How do Artificial Intelligence and Robotics Stocks co-move with traditional and alternative assets in the age of the 4th industrial revolution?

Implications and Insights for the COVID-19 period

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Abstract

This study investigates the interdependence between AI & Robotics stocks and traditional (including stocks and bonds) and alternative (commodities and cryptocurrencies) assets, employing wavelet coherence analysis in time-frequency space. We further provide a fresh perspective on potential hedging and diversification benefits of AI & Robotics stocks. Overall, our results suggest that co-movements between AI & Robotics stocks and other assets significantly depend on the wavelet decomposition levels, suggesting time-scale-dependent investment benefits. Wavelet coherences and correlations have substantially increased, mostly in the low frequencies, during the COVID-19 pandemic. Government securities exhibit safe haven properties for investors at the highest and lowest scales. Even if cryptocurrencies can provide hedging benefits over the full sample, these benefits seem to be diminished during the COVID-19 period. We observe substantially higher co-movements of AI stocks with the composite stock index, corporate bonds, and commodities at all scales after March 2020, implying that inclusion of these assets in AI & Robotics stock portfolios may not enhance risk-adjusted portfolio performance in times of market turbulence. These results offer potential implications for investors and portfolio managers in terms of hedging/diversification benefits as well as for authorities and policy makers regarding the development of strategies to mitigate financial risk.

1. Introduction

The adoption and use of robotics and artificial intelligence in both manufacturing and service industries have gained significant pace in the last few years. The major advantage brought by the implementation of robotics and artificial intelligence (AI) is the increased efficiency in productivity that stems from cost reduction and quality improvement (Webster and Ivanov, 2020; Huynh et al., 2020a). In order to exploit these foreseen benefits, companies have started to invest extensively in artificial intelligence related technologies and projects. The McKinsey Global Institute (MGI) conjectures between $18 to $27 billion internal corporate investment in AI related projects for the year 2016, whereas the amount of AI related mergers and acquisitions is estimated at $2 to $3 billion.[1] The report by MGI predicts that venture capital investments in AI startups increased by 40% between 2013 and 2016, while, as stated by Furman and Seamans (2019), job positions requiring AI skills rose by five times in 2016 in comparison to 2013.

[1] see Bughin et al. (2017) for the details of the McKinsey Global Institute report.

According to the US Patent and Trademark Office documents, the patent applications with the title "artificial intelligence" show a dramatic increase in 2016 and 2017, almost doubling the average annual applications between 2002 and 2015 (Furman and Seamans, 2019). The productivity growth from artificial intelligence can be achieved with follow-on applications of the technology, particularly in robotics.[2] Acemoglu and Restrepo (2017) acknowledge that about 39% of the robots are owned in the automotive industry in the US, and almost half of all robot deliveries in the US are to the automotive sector in 2016, twice the number for 2004.[3] Apart from the manufacturing industry, artificial intelligence and robotics are also used in services, specifically in banking and finance, transportation, architecture and design, health care, and communications. Therefore, an increasing number of companies enjoy the economic benefits of artificial intelligence in various sectors. Subsequently, investors' preferences shift towards these companies and sectors in portfolio allocation.

Portfolio management and investment strategies have been a long-lived concern and efforts from both academicians and practitioners are dedicated to designate methods for efficient portfolio construction in which risk diversification is satisfactorily accomplished. The extensive globalization of the financial markets leads to ever increasing inter-relations between both returns and volatility of the investment assets. Therefore, alternatives for diversification abate particularly in market turmoil, forcing investors to seek for new investment vehicles that are uncorrelated or negatively correlated with major asset classes.[4] Recently, the investment opportunities of the 4th industrial revolution have started to be considered by investors in portfolio construction. The advancements in the field of robotics and artificial intelligence together with the developments in blockchain systems in the context of the 4th industrial revolution rapidly transform the global economic activity into a new era with almost no boundaries to human interaction.

The new coronavirus originated in the Chinese city of Wuhan in late December 2019 spread quickly across the globe in the first months of 2020, causing a global pandemic. The COVID-19 has completely changed our lives; governments have been adopting strict measures and unprecedented restrictions to reduce community spread. Artificial Intelligence (AI) and Robotics technologies have aided the fight against COVID-19 and played a very crucial role in every aspect of the COVID-19 crisis response. In conjunction with increased investments in automation and technology, AI & Robotics companies elicit strong interest from investors worldwide. Therefore, global investors have recently gravitated towards the stocks of these companies to reap the potential investment benefits.

The novel COVID-19 has ripped the global economy to bits, reminding us our vulnerability to diseases no matter the technological advancements achieved particularly in the last two decades. The rapid splash of the confirmed cases and the rise of the death tolls impelled WHO officials to assess the COVID-19 outbreak as a pandemic on 11th March, 2020. The uncontrollable spread of the virus caused panic and tension, which invoked strict restrictions in social interactions. Curfews were put into order in many countries, ceasing most of the economic activity for months. Henceforth, these restrictions imposed economic contractions, leaving millions of people jobless. Governments one after another started to initialize monetary

[2] Graetz and Michaels (2015) estimate that robotics account for about one-tenth of the GDP growth between 1993 and 2007 in seventeen countries they examined.
[3] See Furman and Seamans (2019) for the details of the International Federation for Robotics reports. The reports show that robot shipments to consumer electronics sector record the fastest growth by 400% in 2016 compared to the level in 2004.
[4] Tversky and Kahneman (1991) suggest that investors' risk aversion motivates them to seek for safe haven assets, as they are in general more concerned with avoiding losses rather than generating prospective returns while constructing their portfolios (Hwang and Satchell, 2010; Conlon et al., 2020).

and fiscal programs to overcome the negative economic impacts of the pandemic. The economic growth rates (GDP) for the second quarter of 2020 signify a dramatic fall in all economies accompanied with high rates of unemployment no matter the size of the monetary and fiscal policy incentives initialized by public authorities.[5]

Despite all the preventions, the Corona outbreak rapidly dispersed to Europe and the USA with the latter becoming the epicenter of the pandemic by the end of March, 2020. Dow Jones Industrial Average (DJIA) plummeted by about 26% in March 2020. Likewise, the S&P500 index plunged by 9.5% on the so-called Black Thursday (March 12, 2020) and declined drastically by about 26% in just a couple of weeks after its record high closing on February 19, 2020. The NASDAQ Composite index dived about 25% in the following four weeks after February 12, 2020. The pervasion of shutdowns in business activities imposed stringent revenue shocks on firms.[6] Companies had to lay off employees to cut off costs, and millions of people became jobless, which consequently diverted individuals from consumption and distorted future revenues and cash flows of businesses. The Coronavirus crash is the fastest decline in the global markets so-far recorded in the history of the financial markets, however, it is a short-lived bear market. In April 2020, the markets started to normalize after massive initiation of stimulus packages in almost all developed and emerging economies one after another. Henceforth, in such a new era of socio-economic uncertainty, investors are almost clueless in managing their portfolio investments.

In this study, we analyze the co-movements between the AI & Robotics stock index and five other traditional and alternative asset indices, namely the S&P500 equity index, the government bond index, the corporate bond index, the commodity index, and the cryptocurrency index. Our data spans from December 19, 2017 to March 31, 2021, which covers the COVID-19 outbreak. We conduct wavelet analysis which allows us to study the relationship between the selected variables within the time scales and investment horizons. More specifically, we employ wavelet coherence, phase difference and wavelet rolling window correlation analysis to identify the linkages as well as the lead-lag relationships. The choice of wavelet analysis enables us to meticulously examine the differences in risk preferences, investor sentiment and heterogeneous market expectations that help investors in their decision-making process (Sharif et al., 2020).

Our paper contributes to the very limited recent literature in AI & Robotics investments by analyzing their co-movements with different asset classes both in time and frequency dimensions. To the best of our knowledge, our study is the first to examine wavelet-based co-movement dynamics of AI & Robotics stocks with other investments and hence brings new insights to the existing body of literature, especially with its implications for the recent public health crisis, which constitutes a systemic risk. Since the NASDAQ Artificial Intelligence and Robotics index was established in December 2017, there has not been any significant attempt in the existing literature to analyze the dependency structure of the AI index with other investments. The only exception is Huynh et al. (2020a) who examine the role of AI & Robotics stocks in portfolio diversification. To fill this gap, we investigate how inter-linkages between AI & Robotics stocks and other investment returns alter over time and vary across scales. Additionally, as a financial tool in the context of the 4th industrial revolution, digital currencies are widely studied with the dominance of Bitcoin in the literature. By analyzing the cryptocurrency index in this study, we also account for the dynamics in the overall virtual

[5] The world is experiencing the most severe economic downturn since the Great Depression of 1929 (see among others Caggiano et al., 2020)
[6] See Mazur et al. (2020).

currency market which has grown rapidly both in terms of number and volume over the last years.

Our findings reveal some interesting dynamics between AI stocks and other index returns. Firstly, wavelet coherence analysis shows weaker (stronger) co-movements at high (low) frequencies, suggesting scale dependency of hedging/diversification benefits. Secondly, the lead-lag relationship in time-frequency space implies a leading role of AI equities for all indices, except for government securities, particularly in the wake of the COVID-19 pandemic. Thirdly, applying rolling window analysis, we observe that the dynamic wavelet correlations substantially vary with time and scale. The last but not the least, we find evidence of significantly heightened correlations at certain scales during the pandemic. All these empirical findings provide fresh evidence for investors and portfolio managers in terms of hedging and diversification benefits in the era of the 4th industrial revolution. Particularly, the use of wavelet analysis can give additional insights and implications for traders to make informed investment decisions as they operate in different time horizons.

The rest of the paper is organized as follows: Section 2 presents the literature review, Section 3 describes the wavelet methodology, Section 4 provides a detailed description of the data and the unconditional correlation analysis, Section 5 discusses the empirical findings, and Section 6 concludes and highlights the potential implications of the results.

2. Literature Review

Traditionally, bonds and stocks have been the two major investment alternatives for decades, the former being deemed as a quality asset, while the latter is accepted as a risky investment. Stock values are computed by discounting the projected future cash flows of a firm at the appropriate discount rate; therefore, equity prices are directly related with the general economic outlook which is the main determinant of the future earnings potential of a business. The linkages between stock markets have been studied extensively particularly with a focus on contagious flows (see among others Christoffersen et al., 2012; Dungey and Gajurel, 2014; Gjika and Horvath 2013; Mobarek and Mollah, 2015; Nitoi and Pochea, 2019; Samarakoon, 2011; Syllignakis and Kouretas, 2011; Tabak et al., 2016; Yarovaya et al., 2016; Virk and Javed, 2017). Besides the equity market interactions, stock-bond co-movements are scrutinized abundantly and some of them are in the context of flight-to-quality phenomenon, which enables investors to shift their portfolios towards less risky assets in adverse market conditions (see among others Hartmann et al., 2004; Li, 2002; Ilmanen, 2003; Baur and Lucey, 2009; Dajcman, 2015; Ferrer et al., 2016; Bayracı et al., 2018).

Some scholars further investigate the potential investment benefits offered by corporate bonds (Kwan, 1996; Burger and Warnock, 2007; Wibaut and Wilford, 2009; Demiralp and Hein, 2010; Kemper et al., 2012; Liu, 2016). The International Capital Markets Association (ICMA) estimates the global corporate bond market at $40.9 trillion making up about 32% of the overall global bond market, whereby, the US and China are the countries with the highest corporate bond issues outstanding, accounting for 45% of the global corporate bonds, as of August 2020.[7] Demiralp and Hein (2010) demonstrate an increase in the correlations between stocks and bonds as the default risk increases, arguing that the stock-bond correlation of a firm can be a proxy of its default risk. Wibaut and Wilford (2009) investigate the period of sub-prime crisis and they find high correlations between stocks and bonds in support of decreasing diversification benefits in distressed markets. Liu (2016) acknowledges that international diversification in the

[7] For the details of the ICMA report please visit https://www.icmagroup.org/Regulatory-Policy-and-Market-Practice/Secondary-Markets/bond-market-size/.

corporate bond market significantly reduces the volatility in portfolio returns, improving the Sharpe ratio for US investors.

In the existing literature, the performance of technological stocks has also attracted the interest of scholars since the dot-com crisis in early 2000s. There are various studies related with technology stocks; some of these indicate a greater potential of future earnings (e.g. Ahmed and Alhadab, 2020), while some suggest almost equivalent returns with those of the non-technology companies (Mason and Harrison, 2004). Another strand of literature underlines higher volatility in high-tech stock returns compared to the non-tech equities, which may signify that investors perceive uncertainty in the profitability of high-tech companies due to the complexity of the implementation in innovative technologies (Pastor and Veronesi, 2009; Liu, 2006; Jiang et al., 2011; Le et al., 2020). Le et al., (2020) provide evidence for poor hedging benefits of Fintech company shares in a portfolio with common stocks, noting the very high connectedness between technology stocks and traditional equities. The relation between technology stocks and energy prices is also studied yielding verified linkages in returns and volatility (Kumar et al., 2012; Bondia et al., 2016). Symitsi and Chalvatzis (2018) document significant return and volatility spillovers from technology stocks to Bitcoin. Chen and Wang (2019) note that gold does not act as a safe haven for technology stocks, however Huynh et al. (2020a) suggest gold may display safe haven properties for NASDAQ AI index since they report a very low shock transmission effect from gold to NASDAQ AI. Furthermore, Tiwari et al. (2020) investigate the dependence structure between the NASDAQ AI index and carbon prices in the era of the 4th industrial revolution and they evince the safe haven property of AI stocks for carbon prices for a sample period including the COVID-19 crisis.

The 4th industrial revolution establishing the foundations of blockchain technologies also paved the way for cryptocurrencies. Scholars discuss that the blockchain technology heralded totally a new economic order and disrupted the standard applications of financial transactions (Swan, 2015; Peters and Panayi, 2016; Yuneline, 2019). Maurer et al. (2013) argue that cryptocurrencies facilitate the application of blockchain technologies, closing the distance between technological advancements and payment procedures. Currently, there are about 2000 cryptocurrencies and their market capitalization is growing amidst the debate on the regulatory issues.[8] In their study, White et al.'s (2020) results substantiate that Bitcoin[9], which is one of the most popular cryptocurrencies, is acting like a technology-based product, an emerging asset or a bubble event rather than a currency. Similar research on cryptocurrencies demonstrate that they are invested in for speculative motives and seen as an alternative investment product[10] whereas the relation between major asset classes and cryptocurrencies are uncorrelated (Burniske and White, 2017; Glaser et al., 2014; Baur et al., 2017, Demiralay, 2020). Corbet et al. (2018) advocate that cryptocurrencies may provide short-term diversification against the conventional markets, while Bouri et al. (2017a) and Demir et al. (2018) acknowledge the short-

[8] Klein et al. (2018) report a market capitalization at its peak of 831 billion USD on January 7, 2018, however the cryptocurrency market is dominated by Bitcoin, Ethereum and Ripple. On the regulatory side, in September 2015, the Commodity Futures Trading Commission (CFTC) in the US publicized that "bitcoin and other virtual currencies are a commodity covered by the commodity exchange act". The Commission declares that virtual currency is a digital store of value, a medium of exchange and a unit of account, however, acknowledges no legal status as tender in jurisdiction.
[9] Nakamoto (2008) has introduced Bitcoin conceptually and since then cryptocurrencies are renowned as investment opportunities providing various functionalities. Bitcoin is argued to bestow diversification opportunities and arbitrage possibilities for investors (see among others Gandal and Halaburda, 2014, Briere et al., 2015).
[10] However, as discussed by Klein et al. (2018) the cryptocurrencies convey significant uncertainty as the market is unregulated and decentralized. In September 2017 Chinese authorities imposed a ban on a cryptocurrency fund raising process which immediately triggered worldwide negative pricing reactions.

term hedging potential of cryptocurrencies only in extreme market conditions. Lee et al. (2018) underline the diversification benefits of cryptocurrencies in portfolio design and construction. The hedging and safe haven property of Bitcoin is confirmed in pre-Covid period against Asia-Pacific stocks (Bouri et al., 2017b). In a similar vein, Wang et al. (2019) report that investors can invest in digital currencies to reduce risk as they act as a safe haven against most of the international indices, particularly before 2017. Klein et al. (2018) state that Bitcoin which is deemed as the new gold with its store of value which is totally independent from monetary policies. However, their results reveal the exact opposite, where both Bitcoin and the cryptocurrency index (CRIX) are positively correlated with downward markets, failing to effectively hedge stock investments. Some recent papers also focus on the relationship between cryptocurrencies and precious metals as both assets are considered as a hedging instrument. For example, Huynh et al. (2020b) suggest that gold can be a good hedging tool for cryptocurrencies as both assets seem to be independent. In a different study, Huynh et al. (2020c) show that higher gold to platinum ratio leads to an increase in the aggregate market risk, which prompts investors to require higher risk premium for Bitcoin investments.

Commodities have been used extensively for portfolio diversification in the last two decades. The reason for the surmounting investors' preference is associated with the fact that commodity returns are expected to have weak and even negative correlations with the returns of the traditional assets. Therefore, commodity markets are assumed to be segmented from the stock and bond markets in general, where prices are determined in the context of the demand and supply dynamics within the economic conjecture. There are various studies confirming the diversification benefits of commodities in portfolio construction particularly when together with bond and equity investments (Erb and Harvey, 2006; Belousova and Dorfleitner, 2012; Mensi et al., 2013; Creti et al., 2013, Demiralay et al., 2019). Daskalaki et al. (2017) confer that commodities offer diversification benefits which are pronounced for second and third generation commodity indices.[11] However, another strand of the literature substantiate the diminished diversification benefits of commodities due to the financialization phenomenon, which results in increased linkages between commodities and the traditional assets (Tang and Xiong, 2012; Cheng and Xiong, 2014; Silvennoinen and Thorp, 2013; Büyüksahin and Robe, 2014). Therefore, the role of commodity investments in portfolio allocations are studied extensively, however, these studies cite mixed results. More recently, Gagnon et al. (2020) annotate that the diversification potentials of commodities were limited in Canada during their financialization, however their results indicate that in the post-financialization period, the inclusion of some commodity indices improves portfolio performance, signifying the importance of the commodity index selection in portfolio diversification. Likewise, Cai et al. (2020) focus on the diversification benefits achieved through mixed commodity portfolios, particularly in medium term investment horizons.

The most recent worldwide economic turbulence has attracted the attention of scholars and the implications of the COVID-19 outbreak are being examined from various dimensions (Akhtaruzzaman et al., 2020; Baker et al., 2020; Conlon & McGee, 2020; Corbet et al., 2020a; Kristoufek, 2020; McKibbin & Fernando, 2020; Ramelli & Wagner, 2020; Yarovaya et al. ,2020; Zhang et al., 2020). Mazur et al. (2020) analyze the March 2020 stock market crash using the data of S&P1500 firms. They find that, during March 2020, industries like airlines, hospitality and entertainment, petroleum, real estate demonstrate a vast decline in their market capitalizations, while food, healthcare, software and technology sectors enjoyed large positive

[11] Most commodity indices were established in early 2000's.

returns.[12] Baker et al. (2020) suggest that the stock markets are affected worst by the COVID-19 pandemic. Akhtaruzzaman et al. (2020) analyze the financial contagion transmission during the Corona crisis and document higher dynamic correlations between the financial firms than that of the non-financial firms during the pandemic. Le et al. (2021) document a strong correlation between the technology index and Bitcoin, the Dollar and the MSCI World indices during the Coronavirus crash. Gupta et al. (2020) advocate the safe haven ability of the US Treasury securities (long, medium and short-term maturities) against the financial market uncertainty during the COVID-19 outbreak. Conlon and McGee (2020) suggest that March 2020 market crash provides an incident where the safe haven properties of Bitcoin can be empirically tested and their findings corroborate that rather than acting as a safe haven, adding Bitcoin to a portfolio may instead increase the downside risk in times of severe market turmoil.

3. Methodology

The vast majority of previous studies analyzing the co-movements across financial markets have applied multivariate time-series models, such as Vector Autoregression or Dynamic Conditional Correlation GARCH (DCC-GARCH) model of Engle (2002). However, as highlighted by Cai et al. (2017) and Bayraci et al. (2018), the time-series models are restricted to time-dimension and allow researchers to capture the relationships only over calendar time. In fact, investors have heterogenous investment horizons and do not operate at only time scales. As suggested by Moya-Martinez et al. (2015), investors with short-term investment horizons, such as noise traders, follow trends and make trading decisions based on market sentiments and occasional events. In contrast, traders with longer term investment horizons, such as large institutional investors, follow more closely macroeconomic fundamentals. For this reason, it is of particular importance to examine interlinkages among financial assets at both time and frequency domains.

Wavelets are suitable tools for analyzing the characteristics of non-stationary series due to their ability to preserve the information from both frequency and time domains. Additionally, they help uncover the interdependencies between series on a scale-by-scale basis which would be cumbersome and time-consuming by using more conventional statistical methods. Thus, wavelet approach is a very convenient method to describe the local behavior of heterogeneous market participants. In this study, we conduct a systematic analysis to investigate the dynamic relationships between AI & Robotics stock index and other assets using wavelet-based techniques. More specifically, we employ wavelet coherence using Morlet specification and wavelet correlation using Maximal Overlap Discrete Wavelet Transform (MODWT) with Daubechies LA8 filter.

3.1 Wavelet

The mother wavelet $\psi(.)$ is a real-valued or a complex-valued function that can generate variety of wavelets by scaling and translation as:

$$\boldsymbol{\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right)} \qquad \textbf{(1)}$$

[12] The authors evince about 70 percent decline in the market values of the negatively affected sectors, while positively affected sectors enjoy about a 20 percent increase in marlet capitalizations.

with s denoting the scaling factor which controls the width of the wavelet. $\frac{1}{\sqrt{s}}$ ensures the preservation of energy within unit variance, i.e $||\psi_{\tau,s}||^2 = 1$. τ is a translation parameter controlling the exact location of the wavelet.

There is a number of different wavelet functions which can be utilized to examine time series. In this study, we use the Morlet wavelet which has been extensively applied in economics and finance literature[13].

$$\boldsymbol{\psi_{\omega_0}(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-t^2/2}} \tag{2}$$

where we set $\omega_0 = 6$. As stated by Ferrer et al., (2018), this specific choice for the parameter ω is an appropriate choice since it offers a good balance between time and frequency localization and simplifies the interpretation of the wavelet analysis as the wavelet scale is inversely related to the frequency. Moreover, the Morlet wavelet is a complex wavelet that can be decomposed into real and imaginary parts, enabling us to separate the amplitude and phase of the signal. Hence, the Morlet wavelet can provide more information about phase relationships between the examined time series.

3.2 Wavelet coherence

As mentioned before, wavelet coherency is employed to examine the time-frequency dependencies between the AI and other indices. To calculate wavelet coherence, we firstly introduce the concepts of continuous wavelet transform, cross wavelet transforms and cross wavelet spectrum. By projecting the time series $x(t)$ onto the wavelet family $\psi_{\tau,s}$, we obtain the continuous wavelet transfom as:

$$\boldsymbol{W_x(\tau, s) = \int_{-\inf}^{\inf} x\,(t) \frac{1}{\sqrt{s}} \psi^* \left(\frac{t-\tau}{s}\right) dt} \tag{3}$$

where ψ^* denotes the complex conjugate.

As stated by Vacha and Barunik (2012), an important characteristic of the continuous wavelet transform is the capability to decompose and recreate a time series $x(t)$:

$$\boldsymbol{x(t) = \frac{1}{C_\psi} \int_0^{\inf} \left[\int_{-\inf}^{\inf} W_x\,(\tau, s) \psi_{\tau,s}(t) d\tau\right] \frac{ds}{s^2}, s} \atop \boldsymbol{> 0} \tag{4}$$

The wavelet transform also allows us to preserve the energy of the examined time series. Thus, we define the wavelet variance as:

[13] See among others, Rua and Nunes (2009), Akoum et al. (2012), Vacha and Barunik (2012), Loh (2013), Aloui and Hkiri (2014), Afshan et al. (2018), Ferrer et al. (2018)

$$||\boldsymbol{x}||^2 = \frac{\mathbf{1}}{\boldsymbol{C_\psi}} \int_{\mathbf{0}}^{\mathbf{inf}} \left[\int_{-\mathbf{inf}}^{\mathbf{inf}} |\, \boldsymbol{W_x}(\boldsymbol{\tau}, \boldsymbol{s})|^{\mathbf{2}} \boldsymbol{d\tau} \right] \frac{\boldsymbol{ds}}{\boldsymbol{s^2}} \qquad \textbf{(5)}$$

By using the formulation given by Torrence and Campo (1998), the cross wavelet transform of two series $x(t)$ and $y(t)$ is given by $W_{xy}(\tau, s) = W_x(\tau, s) W_y^*(\tau, s)$ where asterix sign signifies the complex conjuagaiton and the cross wavelet power spectrum is presented as $|W_{xy}(\tau, s)|^2$. The cross wavelet spectrum can be considered as the local covariance between two time series at each scale and shows the region in time-frequency space in which time series have high common power.

Wavelet coherency between two time series $x(t)$ and $y(t)$ can be explained as local correlation both in time and scale in which the two time series in time-frequency domain co-move. The wavelet coherence is formulated by Torrence and Webster (1999) as the squared absolute value of the smoothed cross wavelet spectra normalized by the product of the smoothed wavelet power spectrum of each series:

$$\boldsymbol{R^2}(\boldsymbol{\tau}, \boldsymbol{s}) = \frac{|\boldsymbol{S}(\boldsymbol{s^{-1}} \boldsymbol{W_{xy}}(\boldsymbol{\tau}, \boldsymbol{s}))|^{\mathbf{2}}}{\boldsymbol{S}(\boldsymbol{s^{-1}} |\boldsymbol{W_x}(\boldsymbol{\tau}, \boldsymbol{s})|^{\mathbf{2}}) \boldsymbol{S}(\boldsymbol{s^{-1}} |\boldsymbol{W_y}(\boldsymbol{\tau}, \boldsymbol{s})|^{\mathbf{2}})} \qquad \textbf{(6)}$$

S denotes the smoothing operator with respect to time and scale. $R^2(\tau, s)$ is bounded between 0 and 1, with a high coefficient indicating a strong relationship and vice versa. Thus, a wavelet coherency plot shows regions in the time-scale domain where two series co-move and capture both time and frequency dynamics.

The causality between two times series are shown by wavelet coherence phase differences, which give details about delays of cycles of the time series as defined below:

$$\boldsymbol{\phi_{xy}}(\boldsymbol{\tau}, \boldsymbol{s}) = \mathbf{tan^{-1}} \left(\frac{\mathfrak{I}\left[\boldsymbol{S}(\boldsymbol{s^{-1}} \boldsymbol{W_{xy}}(\boldsymbol{\tau}, \boldsymbol{s}))\right]}{\mathfrak{R}\left[\boldsymbol{S}(\boldsymbol{s^{-1}} \boldsymbol{W_{xy}}(\boldsymbol{\tau}, \boldsymbol{s}))\right]} \right) \qquad \textbf{(7)}$$

where $\mathfrak{I}$ and $\mathfrak{R}$ are the imaginary and real parts of the smooth power spectrum. Phase differences are represented by arrows in the wavelet coherence plots and characterize the direction of relationships between time series. A zero phase difference indicates that the time series move together at a particular frequency. Arrows pointing to the right (left) show that the time series are positively (negatively) correlated. In addition, arrows pointing up indicates that the first time series leads the second one by 90^o, while arrows pointing down shows that the second series leads the first one by 90^o.

3.3 Wavelet correlation

In this paper, we rely on a modified version of the traditional discrete wavelet transform (DWT), which is the maximal overlap discrete wavelet transform (MODWT) to calculate correlation coefficients at different scales between the time series. The MODWT differs from the DWT in the sense that DWT requires sample size must be a power of 2 for the full transformation whereas MODWT relaxes this restriction. As stated by Dajcman (2012), the MODWT is more suitable for the wavelet correlation calculations as it can handle any sample size regardless of whether or not the sample size is the power of 2. The MODWT also provides an increased resolution at higher scales and translation-invariance, which guarantees that the MODWT wavelet coefficients do not change if the time series is shifted in a "circular" fashion. Furthermore, the MODWT is a more asymptotically efficient wavelet variance estimator than the DWT.

With reference to Gallegati (2008) and Hkiri et al. (2018), the MODWT wavelet ($\widetilde{w}_{j,t}$) and scaling ($\tilde{v}_{j,t}$) coefficents are given as:

$$\widetilde{\boldsymbol{w}}_{j,t} = \frac{1}{2^{j/2}} \sum_{l=0}^{L-1} \widetilde{\boldsymbol{h}}_{j,l} \boldsymbol{X}_{t-l}$$

$$\widetilde{\boldsymbol{v}}_{j,t} = \frac{1}{2^{j/2}} \sum_{l=0}^{L-1} \widetilde{\boldsymbol{g}}_{j,l} \boldsymbol{X}_{t-l} \tag{8}$$

The MODWT based wavelet covariance estimator is defined as follows:

$$\widetilde{\boldsymbol{\sigma}}_{XY,j} = \frac{1}{\widetilde{N}_j} N - 1 \sum_{t=L_{j-1}}^{N-1} \widetilde{\boldsymbol{w}}_{j,t}^{X} \widetilde{\boldsymbol{w}}_{j,t}^{Y} \tag{9}$$

Wavelet correlation coefficients between time series X and Y, for scale λ and lag π, can be calculated by using the wavelet cross covariance given in Eq. (9) and the squared wavelet variances of each series:

$$\widetilde{\boldsymbol{\rho}}_{XY,\lambda}(\boldsymbol{\pi}_j) = \frac{\widetilde{\boldsymbol{\sigma}}_{XY,\pi}(\boldsymbol{\lambda}_j)}{\widetilde{\boldsymbol{\sigma}}_{X}(\boldsymbol{\lambda}_j)\widetilde{\boldsymbol{\sigma}}_{Y}(\boldsymbol{\lambda}_j)} \tag{10}$$

For the choice of wavelet and scaling filters, a traditional and popular wavelet function, the Daubechies Least Asymmetric filter with length 8 (LA8), is used for the study. For the multi-resolution level j, this study sets $j = 6$ in the empirical analysis due to the data availability. Here the highest frequency component $D1$ denotes short-term variations due to shocks occurring at a time scale of $2^1 = 2$ (2-4 days), and the lowest frequency $D6$ accounts for variations at a time scale of $2^6 = 64$ (64-128 days).

4. Data and Descriptive Statistics

Our data comprises of six indices, namely, Nasdaq CTA Artificial Intelligence & Robotics Index, S&P U.S. Government Bond Index, S&P U.S. Corporate Bond Index, S&P Commodity Index, the Cryptocurrency Index (CRIX) and S&P 500 Index. Table 1 provides the details of the indices used, their segments and coverage. The data spans from December 19, 2017 to March 31, 2021.[14] The data is daily given that it provides richer information compared to other data frequencies, such as weekly or monthly (Bannigidadmath and Narayan, 2016). The

14 The NASDAQ AI & Robotics index starts from December 19, 2017, that is the reason for the beginning date of the sample in the study.

descriptive statistics of daily returns are presented in Table 2 with the graphical evidence of each index's price behavior presented in Figure 1.[15]

[Insert Table 1 here]

We report summary statistics for the full sample, pre-Covid and post-Covid periods in Table 2.[16] Looking at the full sample results, we observe that the CRIX yields the highest mean return (0.148%), followed by the AI & Robotics index with an average return of 0.071%. Cryptocurrency index is the riskiest among all, as indicated by the highest standard deviation, during the entire study period. In terms of risk adjusted performance, AI index appears to have high return and relatively low risk profile. All the returns, except for the government securities, exhibit negative skewness in the full sample, suggesting that negative returns are more probable. Furthermore, all return series have excess kurtosis, showing a high probability of observing extreme returns in the full-sample period.

[Insert Table 2 here]

Comparing the basic statistics in the pre-Covid and post-Covid periods, the AI index seems to perform well during the pandemic; the average return of the AI index before the Coronavirus crisis is very low (0.0002%) compared to the post-Covid period (0.2198%). However, the unconditional risk measured by standard deviations is higher in the post-Covid sample. We observe higher returns in all the markets, except for corporate bonds and government securities during the pandemic, which is also reflected in the price graphs in Figure 1. This can be linked to investors' optimism and positive expectations about the markets in times of extremely low interest rates and extensive stimulus packages initiated by the public sectors. For this reason, the market crash in March 2020 is short-lived and, by the beginning of April, financial markets were again bullish. Some analysts also claim that certain investments have generated returns even in challenging environments since the Great Recession of 2008 (Dyson, 2020).

[Insert Figure 1 here]

We further apply simple correlation analysis for the three sample periods to identify the inter-linkages between the AI index and the other investments. The unconditional correlation coefficients, together with the associated p-values, are presented in Table 3. The correlation coefficient between AI & Robotics stocks and S&P500 index is the highest, while a negative correlation is observed between the AI index and government securities in all sub-periods. The unconditional correlation analysis shows that there are three indices having statistically significant positive correlations with the AI index in the full sample, namely, commodities, corporate bonds and S&P500. AI & Robotics index does not linearly and significantly comove with cryptocurrencies during the entire study period, which is in line with Huynh et al. (2020a). We also notice that the level of correlations varies between pre-Covid and post-Covid sample periods. For example, the correlation coefficient between AI and corporate bonds is approximately -0.18 in the pre-Covid period, while the coefficient increases to 0.23 in the post-Covid sample. The change in the correlation structure may indicate the adjustment of portfolio allocations during the Coronavirus crash. However, the unconditional correlation analysis assumes a linear dependence structure, which may give misleading conclusions. In the

[15] We used continuously compounded returns, calculated as $R_{i,t} = (\ln P_{i,t} - \ln P_{i,t-1}) \times 100$, where $R_{i,t}$ is the return of index i on trading day t and $P_{i,t}$ is the closing price of index i on trading day t.

16 The pre-Covid sample covers the period from December 19, 2017 to March 10, 2020 and the post-Covid period starts from March 11, 2020 (the WHO announced COVID-19 outbreak as pandemic on that day) and ends on March 31, 2021.

subsequent sections, we will have further insights and implications in terms of potential hedging/diversification benefits and dependence structure of AI stocks based on time and scale.

[Insert Table 3 here]

5. Findings

5.1 Wavelet Coherency

We apply the continuous wavelet coherence, which is a localized interdependence measure, enabling us to examine the co-movements between AI & Robotics returns and the other indices over time and across frequencies. Figure 2 displays the wavelet coherency plots. The horizontal axis exhibits the time component, while the vertical axis shows the frequency component. The coherency ranges from blue, indicating a weak dependence, to red, providing evidence of a strong dependence. The theoretical distribution of the wavelet coherence coefficient is unknown, that is why the statistical significance is obtained from Monte-Carlo simulations using phase randomized surrogate series. The black contours represent regions with statistical significance at the five percent level. The cone of influence denotes the zone affected by the so-called "edge effect".

We further employ wavelet coherence phase differences to identify the cyclical and anti-cyclical relations and the lead-lag relationship in time-frequency dimension. Arrows demonstrate the phase differences between the AI & Robotic stocks and other investigated asset classes. When the arrows point to the left (right), the two markets are anti-phase (in-phase) or they have negative (positive) correlation. When the arrows point to the left-up and right-down, AI & Robotics stocks lag behind other investments while the left-down and right-up arrows imply that AI & Robotics lead the others.

[Insert Figure 2 here]

As shown in Figure 2(a), AI & Robotics stocks and S&P 500 have the highest degree of co-movement across all the frequency bands over the entire study period. This is in line with Huynh et al. (2020a), who state that including the AI index and the composite stock indices in the same portfolio may not be a wise decision for investors. The interdependence seems to be relatively weak for shorter term investment horizons particularly below 16 days. Overall, we report a significantly high positive correlation and a cyclical relation. Our results reveal a mixed lead-lag relationship. For example, we can observe that AI is lagging behind S&P 500 from the beginning of the sample period to mid-2019 in the 64-days frequency band while it leads S&P 500 returns in the 16-32 days band in early 2020.

Based on the plots displayed in Figure 2(b), our results provide evidence of a weak co-movement between AI & Robotics index returns and government bond indices, as shown by the predominance of blue colors. We detect limited and relatively short-lived bands of high coherency. The phase difference arrows indicate an out-of-phase relationship, suggesting a strong negative correlation. In terms of causality, on aggregate, the AI seems to be lagging behind government bonds particularly in the frequency bands below 32 days during 2019 and early 2020 as the arrows mostly point to the left-up. Considering the interdependence in investment horizons above 16 days since the start of the pandemic, government securities may have acted as a flight-to-quality instrument for AI stocks as the coherences after March 2020 seem to be very weak. In other words, when AI stocks plummet, government security prices may rise, indicating that investors gravitate towards safer government securities during the periods characterized by high uncertainty. Brière et al. (2012) suggest that investors pull their money out of risky markets and seek safety in government securities at times of market turbulence, which increases risk premia and reduces the correlations (some already significantly negative) between asset classes. Gulko (2002) also argues that US Treasury bonds provide effective diversification during financial crisis. The flight-to-quality characteristic of government securities is well documented in the existing literature (see among others, Hartmann et al, 2004; Baur and Lucey, 2009; Bayraci et al., 2018). However, we should interpret our results with caution here since the coherency analysis does not give information about the sign of the correlation as the coherence seems to be very low. We will focus on the dynamic correlations in the next section. It is also worth mentioning that the variables are in-phase for a very limited time during January and February 2020 at short-run scales (around 16-days cycle), with AI index leading the government securities.

As for the pairs of AI and corporate bond indices, Figure 2(c) shows that high co-movement is more concentrated across the 8-128 days, mainly during first half of 2020. We also observe some evidence of significant but short-lived coherence in the high frequency bands (below 16 days) during the sample period. There exists a large pocket of high coherency from mid-2019 to mid-2020 where the arrows mostly point to the right-up, indicating that the variables are in-phase and AI is leading the corporate bond index, mostly above 8 trading days scale. In this regard, corporate bonds distinguish themselves from government securities in that they exhibit positive correlation with AI stocks as corporate bonds are riskier securities carrying default risk. However, small regions of high coherency are also visible at short-term horizons (below 16 days) during early 2019, where the arrows face left-down, implying that the relationship is anti-cyclical and AI leads corporate bonds. The existence of negative correlations at higher frequencies before 2020 indicates potential diversification benefits of corporate bonds for portfolios including AI & Robotics stocks. However, during the period of the pandemic, diversification with corporate bonds can be more challenging as the correlations become significantly positive. In this context, investors contemplating AI stock investments should bear changing correlations with corporate bonds in mind when setting strategic asset allocation policy.

Figure 2(d) illustrates that AI stocks display strong significant correlation with commodity index returns starting by late 2018 to the end of the sample period at scales above 8-days cycle. In general, the color code demonstrates that the interdependence is more persistent at medium (16-32 days) and lower frequency scales (64-128 days). In the short-run (4-16 days cycle), there are also some statistically significant regions of high coherence particularly in 2020. The phase difference shows that the variables have positive correlation overall and AI mostly leads the commodity index. Nonetheless, there are small pockets of high coherency with AI lagging behind commodities at periods of 8-16 days during late 2019 and early 2020. Stronger linkages between AI stocks and commodities during the pandemic imply reduced hedging/diversification benefits when needed most. Most of the researchers attribute lower investment benefits at times of crises to the financialization of commodities (Daskalaki and Skiadopoulos 2011; Silvennoinen and Thorp 2013; Büyüksahin and Robe 2014). Although commodities are distinct asset classes, they have become equity-like investments since early-2000s due to the increased trading activity in commodity futures markets.

Considering the co-movement between the AI and cryptocurrency indices, our results provide evidence of an overall weak relationship as shown by the predominance of blue coloring. However, a pocket of strong coherency is visible at investment horizons between 16-128 days around the COVID-19 pandemic. The non-existence of persistent high coherency bands during the study period implies that cryptocurrencies can be a good hedge instrument for AI stocks in general, which is in line with Dyhrberg (2016), Guesmi et al. (2019) and Chan et al. (2019). However, stronger coherency during 2020 suggests that cryptocurrencies may not act as safe haven assets as they have positive correlation and in-phase relationship with AI stocks. In terms of causality, arrows mostly pointing right-up show the leading position of AI stocks.

In a nutshell, wavelet coherency analysis suggests a weaker (stronger) co-dependency between AI and other investments at shorter (longer) investment horizons. This indicates lower hedge and diversification benefits from combining AI stocks with other investments over long trading horizons. In other words, even if a portfolio strategy of mixing AI stocks and other traditional or alternative investments can provide investment benefits, the effectiveness of such trading strategies might depend on the choice of investment horizon. This partially confirms the recent findings of Tiwari et al. (2020), which suggests that investors and portfolio managers should hedge and adjust their trading positions including AI stocks according to holding period. Furthermore, the investment benefits may reduce and the efficacy of investment strategies involving AI stocks may even fail at times of adverse economic conditions, as evidenced by stronger coherence during the pandemic. This supports the findings of Sharif et al., (2020), claiming that the COVID-19 risk is perceived differently over the short and the long-run. Le et al. (2020) also find that shocks originated from technology stocks have a big impact on Bitcoin and global equity returns during the COVID-19 outbreak. They suggest that transmission between the markets intensifies particularly for the frequencies above 16 days.

Our findings provide evidence of mixed causality based on scale and time; the position of the arrows change across scales within periods. The dynamic linkages varying across time and investment horizons can help market participants acquire comprehensive information to make financial decisions. Understanding the dependence structure and the lead-lag relationship across different frequencies can also be extremely useful for investors with different investment horizons for their strategic asset allocation decisions (Reboredo et al., 2017). In general, we do not find significant long-lived coherence pockets where causality is visible in the short run (2-16 days). The absence of lead-lag relations and strong coherency at lower scales suggest that short-term investors investing in AI stocks may use assets such as commodities or cryptocurrencies as a hedge instrument, however, it is very unlikely to predict AI stock returns using the past values of commodities or cryptocurrencies. Looking at the causality at the intermediate and lower frequencies, we can state that market participants may benefit from the forecasting ability of AI stocks, which confirms Tiwari et al (2016), stating that market returns are more predictable in longer-term horizons.

The lead-lag relationships predominantly indicate the leading position of AI stocks, particularly during the COVID-19 outbreak, implying that AI stocks process new information much faster than the other assets in the sample, except for government securities. As for the pairs of AI index with the government bond index, the lead-lag relations are somewhat mixed, with AI leading or lagging behind government securities at different time scales. This suggests that AI index and government securities provide information about each other, which can be useful in adjusting prices towards long-run equilibrium. The causal dynamics can also assist policymakers or authorities in implementing strong and targeted policy measures to avoid financial market risk.

5.2. Rolling Wavelet Correlations

In this section, we apply rolling window analysis to measure wavelet correlations at different frequencies. The rolling window is established at 252 days.[17] The wavelet scales range from 1 to 6: d1 (2-4 days), d2 (4-8 days), d3 (8-16 days), d4 (16-32 days), d5 (32-64 days), d6 (64-128 days). Figure 3 plots the rolling wavelet correlations between the AI stocks and other index

[17] As known, rolling window analysis is very sensitive to the choice of the window size. We test the robustness of our findings using different window sizes, such as 54 and 104 days. Our qualitative results do not change, highlighting that our rolling window correlation analysis is robust.

returns and Figure 4 exhibits the boxplots of average correlation coefficients before and during the COVID-19 pandemic.

[Insert Figure 3 here]

[Insert Figure 4 here]

At a first glance, the correlations given by the rolling window wavelet analysis significantly change across time and frequency, which can give further insights and more comprehensive information for investors and portfolio managers to make informed trading decisions. The rolling correlations between AI stocks and S&P 500 returns presented in Figure 3(a) are highly positive throughout the sample period. In March 2020, there is a significant hike in the co-movements and then on, the correlations almost remain constant until the end of the sample period. The level of correlations is the highest for the 32-64 and 64-128 days cycle, whereas the lowest correlations are recorded for 2-4 days cycle. The boxplot in Figure 4(a) reveals heightened correlations during the epidemic at the d1, d3, d5 and d6 scales. On the other hand, the level of correlations at 4-8 and 16-32 days cycle stays almost the same before and at the time of the Corona crisis.

Looking at the correlation dynamics depicted in Figure 3(b), we can see that the rolling wavelet correlations of the AI index with government bonds show predominantly negative correlations across all frequencies, except for the time period starting by March 2020 in the d3 and d4 cycles. The level of correlations ranges from 0 to -0.7 approximately, before the pandemic hits the global markets. In March 2020, the rolling wavelet correlations display a sudden increase and become positive (approximately 0.2) which persists till the end of the sample period for 8-16 and16-32 days investment horizons. The boxplots of average correlations in Figure 4(b) also indicate that the highest correlation increase is reported for d3 and d4 scales, which is consistent with the previous wavelet coherence analysis. Moreover, we observe the highest correlation decrease at the d6 frequency band, indicating that longer-term investors are more likely to flee from AI stocks to quality assets, such as government bonds, during bearish markets.

Figure 3(c) depicts the rolling correlations between AI stocks and corporate bonds. The time-varying correlations are mostly negative at higher frequencies and have a downward trend until the COVID-19 outbreak in March 2020. However, the dynamic correlations experience a dramatic increase with the spread of the virus globally. The level of the rolling correlations for d3, d4, d5 and d6 scales records abrupt increases to around 0.8 from almost -0.4. The rolling correlations for shorter investment horizons (d1 and d2 scales) rise approximately from -0.2 to 0. The boxplot presented in Figure 4(d) also confirms significant jumps in the wavelet correlations during the pandemic.

As for the pair of AI and commodity index, the correlation plots given in Figure 3(d) reveal positive correlations at all scales. The existence of positive correlations overall is in line with the financialization of commodities, leading to an increasing co-dependency between commodity prices and conventional asset prices since the early 2000’s (Bredin et al., 2015). The correlations during the sample period range from 0.1 to higher than 0.9 across all the scales. However, in general, we can observe higher correlations at lower frequencies, indicating that portfolio diversification with commodities can be better accomplished in the short-run. As seen in the relevant boxplot in Figure 4(d), the correlations are higher during the pandemic. For example, for the very short-term investment horizon, the average correlations rise from 0.25 to 0.5, indicating stronger inter-relations between AI stocks and commodities at the time of the COVID-19 pandemic.

Finally, having looked at the correlation dynamics between AI and CRIX in Figure 3(e), we can see a relatively weak relationship before March 2020; the correlations fluctuate between -0.2 and 0.2 across all the scales except for d6. This shows hedging potential of cryptocurrencies against losses in AI stocks, as they are either uncorrelated or negatively correlated on average. However, with the start of the global Corona outbreak in March 2020, we observe a stronger co-dependency for d4, d5, and d6 scales as indicated by the surges in correlations. Particularly for the d2 and d3 scales, the correlation increase is somewhat milder, showing that the relationship remains stable, which is also reflected in the boxplot in Figure 4(e). For the shortest investment horizon (2-4 days cycle), the wavelet correlations fall from nearly 0 to -0.35, which implies that cryptocurrencies can be treated as a safe haven asset during the pandemic for investors only with very short investment horizons. In other words, investment benefits offered by cryptocurrencies may not be available to medium and longer term investors during the COVID-19 period.

From the wavelet correlations, we can infer that the inter-linkages between the AI stocks and other investments exhibit a sudden dramatic increase at certain scales in March 2020. As we have discussed in the introduction, the WHO announced COVID-19 outbreak as a pandemic on March 11, 2020 and, until the end of the month, global records reached about 1 million cases, forcing countries to shut down their economies to control the spread of the virus. However, the outbreak rapidly dispersed to Europe and the USA with the latter becoming the epicenter of the pandemic by the end of March. The Coronavirus crash is the fastest decline in the global markets so-far recorded in the history of the financial markets, however, it is a short-lived bear market.

The sudden increases in correlations at certain scales suggest potential contagion effects. In the existing literature, contagion is corroborated with rising inter-linkages at times of downward markets (Forbes and Rigobon, 2002; Syllignakis and Kouretas, 2011; Dimitriou et al., 2013). Our results provide support to the contagion effect, as we demonstrate that the correlations between AI and other index returns exhibit jumps across most of the frequencies during the Coronavirus crash. For example, the mean of the correlations between AI and commodity index returns substantially rises across all the frequencies after March 2020. The average correlations between AI and CRIX index at d4, d5, and d6 scales also significantly surge with the Coronavirus crash, which is consistent with the findings of Corbet et al. (2020b) suggesting that cryptocurrencies may not act as hedges or safe havens but rather as amplifiers of contagion in times of severe market downturns. This implies potential contagion incidences particularly for medium and longer-term investment horizons, which can be linked to herding behavior of investors. When economic uncertainty rises, financial market participants tend to mimic each other, and implement similar trading strategies, leading to heightened correlations across markets (Hirshleifer and Hong Teoh, 2003; Chiang et al, 2007; Lao and Singh, 2011). The existence of financial contagion incidences during the COVID-19 period is also recently documented by Akhtaruzzaman et al. (2020) and Li et al. (2020).

Investors tend to have a greater sensitivity to losses than financial gains, as shown by Tversky and Kahneman (1991). Changes in risk aversion and investor behavior may lead to shifts in optimal portfolio allocations and prompt investors to look for safe haven assets, particularly in times of market turbulence. Our findings provide implications and insights for the use of different investments to hedge/diversify portfolios consisting of AI & Robotics stocks. The safest assets seem to be government securities as they exhibit negative correlations with the AI index returns, suggesting that government bonds can act as safe haven assets. However, their safe haven characteristics significantly depend on the trading horizon, as also suggested by Bayraci et al. (2018). US government bonds mostly display safe haven property for investors having allocations in AI & Robotics stocks with 2-4 and 64-128 days trading horizon. This is consistent with Gupta et al. (2020), reporting that US Treasury securities act as a safe haven asset and have the potential of hedging financial market risk in the wake of the COVID-19 pandemic. Our results further support the recent findings of Papadamou et al. (2021) who provide evidence of some short-lived wavelet coherency between government securities and stock markets at high frequency cycles during the pandemic; however they find very low or zero coherence at lower frequencies, suggesting that sovereign bonds may offer some diversification and there is a flight-to-quality effect from stock to bonds for longer-term investors.

Furthermore, a relatively weak linkage between AI and CRIX is visible before the Corona outbreak, positioning cryptocurrencies as a hedge instrument against AI stocks, supporting the findings of Dyhrberg (2016), Guesmi et al. (2019), Chan et al. (2019) and Huynh et al. (2020a). However, starting by March 2020, we see significant increases in correlations at lower frequencies, which depicts that the virtual assets cannot be regarded as safe haven investments for AI stocks. Only short-term investors with 2-4 trading days seem to benefit from adding cryptocurrencies in their portfolios during the pandemic. This is in parallel with the findings of several recent papers. For example, Conlon and McGee (2020) find that Bitcoin is not a safe-haven investment and it increases overall portfolio risk during the COVID-19 bear market. In a more recent paper, Goodell and Goutte (2021) examine diversifying stocks with cryptocurrencies during the pandemic and document that the co-movements between cryptocurrencies and equity markets have gradually increased, suggesting that the virtual assets do not offer a diversification benefit during COVID-19. Therefore, even though the cryptocurrency market has experienced an increase in returns and trading volume since 2020, the inclusion of cryptocurrencies in stock portfolios might add to downside risk.

Our findings further evince significant increases in the level of correlations of the AI index with the commodity and corporate bonds across all the scales, suggesting that a portfolio diversification with these assets may not be optimal in times of market turbulence. In other words, investors who have allocations in the AI & Robotics stocks should not consider adding commodities or corporate bonds into their portfolios when they seek shelter from COVID-19 turbulence. Overall, the evidence of reduced benefits of including commodities in portfolios is also highlighted by Silvennoinen and Thorp (2013) and Büyüksahin and Robe (2014). However, the number of studies analyzing the performance of commodities during the pandemic is extremely limited. Nevertheless, Mensi et al. (2020) claim that gold and oil market have been inefficient during the outbreak, suggesting the possibility of predicting future pricing behavior based on past information and potential mispricing in derivative markets. Our results relating to corporate bonds are in stark contrast to Liu (2016) and Kemper et al. (2012), finding that US corporate bond market provides portfolio gains in times of market crashes, particularly during the Global Financial Crisis of 2007-2009. However, as suggested by Lin and Su (2021), we cannot treat the COVID-19 pandemic like a financial crisis since the coronavirus outbreak is a major public health event.

6. Conclusion and Further Remarks

Till the present day, the hellish dystopia of robots taking over jobs, cleaning our houses and performing surgeries has seemed to be a futuristic fantasy. However, the COVID-19 pandemic has changed our lives, as social distancing advised by the WHO has led to a more virtual existence, which in turn has accelerated the use of Robot and Artificial Intelligence technologies. Consequently, technology stocks, particularly AI & Robotics stocks, have attracted significant investor attention. In this paper, we investigate the dynamic co-movements between AI stocks and other traditional and alternative investments using wavelet-based techniques, which allow us to examine the linkages between variables by simultaneously capturing both calendar time and investment horizon.

The wavelet coherence demonstrates that the interlinkages are both time and frequency variant. Our results suggest weak (strong) co-movements between AI and other investments at shorter (longer) investment horizons over the entire study period, however, we observe much stronger coherencies during the COVID-19 pandemic. The lead-lag relations show mixed causality across time and scale overall, with the AI stocks mostly leading in the wake of the outbreak. Moreover, the rolling window analysis uncovers that significant increases in wavelet correlations at certain scales overlap with the inception of the recent public health crisis. The dynamic correlations between the AI stocks and other investments, except for government securities, at almost all scales, reach their peak after March 11, 2020, when the WHO announced COVID-19 outbreak as a pandemic.

Our results provide potential implications and insights for different stakeholders. The existence of time and scale dependent interactions between AI & Robotics stocks and other investments highlights the importance of dynamic portfolio adjustments based on calendar time and investment horizons. Investors contemplating AI stocks should beware the reduced hedging/diversification benefits in the wake of the COVID-19 pandemic due to the increase in the overall portfolio risk. Heightened cross-market correlations in times of market turmoil corroborates the "contagion hypothesis", postulating that asset prices exhibit abrupt changes when unexpected exogenous shocks occur. The only investment assets displaying negative correlations with the AI stocks at most of the scales during the pandemic are government securities, suggesting that they exhibit safe haven asset characteristics. Another potential safe haven asset can be cryptocurrencies as they have negative correlations with the AI stocks during the pandemic, however they may provide diversification benefits only for 2-4 days trading horizon. Furthermore, understanding the interdependence between AI stocks and different investment assets and their causal relations can help policy makers and authorities devise policy measures to manage financial market risk.

Even though our results provide significant insights and implications for investors contemplating to invest in AI & Robotics stocks, we should acknowledge potential limitations of the study.[18] Firstly, our analysis is based on daily returns; however intraday data could provide richer information for our study. Secondly, we use aggregate indices, which may mask valuable asset-specific information. Furthermore, there are still several possible paths to follow in future studies to improve our understanding of the co-movements between AI & Robotics stocks and other financial assets. For example, future researchers can examine various portfolio diversification strategies for the AI equities during the pandemic more fully and analyse how diversification benefits change with respect to trading horizons and investors' risk aversion.

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[18] We are grateful to the reviewer for inviting us to acknowledge potential limitations.

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Table 1. The index details

Segment	Index	Coverage
Artifical Intelligence and Robotics Stocks (AI)	Nasdaq CTA Artificial Intelligence & Robotics Index (NQROBO)	This index is designed to measure the performance of companies engaged in the artificial intelligence and robotics segment of the technology, industrial, medical and other economic sectors. It comprises of companies in artificial intelligence or robotics that are classified as either enablers, engagers or enhancers.
Commodities	Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI)	The index is designed to be investable by including the most liquid commodity futures. It serves as a benchmark for commodity investments and as a performance measure of commodity markets over time.
Corporate Bonds	Standard and Poor's Investment Grade Corporate Bond Index	The index is designed to measure the performance of U.S. corporate debt issued by constituents in the S&P 500 with an investment-grade rating.
Cryptocurrencies	CRyptocurrency IndeX (CRIX)	The CRyptocurrency IndeX is a benchmark for the crypto market, measuring the performance of the largest cryptocurrencies, such as Bitcoin, Ripple and Litecoin.
Government Bonds	Standard and Poor's U.S. Government Bond Index	This index measures the performance of U.S. dollar-denominated U.S. Treasury and U.S. agency debt issued in the U.S. domestic market.
Stock Index	Standard and Poor's 500 Index	The S&P 500 is a stock market index that measures the stock performance of the largest 500 US companies in terms of market capitalization.

Table 2. Summary Statistics

	A.I.	COM.	C.B.	CRIX	G.B.	S&P
Full sample						
Mean	0.0716	0.0132	0.0189	0.1486	0.0135	0.0481
Median	0.1792	0.1372	0.0313	0.1993	0.0181	0.1058
Maximum	9.1011	7.6832	1.8779	274.7722	1.7415	8.9683
Minimum	-10.4795	-12.5233	-2.8106	-281.0841	-1.6649	-12.7652
Std. Dev.	1.4276	1.5459	0.3372	14.6446	0.2447	1.4458
Skewness	-0.9865	-1.4301	-1.7811	-0.6467	0.3176	-1.0231
Kurtosis	12.8443	16.1213	22.1765	318.4118	12.3906	19.2381
Pre-Covid sample						
Mean	0.0002	-0.0607	0.0275	-0.1746	0.0267	0.0043
Median	0.1123	0.1279	0.0364	-0.0587	0.0277	0.0811
Maximum	2.6536	7.6832	1.0336	22.0266	1.0680	4.8403
Minimum	-8.1195	-12.2688	-1.2738	-30.9005	-0.6251	-7.9010
Std. Dev.	1.1229	1.3038	0.2386	4.9543	0.2106	1.0709
Skewness	-1.2239	-1.6739	-0.2275	-0.5908	0.4750	-1.1614
Kurtosis	8.3815	19.4390	5.1746	7.5321	4.9690	11.2129
Post-Covid sample						
Mean	0.2198	0.1665	0.0011	0.8192	-0.0138	0.1388
Median	0.3504	0.2308	0.0082	0.7168	-0.0176	0.2550
Maximum	9.1011	7.1147	1.8779	274.7722	1.7415	8.9683
Minimum	-10.4795	-12.5233	-2.8106	-281.0841	-1.6649	-12.7652
Std. Dev.	1.9050	1.9489	0.4814	24.6879	0.3020	2.0119
Skewness	-0.9127	-1.2909	-1.7482	-0.4851	0.3261	-0.9046
Kurtosis	10.5769	11.8168	15.5870	121.8769	14.0435	14.1006

Notes. A.I, COM., C.B., CRIX, G.B. and S&P represent Artificial Intelligence & Robotics Index, S&P Commodity Index, S&P U.S. Corporate Bond Index, the Cryptocurrency Index, S&P U.S. Government Bond Index and S&P 500 Composite Stock Index, respectively. The full sample includes 834 observations from December 19, 2017 to March 31, 2021. The pre-covid sample covers the period from December 17, 2017 to March 10, 2020, yielding 552 observations. The post-covid sample includes 266 observations from March 11, 2020 to March 31, 2021.

Table 3. Unconditional Correlations

	A.I.	COM.	C.B.	CRIX	G.B.	S&P
Full sample						
A.I.	1.0000					

COM.	0.4189	1.0000				
	(0.0000)	-----				
C.B.	0.0700	0.0021	1.0000			
	(0.0453)	(0.9518)	-----			
CRIX	0.0229	0.1071	0.0030	1.0000		
	(0.5138)	(0.0022)	(0.9317)	-----		
G.B.	-0.3294	-0.2433	0.7100	-0.0005	1.0000	
	(0.0000)	(0.0000)	(0.0000)	(0.9897)	-----	
S&P	0.8574	0.4279	-0.0271	-0.0088	-0.4407	1.0000
	(0.0000)	(0.0000)	(0.4390)	(0.8010)	(0.0000)	-----
Pre-Covid sample						
A.I.	1.0000					

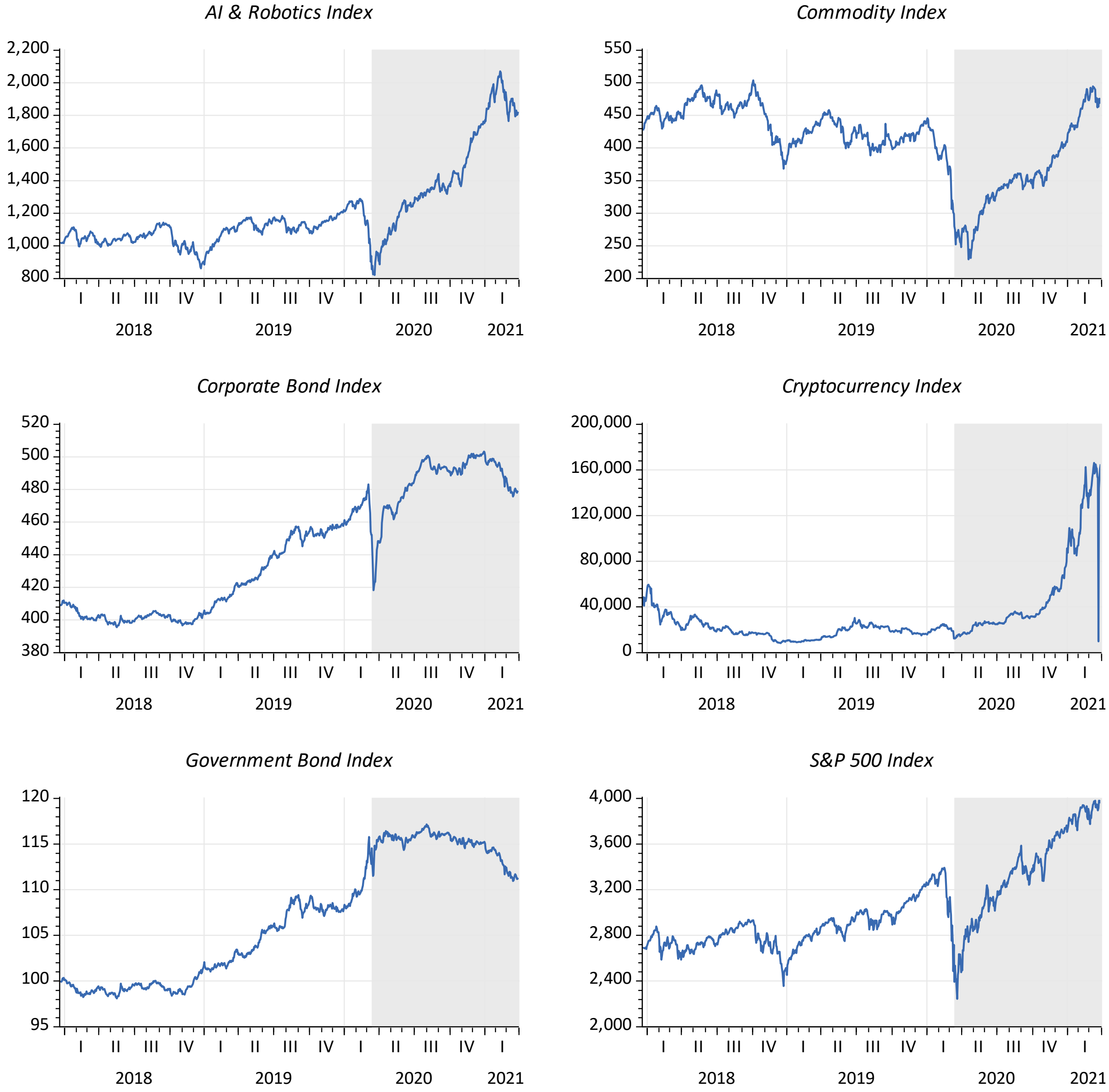
COM.	0.4282	1.0000				
	(0.0000)	-----				
C.B.	-0.1886	-0.0358	1.0000			
	(0.0000)	(0.4015)	-----			
CRIX	0.0775	0.1161	-0.0278	1.0000		
	(0.0690)	(0.0063)	(0.5145)	-----		
G.B.	-0.4484	-0.3126	0.8459	-0.0562	1.0000	
	(0.0000)	(0.0000)	(0.0000)	(0.1877)	-----	

S&P	0.8558	0.4377	-0.2591	0.0651	-0.4886	1.0000
	(0.0000)	(0.0000)	(0.0000)	(0.1264)	(0.0000)	-----
Post-Covid sample						
A.I.	1.0000					

COM.	0.4075	1.0000				
	(0.0000)	-----				
C.B.	0.2321	0.0326	1.0000			
	(0.0001)	(0.5964)	-----			
CRIX	0.0091	0.1198	0.0111	1.0000		
	(0.8821)	(0.0510)	(0.8571)	-----		
G.B.	-0.2229	-0.1681	0.6293	0.0193	1.0000	
	(0.0002)	(0.0060)	(0.0000)	(0.7537)	-----	
S&P	0.8600	0.4227	0.1026	-0.0279	-0.4078	1.0000
	(0.0000)	(0.0000)	(0.0951)	(0.6507)	(0.0000)	-----

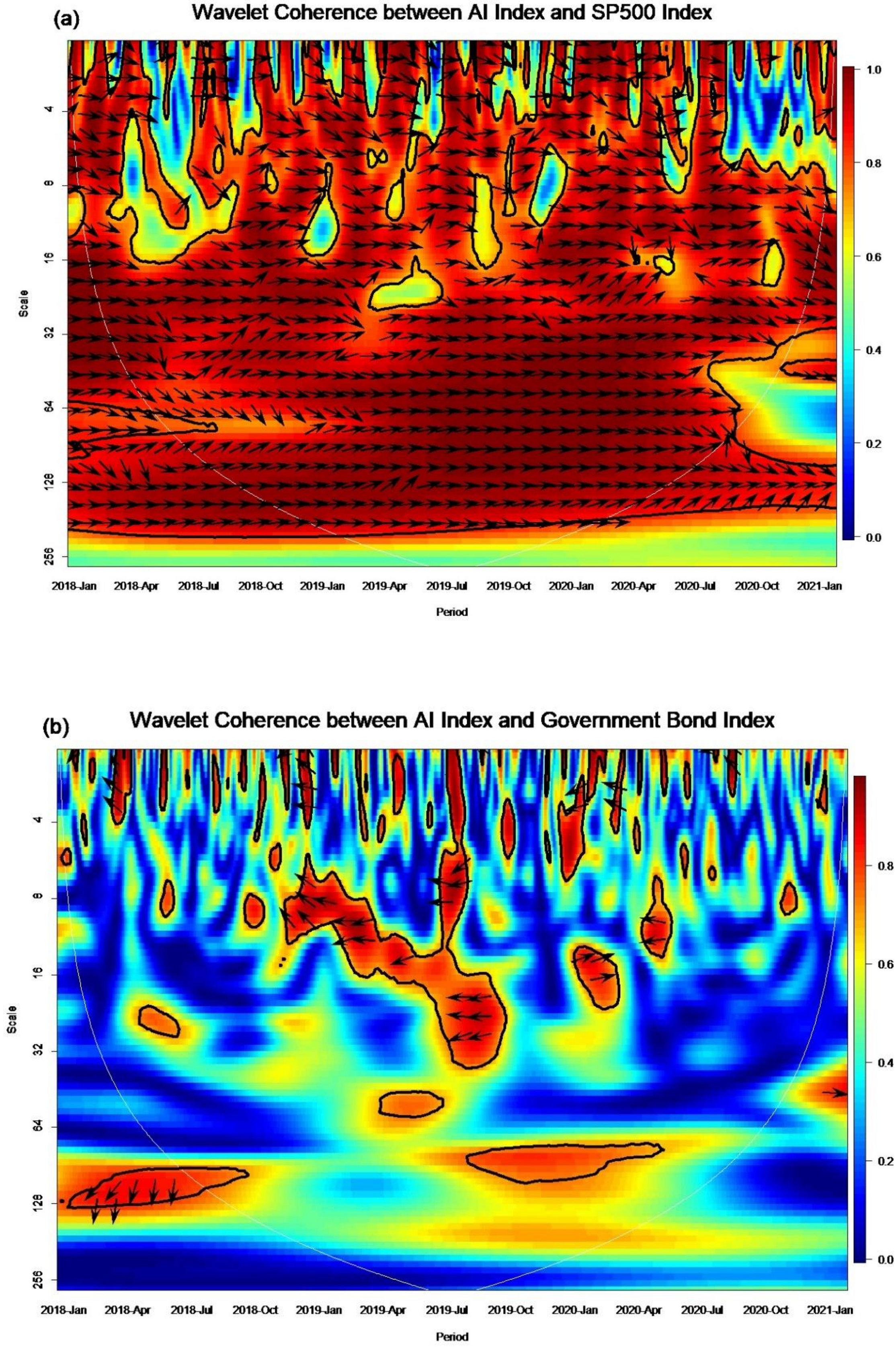
Notes. A.I, COM., C.B., CRIX, G.B. and S&P represent Artificial Intelligence & Robotics Index, S&P Commodity Index, S&P U.S. Corporate Bond Index, the Cryptocurrency Index, S&P U.S. Government Bond Index and S&P 500 Composite Stock Index, respectively. The full sample includes 834 observations from December 19, 2017 to March 31, 2021. The pre-covid sample covers the period from December 17, 2017 to March 10, 2020, yielding 552 observations. The post-covid sample includes 266 observations from March 11, 2020 to March 31, 2021.

Figure 1. Price performance of the indices

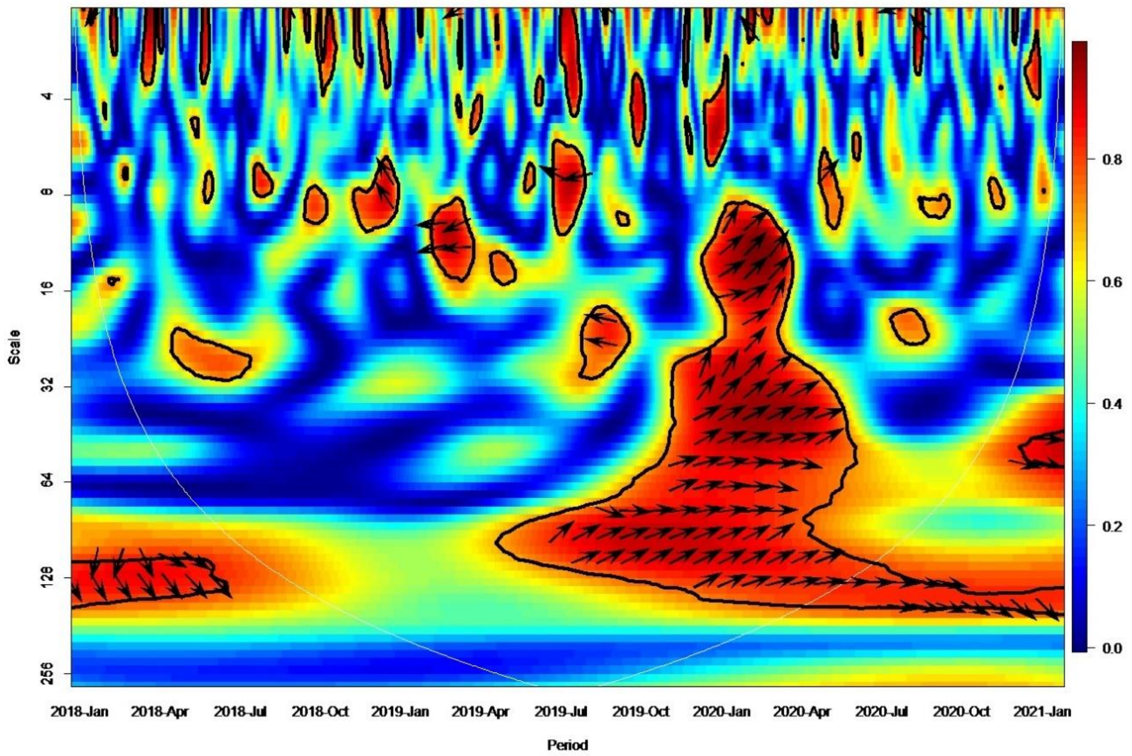


Note: The shaded area represents the COVID-19 period

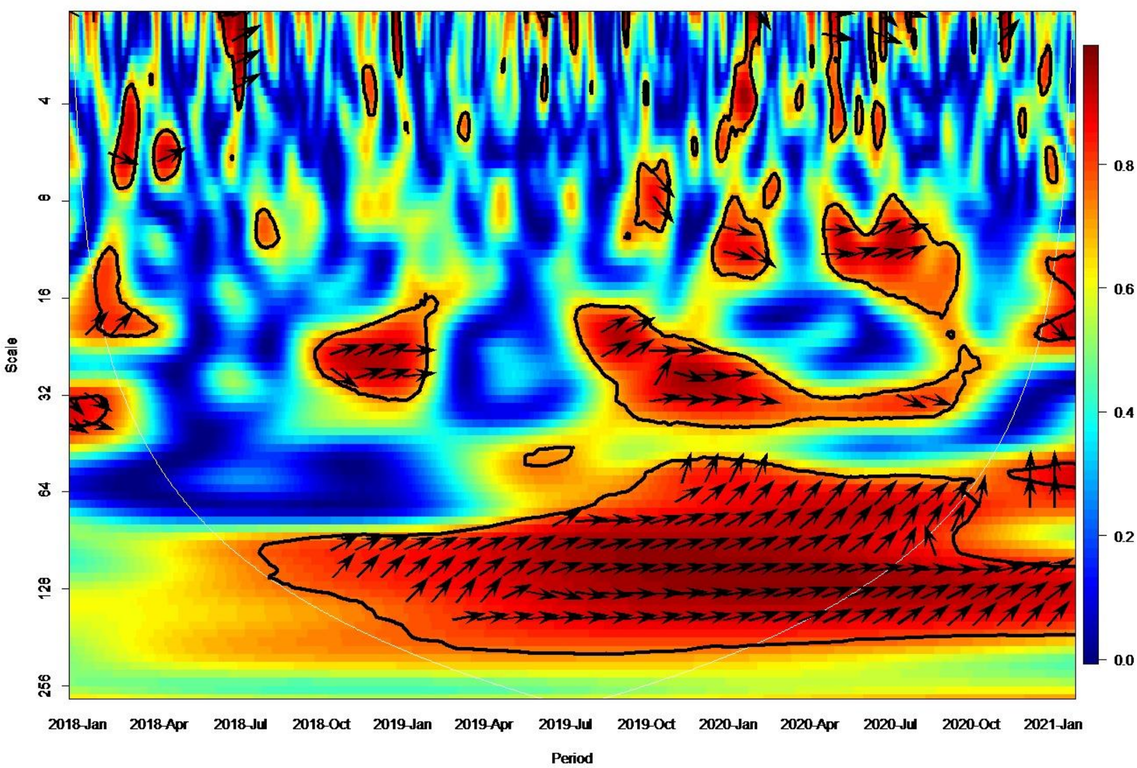
Figure 2. Wavelet Coherence Plots

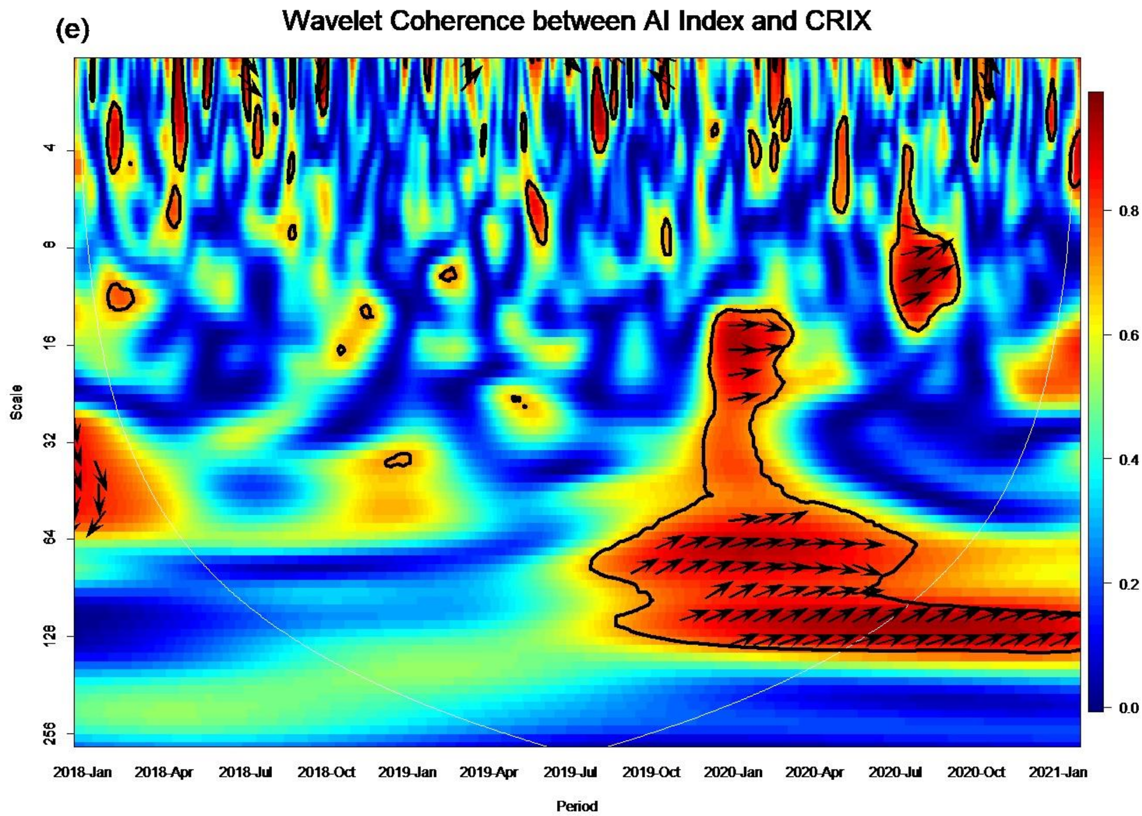


(c) **Wavelet Coherence between AI Index and Corporate Bond Index**



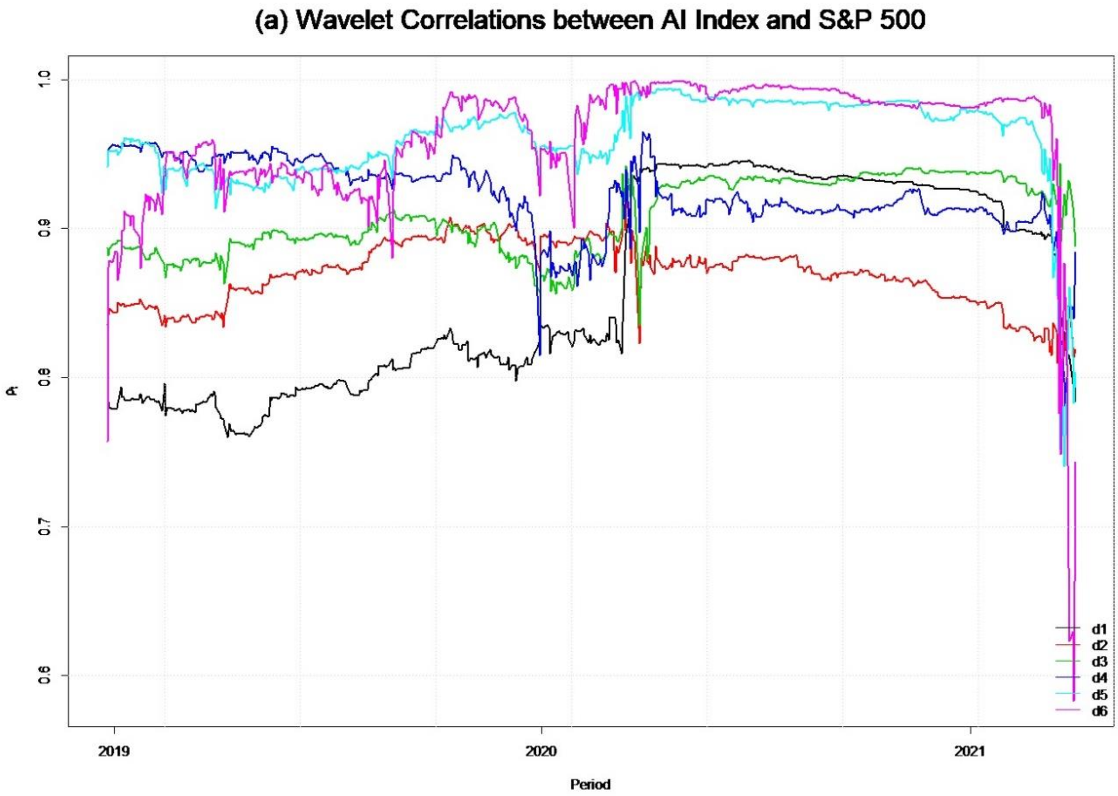
(d) **Wavelet Coherence between AI Index and Commodity Index**

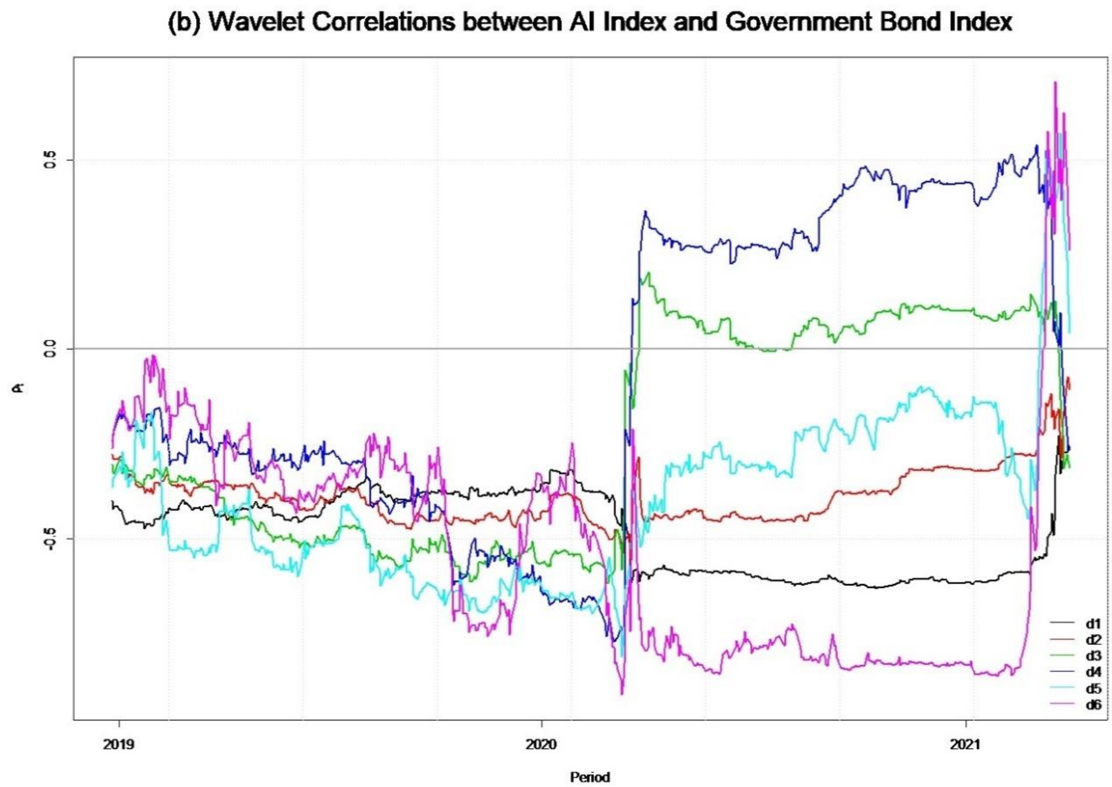




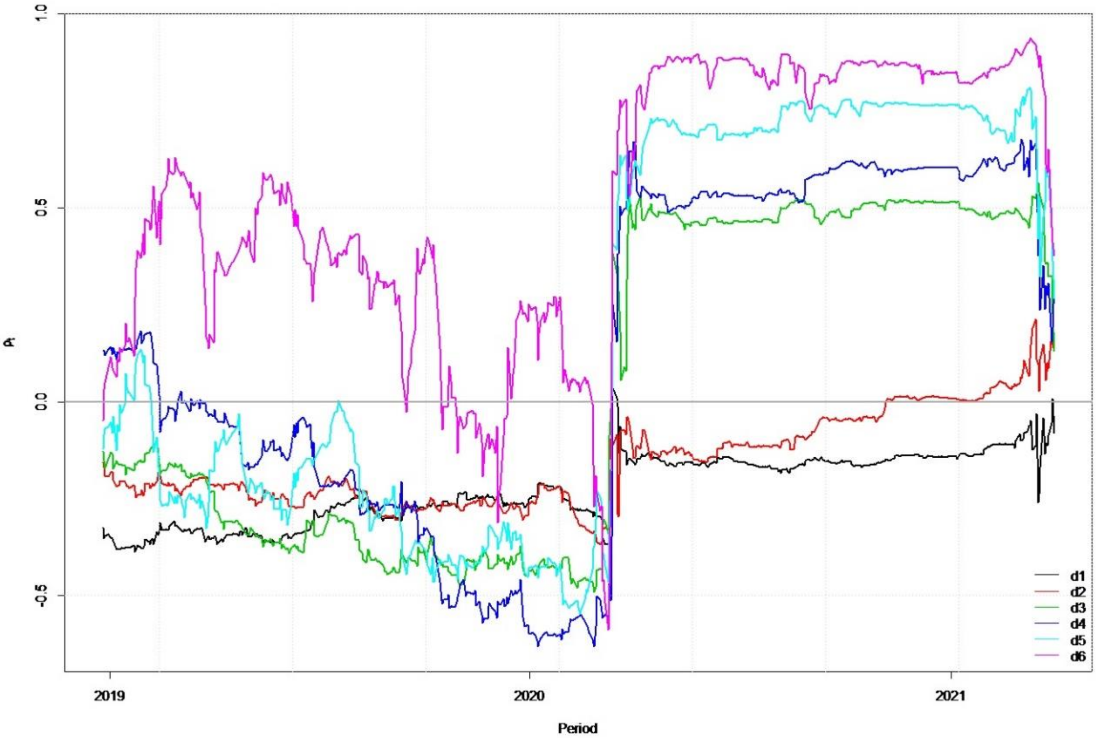
(e)
Wavelet Coherence between AI Index and CRIX
Scale
4
8
16
32
64
128
256
0.8
0.6
0.4
0.2
0.0
2018-Jan
2018-Apr
2018-Jul
2018-Oct
2019-Jan
2019-Apr
2019-Jul
2019-Oct
2020-Jan
2020-Apr
2020-Jul
2020-Oct
2021-Jan
Period

Figure 3. Wavelet Rolling Window Correlations

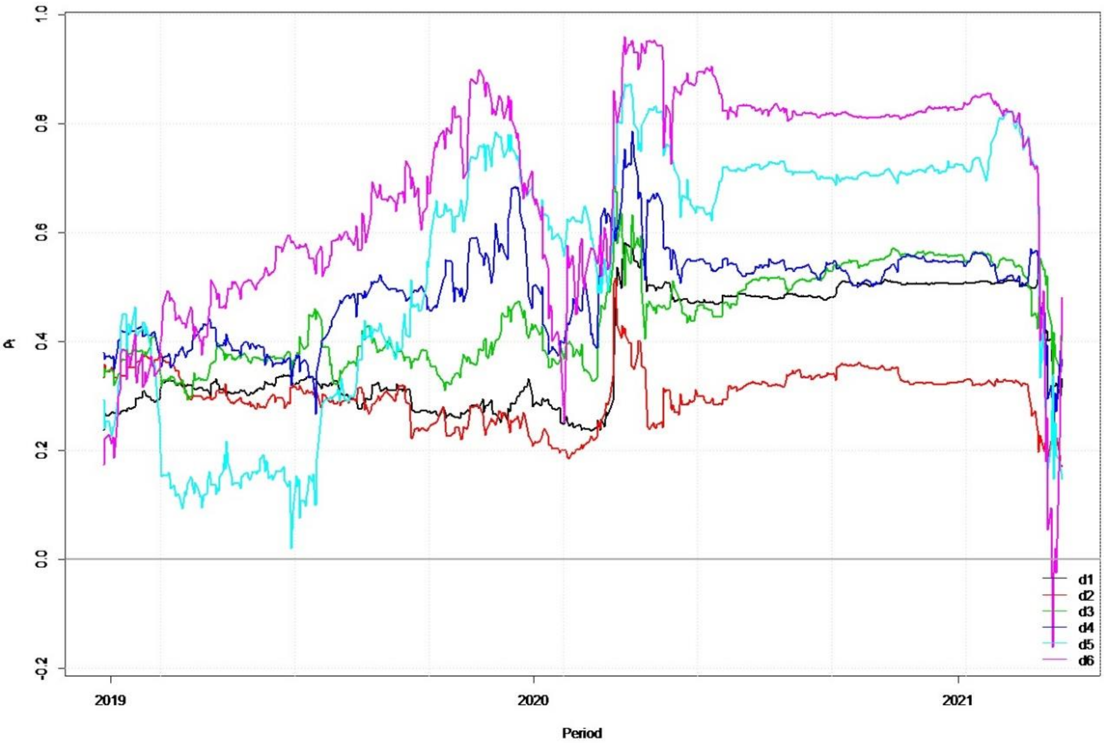


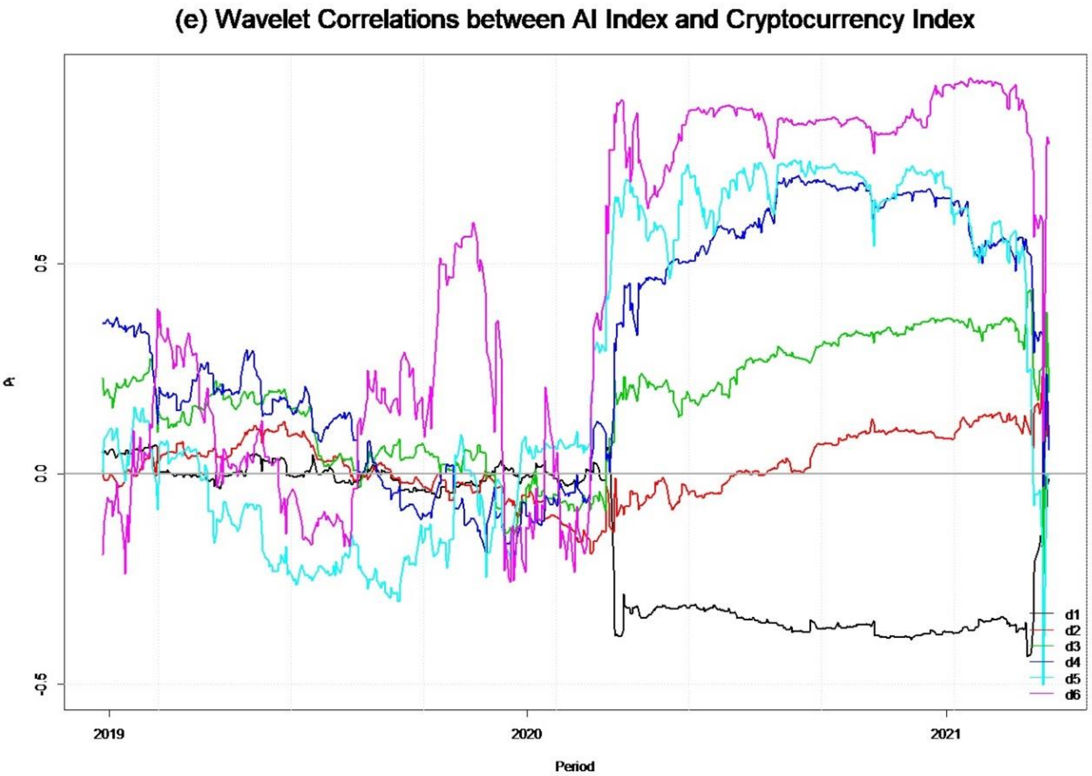


(c) Wavelet Correlations between AI Index and Corporate Bond Index



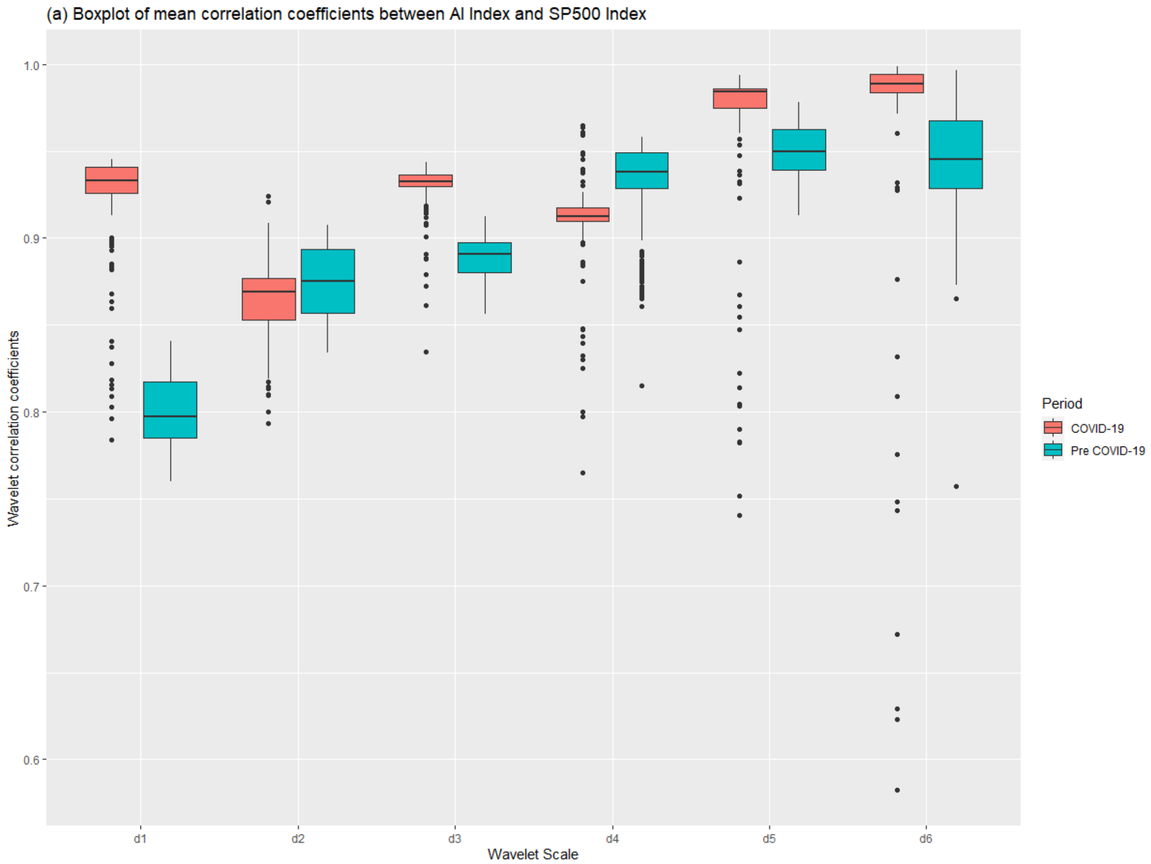
(d) Wavelet Correlations between AI Index and Commodity Index

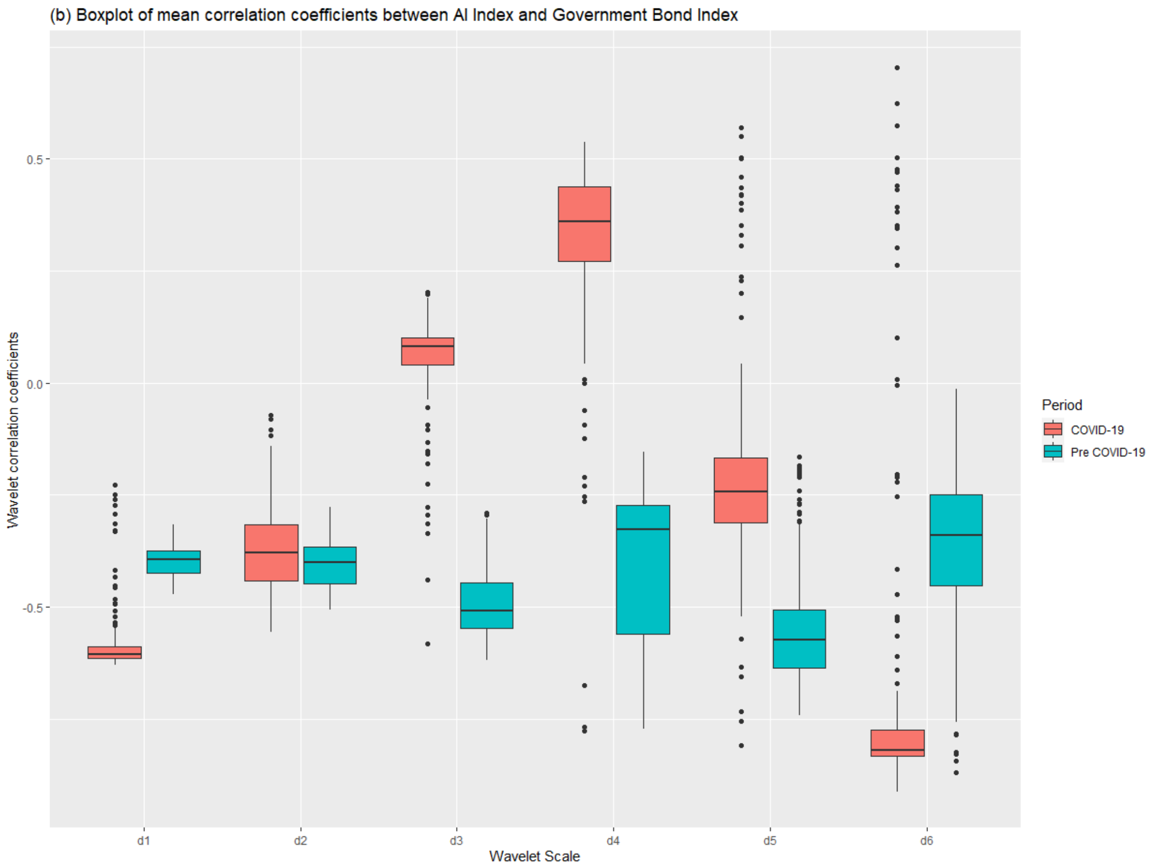


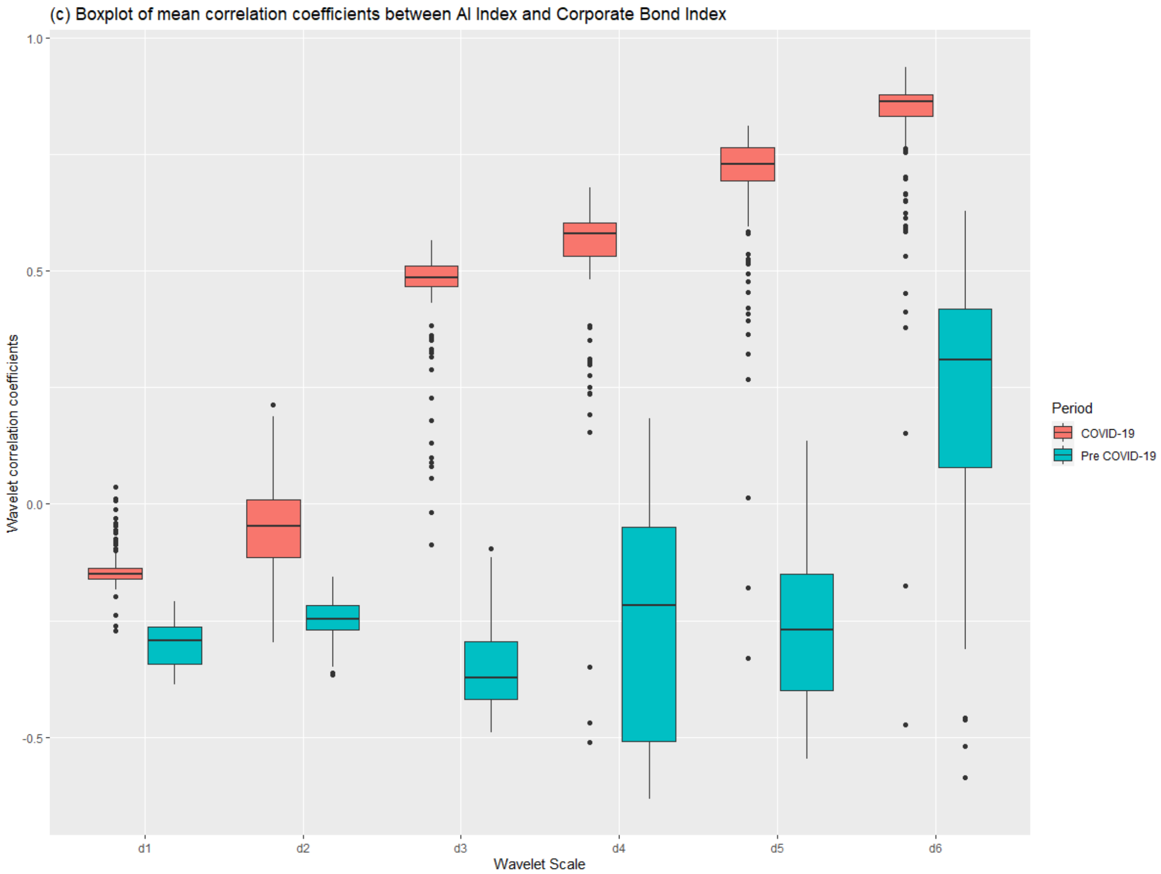


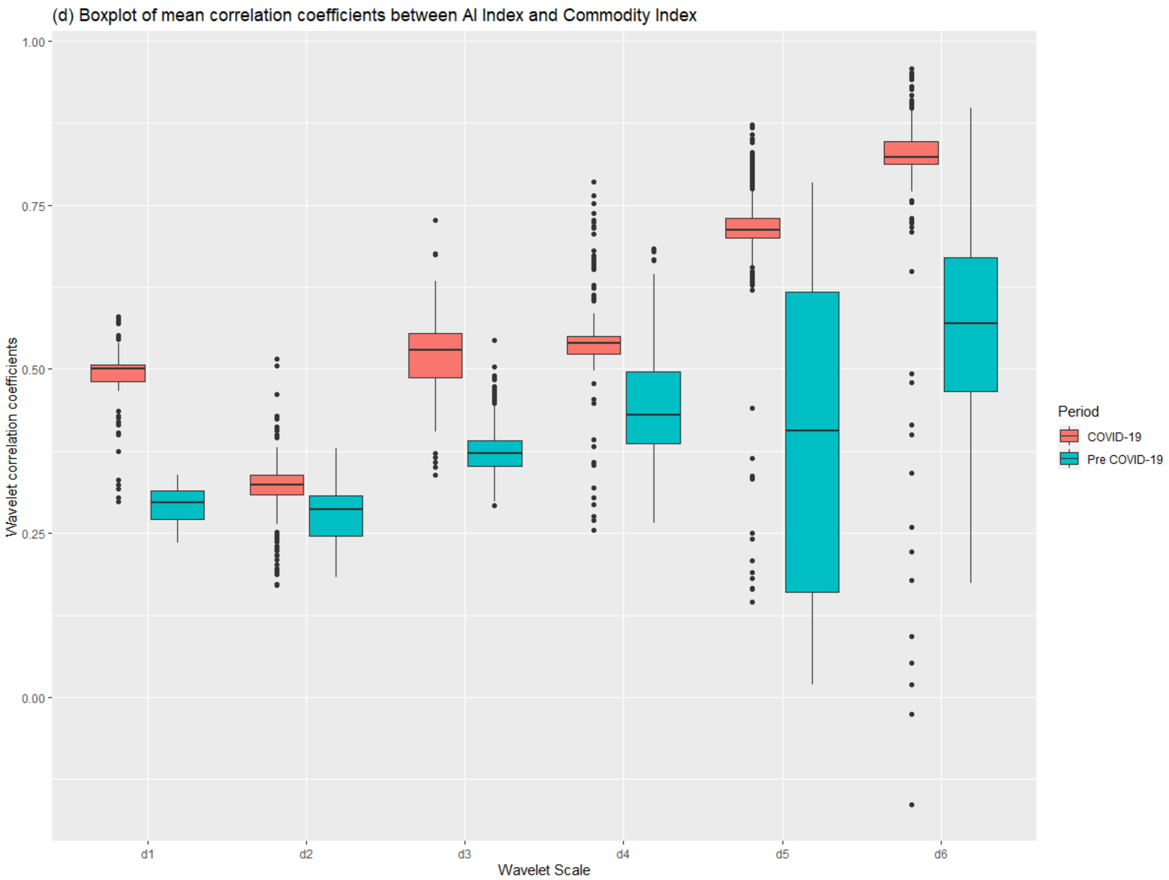
Note: The wavelet scales range from 1 to 6: d1 (2-4 days), d2 (4-8 days), d3 (8-16 days), d4 (16-32 days), d5 (32-64 days), and d6 (64-128 days).

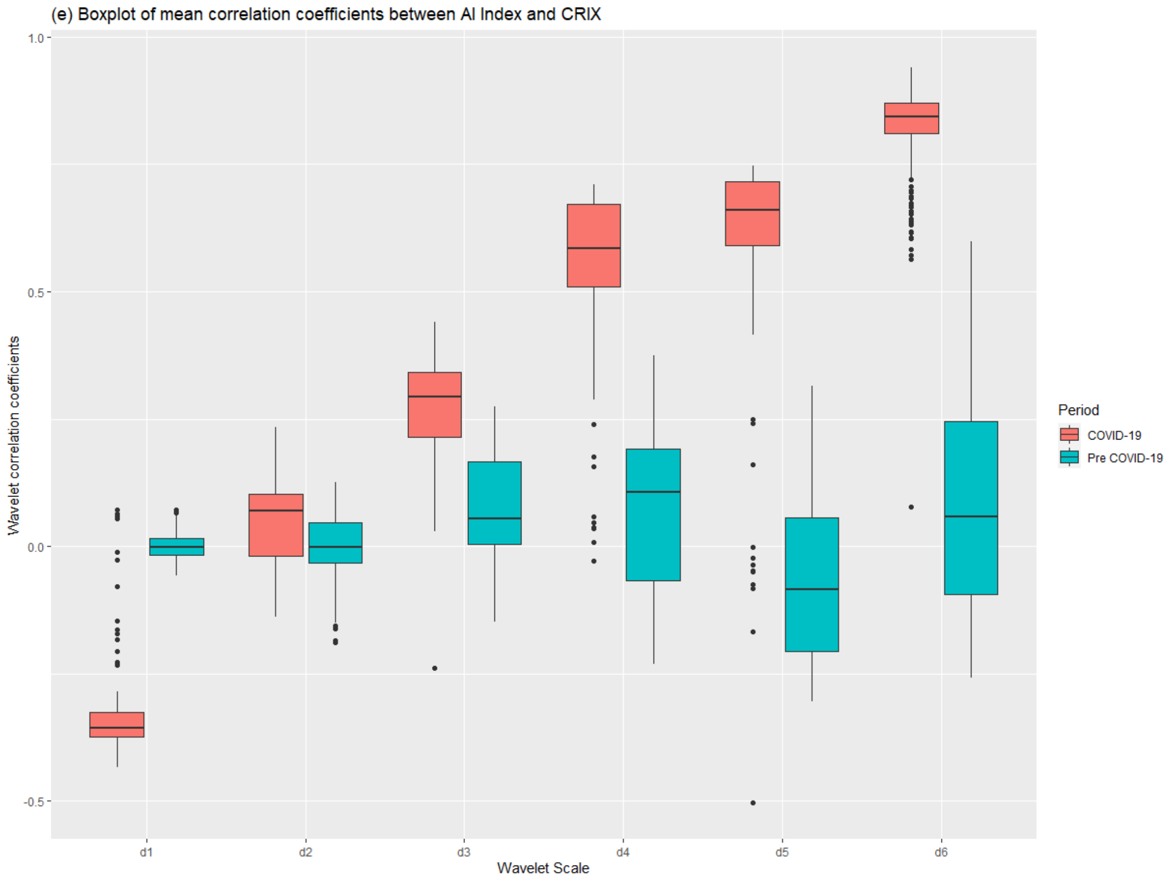
Figure 4. Box Plots






(c) Boxplot of mean correlation coefficients between AI Index and Corporate Bond Index
1.0
0.5
0.0
-0.5
Wavelet correlation coefficients
d1
d2
d3
d4
d5
d6
Wavelet Scale
Period
COVID-19
Pre COVID-19


(d) Boxplot of mean correlation coefficients between AI Index and Commodity Index
1.00
0.75
0.50
0.25
0.00
Wavelet correlation coefficients
d1
d2
d3
d4
d5
d6
Wavelet Scale
Period
COVID-19
Pre COVID-19



Note: The wavelet scales range from 1 to 6: d1 (2-4 days), d2 (4-8 days), d3 (8-16 days), d4 (16-32 days), d5 (32-64 days), and d6 (64-128 days).