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Are FinTech, Robotics, and Blockchain index funds providing diversification opportunities with emerging markets?Lessons from pre and postoutbreak of COVID-19

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Abstract

The study has been inspired by the emergence of technology-based assets, namely, FinTech, Robotics, and Blockchain in the 4th Industrial Revolution. We are examining diversification opportunities with nonconventional technology funds based on FinTech, Robotics, and Blockchain while investing in MSCI Emerging Markets Index, and finally gauging the most resilient fund during the pre-and post-outbreak of COVID-19. The five technology-driven funds considered are ARK FinTech Innovation Exchange Traded Funds (ARKF), Global X FinTech Exchange Traded Funds (FINX), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), Global X Robotics and Artificial Intelligence (BOTZ), and Ishares Robotics and Artificial Intelligence (IRBO) to investigate diversification opportunities with MSCI Emerging Markets Index. The time-varying dynamic spillover using the Vector Auto Regression Model for average, low, and high volatility quantiles and the network of volatility connectedness based on quantile VAR have been applied to capture diversification and identifying the most resilient fund. The study found that ARKF and FINX provide diversification opportunities. In each quantile, these two funds are evidence of diversification, and BOTZ, also shows diversification evidence. Moreover, FINX is the throughout resilient fund, and ARKF is the most resilient in extreme quantiles. Throughout the quantiles, it is perceived a significant impact of COVID-19 on the total connectedness of Funds with the emerging market index.

Keywords FinTech · Robotics · Blockchain · Emerging markets · Diversification · Time-varying dynamic spillover · Network analysis · COVID-19

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1 Introduction

The need for portfolio diversification has been accentuating significantly after the advent of the financial crisis [14]. Investors are interested in safe-haven instruments during the turmoil period. It has been found that correlations among financial assets increased during the crisis due to interdependencies, contagion, and herding behavior of investors [31]. After the financial crisis, the need for diversification and identifying the best hedging opportunities triggered significantly after the outbreak of COVID-19 [6, 8, 37, 40].

In the 4th industrial revolution, investors are showing interest in alternative asset classes, in general and technology-based asset classes, in particular [21, 26, 27]. Among technology-based assets, several studies have been done on Bitcoin and found it a safe investment in a period of turmoil [12, 17, 19]. Cryptocurrency as an asset class created a mixed picture as a financial asset. The peculiar behavior of Bitcoin is backed by its unique structure and is considered a speculative asset class Gronwald [18]. In this paper, we examine FinTech, Robotics, Artificial Intelligence, and Blockchain-based funds to identify diversification opportunities and find the most resilient tech-based index during the pre-and post-outbreak of COVID-19.

Blockchain technology is the outcome of the advent of Bitcoin in 2009 [32]. A Blockchain is a decentralized ledger that initially facilitates peer-to-peer transactions and is now popularised as a smart contract. Blockchain-based smart contracts help to mitigate the trust problem through peer-to-peer networking and public-key cryptography [13]. The Blockchain-based smart contract changed the complete landscape of the traditional production system and created trust within the ecosystem [3]. It has been used robustly in various industries, from the financial sector to healthcare [2, 30, 33, 35]. The trend of Blockchain hovers with a big bang in general, particularly in the various sectors of emerging countries [34]. Artificial Intelligence (AI), Robotics, and FinTech are the outcomes of the 4th Industrial revolution era. AI and Robotics are the disrupted technologies that change the production processes. The adoption of AI and robotics by business processes have increased significantly [16]. Nowadays, robotics technologies facilitate the forecasting of demands and production planning. It is in healthcare, agriculture, hospitality, manufacturing, and the military. Henceforth, the shipment of robots has increased by 150% from 2010 to 2016 [16]. Artificial Intelligence (AI) helps to make strategic business decisions and expedite business operations. It has been shifting businesses that have been proven by the successes of Ola, Uber, Amazon, etc. They used instrument state-of-the-art business models [15]. AI offers huge opportunities in Emerging Markets to lower the cost of production and innovate cutting-edge business models that are resilient and sustainable [39]. FinTech is the advent of technology in the financial world that changed the complete ecosystem. FinTech is the representative of companies that provides digital-based financial services to its customer that is user-friendly, decentralized, efficient, and transparent [26, 27]. Moreover, the FinTech industry is acting as a trigger to promote sustainable economic growth. It ensures financial sustainability of businesses and their financial inclusion. FinTech can promote the funds used in green projects [10]. Both sectors that are sustainable finance and FinTech have many common aspects. FinTech has the potential to complement it and thus provide interesting synergies and great potential [28]. FinTech triggers financial inclusion that ensures sustainable balanced development, which is in tune with UN Sustainable Development Goals (SDGs) [5]. The potential of FinTech to strengthen SDGs will be realized by strengthening the infrastructure to support digital financial transformation [4]. There is enormous scope for FinTech firms in emerging or developing markets. Henceforth, capturing relationships with technology-based assets with the traditional financial market is worth analyzing [27].

Emerging Markets is always in priority of investment for foreign institutional investors [22]. The market backed by high growth and weak efficiencies makes a lucrative investment for investors. The limited literature is available to capture the diversification opportunities in emerging financial markets with technology-based non-conventional assets [26, 27]. The novelty of the current research is based on the scant literature on diversification opportunities with non-conventional asset classes and finding the most resilient asset during the pre- and post-outbreak of COVID-19. The three major studies were on technology-based assets with a blend of conventional assets that are Le et al. [27], Huynh et al. [21] and Le et al. [26]. The study of Le et al. [26], to the best of my knowledge, is the only one to capture the impact of COVID-19 among technology-based assets with other asset classes. Additionally, none of the studies has been done exclusively on tech-based assets that are on FinTech, AI, Robotics, and Blockchain while investing in emerging markets.

With the above discussion, the study tries to reach answers to the following two questions:

Q1. Identifying the impact of COVID-19 on Tech-Based Funds and finding the diversification opportunities for the investors investing in Emerging Markets?

Q2. Capturing Tech-Based Funds that are the most resilient during the Pre and Post outbreak of COVID-19?

To reach these research questions, the study has taken innovative tech-based funds that are capturing the companies that are broadly investing in Blockchain, Robotics, Artificial Intelligence (AI), and FinTech. The five funds considered in the study are ARK FinTech Innovation ETF (ARKF), Global X FinTech ETF (FINX), First Trust Nasdaq Artificial Intelligence and Robotics ETF (ROBT), Global X Robotics and Artificial Intelligence (BOTZ), and ishares Robotics and Artificial Intelligence (IRBO). The study is unique in identifying the impact of the outbreak of COVID-19. For this, the study has divided the time-period into two windows that are pre- outbreak (from 11th March 2019 to 11th March 2020) and the post- outbreak of COVID-19 (from 12th March 2020 to 11th March 2021). Time-Varying Dynamic Spillover using the Vector Auto Regression (VAR) Model for average, low, and high volatilities quantiles and the network of the volatility connectedness based on quantile VAR. Finally, the pre- and post-volatility connectedness has been analyzed. The results capture that ARKF and FINX provide diversification opportunities throughout the quantiles, and BOTZ has shown diversification evidence. FINX is the throughout resilient fund, and ARKF is the most resilient in extreme quantiles. It has captured a significant impact of COVID-19 on the total connectedness of Funds with MSCI Emerging Markets Index in all quantiles.

The rest of the paper is organized as follows. Section 2 presents literature on the diversification of nonconventional assets with emerging markets and a specific discussion on the diversification of Technology-based assets with emerging markets. Section 3 outlines the empirical methods used in the study. Section 4 discusses the data and empirical results of the volatility transmissions, identifies diversification opportunities, then explores the most resilient tech-based fund, and lastly, the overall impact of the outbreak of COVID-19 has been addressed. Section 5 provides concluding remarks and policy suggestions.

2 Literature review

Table 1 captured the detailed literature review based on diversification with tech-based assets that are crypto market, FinTech, Artificial Intelligence, and Blockchain. This section highlights the very recent studies on diversification and identified the similarities and gaps that provide the need and urgency for the current study.

From the above discussion, it has been found that a very limited strand of literature is available to capture the diversification opportunities in emerging financial markets with technology-based nonconventional assets during the pre and post-outbreak of COVID-19. To the best of my knowledge only one study done by Le et al. [26] captured the impact of COVID-19 among technology-based assets with other asset classes. Additionally, none of the studies has been done exclusively on tech-based assets that include FinTech, Artificial Intelligence (AI), Robotics, and Blockchain while investing in emerging markets, and finding the most resilient asset class during times of vulnerabilities, provides scope for the current study.

3 Empirical methods

The empirical strategies are outlined in this section. First, the quantile VAR model is discussed briefly. Second, the quantile generalized forecast error variance decomposition is used to form the volatility spillovers between technologically based funds and MSCI emerging market index.

3.1 The quantile VAR model

In quantile regression, we may estimate the dependence of z_t on y_t at each quantile τ of the conditional distribution of $z_t|y_t$ [25]. It can be shown as:

$$Q_\tau\left(z_t \middle| y_t\right) = y_t\beta(\tau) \tag{1}$$

In Eq. (1), Q_τ is the τ *th* conditional quantile function of z_t; each quantile range is between 0 and 1 and represented by the symbol τ; y_t is a vector of explanatory variable and $\beta(\tau)$ presents the dependency link between y_t and the τ *th* conditional quantile of z_t. In general, the parameter vector $\beta(\tau)$ is estimated at the τ *th* conditional quantile τ via the following expression:

$$\beta(\hat{\tau}) = \alpha\ rg \min \sum_{t=1}^{T} \left(\tau - 1_{\{z_t < y_t\beta(\tau)\}} \left|z_t < y_t\beta(\tau)\right|\right. \tag{2}$$

Consequently, the n-variable quantile VAR process of the pth order is computed as follows:

$$z_t = e(\tau) + \sum_{i=1}^{p} A_i(\tau)z_{t-i} + \varepsilon_t(\tau), \quad t = 1, \dots, T \tag{3}$$

where z_t is the n-vector of a dependent variable, $e(\tau)$ and $\varepsilon_t(\tau)$ represent the n-vector of constant and residuals at quantile τ respectively. $A_i(\tau)$ denotes the lagged coefficient matrix at quantile τ. In order to compute the $A_i(\hat{\tau})$ and $e(\hat{\tau})$, it is assumed that the residual confirms the population quantile restriction, $Q_\tau\left(\varepsilon_t(\tau)\middle|z_{t-1}, \dots, z_{t-p}\right) = 0$. Under this restriction, the computed values of the dependent variable z_t at each quantile are estimated as:

$$Q_\tau\left(z_t\middle|z_{t-1}, \dots, z_{t-p}\right) = e(\tau) + \sum_{i=1}^{p} A_i(\tau)z_{t-i} \tag{4}$$

3.2 The quantile connectedness measures

The connectedness measures at each quantile τ are estimated by following the original work of Ando et al. [1] which is the extended version of mean-based measurement of Diebold and Yilmaz [11].

To compute the connectedness measures at each quantile, we rewrite Eq. (3) as an infinite order vector moving average process:

$$z_t = \varphi(\tau) + \sum_{s=0}^{\infty} d_s(\tau)v_{t-s}(\tau), \quad t = 1, \dots, T \tag{5}$$

with

$$v(\tau) = \left(I_n - G_1(\tau) - \cdots - G_p(\tau)\right)^{-1} e(\tau), d_s(\tau) = \begin{cases} 0,\ s < 0 : I_n, & s = 0 \\ G_1(\tau)d_{s-1}(\tau) + \cdots + G_p(\tau)d_{s-p}(\tau), & s > 0 \end{cases} \tag{6}$$

where z_t denotes the summation of residuals $v_t(\tau)$.

Table 1 Empirical studies on technology-based diversification studies

S. No	Authors name and year	Title	Journal	Purpose and findings	Similarity and gaps identified
Latest empirical studies related to diversification with crypto market					
1	Chemkha et al. [9]	Hedge and safe haven properties during COVID-19	The Quarterly Review of Economics and Finance	The study has identified the safe haven properties of Bitcoin and other conventional assets during COVID-19. It has been found that Bitcoin and gold are providing hedging with international portfolios. However, during the pandemic, it has been found that gold is not safe and Bitcoin is also not found a sahe heaven during the vulnerability. The study has applied the asymmetric DCC model	The study is an extension of the study done by Bouri et al. [7] with an additional feature of diversification during COVID-19. The study further leaves the scope of diversification with other non-conventional-technology-based assets
2	Disli et al. [12]	In search of safe haven assets during COVID-19 pandemic: An empirical analysis of different investor types	Research in International Business and Finance	The study is to find diversification opportunities among Bitcoin, Gold, and Crude oil for Islamic investors during the pandemic in a Wavelet coherence analysis and spillover index It had found that the coherence among select assets and equities had been low before the pandemic, and it increased during COVID-19	The study is limited in scope and thus leaves further scope to gauge diversification opportunities with a unique set of tech-driven assets
3	Goodell and Goutte [17]	Co-movement of COVID-19 and Bitcoin: Evidence from wavelet coherence analysis	Finance Research Letters	The study is a novel attempt to find Bitcoin as a safe investment during the pandemic	The study is specific to identifying the resilience of Bitcoin during the pandemic. However, the attempt is novel but leaves scope for further study

Table 1 (continued)

S. No	Authors name and year	Title	Journal	Purpose and findings	Similarity and gaps identified
				It had found the coherence between the daily world deaths and daily Bitcoin prices. The study applied Wavelet methods to gauge diversification opportunities	
				It had found a strong negative correlation between Bitcoin daily prices and daily world death cases	
4	Guo et al. [19]	Capture the contagion network of bitcoin–Evidence from pre and mid-COVID-19	Research in International Business and Finance	The study contributed to the ongoing discussion on safe hedging properties of Bitcoin with financial markets during the pre and post-outbreak of COVID-19	The study is again a contribution toward identifying the hedging properties of Bitcoin during the pandemic. Henceforth, leaves a gap for including more tech-based assets
				The study has applied a unique set of methods and models- acyclic graph, spillover index, and network topology. The study found that bitcoin was a safe hedge during the pre-outbreak of COVID-19, but during a pandemic it is undermined	

Table 1 (continued)

S. No	Authors name and year	Title	Journal	Purpose and findings	Similarity and gaps identified
5	Jiang et al. [23]	Revisiting the roles of cryptocurrencies in stock markets: A quantile coherency perspective	Economic Modelling	The study is a contribution to the ongoing discussion but the findings differ from the previous studies. The study found that cryptocurrency is not a safe diversifier with stock markets. The study applied a quantile coherency approach with a hedging effectiveness index	The study leaves scope to gauge diversification opportunities with a unique set of asset classes
6	Bouri et al. [7]	Bitcoin, gold, and commodities as safe havens for stocks: New insight through wavelet analysis	The Quarterly Review of Economics and Finance	The study is an attempt to identify diversification opportunities among Bitcoin, Gold, and commodities in a Wavelet Coherence Approach. It has been found that Bitcoin is providing superior diversification opportunities	The study focuses on the technology-based asset that is Bitcoin to find diversification opportunities over and above conventional assets. The study is limited in scope and does not consider other technology-based assets—FinTech, Blockchain, AI, and Robotics and thus, leaves further scope to study further

Table 1 (continued)

S. No	Authors name and year	Title	Journal	Purpose and findings	Similarity and gaps identified
7	Kliber et al. [24]	Bitcoin: Safe haven, hedge,or diversifier? Perception of bitcoin in the context of a country's economic situation—A stochastic volatility approach	Physica A: Statistical Mechanics and its Applications	The study is a novel attempt in the field of diversification in the crypto market. The studies tried to identify diversification under various economic conditions and currency of trade in a multivariate stochastic volatility model. It has been found that Bitcoin is a weak hedge with almost all markets but a safe investment in Venezuela	The study is another contribution to the ongoing discussion that identifies diversification opportunities for a new set of countries. However, the study considers only Bitcoin as a tech-based asset and thus leaves further scope
8	Shahzad et al. [36]	Is Bitcoin a better safe-haven investment than gold and commodities?	International Review Financial Analysis	The paper is another piece of study to discuss the safe heaven properties of Bitcoin during extremely turbulent market conditions with various stock markets. The study also examines the superior hedging opportunity over and above the gold and commodity market in a bivariate cross-quantilogram approach. The results of the study found that the safe-haven properties of Bitcoin, gold, and commodities are varying according to time and select stock markets	The results of the study have shown an indifferent conclusion towards the safe heaven property of Bitcoin. However, the study is limited in scope and thus leaves the further scope of the study

Table 1 (continued)

S. No	Authors name and year	Title	Journal	Purpose and findings	Similarity and gaps identified
9	Stensas et al. [38]	Can Bitcoin be a diversifier, hedge, or safe haven tool?	Cogent Economics and Finance	The study is again finding the safe property of Bitcoin with developed and emerging markets in Multivariate Dynamic Conditional Connectedness (DCC) models. It has been found that Bitcoin is captured as a hedge for the majority of developing markets and as an asset of diversification with developed markets	The study is repetitive with a unique set of markets and in consensus with the safe-haven property of Bitcoin. The study is limited to single-asset cryptocurrency and also limited to a single tech-based asset class i.e. crypto market, leaving scope to gauge diversification with other tech-based asset classes
10	Mai et al. [29]	How does social media impact Bitcoin value? A test of the silent majority hypothesis	Journal of Management Information Systems	The study is an altogether different and unique contribution to the literature on Bitcoin. However not address the diversification with Bitcoin. It addresses the dynamic interactions between Bitcoin value and social media. The study is contributing to the ongoing discussion on the valuation of Bitcoin	The study is contributing to the literature on the valuation of Bitcoin rather than identifying diversification with Crypto markets and thus, leaves scope for diversification with crypto and other tech-based assets

Table 1 (continued)

S. No	Authors name and year	Title	Journal	Purpose and findings	Similarity and gaps identified
Latest empirical studies related to diversification with FinTech, AI,and Blockchain					
11	Le et al. [26, 27]	Time and frequency domain connectedness and spillover among fintech, green bonds,and cryptocurrencies in the age of the fourth industrial revolution	Technological Forecasting and Social Change	The study analyzed spillover among FinTech, green bonds, and cryptocurrencies in a time and frequency connectedness of return series. The study applied Diebold and Barunik models to examine the volatility spillover. It has been concluded that FinTech and equities are not good hedging assets in a single portfolio, and the shocks are found in the short-term rather than in the long-term. Henceforth, long-term positions have been suggested to mitigate risk. Conventional and sustainable funds that are green bonds are considered a good hedge	The study is a novel contribution to the literature on cryptocurrency by including FinTech and green bonds. However, the study further leaves scope for more meticulous diversification opportunities and finding the most resilient asset during the pre and post-outbreak of COIVD-19

Table 1 (continued)

S. No	Authors name and year	Title	Journal	Purpose and findings	Similarity and gaps identified
12	Le et al. [26, 27]	Did COVID-19 change spillover patterns between FinTech and other asset classes?	Research in International Business and Finance	The study found the spillover transmissions among FinTech stocks and other assets that are Bitcoin, the Stock market, Crude oil, and the US dollar. The study captured the pre and post-COVID-19 volatility transmissions. It has been found that COVID-19 accelerates volatility transmissions among assets while decreasing subsequently as the new confirmed cases decreased globally. The USD and gold proved as safe heaven opportunities. The results of gold as a safe haven are in the consensus of Huynh et al. [21] and Le et al. [26, 27]. However, technology-based assets are volatile with external shocks	The study is again a unique attempt in the literature of tech-based assets diversification by including conventional assets and also capturing the impact of COVID-19. The current study is very close and meticulous by having a unique set of tech-based assets to gauge diversification opportunities. Moreover, finding the most resilient tech-based fund during the pre and post-outbreak of COVID-19 is a unique contribution.

Table 1 (continued)

S. No	Authors name and year	Title	Journal	Purpose and findings	Similarity and gaps identified
13	Hyunh et al. [21]	Diversification in the age of the 4th industrial revolution: The role of artificial intelligence, green bonds, and cryptocurrencies	Technological Forecasting and Social Change	The study gauged diversification in the era of the 4th industrial revolution. The study has taken non-conventional asset classes based on technology and sustainable funds, and investigated diversification among AI, Robotics, stocks, crypto, and green bonds in a tail dependence as copulas and Generalised Forecast Error decomposition framework. It has found short-term transmission of volatility in comparison to long-term. The study also found that Bitcoin and gold are significant for hedging, and gold is a safe investment during the turbulent period with NASDAQ AI. Finally, it has been concluded that NASDAQ AI and general equities are not suitable for hedging with each other	The study is very closely connected with the current study. The study is more meticulous than the previous studies that were dedicated to the cryptomarket by including more non-conventional asset classes. They examined diversification opportunities among Artificial Intelligence, Robotics, crypto, and green bonds with equities. However, the discussion of the impact of the outbreak of pandemic is limited. The current study is the extension of tech-based assets that are FinTech, Artificial Intelligence, Robotics, and Blockchain with an extended discussion on the impact of the outbreak of COVID-19

Next, the H-step ahead generalized forecast error variance decomposition (GFEVD) is computed to show how a shock in one variable j affects another variable k:

$$\theta_{jk}^{g}(H) = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H-1} \left(v_j' d_s \sum v_k \right)^2}{\sum_{h=0}^{H-1} \left(v_j' d_s \sum v_k \right)} \tag{7}$$

Equation (7), $\theta_{jk}^{g}(H)$ shows the role of the kth variable to the variance of forecast error of the variable jth to horizon H, $\sum$ explains the variance matrix of the vector of errors, σ_{kk} represents the kth diagonal element of the $\sum$ matrix and v_j represents a vector of value 1 for the ith element and 0 otherwise. Afterward, the variance decomposition matrix is normalized using the following expression:

$$\theta_{jk}^{\sim g}(H) = \frac{\theta_{jk}^{g}(H)}{\sum_{k=1}^{N} \theta_{jk}^{g}(H)} \tag{8}$$

In the next step, GFEVD is used to formulate four estimates of connectedness at each quantile. The quantile total spillover index (Q_{TSI}) is computed as:

$$Q_{TSI} = \frac{\sum_{j=1}^{N} \sum_{k=1,j\neq k}^{N} \tilde{\theta}_{jk}^{g}(\tau)}{\sum_{j=1}^{N} \sum_{k=1}^{N} \tilde{\theta}_{jk}^{g}(\tau)} \times 100 \tag{9}$$

Quantile directional spillover index ($QDSI$) from asset j to assets k (represented by TO) is:

$$QDSI_{j\to k} \frac{\sum_{j=1,j\neq k}^{N} \tilde{\theta}_{jk}^{g}(\tau)}{\sum_{j=1}^{N} \tilde{\theta}_{jk}^{g}(\tau)} \times 100 = TO \tag{10}$$

Quantile directional spillover index ($QDSI$) from asset k to assets j (represented by FROM) is:

$$QDSI_{j\leftarrow k} = \frac{\sum_{j=1,j\neq k}^{N} \tilde{\theta}_{kj}^{g}(\tau)}{\sum_{j=1}^{N} \tilde{\theta}_{kj}^{g}(\tau)} \times 100 = FROM \tag{11}$$

The net quantile spillover index (N_{QSI}) is:

$$NQSI = QDSI_{j\to k} - QDSI_{j\leftarrow k} \tag{12}$$

4 Empirical discussion

4.1 Data and preliminary analysis

In the study, we are identifying the diversification opportunities among technology funds that are based on Artificial Intelligence, Blockchain, FinTech, and Robotics and emerging markets from 11th March 2019 to 11th March 2021. The study has considered five nonconventional-tech based funds that are: ARK FinTech Innovation ETF (ARKF), Global X FinTech ETF (FINX), First Trust NASDAQ Artificial Intelligence and Robotics ETF (ROBT), Global X Robotics & Artificial Intelligence (BOTZ), and ishares Robotics and Artificial Intelligence (IRBO). The MSCI Emerging Markets Index is a proxy of emerging markets. Furthermore, to study the impact of the outbreak of COVID-19 on technology funds, the data is divided into two sub-windows that are pre-outbreak of COVID-19 (from 11th March 2019 to 11th March 2020)[1] and post-outbreak of COVID-19 (from 12th March 2020 to 11th March 2021). The daily closing price data of select indices has been fetched from www.investing.com.

The empirical analysis starts from the preliminary analysis, visualization of the charts, and descriptive analysis. Figure 1 captures the visualization of prices and returns of tech-based funds and the MSCI Emerging Markets Index from 11/03/2019 to 11/03/2021.

The figures captured a sharp decline in the prices of all asset classes due to the outbreak of COVID-19. However, the negative impact was sharp with short duration, followed by a quick recovery, the inferences are aligned with the studies of Harjoto et al. [20], Chemka et al. [9], Disli et al. [12], Guo et al. [19], and Le et al. [26]. The price patterns are almost similar across all tech funds, but the MSCI Emerging Markets Index is a relatively different set of patterns. The volatility of returns has also increased in the post-pandemic period, and it persists more in ARKF and IRBO, whereas the rest had shown the same patterns of volatilities. The leverage effects have also been captured in the returns of the select asset class. It means the negative spikes are more volatile than the positive, and during the period of crisis, the leverage effect has increased compared to during the non-pandemic period.

Table 2 shows the descriptive statistics of the returns of the asset class. The maximum average returns are shown by ARKF (20%), followed by IRBO (13%), then 11% returns fetched by BOTZ, FINX, and ROBT. MSCI Emerging Markets Index provides an average yield of 6%. Across the asset class, all mean returns are less than median returns, thus the skewness is negative ranging from − 1.65 to − 0.85. The negative skewness provides evidence of the probability of getting negative returns. Kurtosis is more than the threshold level ranging from 10.35 to 16.08, showing the distribution is leptokurtic, and thus investors perceive the assets are volatile. The normality of returns is addressed by JB-Test, providing significant evidence that the returns varied from normality. However, the ADF-Test, test of stationarity reflects that the returns are stationary, the mean and variance are constant over time, and thus the returns series are suitable for further analysis.

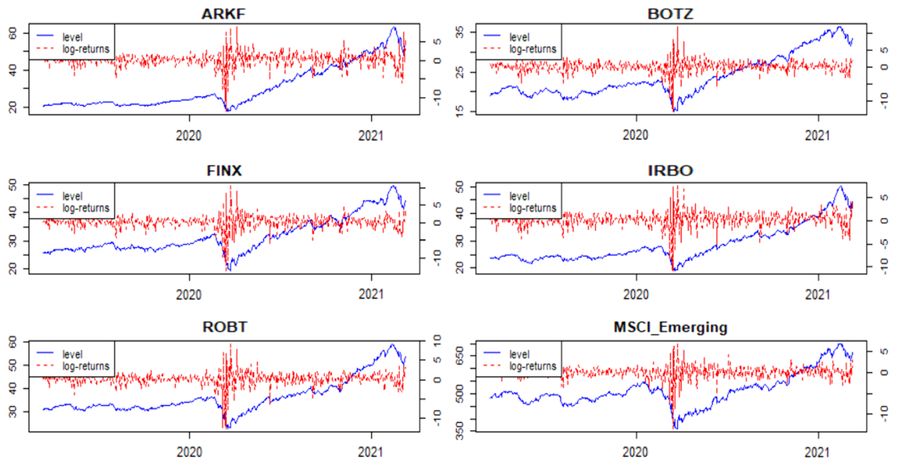

Fig. 1 Time series plots of closing prices and returns of ARKSM, BOTZ, FINX, IRBO, ROBT, and MSCI Emerging Markets Index. *Note* Closing Prices (in Blue) and Log transformed returns (in Red) of select Tech-based assets i.e. ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics and Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets Index from 11th March 2019 to 11th March 2021

Figure 2 Capturing the unconditional correlation between Technology-based funds and MSCI Emerging Markets Index. The results showed that tech-based funds correlation is significant at a 1% level, with the MSCI Emerging Markets Index ranging from 0.86 to 0.81. The maximum correlation was found with IRBO, followed by ROBT, then by BOTZ, and the most minor correlated assets are ARKF and FINX.

Figure 3. showed the pairwise correlations network analysis among tech-based funds and MSCI Emerging Markets Index. The two clusters captured, first is among MSCI Emerging Markets Index, RBOT, and ARKF, and the second is among RBOT, BOTZ, and FINX. The formation of clusters showed correlation magnitude based on the absolute values of correlations. The proximity or closeness of the variables reflects the overall magnitude of the correlation between the two variables.

Figure 4 provides the visualization of partial contemporaneous correlations and partial causal correlations. The results of partial contemporaneous correlations are in the consensus of the above plot. The partial directed/causal correlations captured, the significant negative causality from MSCI Emerging Markets Index to ARKF, and mild negative causality to FINX. The previous results showed that both were the least correlated, and with the results of partial causal correlation, the negative relations were established. Henceforth, it provides evidence of diversification and hedging opportunities. The results of diversification with tech-based assets are in consensus with the study done by Bouri et al. [7], Hyunh et al. [21], and not by Jiang et al. [23] and Le et al. [26, 27].

Table 2 Results of descriptive statistics

	Mean	Median	Max	Min	Std Dev	Skewness	Kurtosis	Jarque–Bera	ADF-Test
ARKF	0.20	0.32	9.01	– 13.64	2.09	– 0.97	10.35	1202.80***	– 7.93***
BOTZ	0.11	0.22	12.02	– 13.25	1.96	– 0.85	14.43	2773.90***	– 8.56***
FINX	0.11	0.24	10.58	– 13.74	2.07	– 1.06	12.94	2147.30***	– 7.99***
IRBO	0.13	0.25	7.46	– 10.78	1.76	– 1.13	10.82	1377.60***	– 7.88***
ROBT	0.11	0.19	9.21	– 12.62	1.87	– 1.50	15.97	3683.40***	– 7.94***
MSCI_ Emerging	0.06	0.20	6.91	– 13.43	1.67	– 1.65	16.08	3784.60***	– 7.91***

Captures descriptive statistics of the Log transformed returns of select Tech-based assets i.e., ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics and Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets Index. Max, Min, SD, Skew, Kurt, and ADF-Test represent maximum, minimum, standard deviation, skewness, kurtosis, and Augmented Dickey-Fuller test, respectively

***Indicates significance at 1%

4.2 Empirical results and discussion

4.2.1 Time-varying dynamic spillover using the VAR model for average, low, and high volatilities quantiles

The findings presented in Tables 3, 4, and 5 demonstrate the time-varying dynamic

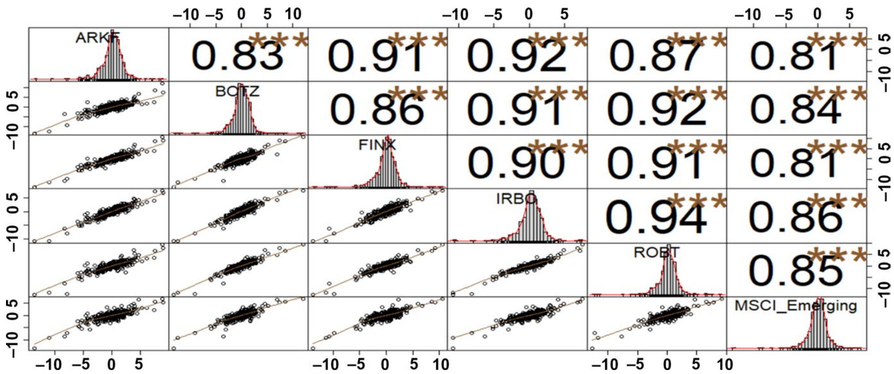

Fig. 2 Plots of the distribution and the pair-wise correlations of ARKF, BOTZ, FINX, IRBO, ROBT, and MSCI Emerging Markets Index. *Note* Captures Karl Pearson's coefficient of correlation among the Log transformed returns of select Tech-based assets, i.e., ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics and Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets Index. ***Indicates significance at 1%

spillover using the VAR model for the average volatility (50th), extremely low volatility (5th), and extremely high volatility (95th) quantiles. Sequentially we have examined the pattern of time-varying volatilities.

Table 3 provides the results of time-varying connectedness in the average volatility quantile. The result shows the total connectedness index (TCI) is 79.2%. It means that the system is well integrated. The 20.8% is idiosyncratic shock derived from others, out side the system. The standalone spillover was captured diagonally. We found that tech-based funds' volatilities range from 19.7 to 20.8%, the maximum volatility captured in MSCI Emerging Markets Index. MSCI Emerging Markets Index contributes the maximum to the volatilities of BOTZ (14.5%) and contributes the least to the volatilities of ARKF (13.7%) and FINX (13.7%). Henceforth both tech-driven funds are providing diversification opportunities with MSCI Emerging Markets Index. The results are in the consensus of the previous studies done by Bouri et al. [7], and Hyunh et al. [21], and not by Jiang et al. [23] and Le et al. [27]. However, the funds contributing least to the volatility of the MSCI Emerging Markets Index are ARKF (14.4%), followed by FINX (15.1%). The results further strengthen the previous evidence. The least contributing/transmitter tech fund in the overall market is ARKF (76.9%), followed by BOTZ (77.8%) and FINX (80.2%). However, the asset class receiving maximum volatilities from others within the system are IRBO (80.3%) and ARKF (79.2%), whereas BOTZ (79.2%) and FINX (79.3%) are the most miniature volatilities receivers. Finally, ARKF and BOTZ are net receivers, whereas FINX, IRBO, and ROBT are net transmitters.

Figure 5. captures the total dynamic volatility spillover in the average quantile VAR. The results perceived the impact of the outbreak of COVID-19 on the connectedness of the assets in the sample. The volatilities have increased significantly after the outbreak of COVID-19. The total volatility connectedness before the outbreak of CIVID-19 ranged from 80 to 83%. However, during the post-outbreak of COVID-19, the connectedness ranges from 76 to 88%. Gradually, the volatility reduces. The results are in consensus with Chemka et al. [9], Disli et al. [12], Guo et al. [19], and Le et al. [26].

Table 4 provides the results of time-varying connectedness in low volatility quantile. The result shows the total connectedness index (TCI) is 82%. It means that the system is well integrated, and 18% is the idiosyncratic shock from others. Among tech-based funds, ARKF (18.2%) is the most volatile, followed by BOTZ (17.9%) and FINX (17.9%). The results of low volatilities depart from the average quantile volatilities. MSCI Emerging Markets Index contributes the maximum to the volatilities of BOTZ (16%) and FINX (16%) and least in the volatilities of ARKF (15.6%). The result regarding the maximum contribution of the MSCI Emerging Markets Index does not agree with the previous results. However, the funds contributing to the volatilities of the MSCI Emerging Market Index, again ARKF (16%), followed by FINX (16.2%), are the least contributing funds. The results further strengthen the inferences drawn from average quantile time-varying volatilities. ARKF (81.5%), followed by FINX (82%), and BOTZ (82%) are the least contributing tech funds in the volatilities of the others in the system. The results are in consensus with the previous. However, the asset class receiving the least volatilities from others within the system is ARKF (81.8%), followed by BOTZ (82.1%), and FINX (82.1%) are

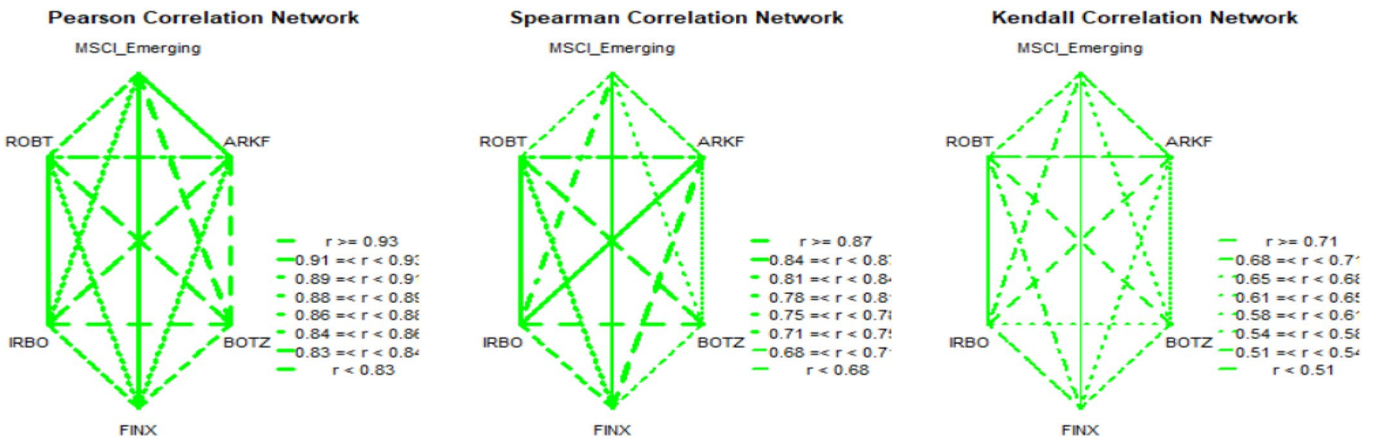

Fig. 3 A network analysis of the pairwise correlations among ARKSM, BOTZ, FINX, IRBO, ROBT, and MSCI Emerging Markets. *Note* Network analysis of the pairwise correlations, and the partial contemporaneous and partial directed correlations among ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics and Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets Index

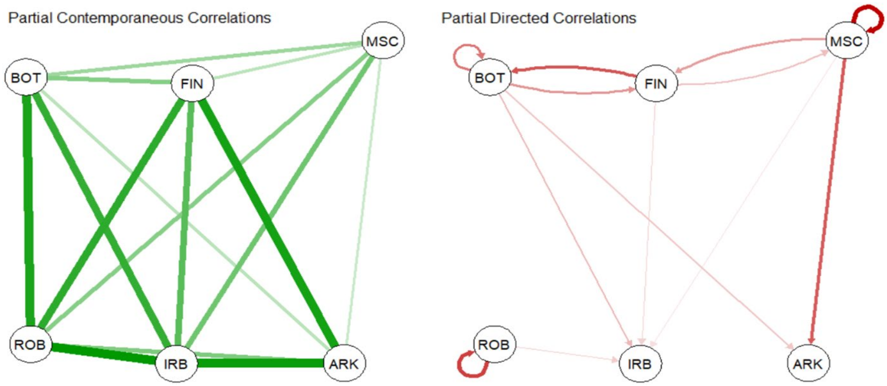

Fig. 4 Plots of the partial contemporaneous and partial directed correlations. *Note* Network analysis of the pairwise correlations, and the partial contemporaneous and partial directed correlations among ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics and Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets

Table 3 Static spillover dynamics at Q = 0.5

	ARKF	BOTZ	FINX	IRBO	ROBT	MSCI_Emerging	FROM
ARKF	20.8	14.5	17.2	17.8	15.9	13.7	79.2
BOTZ	14.4	20.8	15.6	17.1	17.6	14.5	79.2
FINX	16.8	15.2	20.7	16.5	17.1	13.7	79.3
IRBO	16.5	16.1	15.8	19.7	17.5	14.4	80.3
ROBT	14.8	16.6	16.6	17.6	20.1	14.2	79.9
MSCI_Emerging	14.4	15.5	15.1	16.4	16.2	22.5	77.5
Contribution To others	76.9	77.8	80.2	85.5	84.3	70.7	475.4
NET directional connectedness	−2.3	−1.4	0.9	5.1	4.4	−6.8	TCI = 79.2

Shows Static Spillover Dynamics connectedness at 50th quantile among ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics and Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets

the least volatilities receivers. Finally, ARKF, BOTZ, and FINX are net receivers, whereas IRBO, and ROBT are net transmitters. The results consistently provide evidence of diversification with ARKF and FINX. The results of diversification of the stock market with tech-based assets are in consensus with Bouri et al. [7] and Hyunh et al. [21], and not with Jiang et al. [23] and Le et al. [27].

Figure 6 shows the total dynamic volatility spillover in the lowest quantile VAR. The visibility of high connectedness among asset classes has been captured significantly during the post-outbreak of COVID-19. The results perceived the impact of the outbreak of COVID-19 on the total connectedness of the assets in the sample, is in consensus with the average quantile. The total connectedness index varied before

Table 4 Static spillover dynamics at Q = 0.05

	ARKF	BOTZ	FINX	IRBO	ROBT	MSCI_Emerging	FROM
ARKF	18.2	16.1	16.7	17	16.4	15.6	81.8
BOTZ	16	17.9	16.4	16.8	16.9	16	82.1
FINX	16.5	16.4	17.9	16.5	16.6	16	82.1
IRBO	16.7	16.6	16.3	17.7	16.9	15.9	82.3
ROBT	16.2	16.7	16.4	17	17.7	15.9	82.3
MSCI_Emerging	16	16.3	16.2	16.5	16.5	18.5	81.5
Contribution TO Others	81.5	82	82	83.9	83.3	79.4	492.1
NET directional Connectedness	−0.3	−0.1	−0.1	1.6	1	−2.2	TCI
NPDC transmitter	1	2	3	5	4	0	82

Shows Static Spillover Dynamics connectedness at 5th quantile among ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics and Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets

Table 5 Static spillover dynamics at Q = 0.95

	ARKF	BOTZ	FINX	IRBO	ROBT	MSCI_Emerging	FROM
ARKF	18.2	15.9	16.7	17.2	16.5	15.5	81.8
BOTZ	15.8	18	16.4	16.8	17.2	15.7	82
FINX	16.8	16.1	18.1	16.6	17	15.4	81.9
IRBO	16.8	16.5	16.3	17.8	17	15.7	82.2
ROBT	16.1	16.6	16.6	17	18	15.6	82
MSCI_Emerging	15.7	16.3	15.9	16.5	16.5	19.1	80.9
Contribution To others	81.3	81.4	82	84.1	84.2	77.8	490.8
NET directional connectedness	−0.6	−0.6	0.1	2	2.2	−3.1	TCI
NPDC transmitter	2	2	2	5	4	0	“81.8”

Static Spillover Dynamics connectedness at 95th quantile among ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics and Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets

the outbreak of COVID-19 from 73 to 77%, and post COVID-19 index from 70 to 82%. The figure captures that after the outbreak of COVID-19, the overall connectedness has increased sharply, and gradually it was reduced. The results are in consensus with studies were done by Harjoto et al. [20], Chemka et al. [9], Disli et al. [12], Guo et al. [19] and Le et al. [26].

In Table 5, TCI is 81.8%, the most volatile quantile in time-varying connectedness. It means 18.2% of idiosyncratic shock received from others that are outside the system. The highest volatile funds are ARKF and FINX. The MSCI Emerging Markets Index contribute maximum to the volatilities of IRBO (15.7%) and BOTZ (15.7%) and least contributing to the volatilities of FINX (15.4%) and followed by

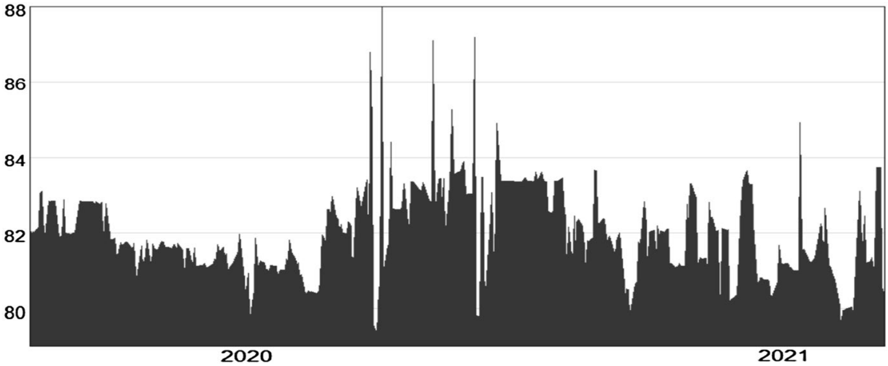

Fig. 5 Dynamic volatility spillover in the quantile VAR (median quantile Tau = 0.5). *Note* This Figure shows the rolling-window version of total volatility connectedness at the 50th quantile among ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics and Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets

ARKF (15.5%). However, the least contributing funds in the volatilities of the MSCI Emerging Markets Index are ARKF (81.3%), followed by BOTZ (81.4%) and then by FINX (82%). ARKF and FINX provide diversification opportunities consistently with MSCI Emerging Markets Index and some evidence captured with BOTZ. The results of diversification with tech-based assets are in consensus with Bouri et al. [7] and Hyunh et al. [21], and not with Jiang et al. [23] and, Le et al. [27]. The ARKF (-0.6) and BOTZ (−0.6) are net receivers, whereas the rest are net transmitters. Among tech-based funds, the overall least contributing fund is ARKF (81.3%), followed by BOTZ (81.4%) and FINX (82%). The least volatilities receiver fund from the system are ARKF (81.8%), followed by FINX (81.9%), and then BOTZ (82%).

Figure 7 shows increased volatility during the post-outbreak of COVID-19. Before COVID-19, it ranges from 77 to 81%, whereas post-COVID-19 ranges from approx. 76–87.5%. The results throughout the average, low and high quantiles are consistent. The results are in agreement with the previous studies were done by Harjoto et al. [20], Chemka et al. [9], Disli et al. [12], Guo et al. [19] and Le et al. [26].

4.2.2 Network pairwise directional spillover in average, low, and high quantiles

After the discussion on dynamic connectedness, next, the network diagrams of pairwise directional spillover in Figs. 8, 9, and 10 in average, low, and high quantiles, respectively. Figure 8A portrays the network of volatility connectedness based on average quantile VAR. The results show that the MSCI Emerging Markets Index is connected with IRBO and ROBT, whereas less connected with ARKF, FINX, and BOTZ. However, in the volatility spillover based on lower quantiles VAR, the network connectedness with ARKF, and BOTZ are significant. Interestingly, the risk spillover in extreme high quantile where a strong network connectedness captured with IRBO, ROBT, and BOTZ and comparatively less connected with FINX.ARKF

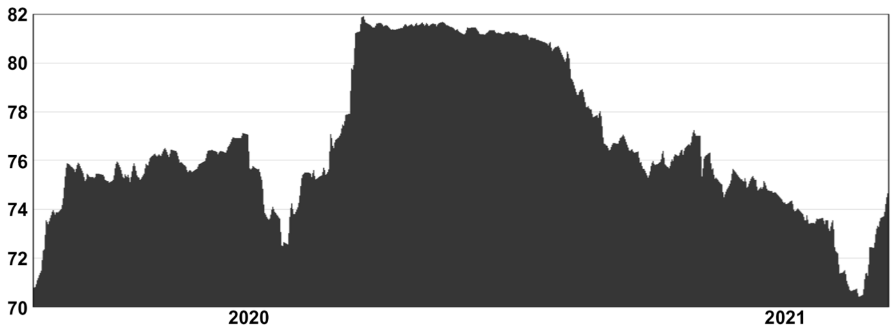

Fig. 6 Dynamic volatility spillover in the quantile VAR (extreme low quantile Tau = 0.05). *Note* This Figure shows the rolling-window version of total volatility connectedness at the 5th quantile among ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics & Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets Index

is the most resilient during high volatilities. Henceforth, ARKF is less connected throughout with MSCI Emerging Markets Index, followed by FINX and BOTZ. The results of diversification with tech-based assets are in consensus with Bouri et al. [7] and Hyunh et al. [21], and not with Jiang et al. [23] and Le et al. [27].

4.2.3 Volatility spillovers, connectedness, and TSI before and after the outbreak of COVID-19

Figures 11 and 12 captured the volatility spillovers based on average, lowest and highest quantile VAR and partial contemporaneous and partial directed correlations, respectively, subdivided into two samples pre-and post-outbreak of COVID-19. Figure 11 volatility spillovers in median quantile, during pre-outbreak of COVID-19, MSCI Emerging Markets Index is less connected with FINX and BOTZ and during post-outbreak of COVID-19, less connected with ARKF, FINX, and BOTZ. In the lowest quantile and during pre-COVID-19, MSCI Emerging Markets Index least connected with FINX only, and during post-outbreak of COVID-19, MSCI was less connected with ARKF, FINX, and BOTZ. In the extreme high quantile and pre-pandemic, the MSCI Emerging Markets Index is highly connected with ROBT and IRBO and less comparatively connected with ARK, BOTZ, and FINX. However, in extreme high quantile and post-outbreak of COVID-19, less connected with ARKF followed by FINX and BOTZ and directly connected with ROBT and IRBO. Thus, it has been concluded that ROBT and IRBO are not providing diversification with MSCI Emerging Markets Index in both pre-and post-outbreak of COVID-19. Whereas FINX is resilient, and ARKF has shown its resilience during extreme volatile quantiles. The results strengthen the previous results of diversification.

Furthermore, Fig. 12 plots the partial contemporaneous and partial directed correlations during the pre and post-outbreak of COVID-19. Again, it strengthens

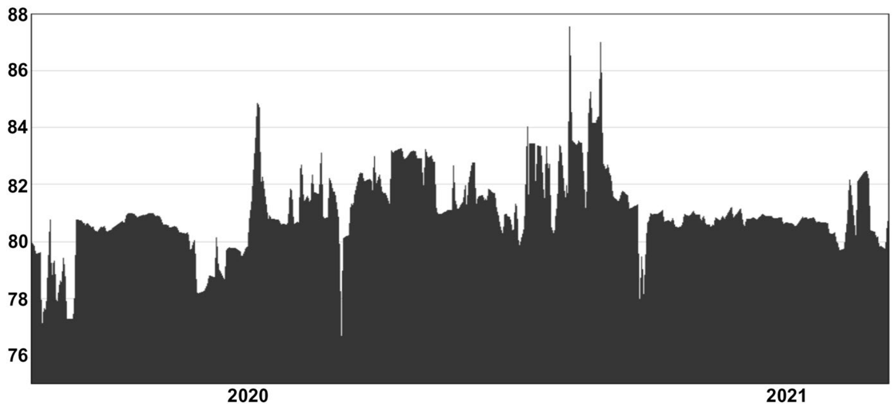

Fig. 7 Dynamic volatility spillover in the quantile VAR (extreme high quantile Tau = 0.95). *Note* This Figure shows the rolling-window version of total volatility connectedness at the 95th quantile among ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics and Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets Index

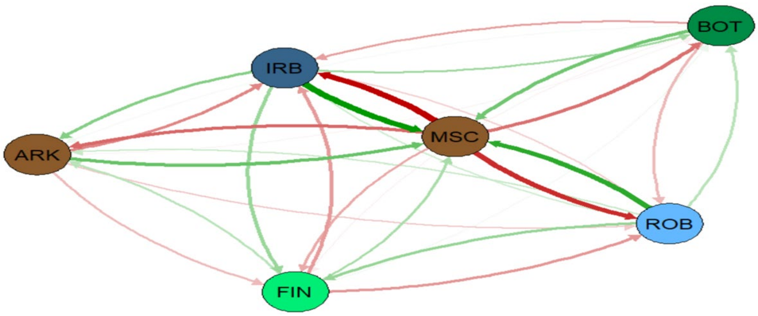

Fig. 8 Volatility spillovers based on quantile VAR (Median Tau = 0.5): The network of volatility connectedness. *Note* The network volatility connectedness among ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics and Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets Index based on quantile VAR (Median Tau = 0.5), quantile VAR (Low Tau = 0.05), and quantile VAR (High Tau = 0.95) respectively

the previous results, and we found that MSCI Emerging Market Index is least correlated with ARKF and FINX during pre and post-outbreak of COVID-19, and thus found the most resilient funds. Henceforth, the investors looking for emerging markets can put their funds in these two tech-based funds. The results of diversification with tech-based assets are in consensus with Bouri et al. [7] and Hyunh et al. [21], and not with Jiang et al. [23] and Le et al. [27].

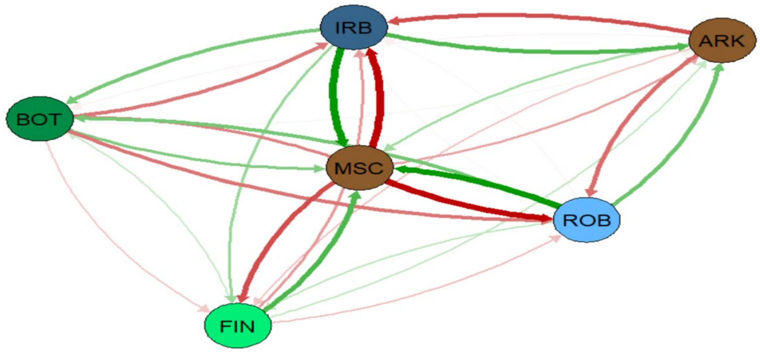

Fig. 9 Volatility spillovers based on quantile VAR (Low Tau = 0.05): The network of volatility connectedness. *Note* The network volatility connectedness among ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics & Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets Index based on quantile VAR (Median Tau = 0.5), quantile VAR (Low Tau = 0.05), and quantile VAR (High Tau = 0.95) respectively

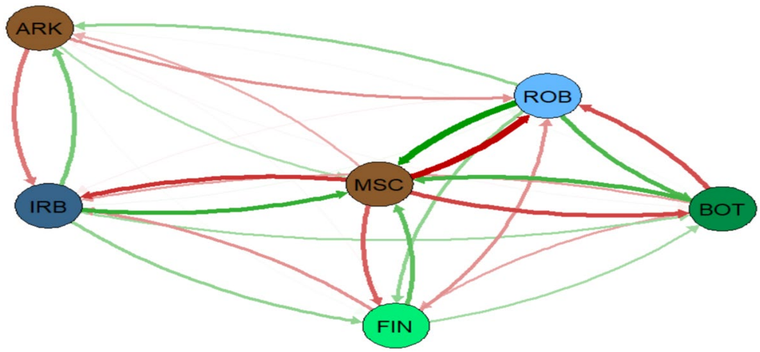

Fig. 10 Volatility spillovers based on quantile VAR (High Tau = 0.95): the network of volatility connectedness. *Note* The network volatility connectedness among ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics & Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets Index based on quantile VAR (Median Tau = 0.5), quantile VAR (Low Tau = 0.05), and quantile VAR (High Tau = 0.95) respectively

5 Conclusion and policy implications

The study identifies the diversification opportunities in the era of the 4th Industrial revolution among Technology-based funds dedicated to Blockchain, FinTech, and AI during the pre-and post-outbreak of COVID-19. The study has innovated methodologically in the literature on diversification with Tech-based funds by employing Time-Varying Dynamic spillover using the VAR Model for average, low, and high volatilities quantiles and the volatility connectedness-based

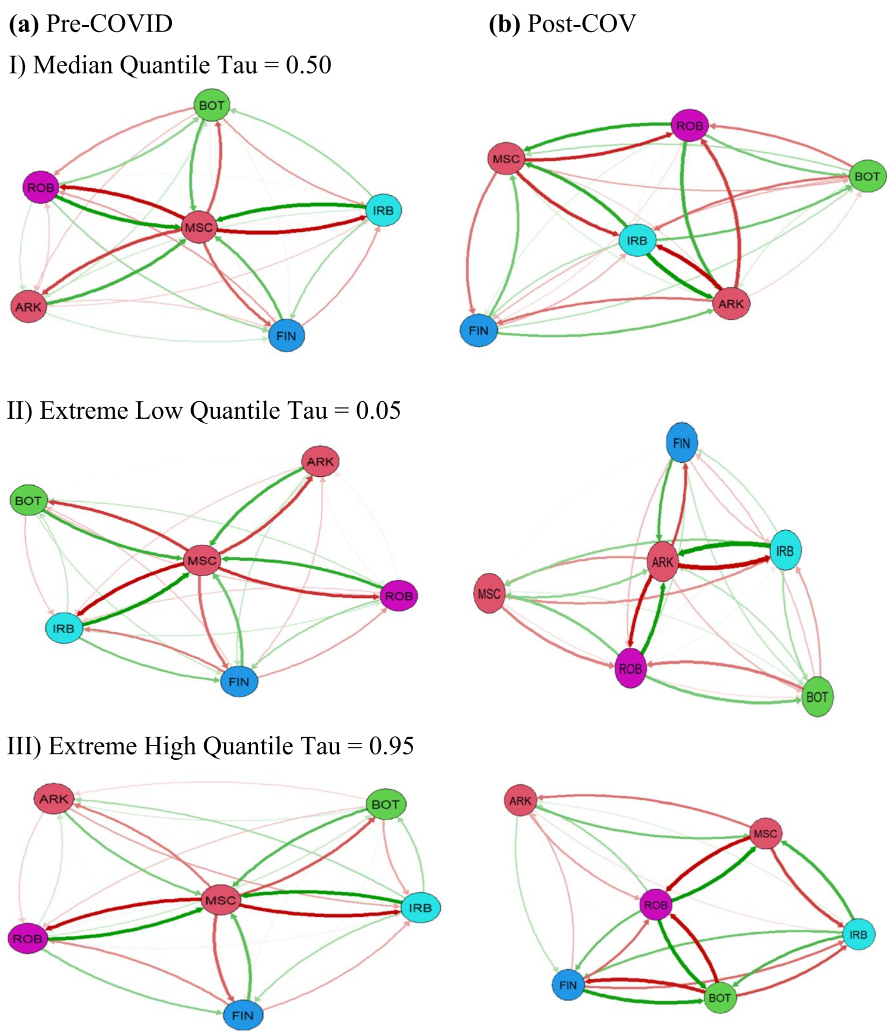

Fig. 11 Volatility spillovers based on quantile VAR—sub-sample analysis. *Note* Segregated into two sub-windows i.e. pre-Outbreak of COVID-19 (11th March 2019 to 11th March 2020) and post-outbreak of COVID-19 (from 12th March 2020 to 11th March 2021) and shows the network volatility connectedness among ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics and Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets Index based on quantile VAR (median Tau = 0.5), quantile VAR (Low Tau = 0.05), and quantile VAR (High Tau = 0.95) respectively

network on quantile VAR. The preliminary analysis captures a sharp decline in the prices of all asset classes due to the outbreak of COVID-19. However, the negative impact is strong and captured the quick recovery; the result is in consensus with the studies done by Harjoto et al. [20], Chemka et al. [9], Disli et al. [12], Guo et al. [19], and Le et al. [26]. We have found that technology-based

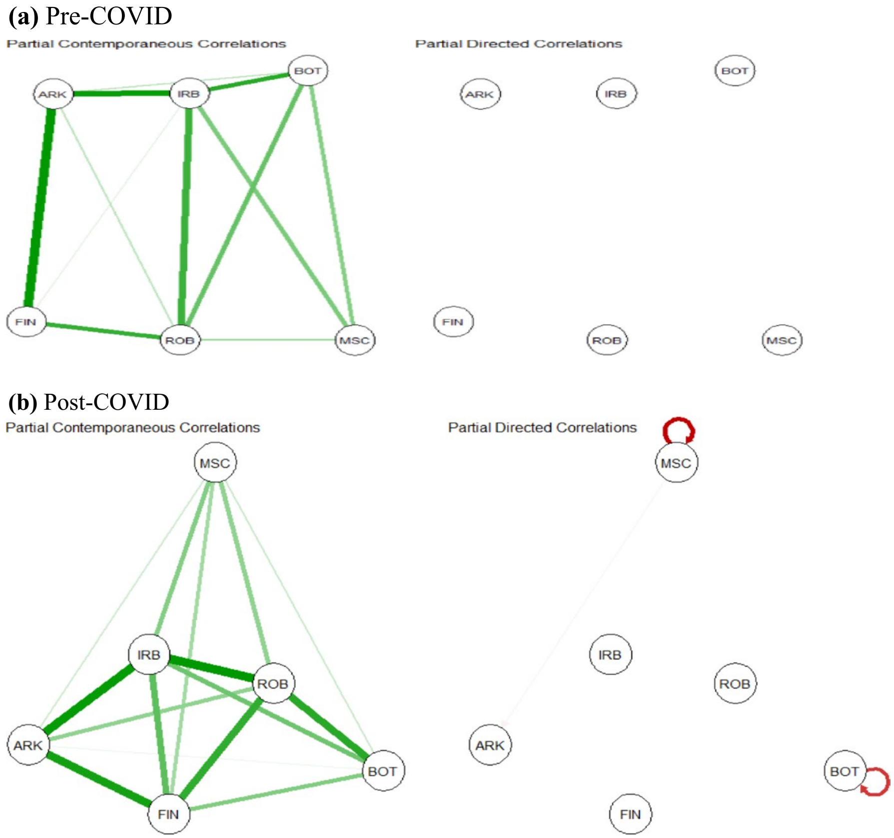

Fig. 12 Plots of the partial contemporaneous and partial directed correlations—sub-sample analysis. *Note* Segregated into two sub-windows i.e. Pre-Outbreak of COVID-19 (11th March 2019 to 11th March 2020) and post-outbreak of COVID-19 (from 12th March 2020 to 11th March 2021), and shows the partial contemporaneous and partial directed correlations among ARK Fintech Innovation Exchange Traded Funds (ARKF), Global X Robotics and Artificial Intelligence (BOTZ), Global X FinTech Exchange Traded Funds (FINX), ishares Robotics, and Artificial Intelligence (IRBO), First Trust NASDAQ Artificial Intelligence and Robotics Exchange Traded Funds (ROBT), and MSCI Emerging Markets Index

funds are outperforming. In the results of unconditional correlation, we have captured the maximum correlation found with IRBO, followed by ROBT, then by BOTZ, and the low correlated assets are ARKF and FINX. The results of partial directed/causal correlations are found to have negative and significant causality from MSCI Emerging Markets Index to ARKF and mild negative causality to FINX. The results of time-varying dynamic spillover using the VAR Model for average, low, and high volatilities quantiles, explain that ARKF and FINX provide diversification opportunities. In each quantile, these two funds are suitable for diversification, and BOTZ is also showing diversification evidence. FINX is resilient throughout, and ARKF is the most resilient in extreme quantiles.

In all quantiles, it has been perceived that there is a significant impact of COVID-19 on the total connectedness of funds with MSCI Emerging Markets Index. The results of network pairwise directional spillover in average, low, and high quantiles have also strengthened the previous results that ARKF is the throughout less connected with MSCI Emerging Markets Index, followed by FINX and BOTZ. The results of diversification with tech-based assets are in consensus with Bouri et al. [7], and Hyunh et al. [21], and not with Jiang et al. [23] and Le et al. [27].

Finally, to capture the impact of COVID-19 and identify the most resilient fund pre- and post-outbreak of COVID-19, we found a sharp decline in the prices of all asset classes due to the outbreak of COVID-19. However, the negative impact was significant and further captured the recovery, this inference is in consensus with the results of Harjoto et al. [20], Chemka et al. [9], Disli et al. [12], Guo et al. [19], and Le et al. [26]. The results of volatility spillovers based on average, lowest, and highest quantile VAR, the ARKF is less connected with MSCI Emerging Markets Index, followed by FINX and BOTZ. The partial contemporaneous and partial directed correlations during the pre-and post-outbreak of COVID-19 again strengthen the previous results. We found that the MSCI Emerging Market Index is low correlated with ARKF and FINX during the pre-and post-outbreak of COVID-19.

We found diversification opportunities for investors investing in emerging markets with technology-based funds . We captured MSCI Emerging Markets Index is least correlated with ARKF and FINX during the pre- and post-outbreak of COVID-19, and thus found the most resilient funds. Henceforth the investors investing in emerging markets and looking to make their portfolio with tech funds can put their funds in these two tech-based funds.

The technology-based diversification opportunities provide significant implications to emerging market policymakers. The diversification opportunities with the tech funds offer a greater probability of investments that assist the infusion of capital that reinforces growth. Past studies support that capital markets are closely linked to economic growth. Henceforth, these diversification opportunities lead to increase in emerging markets. The policy decision to endorse or promote investments in technology-based funds would help to promote economic growth.

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