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Time and frequency domain connectedness and spill-over among fintech, green bonds and cryptocurrencies in the age of the fourth industrial revolution



TN-Lan Le^{a,b,*}, Emmanuel Joel Aikins Abakah^c, Aviral Kumar Tiwari^d

^a The University of Sydney, Business School, Australia

^b University of Finance-Marketing, Vietnam

^c The University of Adelaide, Business School, Australia

^d Rajagiri Business School, Rajagiri Valley Campus, Kochi, India

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ABSTRACT

The study in the age of the 4th industrial revolution examines the time and frequency domain connectedness and spill-over among Fintech, green bonds, and cryptocurrencies. Using daily data from November 2018 to June 2020, we use both DY (Diebold & Yilmaz, 2012) and BK (Baruník et al., 2017) to examine the volatility connectedness of returns series. The results of DY suggest that, first, the total connectedness of 21st century technology assets and traditional common stocks is very high, and hence in the turbulent economy, there is a high probability of contemporaneous losses. Second, Bitcoin, MSCIW, MSCI US, and KFTX are net contributors of volatility shocks whereas US dollar, oil, gold, VIX, green bond and green bond select are net receivers. Therefore, Fintech and common equities are not good hedging instruments in the same portfolio. Third, the short-term witnesses higher volatility transmission than the long-term. That is, holding assets for a long-term is likely to mitigate risks whereas trading financial assets in the short-term can increase risk because of higher volatility. Fourth, the traditional assets, gold and oil, as well as modern assets, green bonds, are useful as good hedgers compared with other assets because shock transmissions from them to Fintech, KFTX are below 0.1% and, more importantly, the total volatility spill-over of all assets in the sample is moderately average, accounting for 44.39%.

1. Introduction

The integration of international financial markets and synchronization of business cycles are now fundamentals for the market turbulence and spillover (Nasir and Du 2018; Rejeb and Arfaoui 2016). The global financial crisis of 2008 enhanced seemingly uncorrelated financial markets and therefore emphasized the importance of portfolio diversification. Simultaneously, the benefits from a risk-return trade-off through international diversification of portfolios compensates if investing in assets with low correlations. However, globalization has induced a significant increase in spill-overs and the volatility range of markets and, therefore, in a major financial market, traditional assets (gold, oil, equity indexes) have become highly correlated with green bonds, or with 21st century assets (Fintech and bitcoin), and with assets in the age of the 4th industrial revolution. The emergence of FinTech companies, green bonds associated with environmentally friendly projects, and the leading product of cryptocurrency provide more

investment strategies combined with traditional strategies such as gold as a safe-haven asset in the times of market turmoil (Baur and Lucey 2010; Shahzad et al., 2019).

The term "FinTech", which is the short form of the phrase *Financial Technology*, denotes companies, or representatives of companies, that combine financial services with modern, innovative technologies. As a rule, new market participants offer Internet-based and application-oriented products. FinTech generally aims to attract customers with products and services that are more user-friendly, efficient, transparent, and automated. In addition to offering products and services in the banking sector, there are FinTech that distribute insurance and other financial instruments or provide third-party services. In a generous sense, the term "FinTech" encompasses companies that simply provide technology (such as software solutions) to financial service providers. As markets emerged from the 2008 global financial crisis, many customers had lost faith in traditional financial services. The customers realized that traditional banking and financial services can engender

* Corresponding author.

E-mail addresses: lan.le@sydney.edu.au (T.-L. Le), emmanuel.abakah@adelaide.edu.au (E.J.A. Abakah).

systematic risk. Since then, many Fintech companies have been re-designing the financial services industry, offering customer-centric services capable of combining speed and flexibility, backed by forward-looking strategies, and cutting-edge business models. Highly developed FinTech firms also initiated multiple interconnections between Fintech and other financial indexes because of the similarity of their market segments and businesses (Dorfleitner et al., 2017; Kommel et al., 2018; Yao et al., 2018), and there were more investments into Fintech firms from traditional financial institutions (Lee and Shin 2017). FinTech has brought new opportunities and challenges to the traditional industry and, as a result, the relationship between innovative and traditional financial markets is worth studying.

A recently emerged financial asset also has a part in a diversified portfolio because of its uniquely mixed characteristics of financial resources and environmental protection. Green bonds, although they comprise similar features to conventional fixed-income corporate bonds, they gain their earnings through only environmentally friendly projects (Reboredo and Ugolini 2020). Green bonds have become increasingly popular because they are recognized as an appropriate financial instrument for the transition to a low-carbon economy (Monasterolo and Raberto 2018). Moreover, green bonds contribute to improved financial performance together with environmental performance by enhancing green innovations and long-term green investments (Flammer 2018). Governments have standardized global rules for green bonds, e.g., the Green Bond Principles (GBP) set by the International Capital Markets Association (ICMA). Consequently, green bonds have been attractive to issuers and investors as a distinct financial instrument in stock markets around the world, making green bonds a sustainable, well-established investment instrument (Febi et al., 2018).

In turbulent, uncertain markets, the cryptocurrency bitcoin or “digital gold” has gained amazing popularity (Abakah et al., 2020; Barber et al., 2012; Dyhrberg 2016a) because of its potential hedging and safe haven role and, therefore, it has posed challenges and opportunities for policy makers since its establishment (Nakamoto 2008). As financial innovation in the 4th industrial revolution, the blockchain technology has been heralded as a great financial disruptor (White et al., 2020). Consequently, bitcoin brings more diversification possibilities (Briere et al., 2015) and arbitrage opportunities (Gandal and Halaburda 2014). Therefore bitcoin can be added to diversified portfolios in conjunction with gold and other rational financial assets to minimize risk. The cryptocurrency market has accumulated an enormous market capitalization increase from \$10 to \$80 billion US dollar from October 2016 to October 2017 with thousands of various cryptocurrencies (Corbet et al., 2019). However, the role of cryptocurrencies is still ambiguous in financial markets because they can be classified as technology-based products, securities, or a financial bubble (White et al., 2020), or they may more resemble an asset or speculative investment than a currency (Gronwald 2019).

Contextualizing this debate, this study analyses the connectedness between Fintech and cryptocurrencies, new instruments 21st century technology and alternative assets, such as green bonds, using multiple approaches. First, daily data on the KBW NASDAQ The Technology Index (KFTX) is the first part of the study that specifically uses the role of the financial technology index for portfolio diversification. KFTX was created in July 2016 to track the performance of financial technology companies that are publicly traded in the U.S. Hence, this proxy represents the performance of an asset in the 4th industrial revolution. Previous empirical studies have examined only the interdependence of technology intensive firms, oil prices, and clean energy (Nasreen et al., 2020), risk and return of technology firms (Ortas and Moneva, 2013), or technology-based firms in general (Kumar et al., 2012). This study focuses on the dynamic interdependence with other assets, bitcoin and green, both of which are rapidly gaining high attention from recent researchers (Corbet et al., 2019; Dyhrberg 2016a; Febi et al., 2018; Gandal and Halaburda 2014; Monasterolo and Raberto 2018; Pham 2016; Reboredo and Ugolini 2020; Selmi et al., 2018).

This study analyses highly correlated markets in short- and long-run volatility spill overs following the approach of Elsayed et al., (2020); Tiwari et al., (2020); Tiwari et al., (2020) and Tiwari et al., (2020). Giving that findings of prior studies investigating the association between different markets such as equities, commodities, bonds, and other financial asset classes are, in general, mixed and quite ambiguous because of the use of different methodologies based on different assumptions and analysis of different time scales (Ewing and Malik, 2017; Corbet et al., 2019; Gil-Alana et al., 2020; Lucey and Li 2015; Ortas and Moneva 2013; Hachenberg and Schiereck 2018; Pham 2016), this study uses a time-series framework proposed as a methodology that comprises the estimation of DY (2012) and BK (2017) based spill over indices in a multivariate framework for various reasons. The frequency methods used in this study have significant advantages over the traditional linear and Granger causality test often used in prior studies when timescales under study are stationary. DY (2012) suggests a unified framework for measuring the spill over and dependencies. This method allows one to track the spill overs at all levels, from pairwise to system wide, in a coherent, mutually consistent way even though their insights are restricted to only the time domain. DY (2012) (Diebold and Yilmaz 2012) introduces a variance decomposition into the vector autoregression (VAR) model that focuses on computing the forecast error variance decomposition (FEVD) from a generalized vector auto-regression to examine connectedness. However, because of the limitations associated with the standard VAR estimator, we follow Baruník et al., (2017) and discuss the frequency dynamics of the connectedness among the variables in the component system and further describe the spectral formulation of the variance decomposing in a frequency domain. BK (2017) points out that the frequency dynamics are particularly insightful because they enable one to study the varying degree of persistence stemming from shocks with a heterogeneous frequency.

Our study contributes to the literature in two ways. First, it analyses spill overs between returns from FinTech, green bonds and cryptocurrencies, using the Diebold-Yilmaz (2012) approach in the time domain. This complements the studies mentioned above, by covering a different set of assets and times. Second, we analyze spill overs in the frequency domain, applying the recent Baruník and Křehlík (2017) methodology. This brings further insights into the time horizons at which different spill overs play. In particular, we show that constructing a portfolio comprising Fintech and equities is not prudent.

Our key finding from the DY spill over analysis is that the highest gross directional volatility comes from MSCIW contributing 10.3% to other markets, followed by over 9% for Bitcoin, MSCI US and KFTX. This finding implies that the total connectedness of the 21st century technology assets and traditional common stocks is very high. In other words, in a turbulent economy, and when the worst case happens, the 4th industrial age asset and traditional equities have a high probability of simultaneous significant losses and, therefore, stakeholders should consider when constructing a portfolio with these two sectors. Second, Bitcoin, MSCIW, MSCI US, and KFTX are net contributors to volatility shocks whereas U.S. Dollar, Oil, Gold, VIX, Green Bonds and Green Bond Select are net receivers, according to the results of the net pairwise volatility spill over. Third, the short-term witnesses higher volatility transmission than the long-run. That is, holding assets for a long time is likely to mitigate risks whereas trading financial assets in the short-term can increase risks because of higher volatility. Fourth, traditional assets, gold and oil, and modern assets, green bonds, are useful as good hedgers compared with other assets because the shock transmissions from them to the Fintech KFTX is at or below 0.1% and the total volatility spill overs of all assets in the sample is average, accounting for 44.39%, which implies a self-transmitting risk among the sampled assets. Fintech and common equities are not good hedging instruments in the same portfolio. The findings have the implications for the dynamic strategies of portfolio diversification in the 4th industrial revolution.

The remainder of the paper is as follows: Section 2 reviews the

literature. Section 3 presents the DY (2012) and BK (2017) models. Section 4 describes our data, and Section 5 discusses the empirical results. Section 6 presents the conclusion.

2. Literature review

The portfolio strategies of investors are correlated with the connectedness between financial assets and investors change them based on the connectedness framework evolving over time. In other words, different asset classes are likely to have cross-market influences, and this helps market participants have different hedging strategies. Among financial assets, gold has a dynamic linkage with the other important financial prices. Stated differently, gold price volatility has both direct and indirect impacts on number of assets. Ciner et al., (2013) provide evidence that gold can act as a safe-haven for equities, bonds, and currencies during turbulent times, such as the global financial crisis 2008–2009. Recently, Huynh et al., (2020) emphasized that gold may act as a safe haven, as its shock transmission to NASDAQ AI is just around 1.41%. Therefore, a general conclusion from the extensive literature confirms that gold is a good hedging tool and, thereby, plays a significant part in a diversified portfolio. However, the role of safe haven gold holds only for the short run (Baur and Lucey 2010); it is unlikely to be strongest safe haven for stocks compared with other precious metals such as palladium, silver, or platinum (Lucey and Li, 2015).

With regard to portfolio diversification between financial assets in the 4th industrial revolution, Fintech and cryptocurrencies, and the alternative investment, green bonds, the empirical literature is in three broad strands. The first strand is in terms of the stocks of Fintech and technology companies. Fintech has emerged as start-ups that offer an alternative source of financial services in terms of Fintech lenders that include equity crowdfunding, invoice and supply chain financing and marketplace lending. The app-based companies have brought more competition, more efficiencies and ultimately are more profitable (Forum 2015) to traditional financial services. Although the development of Fintech has evolved significantly post the global financial crisis of 2008, to the best of our knowledge, no prior study has examined the role of Fintech company stocks in portfolio diversification. Therefore, a closer look at extant stocks of technology-related companies reveals key issues that need research attention. For example, Ahmed and Alhadab (2020) indicate stocks of high-tech firms generate greater momentum returns for a sample of in U.S. stock, but Mason and Harrison (2004) confirm that the overall returns of technology firms are not different from those of non-technology firms for a sample of firms in the UK and European Union. High tech firms have experienced more volatility than low tech firms (Pastor and Veronesi, 2009). Stated differently, the new economy ‘high-tech’ stocks provide uncertainty of success and profitability thereby adding volatility to the price. One example is that high-tech NASDAQ stocks are more volatile than the overall stocks presented by the S&P index and, more importantly, the aggregate idiosyncratic volatility for NASDAQ firms is four times higher than that of NYSE/AMEX firms (Schwert 2002), and higher than those of overall equity markets (Jiang et al., 2011). The higher volatility of high-tech firms generates a complexity of innovation with many different stages therefore creating various sources of risk (Liu 2006). Overall, it is likely that the returns and volatility of Fintech companies and technology firms are relatively greater than those of non-technology firms.

Further, technology stocks have different effects across industries or sectors (Chen and Lin 2014; Chen and Wang 2019; Hansda and Ray, 2002; Jawadi et al., 2013; Kumar et al., 2012; Smales, 2019; Symitsi and Chalvatzis, 2018). For example, the spill over effects between different assets, such as oil, clean energy, and technology-based stocks, have gained popularity in recent studies (Ahmad 2017; Bondia et al., 2016; Kumar et al., 2012). In particular, Ahmad (2017) and Lundgren et al., (2018) discover the directional spill over between

technology stocks, crude oil, and clean energy. The former indicate that the volatility of technology stocks has a greater impact on alternative energy stock prices than crude oil, whereas the latter explain that an increase in the oil price often results in a jump in clean energy stock prices and, ultimately, an increase in technology stock prices. Using the VAR-Causality empirical framework, Kumar et al., (2012) report that the volatility of energy prices is linked to that of technology stocks and oil prices. However, the connectedness between alternative energy stock prices, technology stock prices, and crude oil is found in the short-run not in the long-run (Bondia et al., 2016). In another hedging strategy, though gold may act as a safe haven against extreme market movement and is a hedge on average, it is not a safe haven for technology stocks (Chen and Wang 2019).

The hedging strategy between technology stocks and cryptocurrencies has also received burgeoning academic interest (Smales 2019; Symitsi and Chalvatzis 2018). For example, using the VAR-AGARCH model, Symitsi and Chalvatzis (2018) analysed the effects between Bitcoin and energy and technology companies and conclude that there is significant return spill-over from energy and technology stocks to Bitcoin. Cryptocurrencies show the role as a safe haven for different assets, such as oil (Selmi et al., 2018), gold and other commodities (Shahzad et al., 2019). Most studies pay attention to a single cryptocurrency, very often Bitcoin, in which Bitcoin plays a role either as a safe-haven, diversifier, or hedging asset (Baur et al., 2018; E. Bouri et al., 2017; E. Bouri et al., 2017; Briere et al., 2015; Dyhrberg 2016b; Giudici and Abu-Hashish 2019; Shahbaz and Sinha 2019). In contrast, only few studies pay attention to the correlation between various cryptocurrencies (Corbet et al., 2018; Huynh 2019). For instance, using three popular cryptocurrencies (Bitcoin, Ripple, and Litecoin) to examine the spill-over effects on traditional financial assets, such as foreign exchange, stock, VIX, gold and bond, Corbet et al., (2018) present a non-correlation with financial assets and, hence, cryptocurrencies benefit investment diversification. Overall, the spill-over effects of different markets with Bitcoin are mixed because of speculative bubbles in Bitcoin (Huynh 2019). The fundamental price valuation of modern assets, Bitcoins and cryptocurrencies, are affected by digital currency unique factors, such as social media forums (Mai et al., 2018) and the highly attractive features of cryptocurrencies to investors (Ciaian et al., 2016).

As a stable, sustainable investment for long-term social projects, green bonds are likely to be a part of a diversified portfolio and have gained the attention of researchers (Huynh 2020). In particular, previous studies indicate clean technology indexes outperform a market portfolio in terms of returns and volatility (Ortas and Moneva 2013) though green bonds have lower returns than traditional bonds (Hachenberg and Schiereck 2018; Reboredo et al., 2017). Park et al., (2020) confirm that although green bonds do exhibit the asymmetric volatility phenomenon, their volatility, unlike that of equity, is also sensitive to positive return shocks. Using the threshold GARCH model, Pham (2016) examined the volatilities of different bonds and shows that shocks in the conventional bond markets are disposed to spill-over into the green bond market, Reboredo (2018) shows that there is no diversification effect between green bonds and traditional bonds. Reboredo and Ugolini (2020), with a structural vector autoregressive (VAR) model, emphasize the weak correlation between green bonds, energy, and high-yield corporate bonds. The findings regarding green bonds with different financial assets provide implications for building a diversified portfolio and risk-return strategy for investors, which is consistent with the findings by Pham and Huynh (2020).

Although there is the flourishing literature on 21st century technology based firms, on cryptocurrencies, and on modern assets like green bonds, the research on the time and frequency domain connectedness and spill-over effect among Fintech, green bonds and cryptocurrencies in the 4th industrial revolution remain limited thereby offering a gap for this study.

3. Empirical methodology

3.1. Diebold and Yilmaz's (2012) time domain spill-over index model

To start our analysis, we use the multivariate time-series analysis model advanced by Diebold and Yilmaz (2012). In their approach, DY introduce a variance decomposition into the vector autoregression (VAR) model that focuses on computing the forecast error variance decomposition (FEVD) from a generalized vector auto-regression to examine connectedness. The definition of the K-variable, VAR (p) system, is:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + u_t \tag{1}$$

Where: y_t stands for the $K \times 1$ vector of variables at time t , and c depicts the constants of the $K \times 1$ vector of variables. The coefficients of the $K \times K$ dimension matrix are represented by A . A simpler form of Eq. (1) above is:

$$Y_t = C + AY_{t-1} + U_t \tag{2}$$

where: A denotes a $pK \times pK$ dimensional matrix; and Y , C and U denote $pK \times 1$ vectors as defined below:

$$Y = \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p} \end{bmatrix}, C = \begin{bmatrix} c \\ 0 \\ \vdots \\ 0 \end{bmatrix}, A = \begin{bmatrix} A_1 & A_2 & \dots & A_{p-1} & A_p \\ I_K & 0 & \dots & 0 & 0 \\ 0 & I_K & 0 & 0 & \vdots \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & I_K & 0 \end{bmatrix}, U = \begin{bmatrix} u_t \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{3}$$

In the VAR model estimation, we use variance decomposition to investigate the extent to which each variable influences or contributes to other variables in explaining the variation across the variables. The H-step forecast of the mean square error of variable y_{it} is given by:

$$MSE[y_{i,t}(H)] = \sum_{j=0}^{H-1} \sum_{k=1}^k (e'_i \Theta_j e_k)^2 \tag{4}$$

where: e_i represents the $i - th$ column of I_K , $\Theta_j = \Phi_j P$, and P denotes the lower triangular matrix. To estimate P , the lower triangular matrix, we use the generalised decomposition of the variance covariance matrix $\Omega_u = E(u_t u'_t)$ following Koop et al. (1996) and Pesaran and Shin (1998). In addition, $\Phi = JA^j J'$, where $J = [I_K, 0, \dots, 0]$. We estimate k 's contribution to variable i as:

$$\theta_{ik,H} = \sum_{j=0}^{H-1} (e'_i \Theta_j e_k)^2 / MSE[y_{i,t}(H)] \tag{5}$$

From Diebold and Yilmaz (2012), we estimate dependency of the variables in the system to abridge all elements in $\theta(H)$ from 1 to K . We measure connectedness as:

$$C_H = \frac{1}{K} \sum_{ij=1}^K \theta_{ij}^H (i \neq j), \tag{6}$$

Eq. (6) above ignores from the system all diagonal elements to ensure the estimated total connectedness among the variables ranges between 0 and 1. This measure therefore examines the extent to which system's components' role in variations is initiated by another variable and not the variable itself. A value of zero surmises that the components of the system are independent with no existence of spill-over effects. However, when the value equals one, it implies that the system's components are highly connected.

Since the variance decomposition or impulse response results could be affected by the order of the variables in the VAR framework, we use Diebold and Yilmaz's (2012) model with the generalized decomposition framework of Koop et al. (1996) and Pesaran and Shin (1998) to test the robustness of our results.

$$\theta_{ik,H}^g = \sigma_{ii}^{-1} \sum_{j=0}^{H-1} (e'_i \Phi_j \sum_k e_k)^2 / MSE[y_{i,t}(H)]. \tag{7}$$

3.2. Baruník and Křehlík (2018) frequency domain spillover method

We now examine the method to measure the connectedness in the frequency domain following Baruník and Křehlík (2018). BK provides results in greater detail which strengthened our understanding of the variables under examination. We want to examine at which frequency the spill-over is highest, since that will help investors decide whether to invest in the long- or short-run because we have investors with different investment horizons. Baruník and Křehlík (2018) develop a method that decomposes the original DY spill-over at several frequencies. Specifically, their formulation is based on the use of a spectral formulation of the decomposing variance that may be described as follows. Consider a frequency response function defined as: $\Psi(e^{-i\omega}) = \sum_h e^{-i\omega h} \Psi_h$, obtained from the Fourier transformation of the coefficient Ψ , with $i = \sqrt{-1}$.

The generalized causation spectrum over frequencies, $\omega \in (-\pi, \pi)$, is defined as:

$$(f(\omega))_{j,k} \equiv \frac{\sigma_{kk}^{-1} |((\Psi(e^{-i\omega}) \sum)_{j,k})|^2}{(\Psi(e^{-i\omega}) \sum \Psi'(e^{+i\omega}))_{jj}} \tag{8}$$

where: $\Psi(e^{-i\omega}) = \sum_h e^{-i\omega h} \Psi_h$, denotes the Fourier transformation of the impulse response function Ψ and $(f(\omega))_{j,k}$, which indicates the part of the spectrum of the j -th variable under the frequency ω as a result of shock in the k th variable. Following that denominator holds the spectrum of the j -th variable under frequency ω , we deduce Eq. (8) above as the quantity within the frequency causation. The generalized decomposition of the variance is obtained under frequency ω by weighting the function $(f(\omega))_{j,k}$ by the j -th variable frequency share of the variance. Following the above, the weighting function is:

$$\Gamma_j = \frac{(\Psi(e^{-i\omega}) \sum \Psi'(e^{+i\omega}))_{jj}}{\frac{1}{2\pi} \int_{-\pi}^{\pi} (\Psi(e^{-i\lambda}) \sum \Psi'(e^{+i\lambda}))_{jj} d\lambda} \tag{9}$$

Eq. (9) shows j -th variable power in the system under frequency ω and sums the frequencies to a constant value of 2π . It is noteworthy that even though the Fourier transformation of the impulse response is a complex number, the generalized spectrum is the squared coefficient of the weighted complex number and, as result, is a real number. We set the frequency band formally as: $d = (a, b)$: $a, b \in (-\pi, \pi)$, $a < b$. In Eq. (10), the generalized variance decomposition under the frequency band d is:

$$(\Theta_d)_{j,k} = \frac{1}{2\pi} \int_d^\infty \Gamma_j(\omega) (f(\omega))_{j,k} d\omega. \tag{10}$$

The generalized variance decomposition is scaled under the frequency band $d = (a, b)$: $a, b \in (-\pi, \pi)$, $a < b$. as shown in Eq. (11):

$$(\tilde{\Theta}_d)_{j,k} = (\Theta_d)_{j,k} / \sum_k (\Theta_\infty)_{j,k}. \tag{11}$$

The within connectedness is formulated under the frequency band d as:

$$C_d^W = 100. \left(1 - \frac{Tr\{\tilde{\Theta}_d\}}{\sum \tilde{\Theta}_d} \right) \tag{12}$$

Finally, we estimate the frequency connectedness under the frequency band d as:

$$C_d^F = 100. \left(\frac{\sum \tilde{\Theta}_d}{\sum \tilde{\Theta}_\infty} - \frac{Tr\{\tilde{\Theta}_d\}}{\sum \tilde{\Theta}_\infty} \right) = C_d^W \frac{\sum \tilde{\Theta}_d}{\sum \tilde{\Theta}_\infty}. \tag{13}$$

4. Empirical findings and interpretation

4.1. Data and preliminary analysis

In this study, we examine the connectedness between 10 financial asset classes from 28 November 2018 to 29 June 2020. The study period includes 398 observations for each variable. Specifically, the

Table 1
Descriptive statistics of the analysed variables.

	Bitcoin	MSCIW	MSCIUS	US Dollar	Oil	Gold	KFTX	VIX	Green. Bond	Green Bond select
Mean	0.056	0.018	0.03	0.009	0.162	0.095	0.043	0.136	0.015	0.019
Median	0.153	0.081	0.109	-0.005	0.1	0.056	0.179	-1.022	0.011	0.019
Std. Dev.	1.653	1.509	1.805	0.32	5.728	1.136	2.037	8.862	0.342	0.413
Skewness	-1.094 *	-1.387 *	-0.976 *	0.353 *	1.136 *	0.898 *	-0.911 *	1.209 *	-1.521 *	-1.392 *
Kurtosis	13.647 *	17.953 *	16.081 *	10.402 *	21.084 *	11.868 *	14.080 *	6.380 *	18.660 *	16.719 *
Jarque-Bera	1954.5 *	3825.7 *	2893.4 *	914.6 *	5495.2 *	1354.3 *	2085.8 *	285.7 *	4209.5 *	3241.5 *
ADF	-5.213 *	-5.052 *	-4.933 *	-5.712 *	-4.816 *	-7.467 *	-4.982 *	-5.744 *	-6.352 *	-6.312 *
PP	-20.118 *	-23.293 *	-26.517 *	-19.028 *	-20.619 *	-22.369 *	-24.841 *	-22.814 *	-14.608 *	-15.205 *
KPSS	0.058	0.054	0.046	0.102	0.154	0.026	0.059	0.079	0.051	0.049
ZA	-6.252 *	-6.035 *	-5.875 *	-6.275 *	-6.894 *	-7.760 *	-6.016 *	-6.409 *	-7.109 *	-7.047 *
L-B	79.4 *	146.5 *	205.8 *	38.8 *	51.7 *	23.4 *	152.0 *	20.24818	122.7 *	106.0 *
L-B ²	272.7 *	418.9 *	513.6 *	259.5 *	204.7 *	35.3 *	543.5 *	81.9 *	240.3 *	235.0 *
ARCH-LM(10)	111.1 *	148.7 *	168.2 *	112.8 *	95.5 *	30.9 *	171.1 *	51.3 *	121.2 *	126.5 *
Obs.	397	397	397	397	397	397	397	397	397	397

Notes: The table reports the summary statistics for daily returns of all assets under examination. Std. Dev denotes standard deviation; JB denotes the Jarque-Bera test for normality; **L-B** and **L-B²** are the Ljung-Box test for serial correlation in all series; ARCH(2) is the Lagrange multiplier test for autoregressive conditional heteroscedasticity of order 10.

* L-B representing Ljung-Box Test.

KBW NASDAQ Technology Index (KFTX) was established to track the performance of financial technology companies that are publicly traded in the U.S. Hence, this proxy represents the performance of an asset in the 4th industrial revolution. Additionally, various indexes, such as the cryptocurrency-bitcoin, MSCI equity indices (MSCI US and MSCI World), US Dollar, Crude oil (S&P GSCI WTI), gold (S&P GSCI), and CBOE volatility (VIX), are well-known either as hedges or safe-havens in investors' diversified portfolios. The S&P Bond US Dollar Index is designed to measure the performance of US dollar-denominated, green-labelled bonds from the S&P Green Bond Index. Although the market size of green bonds (S&P Green Bond US Dollar and S&P Green Bond Select) is relatively small compared with the boom of cryptocurrencies since 2013, both are evoking the interest of investors. All proxies in this study are from Thomson Reuters Eikon.

Daily log-returns of price series are used in estimation. We estimate returns as $\ln(P_t) - \ln(P_{t-1})$, thus the logarithmic difference between the opening price on data t and closing price of day $t - 1$.

Table 1 summarises the statistics of the daily returns of prices examined in this study. The daily mean of all series is positive with Oil recording the highest mean return of 0.162 followed by VIX with a mean return of 0.136. The lowest average return of 0.009 was recorded by the US Dollar. VIX, with a standard deviation of 8.862 is most volatile followed Oil (5.728), which means that a one-dollar investment offers higher return for Oil than for VIX. The smallest standard deviation was for the US Dollar (0.32). It is evident that high volatility is associated with higher returns. On the other hand, we observe significant negative skewness for the Bitcoin, MSCIW, MSCIUS, KFTX, Green Bond and Green Select Bond returns series. Negative (Positive) skewness denotes a tendency of higher negative (positive) returns without matching the tendency of positive (negative) returns. In addition, all series examined recorded kurtosis exceeding the threshold of 3, which suggests that the asset returns under examination for the period have flatter tails than what would be anticipated from a normally distributed series. We use the Jarque-Bera (JB) test for the normality assumption of the series. We reject the null hypothesis of normality for all series at 1% level. We adopt the ADF test of Dickey and Fuller (1979), the PP and KPSS tests to examine the stationarity of the study variables. Our results from the insignificant KPSS statistics show that all variables are stationary, which is confirmed by the ADF and PP unit root tests. The presence of autocorrelation was tested using the Ljung-Box test. The results confirm the presence of autocorrelation for all series. The test for ARCH effects using Engle's (1982) ARCH-LM test confirms the presence of ARCH effects in all variables.

Table 2 reports the diagnostic tests of the series. From Panel A, we find that further tests of normality (Bartels Test, Robust Jarque Bera

Test, Test of Normality SJ Test, Bootstrap Symmetry Test, Difference Sign Test, Mann-Kendall Rank Test, Mann-Kendall Rank Test) reject the null hypothesis of a normal distribution, which cements our findings that the series examined do not follow a normal distribution. In Table 2, Panel B, the test statistics for all the estimated nonlinearity tests of normality (Teraesvirta Neural Network Test, White NN Test, Keenan Test, Tsay Test, Likelihood Ratio Test,) reject the null hypothesis that the time series follow some AR process. Finally, in Table 2 Panel C, we test the multivariate normality of all series together because we intend to use them in a VAR framework for the spill-over analysis. We find that all series combined do not follow a normal distribution.

Fig. 1 displays the overall distribution of the data together with the pairwise correlations between the asset returns under examination. Fig. 1 confirms that the data used in this study are not normally distributed. The highest correlation between Bitcoin and other assets, for Bitcoin and MSCIW, is equivalent to 0.95 followed by Bitcoin and MSCIUS (0.91). We find a negative correlation coefficient between Bitcoin and the US Dollar (-0.52), and KFTX (-0.90). For the entire sample, the highest correlation coefficient, 0.99, is between Green Bond and Green Bond Select, which is not surprising since they are related assets. The lowest correlation coefficient is between VIX and MSCI US (-0.72).

Fig. 2 shows the network analysis of the pairwise correlations between all variables in the sample. Red lines show negative correlations and green lines positive ones. The clusters of variables are based on the correlation magnitude using the absolute values of the correlations as the proximity or distance metric. The closeness of one variable to another shows the overall magnitude of the correlation between the two variables. In Fig. 2, some variables are clustered, e.g., Green Bond, Green Bond Select and Bitcoin price indices are clustered and Gold, US Dollar and Oil indices are clustered.

Fig. 3 illustrates the plotted estimates of two network structures, i.e., partial contemporaneous correlations and partial directed correlations. The partial contemporaneous correlations are similar to the plot reported above. However, the partial directed correlations that show the direction of causality and connectedness from KFTX to the US Dollar, Green Bond and Green Select Bond indices is negative. This confirms the negative correlation between KFTX and assets in our sample as discussed above (Fig. 1).

4.2. Empirical results

Table 3, Panel A, presents the DY spill-over empirical results. They reveal substantial differences in the magnitude of volatility shocks transferred from one market to another. The lowest value of volatility

Table 2
Diagnostics tests of the variables.

	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green. bond	Green. and. select
Panel A: normality test results										
Bartels Test	-1.858	-0.465	1.968	-0.101	-0.670	1.127	2.159	1.844	-1.810	-1.307
Robust Jarque Bera Test	6888.205 *	29,244.627 *	22,859.464 *	1767.315 *	95,682.638 **	4020.251 *	10,205.534 *	519.684 *	13,346.720 *	8652.196 *
Test of normality SJ Test	20.343 *	30.660 *	30.624 *	13.158 *	42.435 *	17.910 *	24.219 *	9.472 *	20.203 *	17.976 *
Bootstrap symmetry test	-1.960	-1.572	-1.626	1.340	0.449	1.118	-2.329	3.885 *	0.379	0.019
Difference sign test	-0.521	-1.215	-1.389	1.215	-1.389	-0.521	-1.042	-0.347	-1.215	-1.042
Mann-Kendall rank test	0.683	0.453	0.636	0.500	-0.395	-0.326	0.365	-0.254	0.120	0.168
Runs Test	-1.710	-0.355	1.437	-0.342	-0.518	0.695	0.590	1.977	-0.599	-0.146
Panel B: nonlinearity test for normality										
Teraesvirta NN test	7.821**	11.784*	20.739*	0.691	11.820*	3.888	1.028	13.109*	12.081*	13.369*
White NN test	4.602	18.320*	24.678*	0.395	5.932***	0.462	9.515*	13.653*	23.359*	25.219*
Keenan test	9.409*	24.515*	24.433*	0.199	5.919*	12.160*	21.037*	0.278	0.174	1.762
Tsay test	4.767*	7.467*	5.751*	3.641*	7.875*	2.337*	5.736*	0.172	3.545*	4.014*
Likelihood ratio test	80.655*	149.663*	111.761*	61.516*	165.438*	35.043*	85.507*	9.832***	54.657*	46.105*
Panel C: Multivariate normality test results										
Energy test	E-statistic	p-value								
	3.7016	2.20E-16								
Mardia-Kurtosis test	Beta-hat	Kappa	p-value							
Skewness	82.431	5454.193	0							
Kurtosis	400.45531	180.353	0							

Notes: We test for normality using several methods;

* L-B representing Ljung-Box Test.

** denotes significance at 1%.

*** denotes significance at 10%.

transmitted from one market to another is Green Bond Select followed by returns of Green Bond. The highest spill-overs are from the returns of the MSCIW price index to the returns series of MSCI US, KFTX and Bitcoins price indices with the transmission component from the returns of MSCIW price series to MSCI US, KFTX and Bitcoins being 2.14%, 2.04% and 2.0%, respectively. The result for the transmission between

equity markets and Bitcoin returns agrees with the findings of [Gil-Alana et al., \(2020\)](#) who document significant spill-overs between US equity markets and several cryptocurrencies as a result of market integration using the fractional cointegration approach. For volatility shocks transferred from the technology index, KFTX, to other assets, we observe that MSCIW, MSCI-US and Bitcoin are the largest receivers of

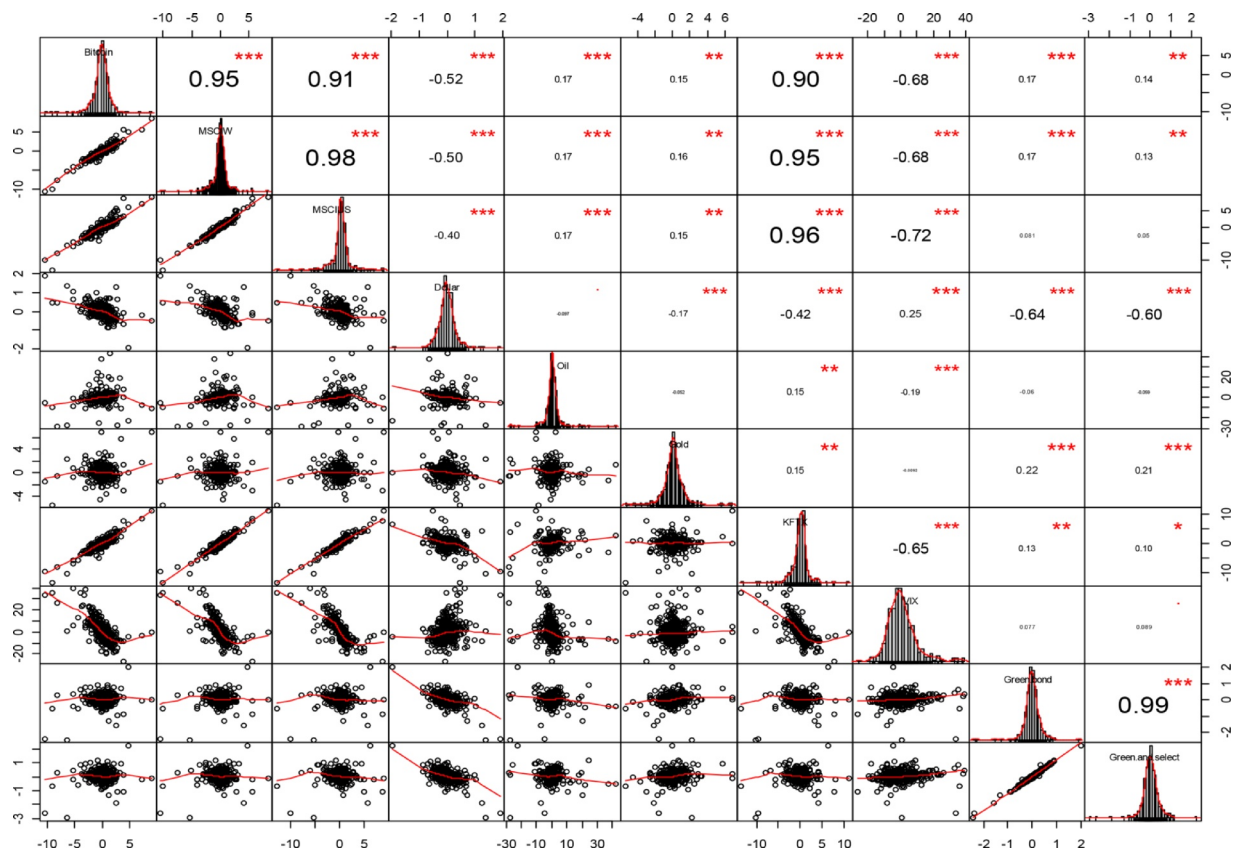


Fig. 1. Plots of the distribution and the pair-wise correlations of KFTX and other assets' returns.

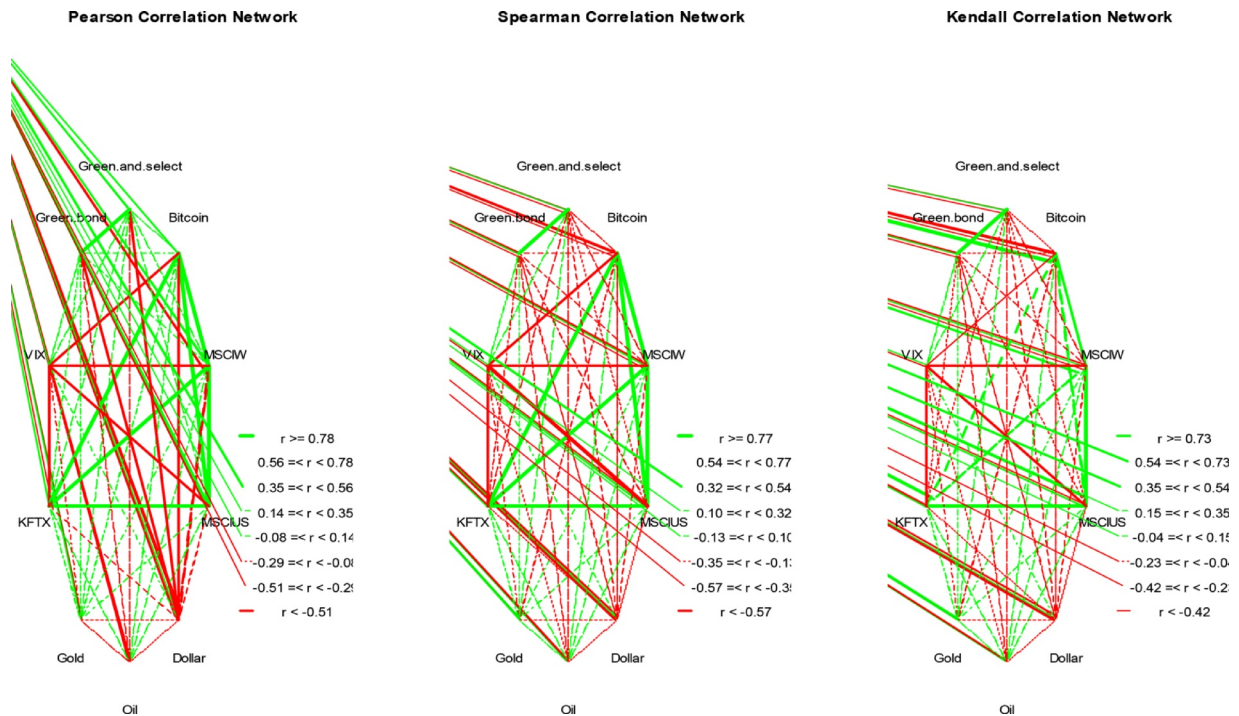


Fig. 2. A network analysis of the pairwise correlations between Bitcoin and other assets' returns.

shocks spilled from KFTX. This finding for KFTX and Bitcoin aligns with the results in [Symitsi and Chalvatzis \(2018\)](#) who document significant return spill-overs from technology stocks to Bitcoin. This result is not surprising since Bitcoin has been classified as a technology based product ([White et al., 2020](#)). For volatility shocks transmitted from other markets to KFTX, it is interesting to note that KFTX is a major receiver of shocks from MSCIW, MSCI US and Bitcoin taking into consideration all assets in our sample. These findings are somewhat different from the conclusion of [Smales \(2019\)](#) who finds no evidence of volatility transmission between technology stocks and cryptocurrencies. Arguably, from our results, we surmise that KFTX, MSCIW and Bitcoin are intertwined as shocks from each individual market spill to the other markets.

Focusing on the volatility shocks spilled from other assets to Bitcoin, we find that the returns of the Gold and Green Bond Select price indices exhibit the lowest volatility transmission to the Bitcoin price index in our sample. Overall, volatility shocks transmitted from Green Bond to other markets and vice versa is very marginal compared with the other assets in our sample. The finding is not surprising since, recently, Green Bonds have emerged as an investable asset class because of its diversification benefits. For example, [Reboredo and Ugolini \(2020\)](#) find a weak correlation between Green Bonds and traditional assets. Thus, our findings support their conclusion.

Concerning the contribution to others, we find that the gross directional volatility spill-over to other forms each of the 10 market-index

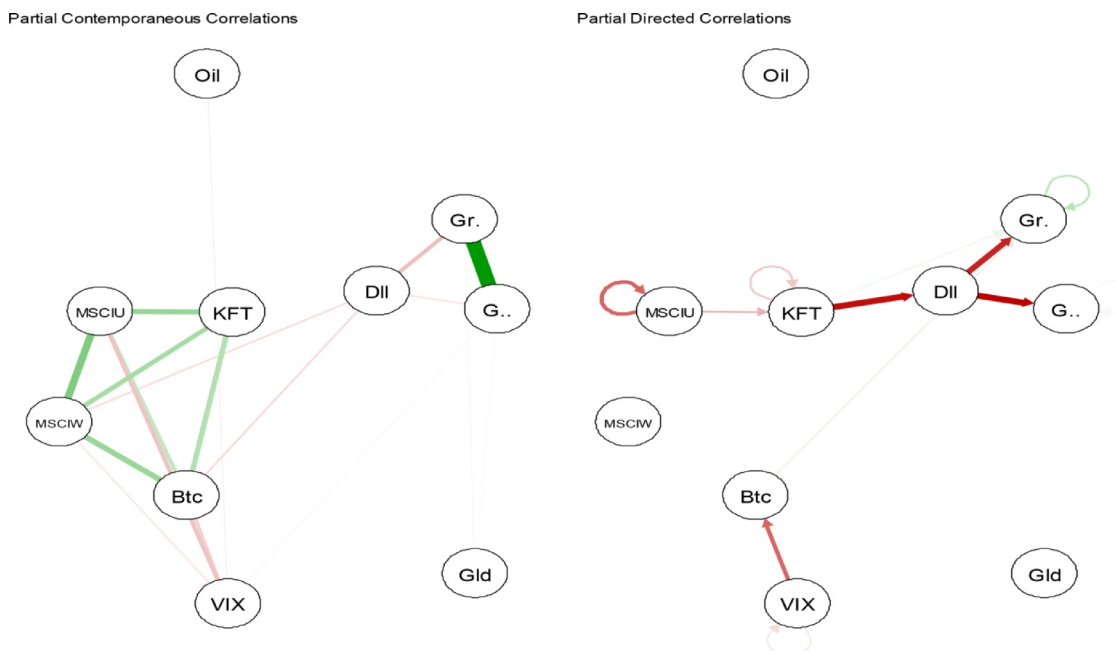


Fig. 3. Plots of the partial contemporaneous and partial directed correlations.

Table 3
Volatility spill-over results.

Panel A: DY (2014) spill-over results											
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green. bond	Green. and. select	FROM
Bitcoin	2.23	2.00	1.91	0.69	0.07	0.05	1.85	1.09	0.07	0.05	7.77
MSCIW	1.88	2.15	2.08	0.71	0.07	0.07	1.89	1.02	0.09	0.06	7.85
MSCIUS	1.81	2.14	2.22	0.58	0.06	0.07	1.93	1.12	0.05	0.03	7.78
US Dollar	1.13	1.14	0.93	3.02	0.09	0.10	1.10	0.38	1.14	0.98	6.98
Oil	0.30	0.33	0.30	0.26	8.15	0.07	0.28	0.30	0.02	0.01	1.85
Gold	0.22	0.25	0.22	0.31	0.13	7.62	0.23	0.05	0.50	0.47	2.38
KFTX	1.82	2.04	2.06	0.65	0.05	0.06	2.20	0.95	0.09	0.07	7.80
VIX	1.55	1.61	1.76	0.38	0.11	0.02	1.43	3.11	0.02	0.02	6.89
Green Bond	0.48	0.44	0.33	1.39	0.04	0.22	0.52	0.08	3.29	3.20	6.71
Green Select	0.41	0.37	0.27	1.31	0.05	0.20	0.45	0.08	3.42	3.44	6.56
TO	9.60	10.30	9.86	6.27	0.68	0.86	9.67	5.06	5.39	4.88	62.58
NET	1.8217	2.4481	2.0793	-0.7078	-1.1668	-1.5244	1.8725	-1.8295	-1.3136	-1.6793	

Panel B: BK (2017) spill-over results											
Frequency 1: The spill-over table for band 3.14 to 0.79 that roughly corresponds to 1–4 days											
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green bond	Green Select	FROM_ABS
Bitcoin	1.60	1.51	1.45	0.54	0.05	0.04	1.36	0.74	0.06	0.04	5.79
MSCIW	1.41	1.70	1.65	0.58	0.05	0.05	1.46	0.75	0.07	0.05	6.06
MSCIUS	1.47	1.80	1.87	0.50	0.05	0.06	1.60	0.90	0.04	0.03	6.43
US Dollar	0.63	0.69	0.55	2.15	0.06	0.05	0.61	0.22	0.72	0.63	4.16
Oil	0.27	0.30	0.27	0.22	6.26	0.07	0.26	0.20	0.00	0.00	1.59
Gold	0.10	0.12	0.11	0.25	0.10	6.04	0.13	0.02	0.23	0.21	1.26
KFTX	1.46	1.71	1.73	0.55	0.04	0.05	1.79	0.76	0.07	0.05	6.41
VIX	1.29	1.37	1.50	0.34	0.10	0.02	1.21	2.49	0.01	0.01	5.84
Green Bond	0.18	0.18	0.14	0.70	0.03	0.08	0.22	0.05	1.85	1.83	3.41
Green Select	0.17	0.16	0.13	0.66	0.04	0.08	0.20	0.06	1.98	2.03	3.45
TO_ABS	6.97	7.83	7.53	4.32	0.52	0.49	7.04	3.69	3.17	2.84	44.39
TO_WTH	9.66	10.84	10.43	5.99	0.72	0.68	9.75	5.12	4.39	3.93	
NET	1.1870	1.7632	1.093	0.1638174	-1.07191	-0.7727	0.630	-2.144	-0.2387	-0.6104	

Frequency 2: The spill-over table for band 0.79 to 0.39 that roughly corresponds to 4–8 days											
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green. bond	Green. and. select	FROM_ABS
Bitcoin	0.29	0.23	0.22	0.07	0.01	0.01	0.23	0.16	0.01	0.00	0.92
MSCIW	0.21	0.21	0.20	0.06	0.01	0.01	0.20	0.12	0.01	0.01	0.82
MSCIUS	0.16	0.16	0.16	0.04	0.01	0.01	0.16	0.10	0.00	0.00	0.62
Dollar	0.21	0.20	0.16	0.39	0.01	0.02	0.21	0.07	0.17	0.14	1.19
Oil	0.02	0.02	0.02	0.02	0.92	0.00	0.02	0.05	0.00	0.00	0.16
Gold	0.05	0.05	0.04	0.03	0.01	0.76	0.04	0.01	0.12	0.12	0.47
KFTX	0.16	0.15	0.15	0.04	0.01	0.01	0.19	0.09	0.01	0.01	0.63
VIX	0.14	0.12	0.13	0.02	0.01	0.00	0.11	0.30	0.00	0.01	0.54
Green Bond	0.12	0.10	0.08	0.29	0.01	0.05	0.12	0.02	0.61	0.58	1.37
Green Select	0.10	0.09	0.06	0.27	0.01	0.05	0.11	0.01	0.62	0.61	1.31
TO_ABS	1.16	1.11	1.06	0.85	0.08	0.15	1.18	0.62	0.95	0.86	8.02
TO_WTH	9.33	8.95	8.52	6.81	0.60	1.19	9.46	5.00	7.62	6.95	
NET	0.2453	0.2973	0.4398	-0.3407	-0.0827	-0.3236	0.5499	0.0774	-0.4211	-0.4415	

Frequency 3: The spill-over table for band 0.39 to 0.20 that roughly corresponds to 8–16days											
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green. bond	Green. and. select	FROM_ABS
Bitcoin	0.16	0.12	0.11	0.04	0.01	0.00	0.12	0.09	0.00	0.00	0.49
MSCIW	0.12	0.11	0.11	0.03	0.00	0.00	0.11	0.07	0.01	0.00	0.44
MSCIUS	0.08	0.08	0.08	0.02	0.00	0.00	0.08	0.05	0.00	0.00	0.33
Dollar	0.13	0.12	0.10	0.22	0.01	0.01	0.12	0.04	0.11	0.09	0.72
Oil	0.01	0.01	0.01	0.01	0.45	0.00	0.00	0.02	0.00	0.00	0.05
Gold	0.03	0.03	0.03	0.02	0.01	0.38	0.03	0.01	0.07	0.07	0.29
KFTX	0.09	0.08	0.08	0.02	0.00	0.01	0.10	0.05	0.01	0.00	0.34
VIX	0.06	0.05	0.06	0.01	0.00	0.00	0.05	0.15	0.00	0.00	0.24
Green Bond	0.08	0.07	0.05	0.18	0.00	0.04	0.08	0.01	0.37	0.35	0.85
Green Select	0.06	0.06	0.04	0.17	0.01	0.03	0.07	0.01	0.37	0.36	0.80
TO_ABS	0.66	0.61	0.58	0.49	0.04	0.10	0.66	0.34	0.57	0.52	4.56
TO_WTH	9.46	8.87	8.33	7.11	0.58	1.37	9.46	4.89	8.20	7.54	
NET	0.1680	0.1730	0.2463	-0.2283	-0.0142	-0.1926	0.3119	0.0952	-0.2833	-0.2760	

Frequency 4: The spill-over table for band 0.20 to 0.10 that roughly corresponds to 16–30days											
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green Bond	Green Select	FROM_ABS

(continued on next page)

Table 3 (continued)

Frequency 4: The spill-over table for band 0.20 to 0.10 that roughly corresponds to 16–30 days											
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green Bond	Green Select	FROM_ABS
Bitcoin	0.11	0.08	0.08	0.03	0.00	0.00	0.08	0.06	0.00	0.00	0.33
MSCIW	0.08	0.08	0.07	0.02	0.00	0.00	0.07	0.05	0.00	0.00	0.30
MSCIUS	0.06	0.06	0.06	0.01	0.00	0.00	0.06	0.04	0.00	0.00	0.23
Dollar	0.09	0.08	0.07	0.15	0.01	0.01	0.09	0.03	0.08	0.07	0.52
Oil	0.00	0.00	0.00	0.00	0.30	0.00	0.00	0.01	0.00	0.00	0.03
Gold	0.02	0.02	0.02	0.01	0.00	0.25	0.02	0.01	0.05	0.05	0.20
KFTX	0.06	0.06	0.06	0.02	0.00	0.00	0.07	0.03	0.00	0.00	0.24
VIX	0.04	0.03	0.04	0.01	0.00	0.00	0.03	0.10	0.00	0.00	0.15
Green..Bond	0.06	0.05	0.04	0.13	0.00	0.03	0.06	0.01	0.26	0.25	0.61
Green Select	0.05	0.04	0.03	0.12	0.00	0.02	0.05	0.01	0.26	0.25	0.57
TO_ABS	0.46	0.42	0.40	0.35	0.03	0.07	0.45	0.23	0.40	0.37	3.18
TO_WTH	9.51	8.84	8.26	7.21	0.58	1.43	9.46	4.85	8.39	7.74	
NET	0.1247	0.1217	0.1702	-0.1702	-0.0003	-0.1339	0.2163	0.0788	-0.2087	-0.1986	

Frequency 5: The spill-over table for band 0.10 to 0.00 that roughly corresponds to 30 days to infinity											
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green Bond	Green Select	FROM_ABS
Bitcoin	0.08	0.06	0.06	0.02	0.00	0.00	0.06	0.04	0.00	0.00	0.25
MSCIW	0.06	0.06	0.05	0.02	0.00	0.00	0.06	0.04	0.00	0.00	0.23
MSCIUS	0.04	0.04	0.04	0.01	0.00	0.00	0.04	0.03	0.00	0.00	0.17
Dollar	0.07	0.06	0.05	0.12	0.00	0.01	0.07	0.02	0.06	0.05	0.40
Oil	0.00	0.00	0.00	0.00	0.22	0.00	0.00	0.01	0.00	0.00	0.02
Gold	0.02	0.02	0.02	0.01	0.00	0.19	0.01	0.00	0.04	0.04	0.15
KFTX	0.05	0.04	0.04	0.01	0.00	0.00	0.05	0.03	0.00	0.00	0.18
VIX	0.03	0.03	0.03	0.00	0.00	0.00	0.02	0.07	0.00	0.00	0.11
Green Bond	0.04	0.04	0.03	0.10	0.00	0.02	0.05	0.01	0.20	0.19	0.47
Green Select	0.04	0.03	0.02	0.09	0.00	0.02	0.04	0.00	0.20	0.19	0.44
TO_ABS	0.35	0.32	0.30	0.26	0.02	0.05	0.34	0.18	0.31	0.28	2.42
TO_WTH	9.52	8.83	8.24	7.24	0.58	1.45	9.45	4.83	8.45	7.80	
NET	0.0967	0.0929	0.1291	-0.1324	0.0023	-0.1016	0.1643	0.0630	-0.1616	-0.1527	

NB: This table presents the volatility spill-over results for the DY and BK approaches in Panels A and B, respectively, using the return data for each market. In Panel B, values in the *i* th row of the *j*-th column indicate the strength of the spill-over effect from the *i* th market to the *j*-th market. Also in Panel B, abs denotes absolute; wth is within. For these differences, see Eqs. (12) and (13). Net denotes the Net Spill-over Index for each individual market.

returns range from 6.8% for the Oil to 10.3% for MSCIW index. The result suggests that shocks from the Oil market have a marginal effect on the other sampled markets, which is a similar finding to Bondia et al., (2016). However, over 10% of the variation in the returns series of MSCIW, which represents a world equity market index, is transmitted to returns of other markets. Over 9% of Bitcoin and KFTX realized variance in the return series of these markets is transmitted to other markets in our sample. This result further cements the emergence of technology stocks and Bitcoin as enviable asset classes in portfolio diversification. For technology stocks in diversified portfolios, Ahmad (2017) reveals that technology stocks’ volatility transmission greatly impacts energy stock prices more than crude oil whereas Nasreen et al., (2020) confirm that technology stocks and clean energy are good hedgers for the oil market. The latter finding contradicts Sadorsky (2012) who indicates that oil is a good hedge for clean energy.

For directional volatility spill-overs from all markets to one specific market, the range of the results is wider with component estimates ranging from 1.85% to 7.85% for returns from Oil and MSCIW, respectively (see last column, Table 3 Panel A). In our sample, Oil is least affected by shocks transmitted from other markets (Bondia et al., 2016). Since the significant variations in the results of the different markets is continuous, we conjecture that the volatility in all observed markets starts from 1%. We note that MSCIW (7.85) is most affected by shocks from other markets followed by KFTX (7.80), MSCI US (7.78), and Bitcoin (7.75). Overall, from the DY spill-over analysis, shocks related to volatility from other markets account for 62.58% of the volatility forecast error variance in our sample.

Table 3, Panel A, reports the net directional connectedness that measures the net spill-over indices for each specific market. A positive net spill-over value indicates that the market index is a spill-over contributor and a negative spill-over indicates that the specific market is a

net receiver; it receives spill-overs from other markets. We find that Bitcoin, MSCIW, MSCI US, and KFTX have positive net spill-over value, which implies that these markets are net contributors to volatility whereas US Dollar, Oil, Gold, VIX, Green Bond and Green Bond Select are net receivers. As expected, the biggest net contributor of volatility is MSCIW (2.448) followed by MSCIUS (2.079), KFTX (1.873) and Bitcoin (1.822); the biggest receiver is VIX followed by Green Bond Select.

In Table 3, Panel B, we report detailed information on the direction and magnitude of the volatility spill-overs by estimating the net pairwise spill-over across the markets examined at different frequency cycles. In the past, studies of this nature have examined market volatility transmission across several markets by applying the causality analytical framework, the systematic risk co-movement and the spill-over index (Kommel et al., 2018; Monasterolo and Raberto 2018; Ortas and Moneva 2013). In this study, the interest is in the empirical importance of frequency sources of connectedness by arguing that volatility shocks will have different, varied impacts on future uncertainty.

Table 3, Panel B, shows the contribution of the volatility of technology index, Bitcoin, and Green Bond differs with the various frequencies used. In the short period, for example, at frequency 1, the two highest contributions are MSCI US and KFTX, at 6.43 and 6.41, respectively, followed by MSCIW, VIX, and Bitcoin. Evidently, in short term, the technology index adds a high degree of risk to a portfolio among other financial assets. In the remaining frequencies, US Dollar, Green Bond, Bitcoin, and MSCIW are the main contributors to volatility. The findings from frequency-domain show that the total connectedness of the 10 indexes is higher in short-run, indicating fewer opportunities in short-run than in the long-run.

Table 4 reports the net pairwise spill-over results for both the DY and BK methods using the returns data. As expected, the KFTX index acts as a net pairwise contributor of volatility with respect to Bitcoin,

Table 4
Net pairwise spill-over results using returns.

Panel A: DY (2014) Net pairwise spill-over										
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green Bond	Green Select
Bitcoin	0	0.119	0.097	-0.435	-0.232	-0.168	0.024	-0.462	-0.404	-0.361
MSCIW		0	-0.057	-0.436	-0.258	-0.182	-0.155	-0.59	-0.347	-0.305
MSCIUS			0	-0.349	-0.234	-0.153	-0.132	-0.645	-0.281	-0.244
Dollar				0	-0.166	-0.213	0.45	0.001	-0.254	-0.329
Oil					0	-0.06	0.226	0.182	-0.029	-0.043
Gold						0	0.162	0.028	0.28	0.276
KFTX							0	-0.475	-0.433	-0.388
VIX								0	-0.065	-0.066
Green Bond									0	-0.22
Green Select										0

Panel B: BK (2017) Net pairwise spill-over										
Frequency 1: The spill-over table for band 3.14 to 0.79 that roughly corresponds to 1–4 days										
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green Bond	Green Select
Bitcoin	0	0.096	-0.025	-0.087	-0.22	-0.052	-0.102	-0.544	-0.128	-0.128
MSCIW		0	-0.149	-0.11	-0.248	-0.068	-0.249	-0.626	-0.11	-0.107
MSCIUS			0	-0.048	-0.22	-0.058	-0.133	-0.606	-0.103	-0.1
Dollar				0	-0.158	-0.201	0.066	-0.112	0.023	-0.027
Oil					0	-0.035	0.218	0.101	-0.025	-0.032
Gold						0	0.088	0.001	0.141	0.128
KFTX							0	-0.45	-0.149	-0.145
VIX								0	-0.041	-0.05
Green Bond									0	-0.151
Green Select										0

Frequency 2: The spill-over table for band 0.79 to 0.39 that roughly corresponds to 4–8 days										
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green.bond	Green.and.select
Bitcoin	0	0.014	0.058	-0.14	-0.014	-0.046	0.062	0.022	-0.109	-0.093
MSCIW		0	0.042	-0.136	-0.012	-0.047	0.044	0.001	-0.095	-0.08
MSCIUS			0	-0.127	-0.014	-0.038	0.002	-0.032	-0.071	-0.059
Dollar				0	-0.012	-0.004	0.162	0.041	-0.118	-0.13
Oil					0	-0.012	0.011	0.042	-0.003	-0.006
Gold						0	0.029	0.011	0.066	0.069
KFTX							0	-0.026	-0.115	-0.1
VIX								0	-0.011	-0.007
Green.bond									0	-0.035
Green.and.select										0

Frequency 3: The spillover table for band: 0.39 to 0.20 that roughly corresponds to 8–16days										
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green.bond	Green.and.select
Bitcoin	0	0.005	0.03	-0.091	-0.001	-0.031	0.03	0.024	-0.073	-0.061
MSCIW		0	0.023	-0.083	-0.001	-0.029	0.023	0.012	-0.062	-0.052
MSCIUS			0	-0.077	-0.002	-0.025	0	-0.006	-0.046	-0.037
Dollar				0	0	-0.004	0.098	0.031	-0.071	-0.076
Oil					0	-0.006	0	0.019	0	-0.003
Gold						0	0.02	0.007	0.034	0.037
KFTX							0	-0.003	-0.074	-0.063
VIX								0	-0.006	-0.004
Green.bond									0	-0.017
Green.and.select										0

Frequency 4: The spill-over table for band 0.20 to 0.10 that roughly corresponds to 16–30days										
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green Bond	Green Select
Bitcoin	0	0.002	0.019	-0.066	0.001	-0.022	0.02	0.02	-0.053	-0.044
MSCIW		0	0.016	-0.061	0.001	-0.021	0.015	0.012	-0.045	-0.038
MSCIUS			0	-0.055	0.000	-0.018	0.000	-0.001	-0.034	-0.027
Dollar				0	0.002	-0.002	0.07	0.024	-0.05	-0.053
Oil					0	-0.004	-0.001	0.012	0.000	-0.001
Gold						0	0.015	0.005	0.023	0.024
KFTX							0	0.002	-0.054	-0.045
VIX								0	-0.005	-0.002
Green Bond									0	-0.01
Green Select										0

Frequency 5: The spill-over table for band 0.10 to 0.00 that roughly corresponds to 30days to infinity										
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green Bond	Green Select
Bitcoin	0	0.001	0.014	-0.051	0.001	-0.018	0.015	0.016	-0.042	-0.035
MSCIW		0	0.012	-0.046	0.001	-0.016	0.012	0.01	-0.035	-0.029
MSCIUS			0	-0.043	0.000	-0.013	-0.001	0.000	-0.027	-0.02

(continued on next page)

Table 4 (continued)

Frequency 5: The spill-over table for band 0.10 to 0.00 that roughly corresponds to 30days to infinity										
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green Bond	Green Select
Dollar				0	0.002	-0.002	0.054	0.018	-0.038	-0.041
Oil					0	-0.003	-0.002	0.009	0.000	-0.001
Gold						0	0.011	0.003	0.017	0.018
KFTX							0	0.002	-0.042	-0.035
VIX								0	-0.003	-0.002
Green Bond									0	-0.008
Green Select										0

NB: This table presents net pairwise volatility spill-over results for DY and BK approaches in Panel A and Panel B respectively using the return data for each market. In this table, the values in the i th row of the j -th column indicate the strength of the net pairwise spill-over effect from the i th market to the j -th market.

US Dollar, Oil and Gold price returns. That KFTX is a net contributor of volatility to Bitcoin is not surprising. This is because FinTech firms have become intertwined with cryptocurrencies because of their similar market segment and reliance on technology in their operations (Kommel et al., 2018; Yao et al., 2018). Thus volatility in KFTX price returns is transmitted to Bitcoin returns by causing price fluctuations in bitcoins. MSCIW and MSCI US acts as net contributor of volatility with regard to Bitcoin returns. As expected, Bitcoin, MSCIW and MSCI US are net receivers from US Dollar, Oil and Gold price returns. Not surprisingly, fluctuations in the exchange rate (dollar), Oil and Gold markets directly impact equity and Bitcoin markets, which is consistent with the findings by Corbet et al., (2018) and Gil-Alana et al., (2020). However, the findings differ from the findings of Liu and Tsyvinski (2018) who establish that the risk-return trade-off of cryptocurrencies (Bitcoin, Ripple, and Ethereum) is distinct from those of stocks, currencies, and precious metals. Bitcoin is a major receiver of volatility shocks from Green Bond and Green Bond Select price returns.

Table 4, Panel B, further demonstrates that at lower frequencies (1–4 days), KFTX is the highest net receiver of shocks from MSCI US and lowest receiver of shocks from the Oil price index. Thus, shocks spilled from fluctuations in the oil price marginally affect technology stocks. This is expected, as we earlier documented the weak correlation between these two markets from the correlation analysis. On the other hand, at low frequency, Bitcoin is a net receiver of shocks from several markets, such as the MSCI US, US Dollar, Gold, Oil, KFTX, VIX, Green Bond and Green Bond Select index returns. At higher frequencies (16–30 days and 30 days to infinity), we obtain similar results to those reported for Bitcoin receiving volatility shocks from US Dollar, Gold, Green Bond and Green Bond Select. However, at larger frequencies, Oil and VIX act as net contributors of volatility to Bitcoin returns. At higher frequencies, KFTX is a major net receiver of shocks from Green Bonds.

It is notable that the fourth industrial revolution is still in a nascent period of rapid growth. Hence it is possible that what may be right for the economies currently as documented in this study is likely to change until the integration level stabilizes.

Following the results in Table 4, we constructed a network analysis of the pairwise net spill-overs of all pairs. Using DY (2014) as the estimation technique, we plot the connections between variables in Fig. 4. The arrow direction shows a positive net directional connectedness across the variables. It is evident from the DY results that the returns on VIX play a significant lead role in total connectedness. This is followed by MSCIW, MSCI US, Bitcoin and KFTX. The returns on the VIX price index transmit more than they receive from all other markets. The BK results suggest that, at a low frequency (1–4 days), VIX plays a major role in the total connectedness but at larger frequencies, the roles of Green Bond and Green Bond Select are stronger in total connectedness. At all frequencies, Bitcoin returns is a receiver of volatility from KFTX in total connectedness. Overall, the results further cement our previous findings of Bitcoin acting as net receiver of volatility shocks from the KFTX price index suggesting that Bitcoin returns are extremely affected by the KFTX price index in both the time and frequency domains.

4.3. Robustness check: impact of the COVID-19 outbreak

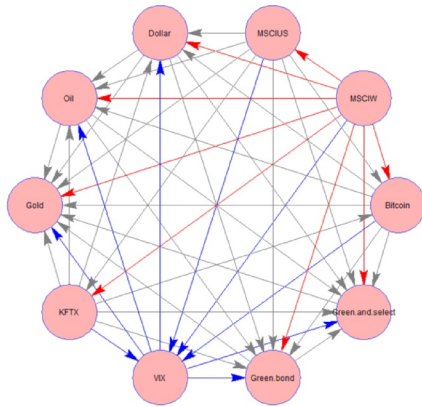
Since this is an empirical study, a robustness check is crucial to test the validity of our results. Since our dataset is quite recent, we use a sub-sample for the COVID-19 pandemic to investigate the connectedness. Since this time is indeed different, it is possible that there are changes in the financial structures concerning the pandemic and the 4th industrial revolution happening simultaneously. Therefore, we test the connectedness between the variables under study for the period 1 January 2020 to 29 June 2020 as a robustness check. Table 5 presents the results extracted from rolling windows of net pairwise spill-over results for whole sample (because using DY and BK models for the small sample size may not be comparable and may give misleading results) for both the DY and BK methods using the return data in Table 5 Panels A and B, respectively.

For the COVID 19 period in Panel A, we observe the KFTX price index acts as a net pairwise contributor of volatility to all variables. Oil acts a net pairwise contributor to Bitcoin, MSCIW, MSCISU and US Dollar. The results are not surprising since the period was characterized by intense price fluctuation in the crude oil market that affected several other markets. Results obtained for spill-overs between KFTX and the studied variables confirms the significant role of KFTX as a major asset class. Comparing the results in Tables 4 and 5, Panel A, we note the significant impact of COVID-19 on volatility spill-over across the studied markets. Again, Bitcoin, US Dollar and KFTX are major net receivers of volatility shocks from Green Bond and Green Bond Select price returns.

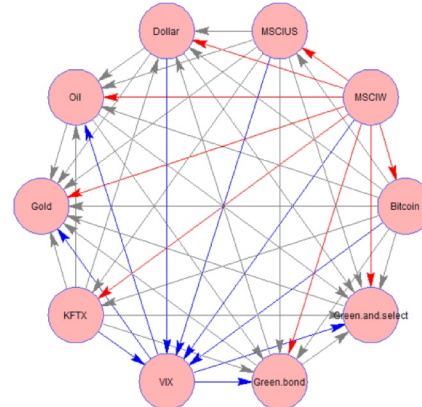
Table 5, Panel B, further demonstrates that at low frequencies (1–4 days), KFTX is a major net contributor of shocks to Bitcoin, US Dollar and MSCI W price indexes. Thus, shocks spilled from fluctuations in technology stocks during the COVID-19 outbreak, greatly affected the Bitcoin, US Dollar and MSCI W price returns. These results were expected since these asset classes, to a greater extent, are intertwined. We document a strong correlation between KFTX and these asset classes throughout the COVID period. With exception of the US Dollar, Green Bond Select is seen to be a net receiver of shocks from all other variables. Thus, Green Bond received shocks from Gold during the COVID-19 period, which differs from what was recorded in Table 4. At higher frequencies (16–30 days and 30 days to infinity), we obtain results that differ significantly from those recorded in Table 4. For instance, for the frequency 16–30 days, all variables are net contributors. Thus, during the period, all assets at higher frequencies transmitted shocks to other markets which emphasises the significant impact of the coronavirus on the global economy.

Overall, the results in Table 5 show that the coronavirus outbreak fueled intense connectedness across the studied asset classes leading to underperformance of several markets. For example, Baker et al., (2020) observe that the COVID-19 pandemic has had the worst impact on stock markets; it has been more than any other infectious disease like Spanish Flu. In addition, Baffes and Nagle (2020) find that the COVID-19 pandemic greatly affected the crude oil market with plummeting oil prices being the largest slump since the Gulf War.

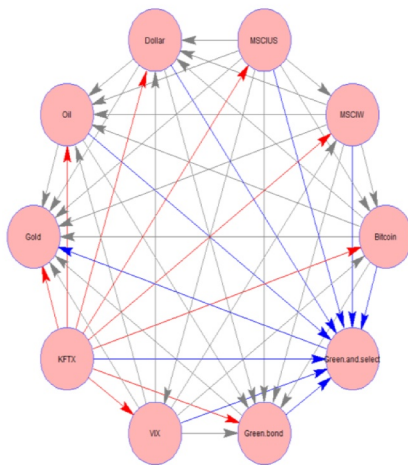
DY



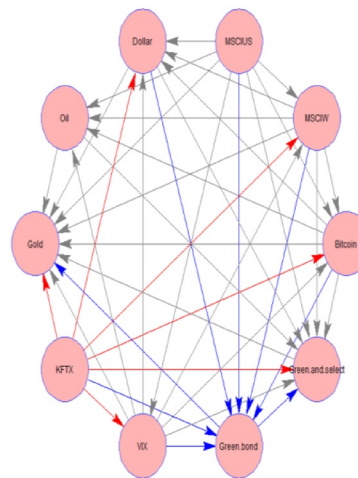
BK-Frequency 1



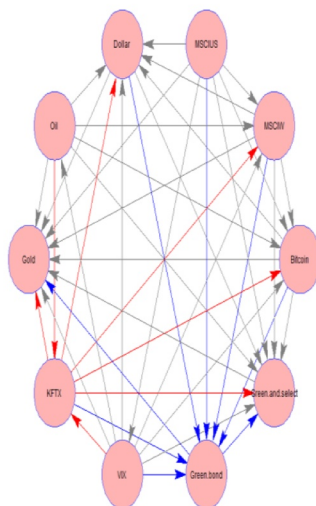
BK-Frequency 2



BK-Frequency 3



BK-Frequency 4



BK-Frequency 5

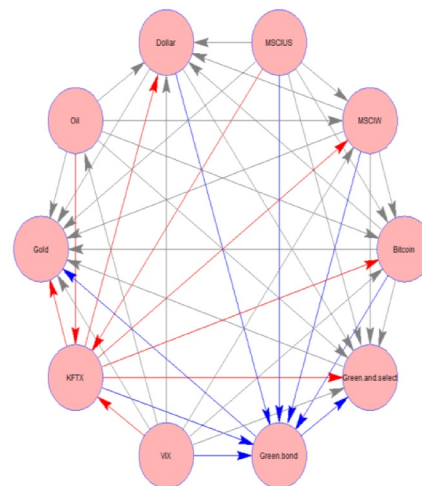


Fig. 4. Network analysis of the pairwise net spill-over.

5. Conclusions and policy implications

The 4th industrial age has brought extraordinary challenges to financial markets, in particular, the global economy, and all stakeholders in society. In addition, as a new market participant, Financial

Technology, Fintech, brings both opportunities and challenges to investors who are always looking for strategies with regard to hedging, diversification, and a safe haven. To contribute to part of tackling the challenges, efforts from various sectors, such as green bonds or cryptocurrencies, have contextualized the background for portfolio

Table 5
Rolling windows net pairwise spill-over results using returns.

Panel A: DY (2014) net pairwise spill-over										
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green Bond	Green Select
Bitcoin	0	0.928	0.774	0.594	0.368	0.106	0.918	-0.391	-0.528	-0.585
MSCIW		0	0.943	0.388	0.230	-0.075	0.775	-0.130	-0.569	-0.623
MSCIUS			0	0.096	0.135	-0.266	0.549	0.155	-0.505	-0.544
Dollar				0	0.177	0.589	0.817	-0.905	-0.290	-0.358
Oil					0	0.461	0.483	-0.321	0.173	0.211
Gold						0	0.409	-0.687	0.050	0.072
KFTX							0	-0.676	-0.401	-0.457
VIX								0	0.048	0.106
Green Bond									0	0.987
Green Select										0

Panel B: BK (2017) net pairwise spill-over										
Frequency 1: The spillover table for band 3.14 to 0.79 that roughly corresponds to 1–4 days										
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green Bond	Green Select
Bitcoin	0	0.945	0.908	-0.531	0.579	-0.512	0.943	0.897	-0.436	-0.448
MSCIW		0	0.989	-0.744	0.566	-0.615	0.938	0.952	-0.653	-0.663
MSCIUS			0	-0.777	0.574	-0.623	0.942	0.967	-0.688	-0.696
Dollar				0	-0.305	0.772	-0.593	-0.696	0.932	0.933
Oil					0	-0.076	0.562	0.655	-0.206	-0.209
Gold						0	-0.562	-0.505	0.748	0.753
KFTX							0	0.929	-0.535	-0.547
VIX								0	-0.608	-0.615
Green Bond									0	0.999
Green Select										0

Frequency 2: The spillover table for band 0.79 to 0.39 that roughly corresponds to 4–8 days										
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green Bond	Green Select
Bitcoin	0	0.869	0.786	0.333	0.584	0.385	0.965	0.574	0.350	0.354
MSCIW		0	0.980	-0.115	0.731	0.017	0.909	0.820	-0.099	-0.095
MSCIUS			0	-0.238	0.760	-0.081	0.857	0.892	-0.229	-0.222
Dollar				0	-0.178	0.889	0.247	-0.398	0.968	0.970
Oil					0	0.076	0.627	0.781	-0.165	-0.153
Gold						0	0.309	-0.190	0.866	0.873
KFTX							0	0.653	0.251	0.255
VIX								0	-0.443	-0.430
Green Bond									0	0.999
Green Select										0

Frequency 3: The spill-over table for band 0.39 to 0.20 that roughly corresponds to 8–16days										
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green Bond	Green Select
Bitcoin	0	0.983	0.962	0.443	0.875	0.751	0.991	0.822	0.499	0.518
MSCIW		0	0.992	0.306	0.917	0.658	0.983	0.874	0.358	0.379
MSCIUS			0	0.262	0.924	0.619	0.972	0.922	0.290	0.315
Dollar				0	0.139	0.835	0.453	0.137	0.950	0.958
Oil					0	0.567	0.872	0.884	0.181	0.208
Gold						0	0.741	0.496	0.839	0.857
KFTX							0	0.849	0.488	0.509
VIX								0	0.075	0.113
Green Bond									0	0.999
Green Select										0

Frequency 4: The spill-over table for band 0.20 to 0.10 that roughly corresponds to 16–30days										
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green Bond	Green Select
Bitcoin	0	0.999	0.997	0.912	0.986	0.980	0.999	0.959	0.914	0.923
MSCIW		0	0.999	0.902	0.988	0.975	0.999	0.963	0.901	0.911
MSCIUS			0	0.902	0.989	0.974	0.999	0.974	0.895	0.906
Dollar				0	0.858	0.962	0.919	0.872	0.968	0.975
Oil					0	0.957	0.984	0.969	0.869	0.879
Gold						0	0.981	0.944	0.959	0.967
KFTX							0	0.967	0.915	0.924
VIX								0	0.839	0.857
Green Bond									0	0.999
Green Select										0

Frequency 5: The spill-over table for band 0.10 to 0.00 that roughly corresponds to 30days to infinity										
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green Bond	Green Select
Bitcoin	0	0.853	0.675	-0.629	-0.255	-0.483	0.671	0.219	-0.807	-0.794
MSCIW		0	0.941	-0.805	-0.300	-0.793	0.347	0.559	-0.629	-0.585
MSCIUS			0	-0.866	-0.195	-0.912	0.075	0.764	-0.474	-0.416

(continued on next page)

Table 5 (continued)

Frequency 5: The spill-over table for band 0.10 to 0.00 that roughly corresponds to 30days to infinity										
	Bitcoin	MSCIW	MSCIUS	Dollar	Oil	Gold	KFTX	VIX	Green Bond	Green Select
Dollar				0	-0.091	0.760	0.010	-0.806	0.461	0.399
Oil					0	0.052	-0.375	-0.001	0.164	0.138
Gold						0	0.090	-0.749	0.177	0.127
KFTX							0	-0.433	-0.617	-0.648
VIX								0	-0.188	-0.113
Green Bond									0	0.986
Green Select										0

NB: This table presents rolling window net pairwise volatility spill-over results for the DY and BK approaches in Panels A and B, respectively, using return data for each market. In this table, the values in the i th row of the j -th column indicate the strength of the net pairwise spill-over effect from the i th market to the j -th market.

diversification. In this paper, we examine portfolio diversification in the presence of the Fintech index, KFTX, Bitcoin, Green Bonds and the pre-industrial revolution indexes, gold, oil, and other traditional equities. This pioneering paper offers evidence of the unique role of financial technology companies in portfolio diversification and contributes to the burgeoning empirical research on cryptocurrencies and green financial instruments.

The results have four main implications. First, the DY spill-over analysis indicates that the highest gross directional volatility comes from the MSCIW, which contributes 10.3% to other markets, followed by over 9% for Bitcoin, MSCI US and KFTX. The findings imply that the total connectedness of 21st century technology assets and traditional common stocks is very high. In other words, in a turbulent economy, and when the worst case happens, the 4th industrial age asset and traditional equities have a high probability of significant simultaneous losses and, therefore, stakeholders should consider this when constructing a portfolio with these two sectors. Second, Bitcoin, MSCIW, MSCI US, and KFTX are net contributors to volatility shocks and US Dollar, Oil, Gold, VIX, Green Bond and Green Bond Select are net receivers, according to the results from net pairwise volatility spill-over. These results reconfirm the risk level of common equities and the newly technology assets of the 21st century.

Third, the short-term witnesses higher volatility transmission than the long term. That is, holding assets for a long period is likely to mitigate risk whereas trading financial assets over the short term can increase risk because of higher volatility. These findings are relevant in identifying hedging and arbitrage opportunities in financial technology companies. If the volatility is lower in the long term, the strategy of 'buy and hold' to reduce volatility spill-over would be advised to investors. Fourth, traditional assets, gold and oil, and the modern age asset, green bonds, are useful as good hedgers compared with other assets because shock transmissions from them to the Fintech KFTX are below 0.1% and the total volatility spill-overs of all assets in the sample is nearly average, accounting for 44.39%, which implies a self-transmitting risk among the sampled assets.

The paper's findings provide useful implications for investors, financial managers, and portfolio managers, but especially for policy makers regarding investment strategies during the 4th industrial revolution. Investors are advised not to combine 21st century assets with traditional equities because, during turbulent times, such a portfolio presents a high risk of large joint losses. By indicating that oil, gold, and green bonds emerge in the role of hedging during normal times, we suggest gold as a safe haven during stressed times. Our paper provides insights into Green Bonds, a new instrument that not only promotes the transition to a low-carbon economy but also creates more diversified strategies for investors for risk hedging. The findings also provoke the attention of policymakers and financial managers about how to mitigate risk and how to reduce shock transmission among different markets. Therefore, the legal framework and clear procedures regarding newly released information in financial technology are significantly important in reducing information asymmetry and internal trading that are the main threats to value at risk and potential losses. In particular,

though Fintech has opened new chances for digital financial services to quicken financial presence amid social distancing, it needs to more closely monitor the risk spill-over from Fintech to traditional financial firms to maintain financial stability and, therefore, active policies are essential to influence the emergence of this new sector.

Our findings are subject to limitations. Specifically, the study stops at the volatility correlation between financial assets and does not measure out-of-sample forecasting. Therefore, this study opens new avenues for future research using different volatility methods such as Dynamic Conditional Correlation MGARCH (DCC-MGARCH) models (Engle, 2002) and stochastic volatility (SV) (Taylor, 1986), to measure both in-sample and out-of-sample. With the development of machine learning and deep learning, we can use these advanced learning approaches to build forecasting models. The development of Fintech is spreading over the world and future research may examine the relationship between traditional and modern financial markets in developing economies.

Acknowledgments

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Dr. Lan Le is a lecturer in School of Finance and Banking at University of Finance and Marketing Ho Chi Minh City (Vietnam). She is also a Research Fellow at University of Sydney, Australia. Her research interests are in the area of financial economics, machine learning and time series, fintech, socioeconomic implications of technological change. She has published on Quarterly Review of Economics & Finance. Her forthcoming publications are in Finance Research Letters, and Journal of Environmental Management. She is the corresponding author of this paper.

Dr. Emmanuel Joel Aikins Abakah works as a Casual Academic at The University of

Adelaide, South Australia where he obtained his PhD in 2019. His-research interests are in the area of empirical corporate finance, financial economics, applied time series econometrics and international finance. His-recent publications are in *International Review of Economics and Finance*, *Applied Economics*, and *International Journal of Managerial Finance*.

Dr. Aviral Tiwari is an Associate Professor at the Rajagiri Business School, Kochi, India. His-main areas of research interest are macro and monetary economics, financial economics, econometrics, and energy and environmental economics, and tourism. He has published a number of high-quality research outputs in reputable journals. Dr. Aviral also has a great interest in socioeconomic issues, financial and ecological stability. His-recent

publications are in the *Journal of Environmental Management*, *Energy Economics*, *Resources Policy*, *Annals of Tourism Research*, *Tourism Management*, *Tourism Economics*, *Current Issues in Tourism*, *Journal of Business Ethics*, *The World Economy*, *Applied Energy*, *Ecological Modelling*, *Journal of Cleaner Production*, *Energy Policy*, *Applied Economics*, [Studies in Nonlinear Dynamics & Econometrics](#), *Scottish Journal of Political Economy*, *Economic Modelling*, [Social Indicators Research](#) etc. Dr. Aviral is a SE Asia Editor of *Journal of Public Affairs*, Senior Editor of *International Journal of Emerging Markets*, Topic Editor of *Journal of Risk and Financial Management*, and Guest Editor of very reputable journals such as *Annals of Operation Research*, *Journal of Strategic Marketing*, *Energy Sources, Part B: Economics, Planning, and Policy*, *Management Decision*, [Energies](#), [Sustainability](#).