced with a base value of $1000.00 on December 18, 2017. It tracks the world's leading robotics and AI companies. The NQROBO will measure businesses engaged in artificial intelligence and robotics throughout the technical, industrial, medical, and other economic sectors. The Index comprises artificial intelligence and robotics companies that fall under the facilitator, engager, or enhancer categories. All variables were obtained from the Refinitiv Eikon database. Initially, logarithmic return series were calculated for all variables, and all analyses were conducted using these series.

To visually demonstrate the price developments, Fig. 1 displays the series for each variable. An examination of the price patterns reveals that during or following 2021, each variable experienced a significant decrease. This behavior is mirrored in the sectoral indices and Bitcoin. Although the AI index plummeted at the end of the third quarter, it subsequently underwent swift V-shaped recovery. However, this recovery has not been sustained long term, leading to a prolonged downward trend that spans three quarters by the end of 2021. In contrast, 2023 and 2024 exhibit relatively less fluctuation, with

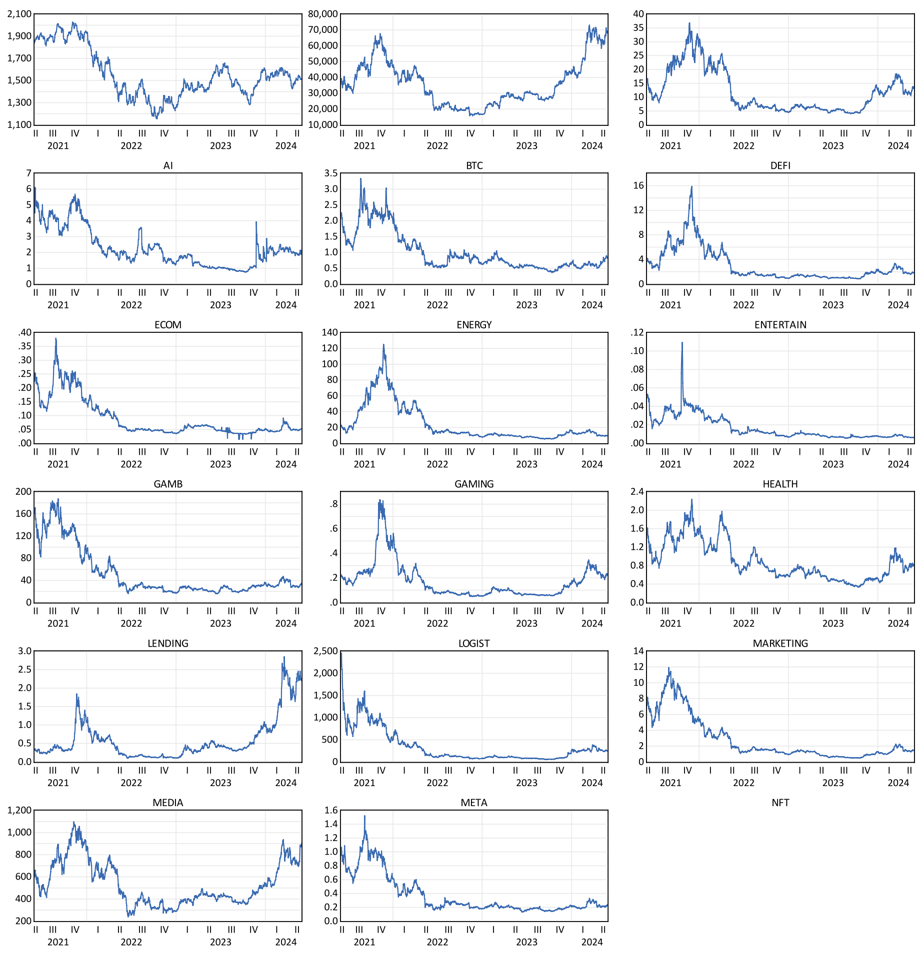


Fig. 1 Price Series of the Variables

prices oscillating between 1300 and 1600. The bear market trend that emerged in 2021 within the cryptocurrency market is notably severe, reflecting the volatile nature of these assets. Most sectoral indices do not show signs of recovery until the end of 2023, except for DeFi, e-commerce, logistics, marketing, media, and smart contracts. Notably, sectors experiencing the sharpest price declines have yet to gain momentum to enter a bull market trend, instead demonstrating horizontal price movements.

Descriptive statistics for the variables are shown in Table 2. According to the results in Table 2, the highest average daily return was obtained from the Media sector, whereas the lowest average return was from the Health sector. On the basis of the standard deviation statistics, the sectors with the highest and lowest volatility are gambling and smart contracts, respectively. Skewness and kurtosis statistics indicate that the return series deviates from the normal distribution. Among the 17 variables, eight exhibit negative skewness, indicating a higher frequency of above-mean returns, whereas nine demonstrate positive skewness, indicating a higher frequency of below-mean returns. Kurtosis statistics further support the presence of non-Gaussian return distributions. Values greater than three, the reference number for a normal distribution, indicate fat tails in returns. Additionally, significant Jarque–Bera test statistics confirm these findings by necessitating the rejection of each variable's null hypothesis of normality. To test the stationarity of the variables, we conducted augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests. The results indicate that all series are stationary at the 1% significance level.

The average total spillover findings for the rolling window technique for the AI and sectoral cryptocurrency indices ($\tau_1 = 0.1, 0.2, \ldots, 0.9$ and $\tau_2 = 0.1, 0.2, \ldots, 0.9$) are shown in Fig. 2. Keep in mind that the figure shows average dynamic relationships obtained from the rolling window approach. Each graph in the figure has a bottom left corner that indicates low returns for both the AI and sector cryptocurrency indices and

Table 2 Descriptive statistics

	Mean	Std. dev	Skewness	Kurtosis	Jarque–Bera	ADF	PP
AI	−0.018	1.172	0.077	5.979	404.849*	−17.43*	−29.93*
BTC	0.057	3.073	−0.3	6.636	618.027*	−33.44*	−33.44*
DEFI	−0.013	4.752	−0.687	6.61	678.983*	−33.21*	−33.21*
E-COMMERCE	−0.073	6.801	8.1	152.137	1,023,945*	−9.15*	−38.38*
ENERGY	−0.09	4.906	0.407	5.855	401.026*	−25.64*	−33.49*
ENTERTAINMENT	−0.063	5.566	−0.446	7.861	1111.229*	−32.20*	−32.21*
GAMBLING	−0.133	9.002	0.767	79.618	267,204.8*	−7.61*	−45.24*
GAMING	−0.075	4.753	−0.011	6.603	590.686*	−31.41*	−31.41*
HEALTH	−0.19	5.695	3.27	58.121	140,189.3*	−13.87*	−30.95*
LENDING	−0.142	5.079	−0.336	5.879	397.65*	−33.35*	−33.35*
LOGISTICS	0.005	5.359	0.501	7.009	777.036*	−15.47*	−33.54*
MARKETING	−0.056	4.313	−0.194	5.541	300.631*	−14.08*	−34.73*
MEDIA	0.178	6.529	0.205	6.35	518.314*	−17.64*	−34.00*
META	−0.204	5.822	0.292	8.64	1462.77*	−33.86*	−33.86*
NFT	−0.144	4.411	−0.71	6.824	757.171*	−18.23*	−33.01*
SMART CONTRACTS	0.035	3.649	−0.445	6.743	673.57*	−18.11*	−34.16*
TOURISM	−0.128	4.987	0.089	14.557	6078.656*	−25.43*	−35.35*

ADF Augmented Dickey–Fuller, *PP* Phillips–Perron. * indicates significance at the 1% level

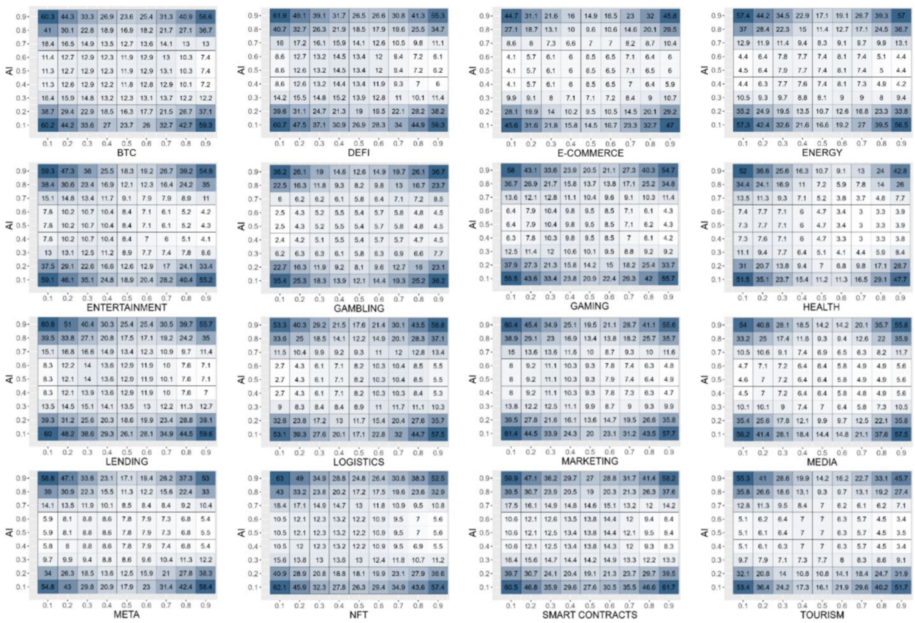


Fig. 2 Averaged dynamic total spillover results between AI and sector cryptocurrency

a top right corner that indicates high returns for both, suggesting directly related quantiles total spillovers. However, indirectly related quantiles total spillovers are represented by the bottom-right corner, which shows periods when AI returns are low and sector cryptocurrency index returns are high ($\tau_1 = 0.1$ and $\tau_2 = 0.9$). The top-left corner, on the other hand, shows the dynamic relationship at quantile levels where AI returns are high and sector cryptocurrency index returns are low ($\tau_1 = 0.9$ and $\tau_2 = 0.1$). The findings of the spillover analysis at the median values for both variables are shown in the center of the graph. The shade of the cells indicates the degree of the spillover effect: white regions indicate low total spillovers, and dark blue areas indicate strong total spillovers.

The findings illustrated in Fig. 2 reveal that the relationship between AI and various sector cryptocurrency indices (and Bitcoin) is notably stronger at extreme quantile levels than at the median. This is demonstrated by the highest total spillover values appearing at the edges of all the graphs in Fig. 2. For example, the total spillover coefficient between AI and Bitcoin is 60.2 at the lowest quantile ($\tau_1 = 0.1$ and $\tau_2 = 0.1$). When the AI return is high and the Bitcoin return is low ($\tau_1 = 0.9$ and $\tau_2 = 0.1$), the total spillover is 60.3. In contrast, the total spillover is 59.3 when the AI return is low, and the Bitcoin return is high (tau sub 1 equals 0.1, and tau sub 2 equals 0.9) and 59.2 when both AI and Bitcoin are high ($\tau_1 = 0.9$ and $\tau_2 = 0.9$). These results indicate a slightly stronger asymmetric relationship between the variables. Furthermore, the total spillover at the median of AI and Bitcoin decreases to as low as 12. This finding suggests that the connectedness between them significantly intensifies during extreme market conditions, marked by excessively high or low returns. As the total spillover at the median is associated with the tranquil phase of the market, the AI index and cryptocurrency sectors display more independent price developments. Exploring the dynamics of these price movements may suggest more reliable price predictions regarding the pathway these assets follow. On the other hand, when their prices begin interacting with other variables, spillovers are likely to occur. These spillovers may be transmitted or received due to negative news associated with left-tail events or positive news linked to right-tail events. Such spillovers can have a significant effect on the price development of these assets, driven by mass market direction and contagion effects.

A closer examination of Fig. 2 shows that the highest total spillover occurs between AI and NFT ($\tau_1 = 0.9$ and $\tau_2 = 0.10$), whereas the lowest spillover occurs between AI and gambling ($\tau_1 = 0.4$ and $\tau_2 = 0.1$). This result shows that during extreme positive returns for AI and extreme negative returns for NFTs, the stress transmission (return spillovers) generated by the interaction of these two variables reaches its highest level. Investors might consider the deterioration in NFT to be a threat to growth opportunities in the AI industry, and mutual reactions may exacerbate tension in portfolios containing these two assets. Across all sectors, total spillover is greater during periods of extreme returns. Additionally, the total spillover scores for directly and indirectly related quantiles are quite similar, ranging from 35 to 63 at the specified quantile levels. This indicates that both the sign of returns, stemming from disseminated information from left- or right-tail events, and their absolute magnitude impact the transmission of stress between variables. This implies that any significant change, regardless of whether it occurs in the left or right tail of the distribution, is sufficient to induce stress on the other asset, as indicated by the spillover of this tension. Since we examine the average total spillover in Fig. 2, the direction of this stress transmission is not emphasized, as it is irrelevant at this stage. Overall, these findings underscore the heightened interconnectedness of AI, Bitcoin, and sectoral cryptocurrencies during periods of extreme market activity, offering valuable insights for investors and policymakers in managing risk and capitalizing on market dynamics. Additionally, the results shown in Fig. 2 are relatively consistent for Bitcoin and sectoral cryptocurrencies, with no significant differences observed across sectors. Given the similarity in spillover effects across both left- and right-tail events, it is essential for investors to adopt risk management strategies that account for extreme positive and negative shocks in the market. This approach can aid in constructing more resilient portfolios by minimizing downside risk and capitalizing on upside opportunities during volatile market conditions. Specifically, while the strong connectedness between AI and cryptocurrency markets during crises indicates that AI fails to serve as a hedge for cryptocurrency investors, the decline in connectedness at median levels suggests that AI offers diversification opportunities, particularly during normal market periods. This dual behavior underscores the importance of tailoring investment strategies to varying market conditions to optimize portfolio performance.

Figure 3 presents the average dynamic net spillover analysis results. The blue cells in the figure indicate the quantile levels where AI acts as a net spillover transmitter. If there were any, the brown cells would show the quantile levels at which AI is a net spillover receiver. Since no brown cells are present in the figures, it is evident that in each pair, AI is the net transmitter of spillovers across the sectors and quantile levels. The results in Fig. 3 indicate that AI consistently provides net return spillovers to all sectors, meaning that the returns of sectoral cryptocurrencies are influenced by AI returns. Specifically, it appears that the spillovers transmitted from AI to sectoral indices are greater than those received in each variable pair. This effect becomes more pronounced at extremely low and high return levels for AI ($\tau_1 = 0.1$ and 0.9), which correspond to the left and

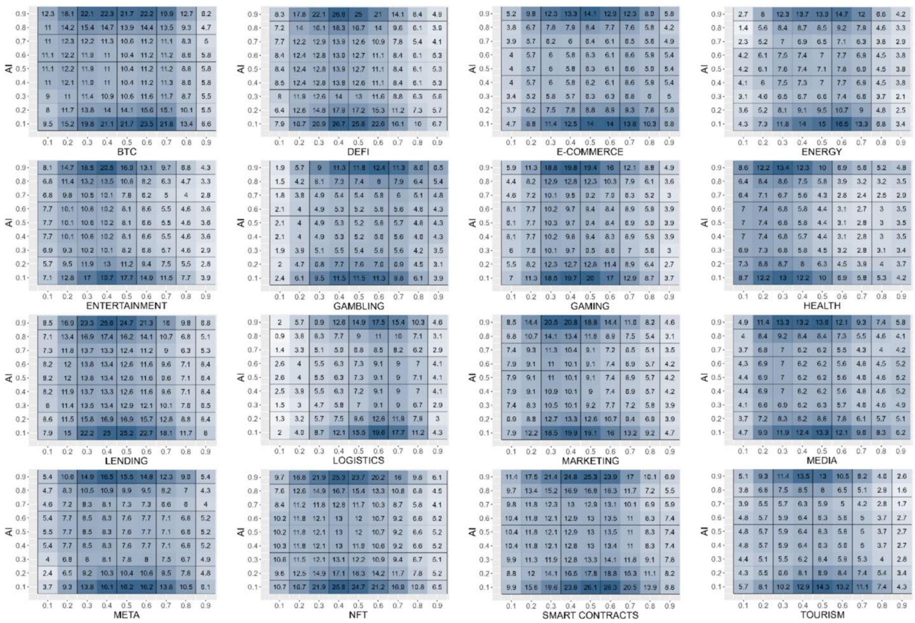


Fig. 3 Averaged dynamic net spillover results between AI and sector cryptocurrency

right tails of the return distributions. Specifically, when artificial intelligence-oriented market returns exhibit substantial changes in either direction (negative or positive), the cryptocurrency market's response to these developments becomes significantly heightened. Large negative or positive price changes in AI can be interpreted as responses to corresponding negative or positive news, highlighting the close association between sectoral cryptocurrency indices (blockchain technology) and developments in the AI industry. As discussed in the introduction, the collaboration between these two technological advancements has the potential to revolutionize business practices. Identifying the direction of these statistical interactions can be valuable for investors who closely monitor opportunities and developments in these markets.

When we look deeper into each pair's interaction, Bitcoin, DEFI, NFT, and Smart Contracts are identified as the sectors that receive the most return spillovers from AI. This result aligns with our theoretical expectations and recent market observations. First, DeFi and Smart Contracts are closely linked, as DeFi tokens facilitate financial transactions—such as banking, insurance, and trading—through smart contracts. These smart contracts are fundamental to DeFi operations, enabling transactions to be processed securely and transparently without intermediaries. Smart contracts are also integral to NFTs, which are unique digital tokens. For example, the smart contract code manages ownership rights and sale agreements in the NFT market, which designates the creator as the owner upon minting the NFT. This finding suggests that, unlike blockchain applications in healthcare, logistics, or gaming, the financial operation-based use of blockchain technology continues to dominate the interactions between the cryptocurrency market and developments in artificial intelligence. The extent of interactions in extremely high and low quantiles of average dynamic total spillovers shows that during periods of extremely low or high sector returns, the reception of return spillovers by sectors significantly decreases. This finding indicates that the association between AI and sectoral cryptocurrency indices is stronger during more stable and predictable market phases. The leading role of AI during these tranquil phases suggests that developments in the cryptocurrency market are increasingly dependent on advancements in the artificial intelligence industry. To conclude, from a statistical point of view, all sectors are net receivers of return spillovers from AI, and spillover transmission becomes more pronounced during extreme market conditions for AI. This result is consistent across all sectors. Additionally, AI consistently acting as a net spillover transmitter across all sectors indicates directional predictability from AI to all cryptocurrency sector returns. This suggests that AI can be considered when forecasting cryptocurrency sector returns in this context.

We present the time-varying average directly related to and averaged inversely related to the total spillover index in Appendix Fig. 7. The results in Fig. 7 indicate that for all sectors, both indices move together, and they are very close to each other. Additionally, the interconnectedness between AI and sector cryptocurrencies has decreased since 2023 compared with that at the beginning of the sample period. The dramatic increase in scams, hacks, and ransomware attacks in the cryptocurrency market may explain the weakened relationship in terms of transmitted returns between AI and sectoral cryptocurrency indices. According to Binance (2024), two significant adverse events in 2022—the bankruptcy of FTX ($10 billion) and the collapse of TerraUSD and Luna ($60 billion)—negatively impacted investor sentiment among cryptocurrency market participants.

Similarly, according to a report by ESET (2023), threats related to crypto theft—80% of which are associated with the Win/Spy.Agent. PRG trojians—increase by 68% in the second half of 2023. These intensified market developments in 2022 and 2023 appear to have significantly impacted the relationship between AI and sectoral cryptocurrency indices. On the other hand, we observe a slight recovery in this relationship around the beginning of 2024. The adverse market developments mentioned above seem to impact the trajectory of Bitcoin prices as well. For instance, the plunge in Bitcoin's price from $65,000–$16,000 between November 2021 and December 2022 displays a recovery toward the end of 2023. This period is associated with renewed momentum in Bitcoin's price. Following October 2023, Bitcoin consistently soared, reaching $72,000 from $26,000 by the end of our analysis period. While adverse market events inducing negative sentiment were reinstated with Bitcoin's price plummeting, overall, the relationship between sectoral cryptocurrency indices and AI was weakened within the domain of spillovers transmitted and received. Nevertheless, the recovery phase of Bitcoin appears to have revived this association. Notably, positive technological developments may also play a role in these interactions, which contrasts with the cryptocurrency-centric perspective emphasized thus far. A significant milestone in AI technology, the introduction of ChatGPT and other AI-powered tools, garnered significant interest among market participants. As this groundbreaking technology offers vast opportunities, it has generated positive sentiment, reflected in the spike of share prices of companies enhancing AI-related infrastructure, such as Nvidia, owing to the increasing demand for AI hardware. According to the IMF's (2024) report, these developments have also acted as price catalysts for tech stock spikes. The report argues that AI's ability to provide faster trading signals than conventional human traders contributes to more efficient markets,

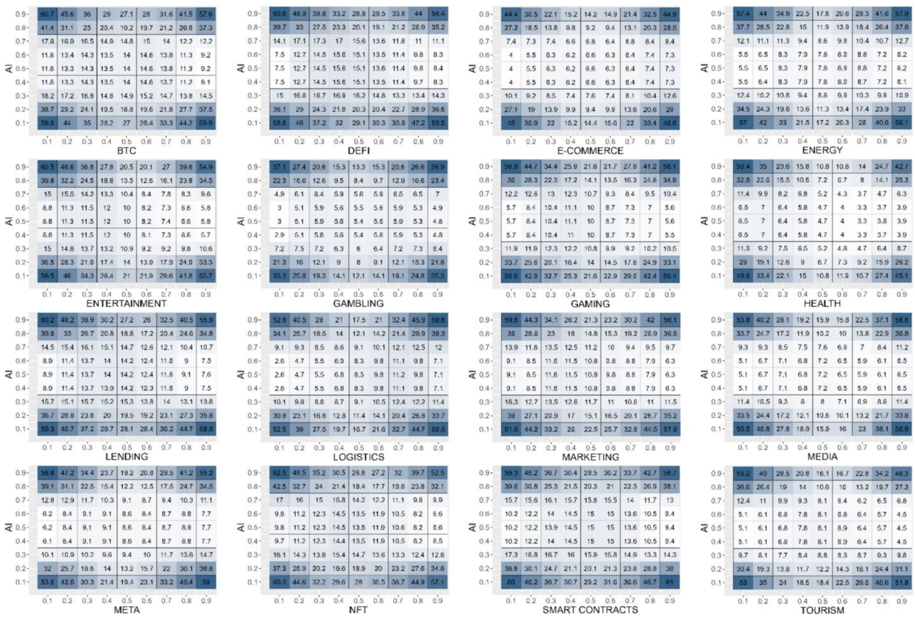


Fig. 4 Averaged dynamic total spillover results between AI and sector cryptocurrency for the 20-day forecast horizon

growing trading volumes, and expanding opportunities. These positive developments, which intensified toward the end of 2023, appear to have played a role in our findings.

Robustness check

In this section, we conducted three different robustness analyses. Following Gabauer and Stenfors (2024), we reemployed quantile-on-quantile analysis with a forecast horizon set to 20. This adjustment allows us to assess the robustness of our findings over a longer-term perspective, ensuring that the observed relationships are consistent and not sensitive to shorter forecast horizons.

The total spillover results presented in Fig. 4 closely resemble those in Fig. 2. Similarly, the net spillover analysis reveals a consistent spillover effect from AI to Bitcoin and sectoral cryptocurrency returns, aligning with the findings in Fig. 3.[2] These findings indicate that variations in model parameters do not substantially alter the results, thereby reinforcing the robustness of the relationship between the variables across different configurations.

Second, we explored whether the relationship between AI and sector cryptocurrencies differs by using a different index for AI. In this context, we considered the Robotics & Artificial Intelligence ETF (BOTZ) index, as in the studies of Sharma et al. (2024) and Loi et al. (2023). This index consists of shares from companies globally focused on robotics and artificial intelligence technologies. Using this new AI index, we repeated the quantile–quantile spillover analysis, and the results are shown in Fig. 5. The results depicted in Fig. 5 closely resemble those in Fig. 2. Specifically, the total spillover between AI and sectoral cryptocurrency returns peaks during periods of extreme market lows

[2] We do not report net spillover analysis results to save space. The results can be provided by the authors upon request.

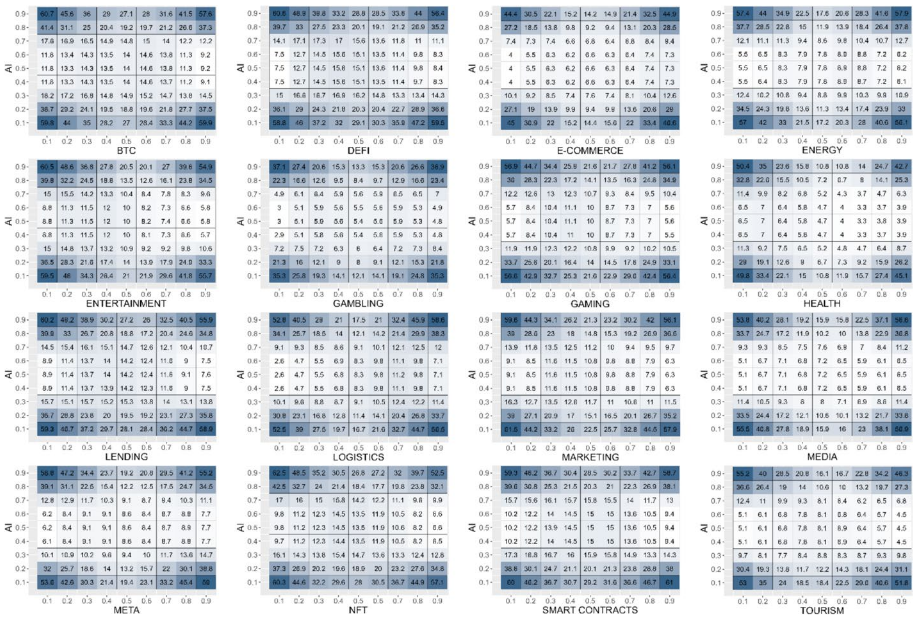


Fig. 5 Averaged dynamic total spillover results between the BOTZ and sectoral cryptocurrency returns

and highs. These findings highlight the consistency in the relationship observed between AI and sectoral cryptocurrency returns. In regard to the net spillover analysis,[3] once again, the AI index has been identified as a net spillover transmitter across all sectors. These findings indicate a directional predictability relationship between AI and cryptocurrency sector returns even after replacing the previous AI index with another alternative. Based on the main findings in Fig. 5, the spillover between AI and Bitcoin is notably strong during extreme market conditions. Additionally, the highest total spillover occurs between AI and NFT ($\tau_1 = 0.9$ and $\tau_2 = 0.10$), whereas the lowest total spillover is observed between AI and logistics ($\tau_1 = 0.5$ and $\tau_2 = 0.1$).

Although the spillover analysis findings of NQROBO and BOTZ are very similar, there are some minor differences between their spillover analysis results. For instance, the total spillover scores derived from BOTZ are slightly higher than those from NQROBO for the Bitcoin, Entertainment, Gambling, Meta, NFT, and Tourism sectors. Notably, at the median level, BOTZ demonstrates a larger total spillover effect in these sectors.

Finally, we examined the robustness of the results obtained from the quantile–quantile spillover analysis via the cross-multiquantilogram method developed by Han et al. (2016). To ensure compatibility with the quantile-on-quantile spillover analysis, we employ the cross-multiquantilogram approach, investigating directional predictability relationships between AI (NQROBO) and sector cryptocurrency returns not only at the same quantile levels but also across different quantile levels. The results in Fig. 6 illustrate the statistical outcomes of directional predictability, assessed via Ljung–Box Q statistics for a lag length of 5.[4] The results for all sectors, except the gambling sector, exhibit similarities with the quantile-to-quantile spillover analysis, indicating directional

[3] Results can be provided by the authors upon request.

[4] For the Q statistics, critical values were determined using 1000 repetitions Monte Carlo simulation.

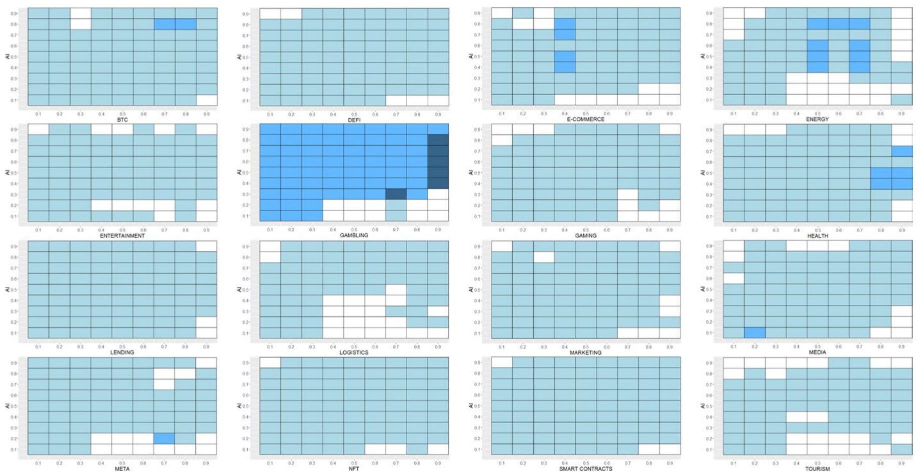


Fig. 6 Directional Predictability Results between AI and Sectoral Cryptocurrency Returns Note: The vertical axis represents quantile levels for AI, and the horizontal axis represents quantile levels for sector returns. The white areas indicate no predictability between the AI and sector returns. The light blue areas ( ) show predictability from the AI to the sector return. Light steel blue areas ( ) suggest predictability from sector return to the AI, and dark steel blue areas ( ) indicate bidirectional predictability

predictability from AI to sectoral cryptocurrency returns.[5] The main result in Fig. 6 shows a causal relationship between AI and Bitcoin and all sectoral cryptocurrencies except for gambling. Moreover, this causal relationship persists across the entire distribution of the return series. In this context, it can be concluded that AI acts as a harbinger of cryptocurrency markets.

When the results in Fig. 6 are compared with those from the quantile–quantile spillover analysis, notable differences emerge for the gambling sector. While the quantile–quantile spillover analysis indicates that spillovers predominantly flow from AI to sectoral cryptocurrencies across all sectors, the results in Fig. 6 suggest that returns in the gambling sector often lead to AI. Additionally, for sectors such as BTC, E-Commerce, Energy, Health, Media, and Metaverse, several causal relationships toward AI were detected, primarily at specific quantile levels. These discrepancies highlight the nuanced dynamics of spillover effects and causality relationships that vary depending on the chosen methodology and quantile levels examined.

In conclusion, employing a different index for AI and utilizing a different method to explore its relationship with sectoral cryptocurrency indices yielded consistent results. In both cases, we observe that AI substantially influences cryptocurrency sectors. Blockchain technology and artificial intelligence have developed over overlapping historical periods. Moreover, these technologies complement each other to achieve more efficient results across various fields. As a result, projects that integrate both platforms may yield significant business advantages. From a financial perspective, effective portfolio and risk

[5] In addition to the initial robustness tests, the analyses were repeated using lag lengths of 1, 3, and 10 to further validate the findings. For example, with a lag length of one, no causality relationship was detected for the DEFI, Entertainment, Lending, Marketing, NFT, and Smart sectors, differing from the results shown in Fig. 6. When the lag length was set to 3, the results were highly consistent with those presented in Fig. 6. However, at a lag length of 10, a causality relationship from cryptocurrencies to AI emerged for the Entertainment, Meta, and Smart sectors, which was not evident in the original analysis. Overall, these findings reinforce the conclusion that AI dominates the cryptocurrency market. Due to space constraints, these additional results are not included in the manuscript but are available from the authors upon request.

Table 3 Summary of spillover analysis and cross-multiquantilogram analysis results

	BTC	DEFI	E-COMMERCE	ENERGY	ENTERTAINMENT	GAMBLING
Spillover from AI	✓	✓	✓	✓	✓	✓
Spillover to AI	X	X	X	X	X	X
Predictability from AI	✓	✓	✓	✓	✓	✓
Predictability to AI	✓	X	✓	✓	X	✓

	Gaming	Health	Lending	Logistics	Marketing	Media
Spillover from AI	✓	✓	✓	✓	✓	✓
Spillover to AI	X	X	X	X	X	X
Predictability from AI	✓	✓	✓	✓	✓	✓
Predictability to AI	X	✓	X	X	X	✓

	Meta	NFT	Smart contracts	Tourism
Spillover from AI	✓	✓	✓	✓
Spillover to AI	X	X	X	X
Predictability from AI	✓	✓	✓	✓
Predictability to AI	✓	X	X	X

Spillover from AI indicates significant spillovers from AI to sectoral cryptocurrencies at least at one quantile. Spillover to AI indicates significant spillovers from sectoral cryptocurrencies to AI. Predictability from AI reflects significant predictability from AI to sectoral cryptocurrencies. Predictability to AI reflects significant predictability from sectoral cryptocurrencies to AI. A √ symbol denotes the presence of significant relationships, whereas a × symbol represents the absence of significant relationships

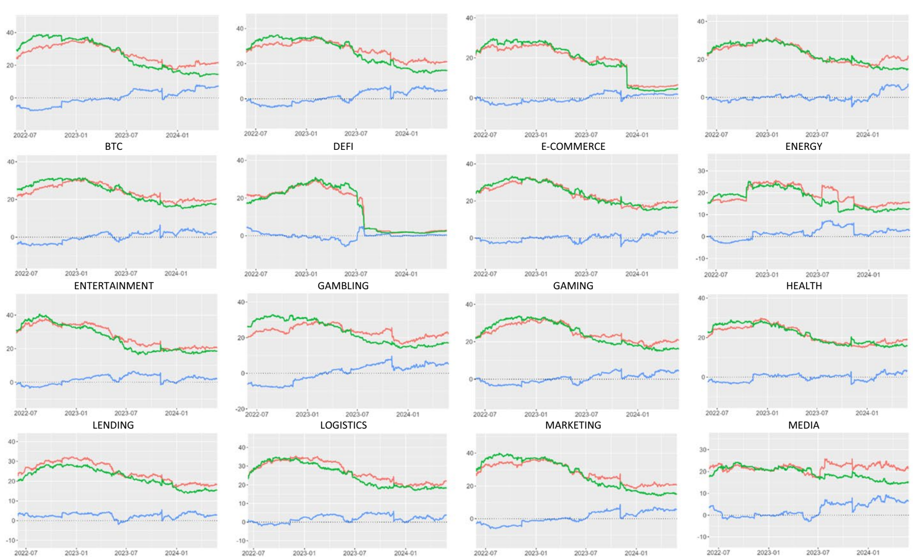


Fig. 7 Dynamic Directly Related and Reversely Related Quantile Total Spillover Results Note: The green line shows a directly related quantile total spillover index, whereas the red line indicates a reversely related quantile total spillover index. The blue line represents the difference between the two indices

management strategies require understanding the extent and direction of interactions between these technologies. The results obtained provide valuable insights in this context, and robustness checks confirm the reliability of our findings.

According to the summary results derived from the spillover analysis and cross-multiquantilogram analysis presented in Table 3, AI has a net spillover effect on all sectoral cryptocurrencies at least at one quantile level. In contrast, no spillover effect from sectoral cryptocurrencies to AI has been detected. Similarly, on the basis of the results of the cross-multiquantilogram analysis, AI demonstrates predictability for all sectoral cryptocurrencies at least at one quantile level. However, Bitcoin, e-commerce, energy, gambling, health, media, and metaverse exhibit predictability for AI at specific quantile levels.

Discussion

The rapid pace of digitalization over the last decade has transformed many aspects of our lives, including how we conduct business. Integrating blockchain technology through cryptocurrencies and adopting artificial intelligence in business operations have already sparked groundbreaking changes. The collaboration of these technologies has the potential to drive further advancements in our social and business environments, offering intelligent automation and tamper-proof solutions. Blockchain technology is already being utilized across various industries, from banking to logistics, whereas artificial intelligence demonstrates flexibility through applications such as machine learning and deep learning.

As reported by Zunino (2024), an AI-powered approach produced smart contracts that were 8–9% more accurate in passing security checks and 12–27% closer to handwritten code than previous methods did. Moreover, generative AI models can proactively identify anomalies, predict potential attack vectors, and recommend countermeasures by analyzing large volumes of blockchain data and network behavior, thereby fortifying blockchain systems against evolving threats. Integrating blockchain technology with AI in decentralized systems offers a promising path toward a user-driven, transparent, and resilient digital ecosystem (Evans 2024). Initiatives such as SingularityNET, Ocean Protocol, and Fetch.ai highlight the potential of combining these technologies, paving the way for a future where individuals control their data, decentralized networks prioritize collaboration over competition, and transparency is an inherent characteristic rather than an afterthought. Finally, Treat and Klein (2024) assert that the convergence of blockchain, AI, and spatial computing opens new possibilities for interaction between the digital and physical worlds. In smart cities, spatial computing can provide immersive, user-friendly interfaces for residents to interact with their urban environment, blockchain ensures secure and transparent civic engagement, and AI enhances municipal services through real-time data analysis. Supported by the immutable security of blockchain, this integration could encompass everything from voting to urban planning, with augmented reality (AR) interfaces enabling residents to visualize and vote on city improvements. The predictive capabilities of AI could further optimize sustainable and efficient design.

However, the integration of blockchain and AI is not without its challenges. First, scalability issues arise when these technologies are combined (Carter 2024). The computational cost and transaction throughput in this integration pose scaling problems, which can exacerbate time and resource constraints, leading to suboptimal outcomes. Second, once market regulations are considered, a comprehensive legal and regulatory framework must be established to address the complexities of this integration (Singh 2022; Butler and O'Brien 2019). Given these market realities, the interconnectedness between blockchain utilization and AI has emerged as a critical area for investigation. The evidence required by academics, investors, and regulators is becoming increasingly vital. By addressing this issue, this study aims to provide valuable insights for various stakeholders in financial markets. The patterns revealed and the relationships identified could offer significant clues about the interactions between these markets under different market conditions, as explored through quantile-based spillover and cross-multiquantilogram analyses.

Conclusion

Empirical findings

In this paper, we aim to reveal the relationship between blockchained cryptocurrency sectors and AI developments to provide evidence for various market participants, including investors, academics and policymakers. Specifically, we analyze 15 sectors that utilize blockchain technology: DeFi, e-commerce, energy, entertainment, gambling, gaming, healthcare, lending, logistics, marketing, media, metaverse, NFT, smart contracts, and tourism. While sectors such as Smart Contracts, NFT, and DeFi emerged directly from blockchain technology, others have transitioned from conventional methods to blockchain-based infrastructure. To analyze these sectors, we constructed sectoral indices using sector-specific token prices, selecting tokens on the basis of their market capitalization. For artificial intelligence developments, we use the NASDAQ CTA artificial intelligence and robotics index. Empirical analyses are conducted via quantile–quantile and cross-multiquantilogram methodologies, which allow for the examination of spillovers and correlations across varying quantiles of the variable pairs.

The quantile-on-quantile analysis has been conducted in three forms: averaged dynamic total spillovers, net directional spillovers, and time-varying spillovers (Appendix A) for positive and negative correlations within the scope of our analysis. According to the averaged dynamic total spillover results, the stress in each variable pair due to transmitted return shocks is more pronounced and peaks at the lowest and highest quantiles. Since these quantiles correspond to extreme loss and gain levels, it is concluded that during tranquil market periods (medium quantiles), the AI and sectoral cryptocurrency indices tend to move more independently. In such periods, return transmissions from AI to sectoral indices become less effective, suggesting that sectoral cryptocurrency price dynamics are likely influenced more by market-specific factors. This reduced external influence may lead to more accurate price predictions in the market during medium-quantile events. Conversely, during extremely low and high return phases of sectoral cryptocurrency indices, the influence of the AI Index significantly increases. Under these conditions, return spillovers from AI to sectoral indices lead to price developments in the cryptocurrency market. Unlike the tranquil market phases, the AI index can be considered a useful early indicator of trends in the cryptocurrency market under such conditions. To enhance the credibility of our findings, we perform a robustness check by replacing the NASDAQ CTA AI Index with the Robotics & Artificial Intelligence ETF (BOTZ) Index. The new results align perfectly with our previous findings, confirming their validity. Regarding net directional spillovers, we find that AI consistently acts as the net return transmitter at each quantile. Extreme low and high return levels (tau values of 0.10 and 0.90, respectively) become the focal points for spillovers from AI to sectoral indices. Among the 15 sectoral indices, the DeFi, NFT, and Smart Contracts sectors presented the largest spillovers, suggesting greater interconnectedness with artificial intelligence in financial operations than with other sectors do. This high sensitivity to positive and negative news affecting the AI industry reflects the strong financial link between these groundbreaking technologies. Finally, when examining time-varying spillovers, we observe a decline in the connectedness between AI and the cryptocurrency market following 2023, which we attribute to increasing scams, hacks, and failures (such as FTX and TerraUSD) in the cryptocurrency sector. To further validate our findings, we employed cross-multiquantilogram analysis to assess the predictive power of the AI industry for cryptocurrency returns. The results for the same quantiles examined earlier show that AI has a significant predictive ability over sectoral cryptocurrency indices, with the exception of the gambling sector.

Policy implications

Our findings reveal a significant connectedness between artificial intelligence and cryptocurrency sectors, with the direction of influence running from AI to sectoral indices in the cryptocurrency market. Both the quantile-on-quantile and cross-multiquantilogram analyses confirmed these results. The implications of this observation are important for various market participants.

First, since the direction of interaction suggests that price developments in the AI industry can serve as an early warning signal for near-future price movements in the cryptocurrency market, investors might use AI trends to anticipate changes in cryptocurrency prices. The predictive power of AI becomes particularly pronounced during periods of extreme price movements, both negative and positive. Asset managers can leverage the price discovery capabilities of AI index developments to achieve more stable and less detrimental portfolio outcomes. Since uncertainty is a critical challenge in investment decisions, individual and corporate investors may feel more confident in environments illuminated by AI index trends within the blockchain-based cryptocurrency sector. Reduced uncertainty can also provide a safer and more predictable platform for entrepreneurs seeking stable conditions for investment. Conversely, the severe volatility inherent in the cryptocurrency market poses significant risks, amplifying uncertainty in price movements. In this context, employing AI indices as predictive tools for the cryptocurrency market could enhance stability, benefiting all market participants.

On the other hand, the extent of connectedness between these markets poses a risk for portfolio managers, especially in highly negative and positive return generations. Our cross-multiquantilogram analysis shows that the associations between variables are significantly amplified during specific market phases. This implies that combining assets from both markets in a portfolio could increase variance for a given level of risk, reducing their effectiveness for diversification. This finding highlights the need for portfolio managers to use phase-based dynamic diversification strategies. Given the predictive power of AI over blockchain-based sectoral cryptocurrency indices, automated weight adjustments could be implemented within the algorithmic trading framework. Leveraging the price discovery capabilities of AI indices, asset managers could design systems to automatically reduce the weights of both AI and token-related assets during periods of extreme market returns, thereby mitigating portfolio volatility.

To protect investors, particularly given that the connectedness mainly occurs at extremely low and high return levels, we suggest that policymakers consider implementing circuit breaker systems in the cryptocurrency market. Although the cryptocurrency market is decentralized and lacks conventional regulatory systems, requiring exchanges to adopt such measures could create a safer environment for investors. Furthermore, our results indicate that DeFi, NFT, and smart contracts exhibit the highest sensitivity to spillovers from the AI index. As a result, additional measures, such as customized limit up- limit down (LULD) applications and other safeguards, may be necessary for these asset classes. Such measures could enhance safety, improve market depth, and increase liquidity, leading to less volatile price developments in the cryptocurrency market.

Furthermore, our findings on sector-specific associations between cryptocurrency and AI indices provide valuable insights for entrepreneurs. The extent of connectedness observed across 15 sectors underscores the potential for blockchain technology to be increasingly employed alongside AI in the future, particularly for enhancing safety and reducing costs. As these two systems are complementary, their currently weak connectedness may reflect the immature dynamics of these emerging markets. For example, sectors other than DeFi, NFT, and smart contracts, which exhibit relatively weaker net directional connectedness, might present promising opportunities for entrepreneurs. For example, decentralized applications (dApps) hold significant potential for advancements in natural language processing. The weak statistical relationships observed today could signify untapped opportunities that might evolve into stronger associations, similar to those currently evidenced in DeFi, NFT, and smart contracts.

Limitations & directions for future research

The application of blockchain technology in conventional sectors remains in its early stages but is expanding rapidly. Consequently, the number of tokens representing the performance of this technology in traditional industries is still quite limited. For example, in constructing the sectoral indices, we use five tokens per sector on average; however, only three tokens are available for the tourism sector due to data limitations. Similarly, our analysis is restricted to 15 groups representing blockchain-related sectors, reflecting these constraints. As blockchain adoption grows, future studies may benefit from broader coverage, including more sectors and extensive data. Additionally, future research could explore volatilities alongside returns in similar contexts, offering a more holistic understanding of risk and return components in investment decisions. This comprehensive approach would provide more robust insights for investors and policymakers. Since the study employs return series in empirical investigations, which are stationary at levels, there was no opportunity to examine cointegration among the variables. However, applying a cointegration framework to the price series could provide valuable insights into the long-term interactions between the variables (Fig. 7).

Appendix A

See Fig. 7

Acknowledgements
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Author contributions
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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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