ORIGINAL RESEARCH

Quantiles dependence and dynamic connectedness between distributed ledger technology and sectoral stocks: enhancing the supply chain and investment decisions with digital platforms

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Abstract

Distributed Ledger Technology (DLT) is highly applicable in various fields, especially the supply chain in many sectors. Against limited empirical evidence, this paper analyzes the relations between the Kensho Distributed Ledger Technology Index and stock indices of 12 sectors, including communication services, consumer discretionary, consumer staples, energy, health care, financials, industrials, information technology, materials, utilities, and real estate, and ESG by employing the quantile coherency and dynamic connectedness techniques. Our results reveal that the quantile coherency between the DLT stock index and the sectoral stock indices in almost all cases is significant and positive. The positive co-movement tends to be stronger in the longer terms and as we move from the lower to the higher quantiles, implying that they are more strongly connected in the long term and during the bearish market condition. Moreover, the dynamic connectedness indicates that the DLT stocks and the sectoral stocks are highly connected, with the former being a net transmitter of spillover shocks. The spillovers are also time-varying, and the results significantly corroborate those of the quantiles coherency methods. Among other relevant implications, DLT can be an important factor in the development and enhancement of these sectors.

Keywords Distributed ledger technology · Supply chain · Quantile coherency · Dynamic connectedness

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1 Introduction

Distributed Ledger Technology (DLT) is increasingly gaining a lot of attention as a crucial innovation regarding storing and updating data in recent years (Deshpande et al., 2017). Many governments and organizations have started to implement or at least consider this innovation seriously (Lemieux, 2017). This technology can be regarded as a sign of the start of a new industrial revolution (Maull et al., 2017; Perez, 2009).

Based on the DLT platform, the transactions are conducted in a peer-to-peer manner so that the central authority that checks and validates the transactions is wholly eliminated from the process (Antal et al., 2021). The network of peers is responsible for confirming the transaction in the DLT platform. The records of transactions are kept in immutable ledgers that cannot be changed or deleted. In addition, several copies of each ledger are produced, such that an attempt to change it would instantly alert other people in the network. Meanwhile, it is very hard to track how people make transactions in the network as every transaction is assigned a fake name or pseudonym. Thus, the application of DLTs is expanding rapidly, and so as their platforms (Chowdhury et al., 2019). In fact, there are several types of DLT. All of them are based on three technologies, including public-key cryptography, distributed peer-to-peer networks, and consensus mechanisms (El Ioini & Pahl, 2017). For instance, Blockchains are one of the most famous DLT. Blockchain is chained blocks of ledgers that contain the transactions. Every block has two hash codes, including its hash and the hash of the previous block. Most cryptocurrencies are based on blockchain technology. Depending on whether the blockchain system is permissioned or permissionless and public or private, there are four types of blockchain, including permissionless public blockchain like Ethereum and Bitcoin, permissioned public blockchain like Ripple and EOS, permissioned private blockchain like Enterprise Ethereum Alliance and Hyperledger, and permissioned private blockchains like Holochain, LTO Network, and Monet.

After the introduction of the first generation of blockchain embodied in bitcoin, two generations of blockchain have emerged that make blockchain applicable not only in finance and economy, but also in health, science, art, culture, social networks, and IoT (Chang et al., 2020; Masood & Faridi, 2018; Swan, 2015). So, many firms try to employ this innovative platform for different purposes (Lee, 2019). However, blockchain faces some drawbacks, such as scalability (Chang et al., 2020; Drescher, 2017; Masood & Faridi, 2018) which refers to slow procedures of creating new blocks due to the sequential nature of the Network. To overcome this issue of scalability, another type of DLT known as Directed Acyclic Graph (DAG) (Thulasiraman and Swamy, 2011) was introduced. In DAG, we have nodes and edges that are lines from one node to the other, and the edges are directed. DAG is described as acyclic, meaning that the nodes do not reference back themselves, and there are no feedback loops. This feature increases the transaction per second of the cryptocurrencies that are based on the DAG much faster than the cryptocurrencies that are based on the blockchain. In addition, there would be no need for miners (Masood & Faridi, 2018). Nano is the first cryptocurrency that was developed based on the DAG (LeMahieu, 2018), and it is best suited for the internet of things and micropayments. Since the creation of Nano, other technologies based on DLT have been increasingly developed to resolve the diverse complexities of internet usage in this era.

Due to the unique features of DLT like anonymity, integrity, resiliency, autonomous control, and decentralization (Chowdhury et al., 2019), it has been employed in various sectors

of the economy, including finance, healthcare, IoT, Insurance, energy, real estate, manufacturing, mining, retail, banking, industries, information governance, and, most importantly, supply chain. Its application in some sectors is presented briefly as follows:

(i) *Smart manufacturing and industry*: The blockchain and DLT can be helpful in the smart manufacturing mechanism by enhancing smart manufacturing security, facilitating tracking and tracing, proving and protecting intellectual property ownership, facilitating quality control and improving customer value, enabling machines as a service model for IoT-based manufacturing machinery, and facilitating the maintenance (Farahani et al., 2021). As a whole, the blockchain and DLT can improve productivity in manufacturing processes. Specifically, using the DLT technology in the food industry can improve the transparency of food product lifecycles and help to track and monitor products to ensure food safety. It also can be used in protecting and developing mineral resources (Litvinenko, 2020).

(ii) *Retailing*: Both producers and customers can collect only useful information about each other to reduce costs for both sides effectively. However, this technology makes the retail sector more transparent and helps authorities track illegal activity. More so, it can make the payment system automated. Finally, the retail sector is benefited from enhanced supply chain management due to the implementation of this technology in the supply chain (Lavanya et al., 2017).

(iii) *Healthcare*: The DLT technology has a very high potential to enhance the healthcare systems completely. For instance, all the patient information can be stored in a ledger that can be accessible to the hospital with his or her permission. So, the health information data can be shared among health institutions easily and effectively (Anderson, 2018; Jiang et al., 2018). The diagnostic procedure becomes smoother and can be stored and monitored. It is also an efficient way to check the practices of doctors. Finally, management and control of the supply chain in healthcare is one of the most critical applications of DLT in healthcare. This is essential to avoid, trace and detect fraudulent activities in the supply chain in healthcare. This information about the patient can also be used by the insurance company to avoid adverse selection.

(iv) *Energy*: DLT can also be a helpful application regarding energy supply. With the middlemen being eliminated, the consumer will buy energy more easily. Moreover, producers can store their additional produced energy using smart contracts. In addition, this technology makes energy trades transparent and well documented so that the monitoring and auditing procedures become easy. Lastly, the energy consumption and waste emissions of consumers can be recorded, stored, and monitored (Hasse et al., 2016).

(v) *Finance*: Blockchain technology has impacted the financial sector initially by introducing bitcoin. The aim was to eliminate the intermediaries. Currently, there are about five thousand cryptocurrency projects, each having unique features. There are some advantages of using cryptocurrencies. First, transactions are stored in immutable ledgers that cannot be changed. Transactions that are done by cryptocurrencies are generally fast, and transaction fees are low relatively. The other important application of blockchain technology is peer-to-peer finance which connects people directly to do financial transactions (Moenninghoff & Wieandt, 2013) by eliminating intermediaries. There are five types of peer-to-peer finance (Moenninghoff & Wieandt, 2013), including peer-to-peer lending, peer-to-peer equity investing, peer-to-peer foreign exchange, peer-based investing, and peer-to-peer foreign exchange hedging. DLT technology also can be useful to the insurance industry. It can improve transparency

to avoid fraudulent activities. The adverse selection can be avoided as customer verification becomes much easier. Also, the settlement process can be automated by using DLT and IoT, while additionally reducing the cost and time of placement so that it can be very useful for reinsurers.

(vi) *Real estate and property transfer and registration*: Any kind of property can be registered on distributed ledgers so people can sell and buy the property with the new information is appropriately stored. This technology can also automate the clearing and settlement process. So, by removing the mediator and reducing the paperwork, the process becomes faster and more transparent (Lemieux, 2017; Masood & Faridi, 2018). Meanwhile, some countries like Georgia, Sweden, and Brazil have implemented this technology in the real estate sector to some extent (Coleman, 2017; Lemieux, 2017).

(vii) *Supply Chain*: (Coppi, 2021) claims that DLT features are most fitted naturally for supply chain and procurement processes. Blockchain and DLT can improve supply chain management in many ways. One of the most important services of this technology to the supply chain is the removal of the third party. This makes the procedure and the delivery of goods and services easier and cheaper. It further improves security and makes the conduct of illegal activities in the system very difficult. In addition, implementing the DLT is very easy as it can be applied as a layer above the current infrastructure (Brody, 2017). Finally, it makes recording and managing of data more efficient. It also helps managers in tracing issues and locating goods in real-time (Farahani et al., 2021).

(viii) *Others*: DLT has many other applications, which include enchanting cloud computing, improving artificial intelligence, making technology more secure (Farahani et al., 2021; Masood & Faridi, 2018), improving the social impact and humanitarian applications to help poor people, and tracking and tracing humanitarian aid funds (Coppi, 2021), and transforming governmental and administrative processes (Ølnes et al., 2017).

The pass-through of DLT into the financial and economic systems and the increasing recognition of technology in financial activities of firms through the general concept of "financial technology (FinTech)", creates the possibility of a dynamic connectedness between its market and the conventional stock market. Besides, the recurring economic, financial, health, and geopolitical crises have intensified the instability and riskiness of the conventional stock markets, thereby casting doubt on their reliability for viable investment returns. Investors are therefore on a consistent search for other hedging assets, with technological assets coming to the stage. The increasing role of financial technology and its tremendous growth in recent years reveals its massive investment consideration. This guides our motivation, in addition to the empirical evidences that financial markets are increasingly interrelated through risk-transmission and contagion mechanisms, to examine the dependence and dynamic connectedness between DLT and sectoral stocks. To the best of our knowledge, we make the first attempt to go in this direction.

2 Research objectives

Against this backdrop, this study has three-fold objectives, which are to:

(i)   Examine the structural (quantile) dependence between DLT and sectoral stocks;
(ii) Determine the quantile dependence across different investment horizons;
(iii) Examine the dynamic return spillovers between DLT and sectoral stocks.

The rest of the paper is organized as follows: Sect. 2 presents a brief literature review of the studies that investigate the application of DLT in other sectors. Section 3 gives a description of the methodologies and data. Section 4 discusses the empirical results, whereas the final section concludes and highlights the policy implications of the findings.

3 Literature review

Many studies have analyzed and tried to explain DLT and its applications (Antal et al., 2021; Chowdhury et al., 2019; El Ioini & Pahl, 2017; Farahani et al., 2021; Lemieux, 2017; Masood & Faridi, 2018; Maull et al., 2017). For instance (Masood & Faridi, 2018) introduced Distributed ledger technologies like blockchain, directed acyclic graphs, and radix ledger. Then they describe the application of DLT in different fields and sectors like finance, energy, supply chain, healthcare, and more. They conclude that DLT is a fast-evolving technology that needs to be matured. However, they mention that this technology has great potential to change procedures and processes everywhere by removing the third parties and making systems much more efficient and battling corruption. (Farahani et al., 2021) address the convergence of DLT and IoT, and they conclude that DLT can solve the weakness and shortcoming of IoT and makes it more secure. They further indicate that they jointly have many applications in different sectors like healthcare, smart manufacturing, and others. However, they mention some challenges towards this convergence, including storage inefficiency, privacy scalability, and others. Analyzing the strengths, weaknesses, opportunities, and threats of four types of DLT technology, namely Blockchain, Tangle, Hashgraph, and Sidechain, using the SWOT method, (El Ioini & Pahl, 2017) conclude that all of the DLTs obviously exhibit some essential weaknesses, with blockchain having the most. They also show that other types of DLT other than blockchain have started to be considerably used more widely.

There are then a few studies that examine the application of DLT in different sectors. Studies such as (Litvinenko, 2020; Ren et al., 2020) investigate the role of the digital economy and, specifically, the distributed ledger technologies like blockchain in the mineral sector. (Ren et al., 2020) show that data sharing based on the blockchain compared to traditional data sharing methods is more secure and can ensure data quality and realize data sharing. (Calvão & Archer, 2021) specifically, examine the role of blockchain in the mineral supply chain and argue that although blockchain technology has the potential to make the global production network and supply chain more traceable and transparent by promoting efficiency, preventing fraud, and ensuring the credibility and effectiveness of ethical certification processes, however, it has associated risk, i.e., these blockchain systems are centralized or permissioned and are in control of the private organizations and companies. So only economic elites and technological experts can have access to the data.

For the role of DLT in the real estate sector, common studies include (Konashevych, 2020; Krupa & Akhil, 2019; Singh & Vardhan, 2019; Spielman, 2016). Specifically, (Spielman, 2016) argues that title record keeping based on blockchain has many advantages over traditional title recordkeeping platforms in the real estate sector. Also, (Krupa & Akhil, 2019) provided another claim that ballock chain technology can revolutionize the real estate sector. They argue that it can increase transparency and reduce fraudulent activities. Regarding the health sector, Badr (2019) study how effective DLT technologies are in knowledge sharing in the healthcare sector that is essential for the pharmaceutical supply chain, medication adherence, and ensuring quality care. They observe that the implementation of the DLT for

the healthcare sector can be useful in enhancing insurance claim processes, improving medical record management, and accelerating clinical research. (Clark & Burstall, 2018) then claim that DLT can help pharmaceutical companies record all detailed information about a product so that the companies can monitor and control the production process effectively. This technology can also guarantee the integrity of the pharma supply chain and ensure its security. Other similar studies have also concluded that DLT plays a significant role in different aspects of the healthcare sector (see Badr, 2019; Bouras et al., 2020; Brogan et al., 2018; Clark & Burstall, 2018; Engelhardt, 2017; Gökalp et al., 2018; Kuo et al., 2017; Mettler, 2017; Shahnaz et al., 2019).

Another set of studies is available on the effectiveness of DLT on the financial sector and the capital markets. Highlighting a few, (Río & César, 2017) argues that central banks worldwide are willing to adopt such technology; however, there are some challenges to adaptation, including security, transparency, speed of processing, scalability, and some others. Another claim by (Collomb & Sok, 2016) shows that the finance sector is affected by the DLT. They claim that DLT can promote e-commerce as its focal application is payment and international transfers. Besides this, technology can also improve many aspects of the firm management process like corporate governance, corporate finance, cash management, and treasury applications. Other studies in this lane of research include (Benos et al., 2017; Collomb & Sok, 2016; Ikeda & Hamid, 2018; Jutila, 2017; Knezevic, 2018; Río & César, 2017; Santo et al., 2016; Tarr, 2018; Van Oerle & Lemmens, 2016; Workie & Jain, 2017; Yoo, 2017).

Also, many studies investigate the role of distributed ledger technologies in the energy sector (Bao et al., 2020; B. Chaudhuri, 2019; Downes & Reed, 2020; Siano et al., 2019; Q. Wang & Su, 2020). For example, (Siano et al., 2019) argue that to match power production and consumption properly and achieve energy efficiency, employing a decentralized approach like Distributed Ledger Technology (DLT) can be the most promising solution. They further propose a proof of energy as a consensus mechanism for the peer-to-peer energy exchanges that are controlled by DLT. A recent study by (Downes & Reed, 2020) revealed that blockchain technology could be used in constructing a global transparency system for sustainability information in the energy value chain. The transparency of the activity can ultimately enhance sustainability. Via blockchain technology, this information can be shared and collected effectively, making sustainability incentives more effective.

We observe further that a couple of studies (Ko et al., 2018a; Leng et al., 2020; Li & Kassem, 2019; Mohamed & Al-Jaroodi, 2019; Mondragon et al., 2018; Pal, 2021) are rather more concerned with the relationship between the DLT technologies and manufacturing and construction industries. Taking (Ko et al., 2018b) as an example, analyzed the impact of employing blockchain technology in the manufacturing industry by employing a theoretic approach. They conclude that the benefit of employing blockchain technology, i.e., real-time transparency and cost savings, can enhance the profitability and competitiveness of manufacturing industries that ensure the sustainability of these industries. Mondragon et al., (2018) argue that employing blockchain in the supply chain of manufacturing industries has many benefits, including reducing lead times, tamper-proof history of processes, and improving provenance, transportation, storage, and handling.

The final strand of the literature on the sectoral application of DLT relates to the connection of DLT in the promotion of responsible investment and ESG-compliant business (Coppi, 2021; Ferraro et al., 2018; Liu et al., 2021; Scott et al., 2018). For instance, (Liu et al., 2021) claimed that blockchains technology can be used to facilitate the ESG-based sustainability evaluation of the listed companies. Another study by (Coppi, 2021) posited that most applications based on DLT can have humanitarian and development applications. They additionally

claim that DLT has social impacts by affecting the supply chain and promoting transparency and trainability.

Until now, many studies that investigated the role of DLT in different sectors have been reviewed. Now, we turn our attention to the studies that consider the impact of DLT on the supply chains (A. Chaudhuri et al., 2021; Choi, 2020; Cole et al., 2019; Fan et al., 2020; Kamble et al., 2021; Park & Li, 2021; Roeck et al., 2020). For instance, Choi (2020) examined the adaptation of blockchain for the financing supply chain, and they indicated that using blockchain technology provides higher profit and lower risk in case of high bank fees. (Park & Li, 2021) mentioned that blockchain technology can make supply chain management transparent, reliable, tracible, and efficient. They concluded that employing blockchain technology can improve supply chain sustainability. Using an abductive research approach, (Roeck et al., 2020) conclude that the DLT solution can have several impacts, including cost reduction, change in power distribution between buyers and sellers, and dependency reduction on the third party. Another prominent study (Cole et al., 2019) revealed that the technology could influence operations and supply chain management in several ways, including improving product safety and security, quality management, and sustainable supply chain management, reducing illegal counterfeiting, the need for intermediaries and cost of supply chain transactions, advancing inventory management and replenishment and impacting new product design and development. Kamble et al. (2021) examined the impact of blockchain technologies (BT) on the information and communication-enabled supply chain integration (SCI) and sustainable supply chain performance (SSCP) and the influence of BT and SCI on SSCP. More specifically, the study was conducted to examine the direct influence of BT on SCI and SSCP and the interactive effect of BT and SCI on SSCP by employing a survey-based approach and confirmatory factor analysis (CFA) and structural equation modeling (SEM) for analyzing the collected data. Their results indicated that BT affects the SSCP positively. They further showed that SCI has a significant mediating role between the BT and SSCP. Fan et al. (2020) analyzed the comparative benefits of adaptation of blockchain technology in the supply chain process, and their results indicated that the benefits are dependent on several factors, including traceability awareness of consumers, the cost of applying the blockchain technology, and the production costs of the suppliers and manufacturers.

Khan, Godil, et al. (2021) examined the impact of blockchain technology on su supply chain practices using partial least squares structural equation modeling (PLS-SEM). The findings indicated that sustainable supply chain practices are affected positively by blockchain technology and green information systems. Khan, Razzaq, et al. (2021); Lopes de Sousa Jabbour et al. (2021), Pinheiro et al. (2022), and Rehman Khan et al. (2021a, 2021b) tried to examine the impact of employment of circular economy in supply chain and organization performance and investigate how blockchain technology and Industry 4.0 technologies influence the circular economy and their collective results indicated that blockchain technology enhance the circular economy practices significantly and circular economy practices promote the performance of organizations and supply chain.

As we investigate the spillovers across stock sector indices during the COVID-19 pandemic, it is worth reviewing some papers that investigate this issue (Bouri et al., 2021; Le et al., 2021; López-Oriona & Vilar, 2021; Shahzad et al., 2021a, 2021b; Shahzad et al., 2021a, 2021b). For instance Le et al. (2021) evaluated tail-dependency networks of financial assets during the COVID-19 pandemic using quantile cross-spectral analysis, and their results indicated that COVID-19 has an asymmetric impact on tail dependence. Besides the tail-dependency of equity, currency and commodity rise significantly during this period showing tail contagion effects, especially the left tail dependency. Moreover, Bitcoin and US

Treasury bonds are not connected to other asset classes. Bouri et al. (2021) analyze the inter-sectoral asymmetric volatility spillover in the Chinese stock market during the COVID-19 pandemic. Their results illustrated that the impact of good and bad volatilities is significantly high, asymmetric, and time-varying during the COVID-19 period and that good volatility spillover shocks are dominated by bad volatility spillover shocks. Shahzad et al., (2021a, 2021b) investigated extreme return spillovers among the US stock market sectors during the COVID-19 outbreak by employing the Diebold-Yilmaz spillover index to the quantiles domain. The findings of the study revealed that the market state determines the network structure and spillovers among sectors. for instance, during the pandemic period, the dominant clusters become more connected while the rest of the network remains separated. Bouri et al. (2021) assessed the impact of the New Zealand government's three policies, namely lockdown, the stimulus package, and the travel ban, to confront the COVID-19 outbreak on stock returns. Empirical results indicated that lockdown had a positive impact on aggregate stock returns, unlike the other two policies that had a negative impact on stock returns. On the other hand, all policies generally have a positive influence on industry stock indices. (Costa et al., 2022; Mensi et al., 2021) investigated connectedness among U.S. stock sectors and they found that connectedness intensified during COVID-19 crisis. Shahzad et al., (2021a, 2021b) found the same results for Chinese stock market.

While the above studies reveal the strength of the literature in terms of how much the role of DLT in different economic sectors has been explored, we observe that many limitations are still available, some of which our study intends to fill. To the best of our knowledge, this is the first study that examines the risk transmissions and spillovers between DLT and different sectoral stocks, having understood from the literature that financial indices are increasingly being connected in terms of risk-sharing (see Adekoya et al., 2022a, 2022b; Asl et al., 2022; Fasanya et al., 2021a, 2021b; Adekoya, et al., 2021; Naeem et al., 2021, inter alia). Furthermore, we explore the quantile dependency between the DLT stock and those of each sector so that we are able to unravel how they connect across different frequencies and time horizons. This has not received any empirical attention for DLT again.

4 Methodology

4.1 Methodology

4.1.1 Quantile cross-spectral (coherency) approach

The quantile cross-spectral method, developed by (Baruník & Kley, 2019), shows the dependence of joint distribution across different frequencies and quantiles (Baumöhl, 2019). It c show the dependency of two variables in the short run and the long run (Baumöhl & Shahzad, 2019). Following (Baruník & Kley, 2019), the quantile coherency kernel, a measure of dynamic dependence between two stationary variables like x_{ti_1}. and x_{ti_2}, can be defined as follows:

$$\xi^{i_1,i_2}(w;\vartheta_1,\vartheta_2) = \frac{\varsigma^{i_1,i_2}(w;\vartheta_1,\vartheta_2)}{\sqrt{\left(\varsigma^{i_1,i_1}(w;\vartheta_1,\vartheta_2)\varsigma^{i_2,i_2}(w;\vartheta_1,\vartheta_2)\right)}} \tag{1}$$

where $\vartheta \in [0,1]$. and $i \in \{1,\ldots,d\}$.. ς^{i_1,i_1}. and ς^{i_2,i_2}. are known as the quantile spectral densities, while ς^{i_1,i_2}. is called the quantile cross-spectral density of x_{ti_1}. and x_{ti_2}.. These

densities can be obtained by taking Fourier transformation from the matrix of quantile cross-covariance kernels as follows:

$$\mathsf{C}_j(\vartheta_1, \vartheta_2) = \left(\psi_j^{i_1, i_2}(\vartheta_1, \vartheta_2) \right). \tag{2}$$

where:

$$\psi_j^{i_1, i_2}(\vartheta_1, \vartheta_2) = COV\left(I\{x_{t+j, i_1} \leq q_{i_1}(\vartheta_1)\}, I\{x_{t, i_2} \leq q_{i_2}(\vartheta_2)\}\right) \tag{3}$$

Again, $\vartheta_1, \vartheta_2 \in [0, 1]$. and $i \in \{1, \ldots, d\}$. and $j \in Z$.. Besides, I. is an indicator function. It is argued that quantile cross-covariance is more informative than traditional cross-covariance that is due to the fact that quantile cross-covariance is dependent on both ϑ_1. and ϑ_2.

In this method, some information on the serial dependence can be obtained byain j Moreover, by setting i ≠ j, we can also gain information on cross-section-dependence. The following expression can be used to obtain a matrix of quantile cross-spectral density kernels in the frequency domain:

$$\varsigma(w; \vartheta_1 \vartheta_2) = \left(\varsigma_j^{i_1, i_2}(w; \vartheta_1, \vartheta_2) \right)_{i_1, i_2 \ldots, d} \tag{4}$$

$$\varsigma_j^{i_1, i_2}(w; \vartheta_1, \vartheta_2) = \frac{\sum_{j=-\infty}^{\infty} \psi_j^{i_1, i_2}(\vartheta_1, \vartheta_2) e^{-i\omega j}}{2\pi}. \tag{5}$$

$\xi^{i_1, i_1}(w; \vartheta_1, \vartheta_2)$ is between 1 and − 1. If it is close to 1 (− 1), it indicates that there is a strong linear positive (negative) relationship between the first difference of orthogonal increment processes. Furthermore, if it is near zero, it shows that the linear relationship between them is weak (Barunık & Kley, 2015). In this study, the quantile coherency matrices for three percentiles, including the fifth percentile indicating the extreme negative returns, the 50th percentile presenting average returns, and the 95th percentile showing extreme positive returns. Also, four frequencies are considered, including daily, weekly, monthly, and yearly, representing the short term, short-medium term, long medium term, and long term, respectively. The main advantage of this method is its ability to show the dependency between two-time series across different quantiles and frequencies. The quantile dimension of the technology indicates its ability to provide evidence across different market conditions, i.e., bearish normal, and bullish market states. On the other hand, its frequency approach makes it possible to examine dependence at different investment horizons, covering the short-, medium-, and long-term.

4.1.2 Transmissions and connectedness analysis

Following (Antonakakis et al., 2019, 2020), we employ the TVP-VAR connectedness approach of (Koop & Korobilis, 2013), which is built on the standard method of measuring connectedness as initially proposed by (Diebold & Yılmaz, 2014) to examine the returns spillover between DLT stock index and the stock indices of 12 sectors. In this method, the variance–covariance matrix changes over time through Kalman Filter estimation with forgetting factors (Antonakakis et al., 2019, 2020). In this method, there is no need for a rolling-window-size method that can result in wandering parameters. In addition, there would be no loss of data (Antonakakis & Gabauer, 2017; Antonakakis et al., 2018, 2019, 2020; Gabauer & Gupta, 2018; Korobilis & Yilmaz, 2018). This method is also helpful in measuring the dynamic connectedness of low frequency and insufficient time series data (Antonakakis et al., 2020).

A TVP-VAR (1) model that is specified based on the Bayesian information criterion (BIC) can shown as follows:

$$\Delta y_t = B_t \Delta y_{t-1} + \varepsilon_t \varepsilon_t \sim N(0, \delta_t)$$
$$vec(B_t) = vec(B_{t-1}) + e_t e_t \sim N(0, u_t). \tag{6}$$

where Δy_t and Δy_{t-1} are $n \times 1$ vectors and B_t and δ_t are $n \times n$ matrices. $vec(B_t)$ and $vec(B_{t-1})$ are $n^2 \times 1$ vectors and u_t is $n^2 \times n^2$ matrix. We follow (Del Negro & Primiceri, 2015; Primiceri, 2005) to determine the prior for the Kalman filter initialization. Using dynamic coefficients and variance–covariance matrices, the connectedness model of (Diebold & Yılmaz, 2014) is estimated using the generalized forecast error variance decompositions GFEVD and impulse response functions (GIRF) defined by (Pesaran & Shin, 1998) and (Koop et al., 1996). Then the TVP-VAR model is transformed into a vector moving average form using the Wold representation theorem to compute GIRF and GFEVD. The transformation can be shown as follows:

$$\Delta y_t = \sum_{i=1}^{p} B_{it} \Delta y_{t-i} + \varepsilon_t = \sum_{j=1}^{\infty} \alpha_{jt} \varepsilon_{t-j} + \varepsilon_t \tag{7}$$

where α_{jt} is $n \times n$ dimensional matrix.

GIRFs that are represented by $\varsigma_{ij,t}^{g}(J)$ indicates the response of j as a result of a shock in i. To compute that, we calculate the differences between an H-step-ahead forecast of two situations that are once i is shocked, and once i is not shocked.

$$\varsigma_{j,t}(J) = \sum_{jj,t}^{-\frac{1}{2}} \alpha_{J,t} \Sigma_t e_j$$

where e_j is defined as a selection vector with the ith element being one and other elements being zeros.

GFEVD that is represented by $\varphi_{ij,t}^{g}(J)$ shows the pairwise directional connectedness from j to i, and it implies the influence of j on i. It can be defined as follows:

$$\tilde{\varphi}_{ij,t}(J) = \frac{\sum_{t=1}^{J-1} \varsigma_{ij,t}^2}{\sum_{j=1}^{n} \sum_{t=1}^{J-1} \varsigma_{ij,t}^2} \tag{8}$$

where $\sum_{i,j=1}^{n} \tilde{\varphi}_{ij,t}(J) = n$. and $\sum_{j=1}^{n} \tilde{\varphi}_{ij,t}(J) = 1$. The total connectedness index can be expressed as follows:

$$S_t(J) = n^{-1} \sum_{i,j=1,i\neq j}^{n} \tilde{\varphi}_{ij,t}(J) \times 100 \tag{9}$$

Now we may be interested in finding how a shock in a variable is transmitted to another variable and how that variable is affected by shocks in other variables. These two pressions indicate total directional connectedness to others (shock transmission from i to others) and total directional connectedness from others (shock transmission from others to i), respectively:

$$S_{i \to j,t} = \frac{\sum_{j=1,i\neq j}^{n} \tilde{\varphi}_{ji,t}(J)}{\sum_{j=1}^{n} \tilde{\varphi}_{ji,t}(J)} \times 100. \tag{10}$$

The net total directional connectedness can be calculated by subtracting total directional connectedness to others from the total directional connectedness from others. Net total directional connectedness implies the influence of the variable on the network. Net total directional connectedness can be defined using the following expression:

$$S_{i,t} = S_{i \to j,t} - S_{i \leftarrow j,t} \tag{11}$$

If $S_{i,t}$ is negative, it indicates that the impact of the network on variable i is higher than the impact of variable i on the network, while if $S_{i,t}$ is positive, it implies that the variable i affect the network more than being affected by the network. The net pairwise directional connectedness between two variables can also be defined as follows:

$$S_{ij,t} = (\tilde{\varphi}_{ji,t}(J) - \tilde{\varphi}_{ij,t}(J)) \times 100 \tag{12}$$

$S_{ij,t}$ shows the bidirectional relationship between two variables. As mentioned earlier, TVP-VAR is an extension of the dynamic connectedness approach proposed by Diebold and Yilmaz (2009, 2012, 2014) that is used to measure connectedness between networks of variables. However, its advantages over the traditional spillover models include overcoming the issue of randomly selecting the optimal rolling-window size and avoiding the problem of valuable observations being lost, making it acceptable for small samples as well.

4.2 Data and preliminary results

We employ datasets of daily data of stock indices of 12 sectors and the Distributed Ledger Technology (DLT) stock Index. The scope of the study is informed by the availability of the DLT stock index, which started on June 1, 2018. The end date of our study is June 29, 2021. To show the stock performance of various sectors, we employ the S&P Composite 1500 stock index of each sector that includes three indexes of that specific sector, namely S&P 500, S&P midcap 400, and S&P small cap 600, which cover approximately 90% of the market capitalization. We consider 12 sectors in this study that almost covers all the sectors in the economy. It should be noted that among all, the S&P Composite 1500 ESG Index is a broad-based, market-cap-weighted index that is designed to measure the performance of securities meeting sustainability criteria. The index is a composite index made up of multiple S&P ESG subindices. On the other hand, the S&P Kensho Distributed Ledger Technology Index serves as the proxy for the DLT stock index. The dataset is extracted from S&P global website. The returns of the data are computed as the difference between the natural logarithmic values of two consecutive periods. Table 1 clearly highlights the list of the variables and their abbreviations as used in the rest of the paper.

The descriptive statistics and results of the stationary test of variables are depicted in Table 2. The results indicate that the DLT stock returns and ENE have the highest and the lowest mean returns, respectively, with others having positive mean returns. Moreover, DLT also exhibits the highest volatility, while the least volatility is associated with STA among the sectoral stock indices. For all the series, the Jarque and Bera (1980) statistics suggest the rejection of the normality null hypothesis, implying that none of them is normally distributed. This evidence strengthens the results of negative skewness and excess kurtosis exhibited by them. On the stationarity property of the series, the various unit root tests indicate, as expected, that all the series are stationary at level. The presence of linear and non-linear serial correlation in all returns series is also confirmed by the Ljung-Box statistics. The trends in the price and returns series are further presented in Fig. 1, with evidence of significant volatility observed therein.

Table 1 Abbreviations of stock indices

Sector	Abbreviation
S&P Composite 1500 Communication Services	COM
S&P Composite 1500 Consumer Discretionary	DIS
S&P Composite 1500 Consumer Staples	STA
S&P Composite 1500 Energy	ENE
S&P Composite 1500 ESG Index	ESG
S&P Composite 1500 Financials	FIN
S&P Composite 1500 Health Care	HEA
S&P Composite 1500 Industrials	IND
S&P Composite 1500 Information Technology	INF
S&P Composite 1500 Materials	MAT
S&P Composite 1500 Real Estate	REA
S&P Composite 1500 Utilities	UTI
S&P *Kensho* Distributed Ledger Technology Index	DLT

Table 2 Descriptive statistics

	Mean	Variance	Skewness	Kurtosis	JB	Q (10)	Q² (10)	ERS	ADF	PP	KPSS
COM	0.077	2.239	− 0.726***	8.919***	2636.704***	94.905***	530.646***	− 11.657***	− 8.7869****	− 35.1796****	0.1105
REA	0.038	2.895	− 2.090***	26.514***	23,264.898***	99.020***	398.793***	− 10.988***	− 15.5246***	− 32.519***	0.0655
UTI	0.027	2.475	− 0.236***	17.656***	10,073.866***	103.420***	945.947***	− 4.732***	− 8.1807***	− 33.7331***	0.0622
HEA	0.056	1.772	− 0.511***	11.777***	4512.827***	128.122***	725.407***	− 5.457***	− 8.526***	− 34.1142***	0.0575
DIS	0.069	2.359	− 1.238***	13.793***	6341.032***	73.584***	431.677***	− 8.478***	− 8.5542***	− 31.7188***	0.0928
INF	0.096	3.286	− 0.695***	11.424***	4276.450***	126.581***	549.628***	− 4.270***	− 8.676***	− 36.7386***	0.1217
ESG	0.063	2.124	− 1.051***	17.159***	9650.779***	164.354***	718.685***	− 6.078***	− 7.9639***	− 35.7726***	0.1124
IND	0.043	2.847	− 0.750***	11.978***	4705.511***	76.505***	713.674***	− 6.657***	− 9.4191***	− 30.906***	0.1108
STA	0.045	1.379	− 0.357***	16.583***	8896.369***	108.051***	998.549***	− 13.740***	− 8.2517***	− 34.9675***	0.0402
FIN	0.036	3.561	− 0.692***	14.021***	6410.166***	116.678***	757.318***	− 7.234***	− 9.2496***	− 33.6166***	0.1464
ENE	− 0.045	6.491	− 1.003***	14.666***	7075.268***	43.747***	249.320***	− 9.801***	− 8.362***	− 30.2619***	0.1913
MAT	0.042	2.797	− 0.715***	10.449***	3591.624***	89.038***	643.744***	− 5.494***	− 9.9253***	− 31.7831***	0.1697
DLT	0.118	6.79	− 0.721***	6.203***	1242.499***	40.224***	471.795***	− 7.800***	− 13.7952***	− 30.0413***	0.2309
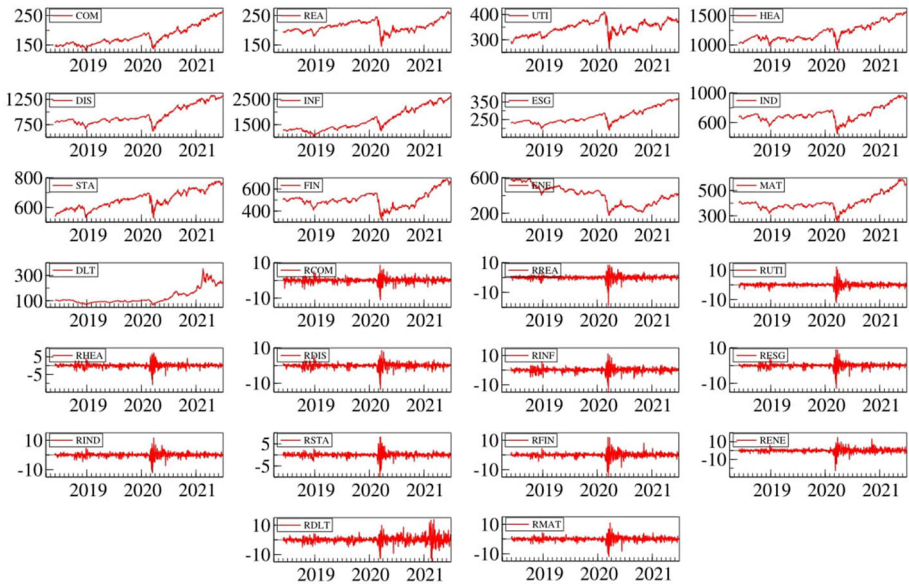
Fig. 1 Quantile coherency trend 0.05|0.05

5 Results

5.1 Quantile coherency results

The results of quantile coherency are shown in Figs. 2 and 3 but are further summarized in Table 3. Figure 2 shows both real and imaginary parts of quantile coherency estimation across different quantiles, including the 5th percentile, 50th percentile, and 95th percentile. W, M, and Y indicate the weekly, monthly, and yearly periods respectively. In addition, the horizontal axis is rescaled to daily cycles. Figure 3 shows the coherency for 0.05|0.95 quantiles.

Regarding the results in Fig. 2, it is evident that the real coherency and imaginary coherency graphs indicate incoherent behavior. In general, real coherency is more persistent than imaginary ones. It is evident that imaginary coherency has a volatile and wandering pattern. More so, in general, real coherency is positive while imaginary coherency is negative. The imaginary coherency generally changes around zero in all the cases, while real coherency usually changes around 0.6 to 0.2 in most cases, implying that it is better to focus on the real coherency more.

Coherency between DLT and COM is positive across all frequencies and under all market conditions. It changes between 0.1and 0.6 and reaches its peak in the long term under normal market conditions. Other sectoral stock indices have almost the same coherency patterns with the DLT index. Besides, in almost all frequencies, DLT and sectoral stock indices have the highest dependencies on each other under normal market conditions.

The result of coherency for 0.05|0.95 quantiles is depicted in Fig. 3. In this case, both the real and imaginary coherences are near zero across all frequencies in all cases. This result implies that extreme negative DLT returns and the extreme positive returns of each of the sectoral stocks are not very dependent on each other.

COM

REA

UTI

DIS

INF

ESG
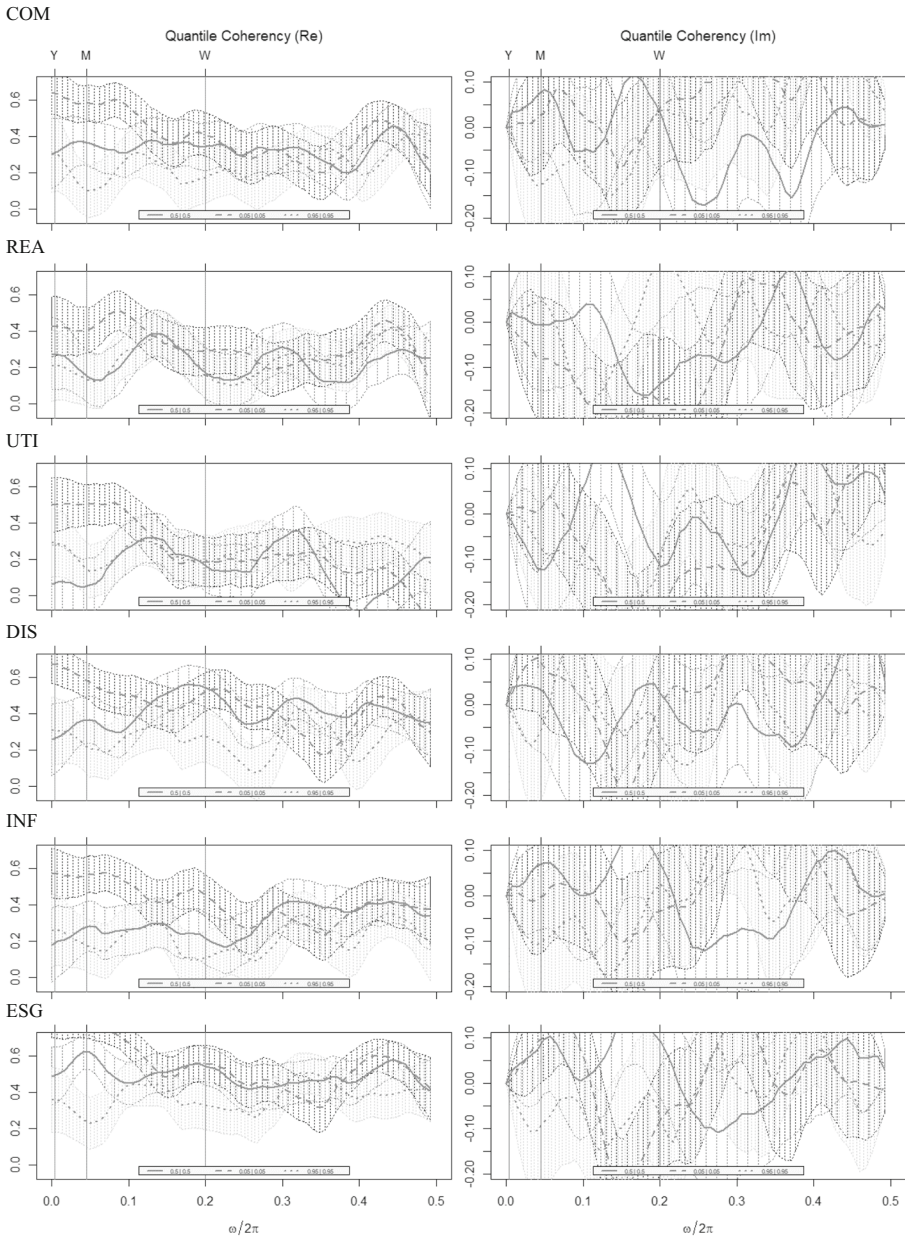
Fig. 2 Quantile coherency trend 0.5|0.5
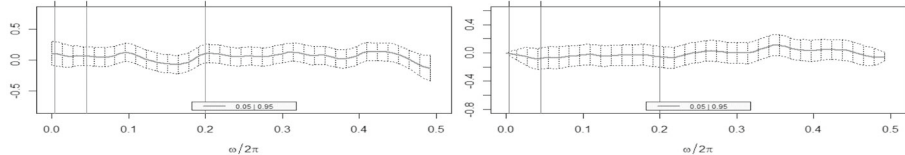
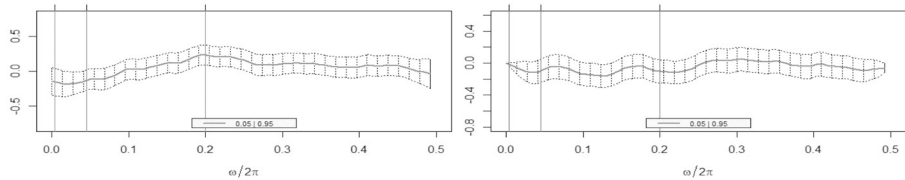INF
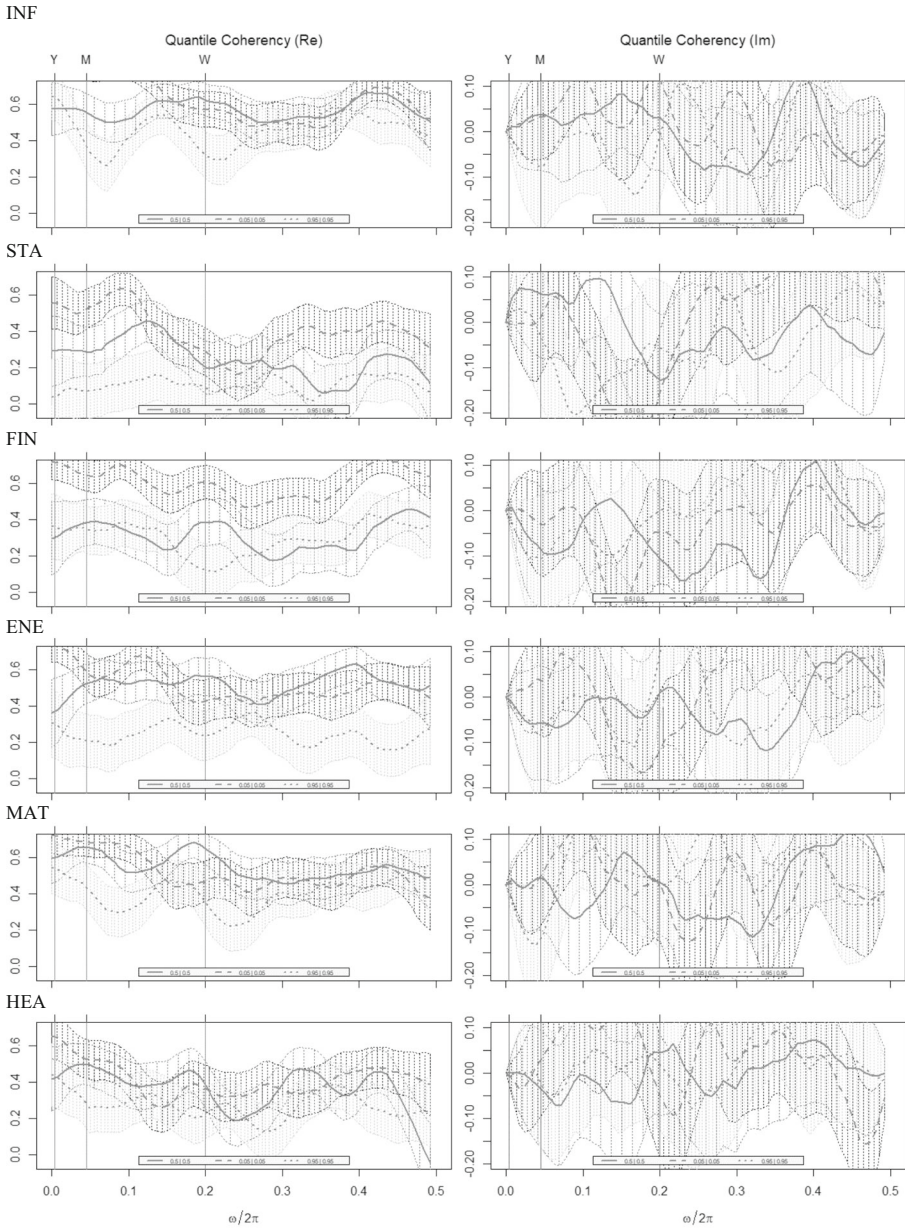
Fig. 2 continued

COM
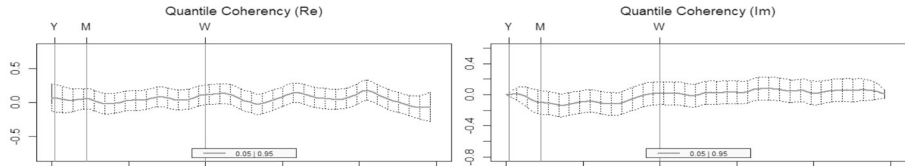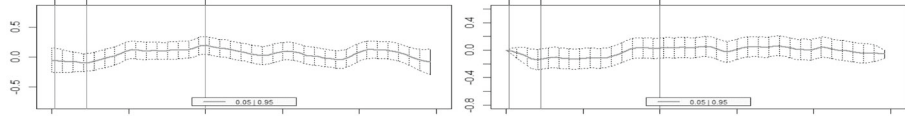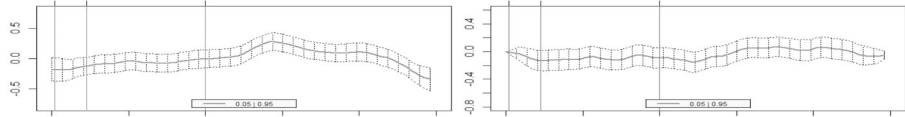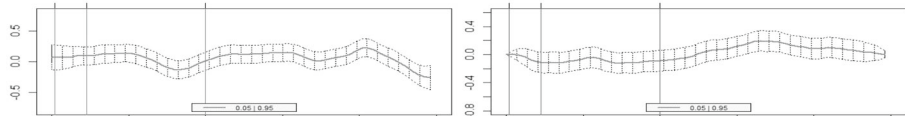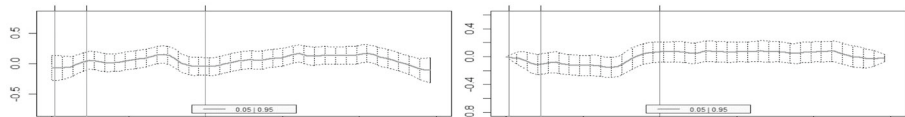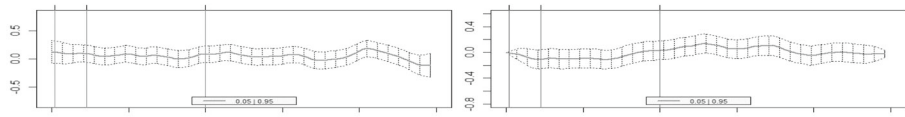
Fig. 3 Quantile coherency trend 0.95|0.95
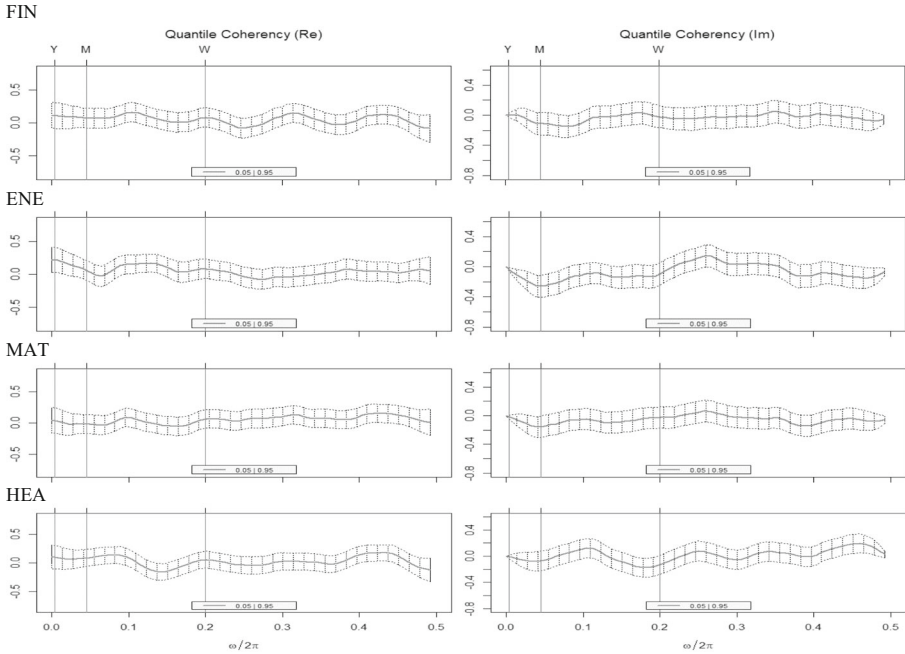
FIN

ENE

MAT

HEA

Fig. 3 continued

Then in Table 3, we present the results of the average quantile coherency between the DLT stock returns and the sectoral stock returns across different quantiles and frequency horizons. For the results at the lower quantile, it can be seen that the coherency between DLT stock returns and the sectoral stock returns tends to increase as the frequency increases, i.e., as we move from the short-run to the long-run. In particular, the coherency is higher in the long run (yearly frequency), except in the case of the real estate sector (0.4985), which is lower than the coherency in the long medium-term (monthly frequency). On the other hand, the short-term (daily frequency) shows the least coherency, except for the financial sector (0.6731), whose dependence is higher than the short medium-term (weekly) period (0.6082). It can also be seen that coherency is higher on the monthly horizon than on the weekly horizon. Another interesting observation from the result is that the coherency between the DLT stock returns and the sectoral stock returns is positive in all cases, except for the utilities sector in the daily frequency. This implies that bad news from the DLT stock market has the tendency to negatively affect the stock market performance of all other sectors. In other words, the decline in the price of DLT stocks has an adverse impact on the stock prices of these sectors.

Highlighting the degree of dependency between each sector and DLT, a closer inspection of the table reveals that in the short term and medium short term, the stocks of the financial, industrial, and energy sectors have the highest coherency with the DLT stocks in that order, implying that the sectors will be impacted more by the adverse movements in the DLT stocks during the periods. The long-term and medium long-term stock index of the industrial sector, followed by the ESG sector, has the highest coherency with the DLT stocks, implying their higher sensitivity to changes in the behavior of the DLT stocks in those periods. On the other hand, in the short term and medium short-term, the stocks of utilities, real estate, and consumer staples sectors have the least coherency with the DLT stocks, implying their weaker

Table 3 Quantile coherency

Horizon	Daily		Weekly		Monthly		Yearly	
Sector/Q	(0.05|0.05)	Sector/Q	(0.05|0.05)	Sector/ Q	(0.05|0.05)	Sector/ Q	(0.05|0.05)
FIN	0.6371	FIN	0.6082	IND	0.7879	IND	0.8086
IND	0.5043	IND	0.5727	ESG	0.7585	ESG	0.7818
ENE	0.4472	ESG	0.5573	MAT	0.6854	ENE	0.7381
ESG	0.4203	DIS	0.5245	FIN	0.6440	MAT	0.7245
HEA	0.3852	MAT	0.4717	COM	0.5825	FIN	0.7198
MAT	0.3799	INF	0.4483	DIS	0.5765	DIS	0.6778
INF	0.3747	ENE	0.4274	ENE	0.5723	HEA	0.6530
STA	0.3035	COM	0.4098	INF	0.5714	COM	0.6444
DIS	0.2954	HEA	0.3634	STA	0.5330	INF	0.5743
COM	0.2645	REA	0.2901	HEA	0.5242	STA	0.5563
REA	0.1241	STA	0.2853	UTI	0.5029	UTI	0.4985
UTI	-0.1298	UTI	0.1838	REA	0.4063	REA	0.4250
Sector/ Q	(0.5|0.5)	Sector/ Q	(0.5|0.5)	Sector/ Q	(0.5|0.5)	Sector/ Q	(0.5|0.5)
IND	0.5199	MAT	0.6458	MAT	0.6542	MAT	0.5973
ENE	0.5118	IND	0.6234	ESG	0.6218	IND	0.5738
MAT	0.4857	ENE	0.5615	IND	0.5467	ESG	0.4893
FIN	0.4113	DIS	0.5428	ENE	0.5289	HEA	0.4179
ESG	0.4070	ESG	0.5428	HEA	0.4946	ENE	0.3621
DIS	0.3504	FIN	0.3824	FIN	0.3865	COM	0.3046
INF	0.3368	HEA	0.3785	DIS	0.3664	FIN	0.2968
REA	0.2530	COM	0.3434	COM	0.3629	STA	0.2892
UTI	0.2072	INF	0.2110	STA	0.2846	REA	0.2757
COM	0.2034	STA	0.1994	INF	0.2830	DIS	0.2562
STA	0.1174	REA	0.1649	REA	0.1395	INF	0.1783
HEA	-0.0444	UTI	0.1596	UTI	0.0580	UTI	0.0629
Sector/ Q	(0.95|0.95)	Sector/ Q	(0.95|0.95)	Sector/ Q	(0.95|0.95)	Sector/ Q	(0.95|0.95)
MAT	0.4622	MAT	0.3491	MAT	0.4171	IND	0.6459
IND	0.4258	ESG	0.3258	FIN	0.3404	MAT	0.5473
ESG	0.4091	IND	0.3165	IND	0.3375	HEA	0.4412
COM	0.3748	DIS	0.2730	HEA	0.2595	FIN	0.3666
FIN	0.3727	ENE	0.2369	ESG	0.2281	ESG	0.3582
DIS	0.3424	HEA	0.2334	ENE	0.2027	ENE	0.3078
ENE	0.2731	UTI	0.1899	DIS	0.2014	DIS	0.3063
HEA	0.2355	COM	0.1742	INF	0.1678	COM	0.2994
REA	0.1924	REA	0.1580	UTI	0.1322	UTI	0.2924
INF	0.1838	FIN	0.1183	REA	0.1275	INF	0.2581
UTI	0.1789	INF	0.1087	COM	0.0976	REA	0.2070
STA	0.0621	STA	0.0847	STA	0.0678	STA	0.0375

susceptibility to movements in the DLT stocks in the short-term. The result is similar in the longer terms as stocks of the real estate sector, followed by those of the utilities sector, have the lowest coherency with the DLT stocks.

Next, we turn to the coherency results across different quantiles, as reported in the second and third panels of Table 3. For the 50th percentiles, the coherency between DLT stock returns and sectoral stock returns is positive, except for the healthcare sector on the daily frequency. This suggests that the DLT stocks and those of the sectors move together across all the frequencies. Moreover, in the short term and medium-short terms, the stock returns of materials, energy, and industrial sectors have the highest coherency with the DLT stock returns, indicating that these sectors are affected most significantly by the DLT stock activities in the short term. In the longer term, the ESG sector tends to replace the energy sector in the top three most coherent sectoral stocks with the DLT stock returns. Giving attention to the sectors with the least coherency with the DLT stocks, we find the utilities, real estate, consumer staples, and healthcare sectors leading the group in the short-term and the short medium-term. In the long term and medium long-term, the utilities, real estate, and information technology sectoral stocks exhibit the least coherency with DLT stocks, implying that these sectors are affected by DLT stocks just slightly.

The result of the coherency between extreme positive returns of DLT stock returns and the sectoral stock returns (i.e., 95th percentile) indicates that the coherency is positive in all cases. This again indicates that good news from the DLT stock market will positively impact all other sectors. However, the reverse is also the case. In the short term and medium short term, the stock returns of the materials, industrials, and ESG sectors have the highest coherency with DLT stock returns, whereas, in the long term and medium long term, stock returns of materials, industrials, and financial sectors have the highest coherency with DLT stock returns. Also, putting the least coherency into perspective, this goes to the utilities, Consumer Staples, Information Technology sectors in the short-term and short medium-term, and the real estate, communication Services, and Consumer Staples sectors in the long medium-term and long-term.

In summary, the following key findings can be presented. First, the quantile coherency between the DLT stock returns and the sectoral stock returns is positive in virtually all cases, except for two sectors. This suggests that the sectoral stock returns and the DLT stock returns are closely related. An increase in the DLT stock index affects the stock indices of all other sectors positively and vice-versa. This evidence is supported by many studies that emphasize the importance of DLT for these sectors (see, for instance, Konashevych (2020), Badr (2019), Siano et al. (2019), and Coppi (2021)). Second, as we move from the lower to the higher quantiles, the quantile coherency between the DLT stock returns and the sectoral stock indices becomes less intense, implying that the connection is stronger when the market is bearish. Third, the quantile coherency between the DLT stock returns and the sectoral stock returns becomes slightly higher in longer terms in general, implying that they are not strongly associated in the short term. The second and third points can be better understood by looking at Figs. 4, 5 and 6, where it is seen that the long-term and long-medium term trends are mostly above others; most of the sectors have lower values at the highest quantile (95th percentile).

## 5.2 Return spillovers and connectedness results

The results of the dynamic connectedness between DLT stock returns and the sectoral stock indices returns are presented in Table 4. The total connectedness index (TCI) is 82.43%,
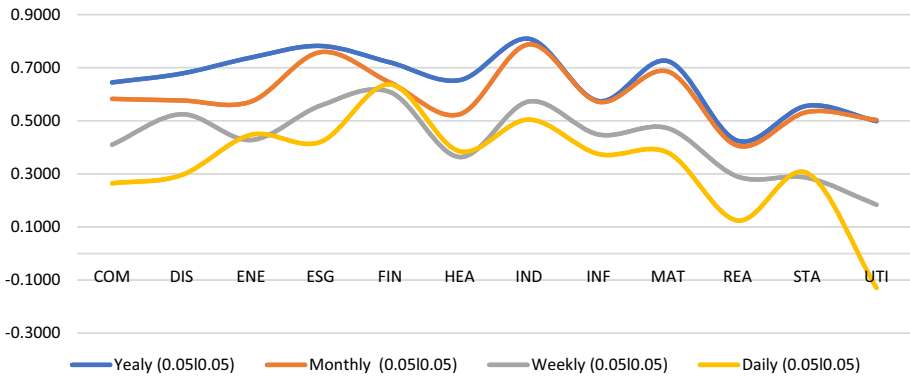
Fig. 4 Quantile coherency: Real (left) and imaginary (right) parts of the quantile coherency estimates for the DLT returns and sectoral stock indices for 0.05, 0.5, and 0.95 quantiles together with 95% confidence intervals. W, M, and Y denotes weekly, monthly, and yearly periods. Data span years 2005–2017
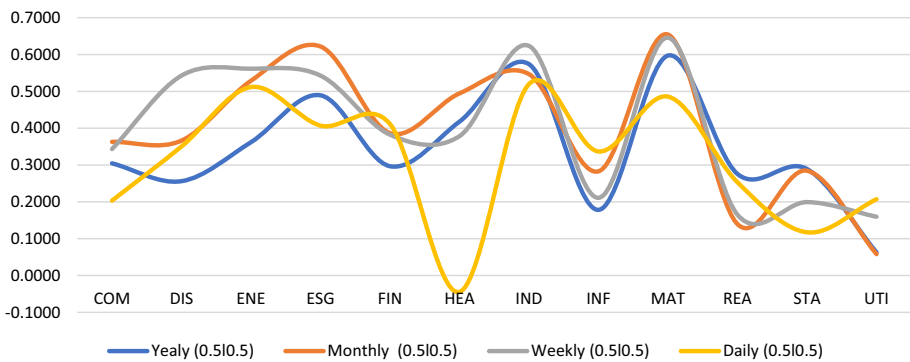
Fig. 5 Quantile coherency 0.05|0.95: Quantile coherency: Real (left) and imaginary (right) parts of the quantile coherency estimates for the DLT returns and sectoral stock indices for 0.05 and 0.95 quantiles together with 95% confidence
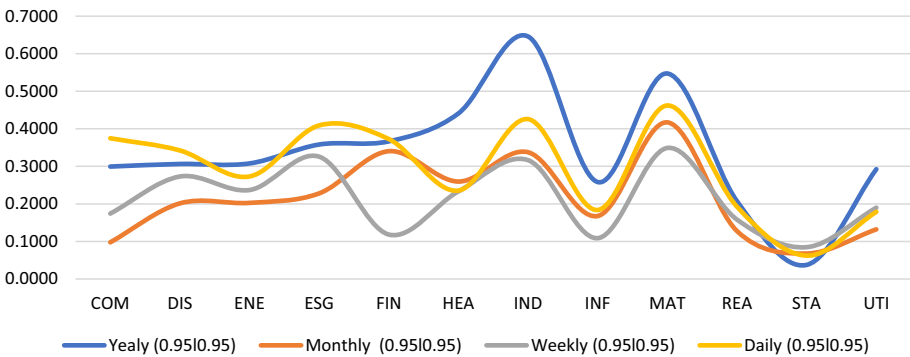
Fig. 6 Quantile coherency trend 0.95|0.95

Table 4 Dynamic connectedness results

TO (i)	COM	REA	UTI	DIS	INF	ESG	IND	STA	FIN	ENE	MAT	HEA	DLT	FROM (i)
COM	18.07	4.35	2.23	10.49	9.73	11.28	7.76	5.69	7.69	4.61	6.83	4.92	6.33	81.93
REA	6.06	21.82	8.56	7.05	5.45	8.74	7.34	8.49	7.66	3.88	6.21	2.84	5.9	78.18
UTI	4.32	12.89	26.82	4.55	4.05	6.85	6	11.64	7.64	3.09	5.14	2.21	4.78	73.18
DIS	8.3	3.82	2.05	14.94	10.86	11.91	9.17	4.55	7.67	4.73	7.99	7.03	6.99	85.06
INF	8.39	3.48	1.89	11.69	15.14	12.82	8.38	4.53	8.56	4.17	7.32	7.54	6.09	84.86
ESG	7.9	4.58	2.53	10.34	10.4	12	9.81	5.48	8.8	5.43	8.51	6.06	8.16	88
IND	6.19	4.45	2.3	8.6	7.65	10.6	14.43	4.71	6.85	7.26	11.05	5.76	10.15	85.57
STA	7.03	7.7	7.2	6.89	6.33	9.9	7.91	17.55	9.28	3.57	7.03	2.85	6.75	82.45
FIN	7.2	5.13	3.53	8.82	8.98	11.53	8.81	6.47	14.71	4.6	7.93	5.3	6.97	85.29
ENE	5.84	3.74	1.47	7.28	6	9.41	11.13	3.28	5.95	19.74	9.86	5.61	10.69	80.26
MAT	5.78	4.15	2.4	8.32	7.45	10.29	12.54	4.61	6.77	6.88	15.09	5.81	9.91	84.91
HEA	5.72	2.21	1.3	10.66	10.65	9.99	8.31	2.83	6.3	4.76	7.63	23.11	6.53	76.89
DLT	5.84	4.36	2.3	8.08	7.26	10.78	12.25	4.36	6.65	7.23	10.28	5.61	15	85
CTO	78.58	60.86	37.76	102.77	94.8	124.11	109.43	66.66	89.84	60.21	95.79	61.54	89.25	1071.59
NET	− 3.35	− 17.32	− 35.41	17.7	9.94	36.11	23.86	− 15.79	4.55	− 20.05	10.87	− 15.34	4.25	**TCI = 82.43**

*, **, *** indicates significance at the 10, 5, and 1% level significance
Source: author's calculation

indicating that the network is highly connected. The total directional connectedness from the DLT index to the sectoral stock indices is 89.25%, while the total directional connectedness from other stock indices to the DLT stock index is 85% [1]. By implication, we can infer that the DLT stock index is very connected with the sectoral stock indices, thus confirming the quantiles coherence results earlier reported [2]. Moreover, DLT is found to be a net spillover of shocks (4.25%) to the sectoral stock indices in the network. As a result, the DLT can be said to have spillover effects on the sectors and thus plays a leadership role in the network.

In order to specifically trace out spillover of risks between DLT and each sectoral stock, we present their directional pairwise spillover results in Table 5. The results indicate that the DLT index transmits the highest percentage of shock spillover to stock indices of energy, industrial and material sectors, in that order. Besides, it also receives the highest amount of shock spillovers from these sectors. Interestingly, these are among the sectors that have the highest quantile coherency with the DLT stocks, depicting the consistency and robustness of our results. On the other hand, the DLT index transmits the least amount of shock spillovers to the utilities, real estate, and information technology sectors, whereas it receives the least shock spillovers from the utilities, real estate, and consumer staples sectors. Again, these sectors are among those with the weakest quantile coherency with the DLT stock, thus creating another sense of validity to our results.

Finally, we examine the time-varying spillovers, particularly for the total connectedness and the pairwise spillover from DLT stocks to the sectoral stocks. The graphical results for these are shown in Figs. 7 and 8. In Fig. 7, we see that the connectedness is very high, with the least index being around 71 and 80% for the adjusted and unadjusted indices, respectively. In general, three jumps can be identified in the graph, one of which is in 2020, and the other two are in 2018. The unprecedented spike in the early May of 2020 is due to the COVID-19 pandemic that depressed many stock markets globally. Many studies (such as Adekoya & Oliyide, 2021; Adekoya et al., 2022a, 2022b; Umar et al., 2021) confirm that connectedness among different financial markets was heightened during the COVID-19 pandemic. Looking at the pairwise spillovers from DLT to the sectoral stocks, significant variations can be observed over time, indicating that the connectedness is not static but dynamic.

6 Conclusion

DLT has great applicability in various fields, especially in the supply chain. However, how trading in the DLT stocks connects with the stock market performances of different sectors, especially at different frequency horizons and market states, has enjoyed less empirical attention. Worse still, there seems to be no study that examines the dynamic connectedness and returns spillover between the DLT stocks and sectoral stock returns. Therefore, this apple attempts to analyze the relationship between the DLT stock index and the stock indices of 12 sectors, namely communication services, consumer discretionary, consumer staples, energy, health care, financials, industrials, information technology, materials, utilities, and real estate, and ESG, using quantile coherency and dynamic connectedness approaches.

We summarize our core findings as follows: One, in most cases, the coherency between the DLT stock index and sectoral stock indices is significant and positive. Two, the coherency between the DLT stock index and sector stock indices weakens in the higher quantiles. So, they are more connected during bearish market conditions. Three, the coherency between the

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[1] Contribution to others.

[2] NET directional connectedness.

Table 5 Dynamic connectedness results for DLT index

	COM	REA	UTI	DIS	INF	ESG	IND	STA	FIN	ENE	MAT	HEA
DLT to	6.33	5.9	4.78	6.99	6.09	8.16	10.15	6.75	6.97	10.69	9.91	6.53
DLT from	5.84	4.36	2.3	8.08	7.26	10.78	12.25	4.36	6.65	7.23	10.28	5.61
DLT net	0.49	1.54	2.48	− 1.09	− 1.17	− 2.62	− 2.1	2.39	0.32	3.46	− 0.37	0.92
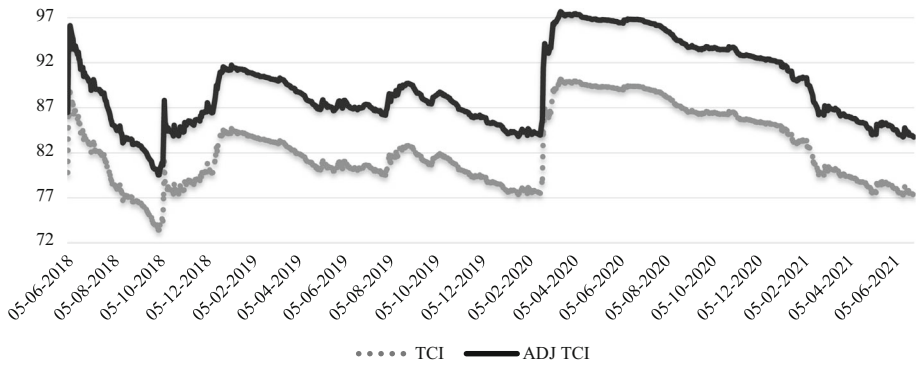
Fig. 7 Total connectedness index and adjusted total connectedness index
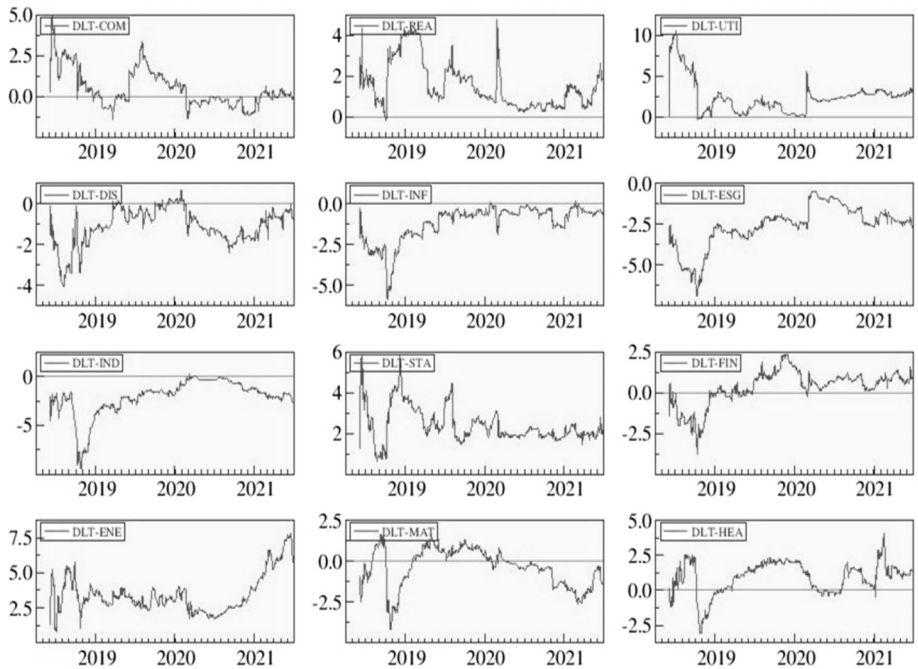
Fig. 8 Net directional spillover from the DLT stocks to the sectoral stocks

DLT stock index and the sectoral stock indices becomes is more intense in the longer terms, implying that they are weakly dependent on each other in shorter terms. Four, the results of the connectedness also indicate that the DLT stock index is highly connected with the whole network of stock indices, as it transmits and receives 89.25 and 85% shock spillovers to the sectoral stocks, respectively.

These results have several implications. In the first instance, the positive quantile dependency established in most cases indicates that the distributed ledger technology can be regarded as a critical factor in the development and enhancement of the sectors. However, it

is more important for some sectors, such as the materials, financial, energy, and ESG sectors. Thus, its adoption will help enhance the performance of these sectors and the general financial system. For investors, we suggest, based on the findings, that including DLT and the sectoral stocks in the same investment portfolio should be carefully done. Factors that must be considered include the market states, investment horizons, and crisis periods. For instance, DLT stocks can effectively hedge against risks in the sectoral stocks with weak dependence or connectedness on them, such as the utilities, real estate, healthcare, and consumer staples sectors. However, the stronger the dependency or connectedness, the greater the possibility of investment losses. Also, the DLT and sectoral stocks can be jointly invested in during normal and bullish market conditions and in the shorter terms. This is because dependency seems to be weak during these market states and investment horizons. Essentially, the weak dependency is an indication that portfolio investment risks can be substantially mitigated with the inclusion of both the technology and the conventional sectoral stocks. Finally, even though the dynamic connectedness results present DLT as a net transmitter of spillovers, its overall and pair-wise strong connectedness with the sectoral stocks indicates its relative vulnerability to the shocks from the conventional stock markets. Policy makers are thus enjoined to develop strategies to solidify the performance of the technological firms that involved in distributed ledger. This would not only promote financial technology advances in the diverse sectors highlighted in the introduction, but assure investors of the safety of their investments.

Future study should extend this analysis to the different components of DLT, rather than the aggregate index employed in this study. This will help to provide more robust results by revealing the heterogeneous dependence of DLT on other financial assets. Moreover, since technology is increasingly being considered as a critical tool for climate change mitigation, we suggest that future researchers examine the connectedness between DLT and diverse green finance and renewable energy assets.

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