Diversification in the Age of the 4th Industrial Revolution: The Role of Artificial Intelligence, Green Bonds and Cryptocurrencies

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Abstract

In the context of the 4th industrial revolution, artificial intelligence (AI) and environmental challenges, this study investigates the role of AI, robotics stocks and green bonds in portfolio diversification. Using daily data from 2017 to 2020, we employ tail dependence as copulas and the Generalized Forecast Error Variance Decomposition to examine the volatility connectedness. Our results suggest that, first, portfolios consisting of these assets exhibit heavy-tail dependence which implies that in the times of economic turbulence, there will be a high probability of large joint losses. Second, volatility transmission is higher in the short term, implying that short-term shocks can cause higher volatility in the assets, but in the long run, volatility transmission decreases. Third, Bitcoin and gold are vital assets for hedging, though the Bitcoin is also affected by its past volatility, a feature it shares with green bonds and NASDAQ AI. During economic downturns, gold may act as a safe haven, as its shock transmission to NASDAQ AI is just around 1.41%. Lastly, the total volatility transmission of all financial assets is considerably high, suggesting that the portfolio has an inherent self-transmitting risk which requires careful diversification. The NASDAQ AI and general equity indexes are not good hedging instruments for each other.

Keywords: Artificial Intelligence; Portfolio Diversification; Green Bonds; NASDAQ AI; 4th Industrial Revolution; Cryptocurrencies.

JEL Codes: G11, G15, G17

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1 Introduction

Portfolio diversification and the need for safe-haven assets have been important elements of investment strategies for many decades. In this context, gold has traditionally played the role of hedging in normal times and of a safe haven in the times of market turmoil (Baur and Lucey, 2010; Shahzad et al., 2020). While the increased investment in gold for speculative and hedging purposes might have altered its safe-haven property (Baur and Glover 2012), new investment opportunities and multiple ways to both diversify portfolios and hedge risk have emerged in the recent years. Specifically, this paper is focused on three of these new investment opportunities that the era of the 4th industrial revolution has brought us. These are the emergence of artificial intelligence (AI) and robotics technology companies, green bonds which provide benefits to environmentally friendly projects and Bitcoin which is the leading cryptocurrency.

AI and robotics are key technologies of the 4th industrial revolution. Through these disruptive technological advances, the 4th industrial revolution is expected to blur the boundaries among physical, digital, and biological worlds, thereby rapidly and fundamentally changing the ways we live, work, and interact with each other. During the past decade, the activities related to AI and robotics have significantly increased (Felten et al. 2018; Furman and Seamans, 2019). For instance, while the worldwide shipments of robots rose by roughly 150% between 2010 and 2016, the share of jobs demanding AI skills was nearly five times higher in 2016 as compared to 2013 (Furman and Seamans, 2019). Similarly, investment in AI has rapidly grown (Bughin et al., 2017). In 2016 alone, established companies spent $18 to $27 billion for internal investments in AI-related projects and between $2 and $3 billion on AI-related mergers and acquisitions. Venture capital investment in innovative AI start-ups increased by 40% between 2013 and 2016. Companies use AI and robotics technologies for various reasons, including lower costs and production times, consistent product quality, and supply chain operations management (Webster and Ivanov, 2020). However, while AI and robotics may help to increase productivity growth, the effects on employment are mixed, particularly in the short-run (Acemoglu and Restrepo, 2018, 2019; Brynjolfsson et al. 2017; Furman and Seamans, 2019; Graetz and Michaels, 2018). At present, AI and robotics technologies are adopted across the world, penetrating not only the manufacturing sectors using industrial robots but also other economic activities, such as trading on financial markets, transportation through autonomous vehicles, customer relationship management using chatbots, legal provision, and medical diagnostics and operations (Webster and Ivanov, 2020). Intuitively, AI and robotics technology companies have become increasingly influential, representing an interesting investment option for portfolio diversification.

Green bonds are also a potential venue for portfolio diversification and have been developed into popular financial instruments in recent years, mainly because they address the need for both financial resources and environmental protection. In general, green bonds have similar characteristics as conventional fixed-income corporate bonds, yet their earnings are used for environmentally friendly projects only (Reboredo and Ugolini, 2019). Consequently, green bonds may help to improve the financial performance of companies as well as environmental performance, by fostering green innovations and long-term green investments (Flammer, 2019). In this regard, green bonds complement the actions of governments which have increasingly implemented environmental policy instruments to induce green innovation, build up clean energy technology capacities and thus improve the environmental quality (Hille et al., 2020). Given the urgent need to fight climate change and potential intergenerational regulatory conflicts, some researchers consider green bonds as the instrument of choice to finance climate change mitigation (Flaherty et al., 2017; Sartzetakis, 2020). The transparency and reputation of green bonds have been enhanced by the publication of the Green Bond Principles (GBP) by the International Capital Markets Association in 2014, establishing standardised rules for labelling bonds as green (Reboredo, 2018). While stock exchanges around the world have opened specific green bond segments in recent years, the size and significance of the green bonds market has been growing, making green bonds a well-established and sustainable investment instrument (Febi et al., 2018; Reboredo and Ugolini, 2019).

Cryptocurrencies such as Bitcoin have been developed as decentralized digital currencies and payment systems. While cryptocurrencies are used to verify transactions, they have become a popular investment instrument and are sometimes considered as a better currency or even as digital gold (Barber et al., 2012; Selmi et al., 2018). The use of blockchain technology has been seen as a great financial disruptor and manifestation of the 4th industrial revolution (White et al., 2020). The cryptocurrencies have accumulated a considerable market capitalization of about $190 billion since the inception of Bitcoin in 2009. At present, there exist more than one thousand cryptocurrencies (Corbet et al., 2019). However, the role that cryptocurrencies will play in future financial markets remains unclear. For instance, Dyhrberg (2016a) argued that the Bitcoin can be classified between gold and US dollar on a scale that considers the advantages of a pure medium of exchange on the one hand, to those of a pure storage of value on the other. Gronwald (2019) argued that the Bitcoin resembles more to an asset or speculative investment rather than a currency. Similarly, instead of a currency or a security, White et al. (2020) saw Bitcoin as a technology-based product, an emerging asset class or a bubble event. Contextualising on this debate, the subject study analyses the role of stocks of AI and robotics companies for portfolio diversification, thereby considering average returns, possible risk, and correlations with alternative investments, such as green bonds and Bitcoin. It contributes to the existing evidence in two main aspects. First, using data on the NASDAQ Artificial Intelligence and Robotics Index (NASDAQ AI), this is the first study that specifically considers the role of AI and robotics company stocks for portfolio diversification. The NASDAQ AI is recently established in December 2017 to track the performance of technology-intensive companies active in the AI and robotics sector. Prior studies have only considered technology-intensive companies in general (Ahmad and Rais, 2018; Kumar et al., 2012) or companies of other specific technology-intensive sectors, such as IT or clean energy technologies (Jawadi et al., 2013; Ortas and Moneva, 2013). Second, the focus of this study is on the dynamic interdependencies with other assets, including green bonds and Bitcoin. Hence, we also supplement the recently popular and rapidly growing empirical literature on green financial instruments and cryptocurrencies (Bouri et al., 2018; Lundgren et al., 2018; Selmi et al., 2018; Tang and Zhang, 2019). To analyse extreme market situations as well as short- and long-term volatility spillovers, we use two main methodological approaches. Specifically, we consider tail dependences via copulas (Embrechts et al., 2001) and frequent interconnectedness via variance decompositions and their spectral representation in combination with the Generalized Forecast Error Variance Decomposition (Baruník and Kocenda, 2019).

Drawing on daily data from 19th December 2017 to 16th January 2020, we employ tail dependence as copulas and the Generalized Forecast Error Variance Decomposition to analyse volatility connectedness. Our key findings suggest that, first, portfolios consisting of the underlying assets exhibit heavy-tail dependence, thus in times of economic turmoil losses can exacerbate with alternative investments, having a high probability of extreme losses at the same time. Second, the volatility transmission is higher in the short term than in the long term, implying that short-term shocks may cause higher volatility in the assets in our portfolio. However, holding this portfolio would decrease the volatility transmission among the assets in the long term. Third, Bitcoin and gold are the most vital assets for hedging, although the Bitcoin is also affected by its past volatility, a feature it shares with green bonds and NASDAQ AI. Gold seems to play an important role in hedging during economic and financial downturns, as the shock transmission of gold to NASDAQ AI is only around 1.41%. Lastly, the total volatility transmission of all financial assets is considerably high, suggesting that the portfolio has an inherent and self-transmitting risk, which requires careful diversification. The NASDAQ AI and the general equity indexes are not good hedges for each other. These findings on AI stocks, cryptocurrencies and green investment opportunities have important implications for portfolio diversification in the age of the 4th industrial revolution. The existing evidence (details in next section) acknowledges the importance of these investment classes. However, despite the irrefutable evidence on the importance of AI, green bonds, and cryptocurrencies for different aspects of the economy and financial sector, their usage in portfolio diversification and hedging against each other is underexplored. Concomitantly, the subject study fills this gap by analysing their role in portfolio diversification in the context of the 4th industrial revolution.

The paper proceeds as follows: Section 2 provides a critical review of the existing literature on the subject. Details on the methodology and data are provided in Section 3. Findings are presented in Section 4, and lastly, Section 5 concludes.

2 Literature Review

There are generally several approaches to the decision on whether an asset is suitable for investment. For instance, from a risk perspective, when an asset is negatively related with other assets in the portfolio, then adding this asset to the portfolio will diversify the portfolio and hence decrease risks (Bouri, 2017). Nonetheless, there is a difference between a diversifier, a hedge and a safe haven (Baur and Lucey, 2010; Ratner and Chiu, 2013). A diversifier is an asset that has a weak positive correlation with another asset on average. While a hedge is an asset that is either uncorrelated or negatively correlated with another asset on average, the same properties hold for a safe haven, but in times of market turmoil. Hence, a diversifier and a hedge provide diversification benefits on average, yet unlike a safe-haven investment, they do not necessarily reduce risk when it is needed the most (Baur and Lucey, 2010). Traditionally, gold has been regarded as a hedge and safe haven, yet more recently these properties have also been tested for other assets, including credit default swaps (Ratner and Chiu, 2013), Bitcoins (Selmi et al. 2018) and a vast literature has considered the broader aspects of portfolio diversification (Arouri et al., 2015; Brière et al., 2015; Guesmi et al., 2019; Reboredo, 2018).

In the context of portfolio diversification, this study has three aspects and hence can be related to three strands of literature. *Firstly*, the stocks of AI and robotics companies. Dirican (2015) and Furman and Seamons (2019) reviewed the impact of AI and robotics on business models and the economy. To the best of the authors' knowledge, no prior study has analysed the role of AI and robotics company stocks for portfolio diversification. However, there have been studies considering the stocks of technology-intensive and technology-related companies, such as of technology companies in general (Chen and Lin, 2014; Smales, 2019), IT companies (Kamssu et al., 2003; Jawadi et al., 2013) and clean-technology companies (Ortas and Moneva, 2013). On average, it is expected that both the returns and volatility of AI and robotics company stocks are higher than those of companies which are in less technology-intensive sectors. These characteristics would generally be in line with those of technology company stocks in general. That is, the volatility of technology stocks has tended to be much higher than that of overall equity markets (Jiang et al., 2011). Similarly, the performance of technology stocks has often exceeded conventional stocks (Kamsu et al., 2003; Ortas and Moneva, 2013). In this regard, a higher market value of R&D-intensive companies is found to be positively associated with a higher R&D capability (e.g. filed patents) of the respective company (Deng et al., 1999; Lin and Liang 2010).

Previous studies have examined the relationship between technology stocks and a variety of other stocks and assets, including general equity markets (Hansda and Ray, 2002; Jawadi et al., 2013), oil prices and clean energy company stocks (Kumar et al. 2012; Sadorsky, 2012), cryptocurrencies (Smales, 2019; Symitsi and Chalvatzis, 2018), gold (Chen and Lin, 2014; Chen and Wang, 2018), and credit default swaps (Ratner and Chiu, 2013). It has been reported that technology stock prices affect conventional domestic and foreign stocks (Hansda and Ray, 2002) and they also react to changes in global capital markets (Jawadi et al., 2013). A comparatively large body of research has analysed the interdependences between technology stocks, oil prices, and clean energy stocks, revealing dependence, causality, and spillovers. One reason is that an increase in the oil price often causes clean energy stock prices to rise, which in turn tends to increase technology stock prices (Lundgren et al., 2018). Consequently, empirical studies have estimated similar market responses of technology stock prices and those of clean energy stocks, often reflected in positive causality (Henriques and Sadorsky, 2008; Kumar et al., 2012; Managi and Okomoto, 2013). Similarly, volatility spillovers between the prices of technology company stocks, oil, and clean energy company stocks have been found (Ahmad 2017; Ahmad and Rais, 2018; Sadorsky, 2012). Concerning the relation with cryptocurrencies, Symitsi and Chalvatzis (2018) reported both returns and short-term volatility spillover from technology company stocks to Bitcoin, yet Smales (2019) detected no significant correlation of the respective returns. While gold has often been attributed as a safe haven for equity markets, this property appears to hold to a limited extent for technology firms (Chen and Lin, 2014; Chen and Wang, 2018). Likewise, credit default swaps have only in parts been a strong safe haven for technology and telecommunication stock indices during periods of market turmoil (Ratner and Chiu, 2013).

Secondly, a related strand of literature has focused on green stocks and bonds. In this context, the results on the performance of environmental investments are mixed. While Ortas and Moneva (2013) found that the returns and risks of clean-technology equity indices are higher than those of conventional stock indices, other studies, such as Climent and Soriano (2011) and Reboredo et al. (2017b), reported that green mutual funds have lower or similar returns and lower downside risk protection than conventional mutual funds. Similarly, green bonds tend to yield lower returns than conventional bonds (Baker et al., 2018; Hachenberg and Schiereck, 2018; Zerbid, 2019), and experience larger volatility (Pham, 2016).

A relatively large number of studies has analysed the dynamic relationship between oil prices and clean energy stocks, reporting causality, tail dependence (Reboredo, 2015; Reboredo et al., 2017a), and volatility spillovers (Sadorsky, 2012; Wen et al., 2014). In line with this, prior studies have found that prices of renewable energy firms are sensitive to oil price changes (Henriques and Sadorsky, 2008; Kumar et al., 2012; Managi and Okimoto, 2013). Related literature, that is particularly relevant to this study, has examined the interdependencies between green bond markets and other markets. For instance, Broadstock and Cheng (2019) and Pham (2016) analysed the relationship between different bond markets. While the former detected that the relation between green and black bond prices is contingent on financial market conditions, such as economic policy uncertainty and volatility, the latter showed that shocks in the conventional bond market tend to spill over to the green bond market. In studies by Reboredo (2018) and Reboredo and Ugolini (2019), weak or no dependencies were found between green bond markets and stock, energy, and high-yield corporate bond markets. On the contrary, the two studies estimated close relationships with treasury and corporate markets on the one hand, as well as with fixed-income and currency markets on the other. Strong dependencies of stock prices are estimated in Lundgren et al. (2018) and Tang and Zhang (2018). Specifically, according to Lundgren et al. (2018), the European stock market depends on changes in renewable energy stock prices, whereas uncertainties play an important role regarding return and volatility spillover to energy investments. In a study by Tang and Zhang (2019), stock prices reacted positively to the announcement of green bond issuance, and both institutional ownership and stock liquidity increased following the issuance of green bonds.

Thirdly, the literature on cryptocurrencies is comparatively more recent, yet rapidly growing. While Corbet et al. (2019) provided an overview of the empirical literature on cryptocurrencies since their introduction as a financial asset, Dwyer (2015) explained the general economic and financial properties of cryptocurrencies. Most of the studies have focused on a single cryptocurrency, very often the Bitcoin (Bouri et al., 2017; Shahzad et al., 2019; Urquhart and Zhang, 2019). Although the volatility of cryptocurrencies is significantly higher than that of traditional assets and currencies (Corbet et al., 2018; Dwyer, 2015), investors may earn higher returns and minimize overall risk by including cryptocurrencies into diversified portfolios (Brière et al., 2015; Guesmi et al., 2019; Selmi et al., 2018). Cryptocurrencies may, in part, act as a safe haven for oil price movements (Selmi et al., 2018), certain national currencies (Urquhart and Zhang, 2019), gold, and commodities (Shahzad et. al, 2019). Nonetheless, investors should also be cautious, because cryptocurrencies may be subject to inherent pricing bubbles (Cheah and Fry, 2015, Huynh et al 2020), regulatory disorientation (Corbet et al., 2019), and cyber-criminality (Gandal et al., 2018). Moreover, cryptocurrencies' valuation is affected not only by traditional market forces but also by digital currency-specific factors, such as social media activities on internet forums (Mai et al., 2018) and the respective cryptocurrency's attractiveness for investors and users (Ciaian et al., 2016).

Several studies have investigated the relationship between cryptocurrency prices and other assets and reported mixed evidence. On the one hand, no or weak links with classic asset prices are reported. For instance, Giudici and Polinesi (2019) found that Bitcoin prices are not influenced by traditional asset prices, yet their volatilities are. According to Baur et al. (2017), this missing relationship is present during both normal times and times of financial turmoil. While cryptocurrency markets are interrelated with each other, Corbet et al. (2018) estimated that cryptocurrency prices are relatively decoupled from a variety of assets, such as stocks, bonds, and gold, hence offering a diversification benefit. Similar conclusions are reached by Bouri et al. (2017) and Dyhrberg (2016b), who estimated small positive correlations, and suggested that such decoupling and diversification benefit is only present in the short run and may vanish in the long run. On the other hand, some studies reported important linkages between cryptocurrencies and other assets, suggesting high price correlations (Jin et al. 2019), tail dependence (Selmi et al., 2018) as well as return and volatility spillovers (Symitsi and Chalvatzis, 2018). For example, Jin et al. (2019) reported that Bitcoin prices are influenced relatively strongly by price fluctuations in gold and oil markets. They found mostly negative dynamic correlations between Bitcoin and the other two markets. White et al. (2020) showed that the Bitcoin market tends to be highly correlated with derivatives and inversely correlated to major currencies. According to Bouri et al. (2018), cryptocurrency returns are relatively strongly related to other assets, especially commodities, and cryptocurrency markets receive more volatility than they transmit. Although estimating low correlations of Bitcoins with stock indices, Symitsi and Chalvatzis (2018) detected return spillovers from energy and technology stock indices to Bitcoins as well as long-run volatility effects from Bitcoins on fossil fuel and clean energy stocks.

To sum up, while no prior research has considered the role of AI and robotics company stocks for portfolio diversification, we expect their characteristics to be similar to those of other technology-intensive companies. Specifically, both the returns and volatility of AI and robotics company stocks are expected to be rather higher than for other stocks. As these firms are participants of a market that is not yet mature, their stocks may tend to react significantly to changes in other asset markets, such as the general equity markets and the oil price. A mixed picture exists concerning the hedging and safe haven properties of other assets for stocks of technology-intensive firms. For green bonds, prior studies have reported lower returns and higher volatility than for conventional bonds. The relationship of green bond markets with other assets is mixed. For instance, while significant interdependencies have been estimated with conventional bond, treasury, and currency markets, green bonds tend to have weak or no dependencies with stock, energy, and high-yield corporate bond markets. The rapidly growing research on cryptocurrencies has shown that both their returns and volatility are comparatively high. Mixed evidence exists regarding cryptocurrencies' relationship with other assets. That is, not only weak or no linkages have been estimated, suggesting that cryptocurrencies may partly act as hedges or safe havens, but researchers have also reported important linkages in the form of high price correlations, tail dependence, and high return and volatility spillovers.

3 Data and methodology

3.1 Data collection and descriptive statistics

We collected daily data from Thomson Reuters for eight financial asset classes for the period from 19th December 2017 to 16th January 2020. The main reason to start from 19th December 2017 is that the data on NASDAQ AI index has been available from this date, whereas the other components were already traded earlier. In total, our time frame includes 544 observations for each variable. The NASDAQ AI was established to track the performance of firms that are active in AI and robotics, including technology, industrial, medical, and other economic sectors. Therefore, this proxy reflects the innovation level of the market as well as the performance of this industry in the era of the 4th industrial revolution. Moreover, oil, gold, CBOE volatility (VIX), and MSCI equity indices (MSCI World and MSCI USA) are well-known investments and, in parts, safe havens for investors. We used the S&P Green Bond Select index as a proxy for the green bond market. This index is a market value-weighted subset of the S&P Green Bond index, designed to track the performance of green-labelled bonds issued globally. Although the market size of green bonds is relatively small compared to the other potential financial investments, green investments have attracted much attention from investors recently, and therefore including a green bond index is important to consider the inherent risk for portfolio diversification. Last, we included Bitcoin in the underlying portfolio, because the boom of cryptocurrencies since 2013 has increased this market's attractiveness for investors.

Table 1. Descriptive statistics

Variables	Mean	Standard Deviation	Skewness	Kurtosis	JB	ADF
NASDAQ AI	0.00041	0.01002	-0.60558	4.41910	78.75***	-19.783***
Oil	0.00004	0.01996	-0.00049	8.36033	650.1***	-22.469***
Bitcoin	-0.00144	0.14705	-0.30783	32.51568	2000***	-35.272***
Green bond	-0.00002	0.00483	0.21941	97.20986	20000***	-32.123***
MSCI World	0.00025	0.01301	0.26417	60.51622	75000***	-26.018***
MSCI USA	0.00039	0.01525	0.04356	62.62450	80000***	-27.623***
Gold	0.00038	0.01376	0.27584	76.08298	12000***	-29.404***
VIX	0.00047	0.09822	0.96772	20.60982	7101***	-26.435***

Notes: The symbols ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. JB denotes the Jarque-Bera test for normality.

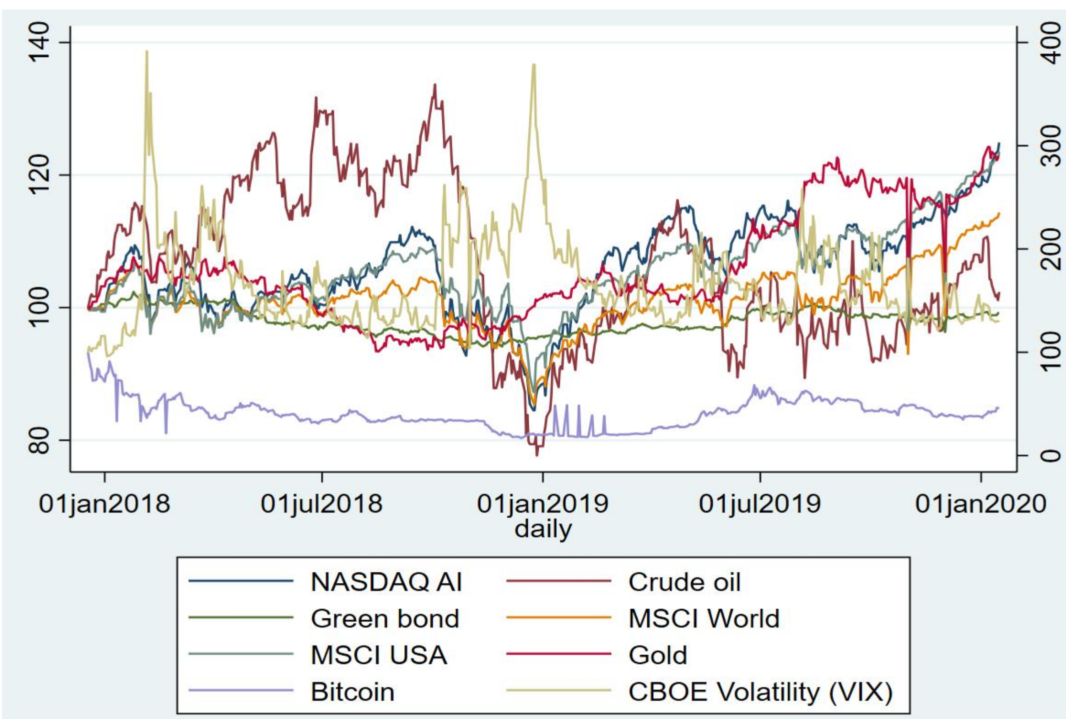


Fig 1. Investment performance from January 2018 to January 2020[a, b]

[a] Source: Self-prepared using the data from Thomson Reuters EIKON.

[b] Note: To make the scales comparable, we normalised the rate of return of the assets to 100. The right y-axis refers to Bitcoin and VIX and the left y-axis to the remaining assets.

As can be seen in Table 1, except for Bitcoin and green bonds that exhibit negative returns, the average returns of the assets were positive during the period of analysis, hence they were potentially promising investments. The highest average return can be observed for VIX, followed by the NASDAQ AI. However, the NASDAQ AI has a much lower standard deviation (0.01) than VIX (0.09), implying that the same one unit of oscillation offers a higher return for NASDAQ AI than VIX. Moreover, it is important to note that all variables have non-normal distributions and are stationary at levels. These characteristics are important to consider when choosing the appropriate econometric approach to examine the possible risk of the diversified portfolio. The general picture of the average values is supported by Figure 2, depicting the normalized returns over time. That is, especially Bitcoin tends to underperform during the period of analysis, while VIX displays high uncertainties, which spike at the beginning of 2018 and 2019. Similarly, crude oil exhibits a highly volatile pattern that peaked above 130 shortly before dropping below 80. Consequently, a thorough analysis is necessary to avoid excessive risks and optimise the portfolio diversification for the different financial assets.

Table 2 depicts the correlations between the underlying variables. First, VIX has a negative correlation with all other investments. That is, based on the mean-variance analysis, VIX can be a good hedging instrument for these assets. We are particularly interested in the price movement of the NASDAQ AI, representing the performance of AI and robotics industry companies. There are three assets with significantly positive correlation with NASDAQ AI, namely oil and the two MSCI equities. Overall, NASDAQ AI does not linearly commove with Bitcoin, green bonds, and gold, whereas it strongly correlates with oil, equities, and VIX. Oil is independent of the movement of Bitcoin, green bonds, and gold, while green bonds are independent of NASDAQ AI, oil, and Bitcoin. Bitcoin appears to be independent of all other assets, which is in line with findings of several prior studies suggesting that it could be used as a safe haven for other financial assets (Bouri et al., 2017), gold and commodities (Shahzad et. al, 2019), other currencies (Urquhart and Zhang, 2019), and oil price movements (Selmi et al., 2018). Regarding the correlations, this only holds to a limited extent for gold, which shows significant association with several assets. Except for Bitcoin, the equity indices are significantly and positively correlated with all other assets. However, correlation is based on a linear dependence structure, while we found non-normal distributions for our variables in Table 1. Hence, the subsequent empirical analysis will provide more insights for a profound diversification strategy in the era of the 4th industrial revolution.

Table 2. Correlation matrix

Variables	NASDAQ AI	Oil	Bitcoin	Green bond	MSCI World	MSCI USA	Gold	VIX
NASDAQ AI	1							
Oil	0.2149***	1						
Bitcoin	0.0293	-0.0117	1					
Green bond	0.0332	-0.0228	0.0135	1				
MSCI World	0.4994***	0.1029**	0.0234	0.6334***	1			
MSCI USA	0.5120***	0.0962**	0.023	0.4357***	0.9539***	1		
Gold	-0.0102	-0.0212	0.028	0.7821***	0.7287***	0.6533***	1	
VIX	-0.6333***	-0.1552***	-0.0409	-0.4131***	-0.6561***	-0.5982***	-0.2863***	1

Note: The symbols ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

3.2 Methodology

To examine the role of diversification of these assets in a portfolio, we follow two main methodological approaches. These are tail-dependence as copulas (Embrechts et al., 2001) and volatility interconnectedness via the Generalized Forecast Error Variance Decomposition (Baruník and Kocenda, 2019). There are also two main reasons to employ these methods. First, we would like to examine how the financial assets co-move in the case of economic downturns, i.e. we are interested in the extreme negative values. Second, it is important to consider the level of volatility spillovers among the assets in the short and long term for diversification strategies.

Copulas are the structure of dependence in terms of joint distribution between two uniform marginal variables. Copulas were first introduced in the form of Sklar's theorem. To account for asymptotically large losses, Nguyen and Huynh (2019), Boako et al. (2019), and Rivieccio and De Luca (2016) demonstrated how to define the dependence structure through the family of heavy-tail and stochastic copulas. To summarize our methodology, we begin with two variables x and y, which are random and continuous. To examine if heavy-tail dependence is present in the portfolio, we examine two kinds of copulas, namely Gaussian copulas for the normal tail and Student-t copulas for the heavy tail. Equation 1 represents the parameter estimation of Gaussian copulas:

$$C(x,y) = -\frac{1}{\theta}\ln\left(1+\frac{(\exp(-\theta x)-1)(\exp(-\theta y)-1)}{\exp(-\theta)-1}\right. \quad (\text{Eq. }1)$$

where θ denotes the linear correlation coefficient. As mentioned earlier, our variables do not linearly commove. Thus, we consider Student-t copulas with heavy-tail estimates. In particular, $t_{\upsilon}^{-1}(u)$ denotes the inverse of the cumulative distribution function of the standard univariate Student-t distribution, with υ being the degree of freedom. Equation 2 demonstrates how the parameter, known as extreme dependence, can be estimated using Student-t copulas:

$$C(x,y) = \int_{-\infty}^{t_{\upsilon}^{-1}(x)}\int_{-\infty}^{t_{\upsilon}^{-1}(y)} \frac{1}{2\pi\sqrt{1-\theta^2}}\left(1+\frac{s^2-2\theta st+t^2}{\upsilon(1-\theta^2)}\right)^{-\frac{\upsilon+2}{2}} ds\,dt \quad (\text{Eq. }2)$$

Following Lourme and Maurer (2017), we also employ the Maximum Likelihood approach to choose the most appropriate copulas and to analyse the dependence structure between variables. After considering the tail structure, we would like to see how these variables transmit volatility in the portfolio. For this reason, we use the Generalized ARCH or GARCH model with GARCH (1,1) to predict the volatility, except for VIX. Afterwards, we employ the generalized VAR and spillover index of Diebold and Yilmaz (2012, 2014) to investigate the directional spillovers. This approach is advantageous in that it is invariant to the ordering of the variables. It also allows for the calculation of both the direction and the strength of spillovers over time and among different variables. We build a VAR(p) process for the vector of volatilities of all variables, $\mathrm{V_t} = (\mathrm{V_{1t}}, \ldots, \mathrm{V_{Nt}})'$, such as:

$$\mathrm{V_t} = \sum_{\mathrm{i=1}}^{\mathrm{p}} \Phi_{\mathrm{i}}\,\mathrm{V_{t-i}} + \varepsilon_{\mathrm{t}} \text{ where } \varepsilon_{\mathrm{t}} \sim \mathrm{N}(0, \sum\nolimits_{\varepsilon}) \quad (\text{Eq. }3)$$

The moving average representation of residual ε_{t} in VAR(p) has the following form:

$$V_t = \sum_{i=1}^{\infty} \Psi_i \, \varepsilon_{t-i} \qquad (\text{Eq. } 4)$$

in which Ψ_i is a matrix of the coefficients. We briefly summarize the total spillovers index by using the H-step-ahead generalized forecast error variance decomposition matrix, having the following elements for H = 1,2…

$$\theta_{jk}^{H} = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H-1} \left(e'_j \Psi_h \Sigma_\varepsilon e_k \right)^2}{\sum_{h=0}^{H-1} \left(e'_j \Psi_h \, \Sigma_\varepsilon \, \Psi'_h e_k \right)}, \qquad j, k = 1, \ldots N \ (\text{Eq. } 5)$$

Specifically, Ψ_h is a matrix of the moving average coefficients, forecasted at time t, whereas Σ_ε denotes the variance matrix for the error vector ε_t, and σ_{kk} is the k^{th} diagonal element of Σ_ε. Furthermore, e_j and e_k are selection errors with 1 as the j^{th} and k^{th} element and 0 otherwise. We refer to Baruník and Kočenda (2019) to measure directional spillovers from asset j to asset k using the following equation:

$$S_{N,j\leftrightarrow\blacksquare}^{H} = 100 \times \frac{1}{N} \sum_{\substack{k=1 \\ j \neq k}}^{N} \tilde{\theta}_{jk}^{H} \qquad (\text{Eq. } 6)$$

The receiving effects are calculated by adding all numbers in rows j, except for the terms on the diagonal that refer to the effect on the asset itself. The sending effects are estimated as the sum of numbers in the column, except for the numbers on the diagonal. To sum up, we employed two general approaches, to answer two main questions: (i) Does a dependence structure exist among the considered investments? (ii) How much volatility do the investments transmit if we construct a portfolio consisting of these assets?

4 Empirical Results

4.1 Heavy-tail dependence

Table 3 summarizes our copula parameters' estimations and Maximum Log-likelihood values. We select the most appropriate copula based on the highest Maximum Log-likelihood value. This approach follows the recommendation of studies, such as Rodriguez (2007). As can be seen, all pairs share the heavy-tail phenomenon, which implies that in the extreme value case that may happen in times of market turbulence, investors would have large joint losses. In other words, a portfolio consisting of these assets will be bearish when there is market turbulence.

Table 3. Copulas estimates

Pairs	Normal-Copula	Student-t Copulas
NASDAQ AI – Oil	0.2382	**0.2469**
	[15.28]	[17.81]
NASDAQ AI – Bitcoin	0.005916	**0.00408**
	[0.0091]	[0.9616]
NASDAQ AI – Green bond	0.02244	**0.01573**

	[0.1313]	[1.198]
NASDAQ AI – Gold	-0.04039	**-0.04523**
	[0.4255]	[2.936]
NASDAQ AI – MSCI World	0.8404	**0.8618**
	[328.2]	[382.5]
NASDAQ AI – MSCI US	0.802	**0.8234**
	[275.6]	[325.9]
NASDAQ AI - VIX	-0.6784	**-0.685**
	[164]	[175.3]

Notes: The table displays the estimated copula dependence parameters for the Gaussian and Student-t copulas. The Maximum Log-likelihoods are in brackets. The parameter range depends on the specific copula. For instance, the Gaussian parameter is restricted to the interval (-1, 1). The parameters measure the magnitude of dependence. Maximum Log-likelihoods were calculated to choose the most appropriate copula model from the recommendation of previous studies, such as Rodriguez (2007).

Compared to earlier research, our paper is the first endeavour to consider the tail-dependence structure of NASDAQ AI with different financial assets. Several prior studies have reported evidence of co-movement for some of under analysis alternative investments, including green bonds and financial markets (Reboredo, 2018), oil and equity markets (Aloui et al., 2013), and gold and stock markets (Nguyen et al., 2016).

4.2 Volatility transmission in the short and long term

We used the Generalized Forecast Error Variance Decomposition to determine the volatility connectedness, and thereby two general features are important. First, we choose two timeframes, namely for the short-term analysis from one to five trading days, and for the long-term analysis from five trading days to infinity. The main reason for this approach is that conventional trading usually takes place for five days every week. A week is a reasonable amount of time for investors to restructure the portfolio, i.e. to balance the portfolio based on performance. Second, as this method is based on Vector-Autoregressive estimations, two trading days are chosen as the optimal lag length using the Akaike Information Criterion. This is also the optimal lag length for our short- and long-term analysis. Tables 4 and 5 show the volatility connectedness for the short- and long-term horizon, respectively. Before going to the detailed analysis, it is worth noting that the total volatility transmission is 60.48%. This implies that the volatility among the assets is higher than the average.

Table 4. Volatility transmission from 1 to 5 trading days

To	**From**							
	NASDAQ AI	Oil	Bitcoin	Green bond	MSCI World	MSCI USA	Gold	VIX
NASDAQ AI	**38.21**	0.26	0.12	0.76	0.25	0.17	0.35	4.42
Oil	0.46	**78.30**	0.07	0.28	0.09	0.16	0.14	0.42
Bitcoin	0.37	0.15	**70.84**	0.12	0.05	0.06	0.04	0.14
Green bond	1.04	0.17	0.10	**71.32**	2.64	13.68	4.12	2.27
MSCI World	1.51	0.13	0.03	10.82	**60.41**	0.10	1.06	3.67
MSCI USA	1.30	0.20	0.04	5.25	64.32	**1.72**	1.46	2.09
Gold	0.71	0.17	0.03	12.11	54.94	0.69	**3.56**	5.22
VIX	0.48	0.34	0.32	3.53	0.35	2.56	1.04	**79.76**

Notes: The values reported are the variance decomposition, which is based on the Diebold and Yılmaz (2014) generalized VAR spillover model with exogenous variables. The optimal lag length for the VAR model is selected using the Akaike Information Criterion.

Overall, the volatility transmission is higher in the short term than in the long term. Taking a closer look at the short term, it can be observed that NASDAQ AI tends to be a more active sender than a receiver. The average percentage that the other financial assets send to this asset ranges between 0.12% and 0.76%, except for VIX with 4.42%. In contrast, this index contributes 0.48%, 1.30%, and 1.51% volatility to VIX, the US equity market, and the global equity market, respectively. While the values for the equity markets are larger than the corresponding received volatilities, their magnitudes are relatively small, suggesting that NASDAQ AI has a quite low oscillation in the equity markets. Similarly, NASDAQ AI transmits larger volatilities to the remaining assets than it respectively receives. Yet the marginal effects are also relatively small, for instance, amounting to 0.46% volatility transmitted to oil vs. 0.26% received from oil. Thus, we can draw two main inferences from our short-term analysis. First, the volatility transmission from other financial assets to NASDAQ-AI is relatively lower than 1.5%, except for self-transmission. Noticeably, our findings also confirm the role of Bitcoin and gold as hedging instruments for a portfolio with stocks of firms of the AI and robotics industry (Arouri et. al, 2015; Baur and Lucey, 2010; Selmi et al., 2018; Urquhart and Zhang, 2019). Importantly, the bilateral transmission between gold and Bitcoin is less than 0.03%. Second, one should be cautious when putting similar categories in one portfolio, specifically, NASDAQ AI, MSCI World, and MSCI USA. However, as these effects are below 2%, they are not large enough to cause significant issues.

When it comes to the longer time horizon as shown in Table 5, the volatility transmission is less persistent, which provides evidence that there is no considerable interconnectedness among the assets. Thus, if investors tend to hold a portfolio in the long run, they should consider two points in particular. First, the spillover effects among equity assets are dominant no matter what the time horizon is. Second, along with NASDAQ AI, other assets including oil, gold, and Bitcoin could be put in the portfolio for diversification purposes.

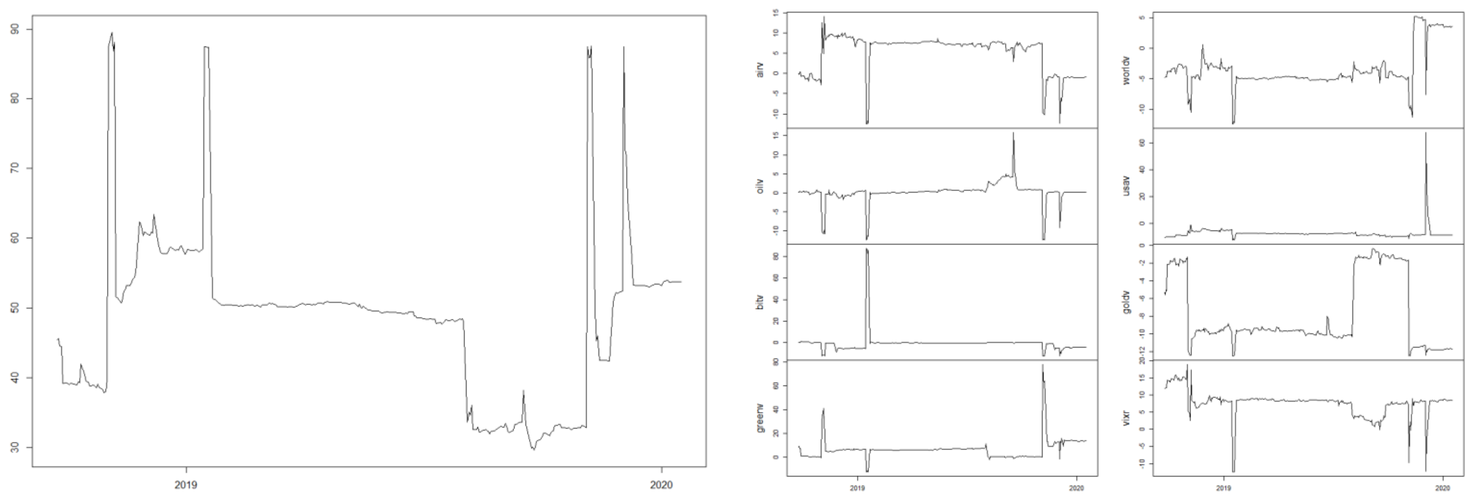
Table 5. Volatility transmission from 5 to infinity trading days

To	From							
	NASDAQ AI	Oil	Bitcoin	Green bond	MSCI World	MSCI USA	Gold	VIX
NASDAQ AI	**41.74**	0.11	0.10	0.18	0.31	0.08	0.13	12.82
Oil	0.41	**19.25**	0.05	0.07	0.00	0.01	0.04	0.25
Bitcoin	0.23	0.09	**27.86**	0.00	0.04	0.00	0.00	0.00
Green bond	0.67	0.01	0.01	**2.69**	0.03	0.69	0.05	0.51
MSCI World	0.23	0.02	0.03	3.30	**18.25**	0.01	0.30	0.14
MSCI USA	0.09	0.05	0.03	1.87	19.83	**0.50**	0.54	0.71
Gold	0.12	0.02	0.05	3.71	18.54	0.02	**0.06**	0.05
VIX	0.46	0.12	0.04	0.42	0.03	0.39	0.06	**10.10**

Notes: The values reported are the variance decomposition, which is based on the Diebold and Yılmaz (2014) generalized VAR spillover model with exogenous variables. The optimal lag length for the VAR model is selected using the Akaike Information Criterion.

4.3 Total interconnectedness

Figure 2 depicts the total interconnectedness for the portfolio consisting of all considered financial assets by using the rolling window for at least 250 trading days. Therefore, our estimates focus on the end of 2018 until the beginning of 2020. To our greatest surprise, the average interconnectedness is around 50%. Meanwhile, in the year 2019, we witnessed two times that this total value spikes at the peak. If we have a closer look at Figure 2, it is clear that the main shock senders are Bitcoin, green bonds, and NASDAQ AI. Furthermore, Bitcoin and green bonds show quite large endogenous shocks (70.84% and 71.32% in the given order), which implies very volatile returns as depicted in Figure 3. Following this, NASDAQ AI also manifests endogenous shocks in the short- and long term (38.21% and 41.74%, respectively). These values support our finding that Bitcoin, green bonds, and NASDAQ AI are shock senders. Moreover, the results suggest that although NASDAQ AI, Bitcoin, and green bonds can be considered as good investments due to high returns, the high volatility in these assets' price movement and hence inherent risk arising from them, needs to be taken into account. On the contrary, the remaining assets are just receivers, because the net spillover values are negative over this period.



(a) Total volatility interconnectedness (b) Net spillover volatility

Fig 2. The total interconnectedness and net spillover volatility in the portfolio

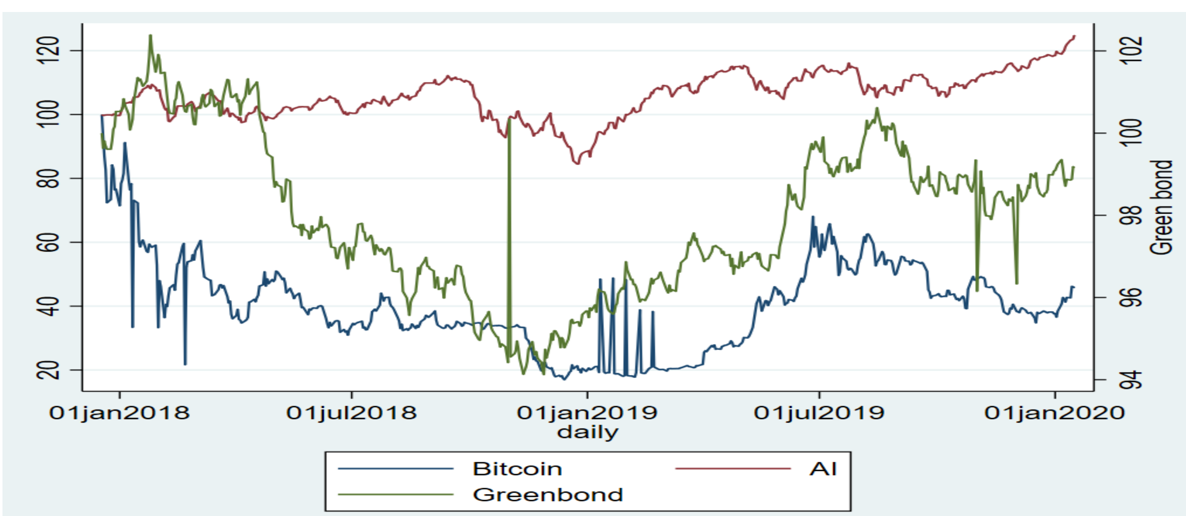


Fig 3. Price movement of Bitcoin, green bond, and NASDAQ AI

5. Conclusion

The 4th industrial revolution has brought a whole set of unprecedented challenges to the global economy, financial markets and all stakeholders of society. It has also brought new opportunities in terms of AI, blockchain, and cryptocurrencies. In parallel to these, climate change poses an existential challenge faced by the world in the 21st century. To tackle this challenge, there are efforts from various sectors, including the financial sector in the form of green investment opportunities like green bonds. Contextualising on this background, this study endeavoured to find the answer to a very old question in the very new era of the 4th industrial revolution. We explored the notion of portfolio diversification in the presence of AI, blockchain or cryptocurrencies, green bonds as well as the pre-industrial revolution assets such as gold, and traditional assets like common stocks. In so doing, this pioneering study provides evidence on the specific role of AI and robotics stocks in portfolio diversification and contributes to the rapidly growing empirical research on green financial instruments and cryptocurrencies.

The overarching findings and conclusion have four main aspects. First, a portfolio consisting of these assets exhibits heavy-tail dependence. This implies that in the times of economic and financial turbulences the worst case happens, as all alternative investments have a high probability of significant losses at the same time. Second, the volatility transmission is higher in the short term than in the long term. Consequently, short-term shocks can cause higher volatility in the other financial assets in the portfolio, whereas holding this portfolio in the long run would decrease the volatility transmission among the assets. Third, the Bitcoin and gold are estimated to be the dominant hedging positions, with the limitation that the Bitcoin is also affected by its past volatility, requiring some cautiousness. This characteristic of volatility persistence is also found in green bonds and NASDAQ AI. To hedge against economic downturn risk in our portfolio, gold, which is one of the oldest assets class, turned out to be very useful. This is due to the reason that its shock transmission to NASDAQ AI is just around 1.41%. Lastly, the total volatility transmission of all financial assets is considerably high, amounting to on average around 50%, with two spikes even close to 90%. This led us to infer that the portfolio has an inherent self-transmitting risk that requires appropriate diversification.

There are several useful implications that can be derived from our findings for both policymakers and investors interested in portfolio diversification in the age of the 4th industrial revolution. Investors, that diversify their portfolio with stocks of AI and robotics companies, cryptocurrencies, and green bonds, need to be aware that some portfolio risks prevail. In particular, during market turmoil, such a portfolio faces a high risk of large joint losses. To hedge risk during both normal times and times of economic downturn, we would particularly emphasize the role of gold as a hedge and safe haven. Given that volatility transmission is lower in the long term, our results suggest a buy and hold investment strategy to reduce the risks associated with volatility spillovers. To address the high total volatility transmission, investors need to diversify carefully. For example, not putting the NASDAQ AI and the general equity indexes into the same portfolio may be a wise choice. Hence, investors need to be aware that besides the performance of AI and robotics firms, the performance of AI indexes is still massively influenced by other sectors. We draw the attention of policymakers and manager based on two main perspectives. First, the legal framework regarding the information asymmetries should be considered to mitigate the potential risk among these markets. It is obvious that Fintech and AI financial assets have brought ambiguous information in terms of financial ratios. Second, managers should consider the threshold of potential losses, i.e. the value-at-risk, the worst-case scenario in the internal guidance for trading. Furthermore, the clear procedure to update the newly released information about financial technologies might help to reduce the risk transmission among these markets.

Our analysis is subject to some limitations since the AI index is a new investment venue, the instruments like AI indexes, cryptocurrencies, and green bonds are yet to mature. Further research can focus on broadening the asset classes and by extending to other developed and developing markets. Furthermore, thanks to the development of machine learning, there are other promising approaches and methodologies, such as xgtboost, which can also be used in future research.

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