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ORIGINAL RESEARCH

Time varying risk aversion and its connectedness: evidence from cryptocurrencies

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Abstract

Changing patterns of risk aversion may follow a non-linear counter-cyclical process. However, the evidence so far has not considered developing cryptocurrency markets. Given some unique features of cryptocurrencies, it is interesting to distinguish how these assets differ from traditional products. This paper investigates the time effects of periodicity on risk aversion for a selection of major cryptocurrencies compared to major financial assets. Significant periodic time-varying patterns are identified when analysing risk aversion. Further, bilateral and bidirectional Granger causalities are identified within cryptocurrencies, as well as between cryptocurrencies and traditional financial assets. Bitcoin is identified as a leading information transmitter of the spillover of risk aversion upon other cryptocurrencies, while estimated risk aversion of traditional financial markets plays a dominant role in the spillover processes upon the cryptocurrency cluster. The latter finding presents further evidence of developing cryptocurrency market maturity. The COVID-19 pandemic is found to have significantly influenced the connectedness of risk aversion among cryptocurrency and traditional financial markets.

Keywords Risk aversion · Periodicity · Cryptocurrencies · Granger causality · Spillover index

1 Introduction

The classical risk-return trade-off theory advises that if the quantity of a risky asset that a rational investor holds is certain, relative risk aversion is gauged by pricing dynamics involving expected return and variance of the asset. In such a sense, it can be argued that risk aversion may vary if the return distribution of an asset changes over time. Bordalo et al. (2012) shed light on this issue, suggesting that risk aversion may vary across time and depends on changing the expected distribution of returns due to major shocks. During the development of cryptocurrency markets over the past decade, shocks, as represented by extreme volatility, were commonplace and a central characteristic of this maturing financial asset (Katsiampa et al., 2019). Therefore, it is quite important to develop further our understanding of investor

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behaviour and the dynamics of risk aversion, particularly due to the significant attention being generated by these digital assets and with such shrouding of associated investor behaviour.

Utilising a broad class of stylised utility functions, the relative risk aversion may be driven by the level of wealth and, consequently, be a function of changes in the level of consumption (Chou et al., 1992). However, the relationship between risk aversion and wealth does not possess a solid evolving pattern, as there is no singular point of evidence as to whether risk aversion decreases, increases or even stays constant with wealth (Chou et al., 1992). Further ambiguity exists about whether relative risk aversion is static or time-varying, where a consensus has yet to be achieved. Some earlier evidence on constant risk aversion is documented in the literature (Safra & Segal, 1998). However, recent literature proposes that changes in risk aversion may be subject to not only some objective conditions (for example, wealth and consumption, expected distributions of returns, and expected future income) but also some subjective conditions (for example, emotions, fears and market sentiment) (Loewenstein, 2000). Some other studies have attempted latent time variation inherent in the risk aversion and drivers.[1] behind that (Brandt & Wang, 2003). A recent study by Joo and Park (2017) supports this view, experimenting using polynomials of a set of non-linear time functions to gauge risk aversion in the crude oil markets, identifying significant non-linear moving patterns of risk aversion associated with investors in the oil markets that are simply dependent on time. The studies by Cohn et al. (2015) and Joo and Park (2017) further provide stylised evidence examining time-varying effects on risk aversion. However, there is a lack of evidence on the risk aversion behaviour of investors that trade cryptocurrencies, despite several works[2] that have analysed how cryptocurrencies compare to modern finance theories (Alexander & Dakos, 2020).

Recent literature has debated whether cryptocurrency market investors are more heterogeneous than those investors trading traditional financial markets regarding risk profile. Some evidence based on heterogeneity with regards to the risk preference of investors trading the cryptocurrencies is found by Hackethal et al. (2022), indicating that cryptocurrency traders are younger, more likely to be male, more active in terms of trading patterns, and more likely to hold riskier assets and more volatile portfolios. Further, cryptocurrency traders exhibit behavioural patterns more aligned with short-term momentum and herding activity than traditional investors. Therefore, the risk aversion of traders in cryptocurrency markets may present a significant differential in dynamics. To date, such a research question has yet to be addressed. Cryptocurrency markets attract rational investors, such as those trading US dollars, and irrational gamblers from the traditional market venues (Mills & Nower, 2019; Jin et al., 2023). These findings imply that some commonalities may exist between those trading cryptocurrencies and those trading traditional financial assets regarding risk preference, which raises questions surrounding the interactions of risk preference between the two cohorts. Furthermore, Hackethal et al. (2022) suggest that Bitcoin investments are positively correlated with equity and alternative asset holdings, and investors who hold Bitcoin have more willingness to take on risk in other types of assets in their portfolio. It is also found that investor sentiment and media attention play a role in Bitcoin investment decisions. This evidence draws an issue as to whether there exist mutual influences or connectedness of risk preference between cohorts of trading cryptocurrency assets and traditional assets as well as

[1] Among a set of well-known factors affecting risk aversion, emotions of fears play an important role in driving a counter-cyclical moving pattern of risk aversion (Cohn et al., 2015) Investors are more fearful and risk-averse during financial crises than in periods of sharp market appreciation. To this end, there might exist periodic time effects on risk aversion that move against the financial cycle.

[2] To date, no studies have been dedicated specifically to the analysis of time variation of risk aversion in the cryptocurrency markets.

within the community of cryptocurrency traders. This issue is underdeveloped and requires further clarification.

Specifically, this study is motivated by an under-explored issue as to whether an investigation on interrelation and connectedness among risk aversion coefficients contributes to the extant knowledge on the spillovers of higher order moments of return distribution, which sheds light on the cross-market risk transmission. Chou et al. (1992) noted risk aversion is a critical determinant of the risk premium and variance of returns for a typical risky asset. Therefore, it can be understood that the interrelation or connectedness of risk aversion among several assets enlightens the spillovers of returns and volatilities pertaining to risk transmission. Further, investigating the connectedness of risk aversion between cryptocurrency cohorts and traditional financial markets reveals information transmission between the two cohorts, which provides evidence to the debate on how cryptocurrency assets are prone to the stereotype of traditional financial assets. Moreover, as implied by Cohn et al. (2015), the dynamics of risk aversion are attributed to the changing emotions of market traders, which heavily impact their trading preferences and behaviour. From this regard, the connectedness of risk aversion among markets may illuminate the cross-border trading activities relating to how risk perceptions transmit across trading venues, which further underpins risk transmission (Hamao et al., 1990). Thus, the evidence on the connectedness of risk aversion may shed light on the cross-market informational linkages regarding price risk.

This study contributes to the literature in several ways. As discussed, the literature has thus far revealed that the relative risk aversion may exhibit non-linear counter-cyclic periodicity subject to changing emotions towards risks and oscillations associated with varying market conditions (Cohn et al., 2015). However, it remains under-explored as to how risk aversion behaves in a time-varying paradigm, particularly across cryptocurrency markets, while considering how the behaviour of risk aversion in those markets differs from the findings identified with regard to traditional financial markets. In such a vein, this study investigates latent periodic patterns of time variations of risk aversion associated with investor risk behaviour when comparing cryptocurrencies and traditional, major financial market products, utilising the Flexible Fourier Form (FFF) Functions[3] nested with an Autoregression Generalised Autoregressive Conditional Heteroscedasticity in Mean (AR-GARCH-in-mean) methodology. Developing upon the pioneering work of Joo and Park (2017), we apply the FFF functions to gauge the periodic feature of time variations in risk aversion of both cryptocurrency and traditional financial markets, the finding of which enriches the evidence on the following two points.[4] First, it is examined as to whether the risk aversion of cryptocurrency traders is in line with the counter-cyclic patterns of that in the traditional financial markets. Unique features relating to cryptocurrencies and associated traders imply that the time-varying risk aversion of such investors might vary significantly from those of traditional major financial asset investors. To specifically address this issue, a comparison is made based on the moving patterns of risk aversion between cryptocurrencies and traditional counterparts. The

[3] According to Park and Hahn (1999), and Park and Zhao (2010), the FFF functions have the advantage of efficiently and robustly inferring smooth periodic time series of model parameters, therefore, capturing the potential periodicity of time variations of risk aversion.

[4] As implied by Joo and Park (2017), the FFF functions are appropriate to estimate the periodicity inherent in risk aversion coefficients due to its trigonometric specification on a sequence of time trends. In addition, Chou et al. (1992) suggests that the GARCH-in-mean model is theoretically reasonable to test the static and time-varying risk aversion. Henceforth, we nest the FFF functions with the GARCH-in-mean model to examine whether such a new model can generate new evidence for the extant knowledge on risk aversion. Daily data from eleven major cryptocurrency markets and four well-known financial markets are used for analysis, including the Standard & Poor S&P500 Index, West Texas Intermediate (WTI) crude oil futures, gold futures and US dollar index, are collected for the study.

finding indicates the proximity of cryptocurrency market investors to those more focused on traditional markets regarding risk preference, further implying growing market integration. Second, since cryptocurrency markets are heterogeneous in light of differential technologies generating coins and tokens, varying trading rules, and distinct cohorts of market participants, it is particularly interesting to explore how the risk preference of trading cryptocurrency assets varies across different market venues. Our finding enlightens such a question by unveiling similarities and distinctions in changing patterns of risk aversion among eleven major cryptocurrency markets. The comparison not only enhances our understanding of how differential characteristics of traders amongst cryptocurrency markets in terms of perceptions towards risk across time, but it also contributes to the knowledge of differing fundamental pricing among cryptocurrency assets.

Moreover, we are specifically interested in investigating the spillovers of risk aversion within cryptocurrency markets and from cryptocurrency markets to traditional financial markets. Such analysis can shed light on the connectedness of risk preferences of investors among different cryptocurrency markets when compared to traditional assets. To conclude this analysis, we utilise Granger Causality testing to analyse the cross-market predictability of risk aversion while developing on the work of Diebold and Yilmaz (2009, 2012). Furthermore, the outbreak and significant elevation of COVID-19 infections in late 2019 have dramatically influenced the global financial systems since the international pandemic began in early 2020. We finally test whether the effects of the COVID-19 pandemic have generated substantiative effects on such market interactions (Seven & Yılmaz, 2021). To this end, this study contributes to the growing literature by examining whether the COVID-19 pandemic impacts time-varying patterns of risk aversion in both traditional financial and cryptocurrency markets.[5]

Results indicate that periodicity is evidenced for risk aversion in traditional financial and cryptocurrency markets. The magnitude of mean risk aversion in cryptocurrency markets is found to be significantly lower than that of the examined traditional financial markets. Risk aversion in traditional markets is found to be more volatile than that in cryptocurrency markets. Furthermore, there is significant evidence presented of two-way Granger causality of risk aversion transfer flowing between Bitcoin and the other major cryptocurrencies analysed. Risk aversion within the four traditional financial markets dominates the directional spillover processes against all the other cryptocurrencies analysed. When analysing market connectedness, information flows of risk aversion sourced from Bitcoin are found to be significant in the majority of major cryptocurrencies analysed. Furthermore, we also uncover the significance of the effects of the COVID-19 pandemic on risk aversion in the markets analysed, with results varying both within and across the different asset groups analysed. Large cryptocurrency markets have experienced heightened risk aversion during the COVID-19 pandemic, whereas risk aversion of the medium- and small-sized cryptocurrencies is found to decrease. Meanwhile, the pandemic is found to have strongly influenced the causality of risk aversion running specifically from Bitcoin to other cryptocurrencies; however, the effects on the causalities running between cryptocurrencies and traditional assets are found to be extremely weak. Regarding the effects on the spillovers of risk aversion, the discontinuity generated within the COVID-19 pandemic presents a substantial shift in investor risk-taking behaviour in traditional financial markets.

[5] Moreover, the impacts of the COVID-19 pandemic on the connectedness of risk aversion, reflecting cross-market connections of risk perceptions, is examined within the cryptocurrency cluster and for crypto-conventional markets' relations.

The remainder of this paper is organized as follows. In Sect. 2, prior related studies are reviewed. Section 3 presents the data used in the analysis that is presented in Sect. 4. Empirical results are presented and discussed in Sect. 5, while Sect. 6 concludes.

2 Previous literature

Risk aversion, referring specifically to an investor's preference for certainty in decision-making, has generated much attention when considering the development of cryptocurrency markets and the extreme levels of risk observed therein. Specifically, the manner in which investors' risk aversion varies over time merits substantial attention. Some evidence suggests that risk aversion does not fluctuate and that investors' risk-taking behaviour remains constant over time (Safra & Segal, 1998). Chou et al. (1992) argue that risk aversion changes along with the level of wealth and is likely driven by the latter, under the context of stylised utility functions, and that risk aversion is eventually affected by changes in the level of consumption. Also, Campbell and Cochrane (1999) find evidence that changes in individual risk aversion follow changes in wealth, which is predicted by the von Neumann-Morgenstern utility function and through a habit persistence model, where aggregate risk aversion is found to fluctuate significantly over time (Guiso et al., 2018). Secondly, Heaton and Lucas (2000) and Guiso and Paiella (2008) found that changes in the outside environment that impact individuals expected future income could explain time variations of risk aversion. A third possible reason for time-varying risk aversion lies in changing the expected distribution of returns due to major shocks (Bordalo et al., 2012). As discussed in Bordalo et al. (2012), individuals place more weight on the salience of negative payoffs; when there is an asset price depreciation, the salience of negative realisations increases, and so do their subjective probabilities. Investors will behave in a more risk-averse manner in response to increased probabilities of salient negative payoffs. Furthermore, the emotions of individual investors can be affected by major shocks. As discussed in Loewenstein (2000), emotions can change the investors' decisions regarding their preference to take a risk. This is due to the affected perceived utility loss of bad outcomes by escalated emotions. Guiso et al. (2018) found evidence that partially supports the wealth-effecting channel to risk aversion. They obtain stronger support for the mechanism of the salience of expected distributions of returns and the channel of the emotion of fear via which the willingness to take the risk during the time of crisis is altered. The working mechanism from emotions to risk aversion, which drives time variations of risk aversion, is also documented in many other prior studies (Baker & Wurgler, 2007; Cohn et al., 2015; Bassi et al., 2013). In addition, several other factors have been identified as key forces influencing changes in risk aversion, which are explored by previous efforts (Pålsson, 1996; Brandt & Wang, 2003). Joo and Park (2017) contribute evidence from a methodological perspective revealing non-linear time effects on risk aversion in the crude oil markets.

With regards to cryptocurrency markets, Corbet et al. (2019) present a systematic analysis of the available literature, analysing the development of several key characteristics surrounding their growth and development. Several comparisons between cryptocurrencies and traditional financial assets have focused on pricing dynamics and specific features. Baur et al. (2018) indicated that cryptocurrencies are prone to speculative investment rather than a medium of exchange or an alternative currency. Ammous (2018) suggested that such assets have the potential as a store of value due to their specific features in production and supply procedures. Further, an interesting and critical question is proposed as to whether the cryptocurrency markets can be integrated into global financial systems, which has focused on the pricing dynamics of cryptocurrencies and their linkages with traditional assets. Wei (2018) find that liquidity plays an important role in market efficiency, return predictability and volatilities. Evidence based on the connectedness of cryptocurrencies with traditional financial markets is analysed in terms of the analysis of higher moments of the return distribution (Briere et al., 2015). The literature has also found significant bubble dynamics in the cryptocurrency markets during several specific time phases (Cretarola & Figà-Talamanca, 2019). Several recent studies reveal various findings relating to investor behaviour and pricing dynamics in the cryptocurrency markets. Ozdamar et al. (2021) unveils a positive and significant relationship between the maximum daily return within the previous month (MAX) and the expected returns on cryptocurrencies. Yao et al. (2021) explore the effect of investor attention on idiosyncratic risk in the cryptocurrency markets and find that investor attention can significantly reduce cryptocurrencies' idiosyncratic risks by increasing liquidity. Such an effect is more substantive for a younger cryptocurrency market. Further, it uncovered the predictability of investors' informed trading behaviour towards cryptocurrency returns in the context of machine learning algorithms (Wang et al., 2022). Finally, some evidence is revealed as to spillovers of return and volatility as well as multi-scale relationships and nonlinear multi-scale causality at the high-frequency paradigm among the cryptocurrency markets, which has some economic implications for portfolio risk management and hedging strategies involving the cryptocurrency assets (Sensoy et al., 2021; Mensi et al., 2021).

The existing literature has a notable gap concerning the heterogeneity of risk aversion between cryptocurrency and traditional markets. There's limited study on whether patterns of risk aversion in cryptocurrency markets mirror those in traditional financial markets or how closely cryptocurrency traders' risk behaviours resemble traditional traders. The relationship and connectedness of risk aversion across these markets remain unclear, especially in the context of the COVID-19 pandemic's impact on global finance. This study uses an FFF function nested GARCH-in-mean model to address these questions. We provide new insights on traders' time-dependent risk preferences in cryptocurrency markets, compare dynamics between crypto and traditional assets, and analyse the interplay of risk preferences between both trading groups. Our findings offer a deeper understanding of how emerging cryptocurrency markets fit into the global financial landscape.

3 Data

This paper collects daily closing prices of eleven major cryptocurrencies based on market share, including Bitcoin, Ethereum, Tether, XRP (Ripple), Bitcoin Cash, Bitcoin SV, Litecoin, EOS, Tezos, Cardano and Stellar. Such diverse sample selection allows for the provision of robustness with regard to evidence-based risk aversion dynamics as well as the interactions amongst such results.[6] In addition, we choose four well-known traditional financial assets as counterparts against cryptocurrency samples, including the Standard & Poor (S&P) 500 stock

[6] It should be noted that in this study, we focus on risk aversion behaviour to individual cryptocurrency markets where the issues on the static and dynamic risk aversion coefficients of the selected eleven cryptocurrency markets are examined. Moreover, based on the estimated series of risk aversion, we investigate the predictability and connectedness of risk profiles within cryptocurrency cohorts and between cryptocurrency and traditional markets. The average risk aversion to a cryptocurrency market index, which refers to the risk profile of an average cryptocurrency investor holding a cryptocurrency portfolio, does not reveal as much evidence in detail as the investigation of the risk behaviour of investors in a specific cryptocurrency market. An average risk aversion of a cryptocurrency market index does not allow for examining the interrelations of risk aversion among individual cryptocurrency markets. Since there may be an overlapping issue as to risk aversion in a

index, West Texas Intermediate (WTI) crude oil futures contracts, Gold futures contracts, and the US dollar index. Daily close prices of these assets are collected. For the time series of futures daily prices, data of the most liquid contracts are collected and collated in terms of the largest trading volumes. All the data are available from Refinitiv Eikon and DataStream. Data is available[7] from January 1, 2010, through to March 31, 2021. Specifically, this study focuses on the heterogeneous effects of the COVID-19 pandemic on pricing dynamics and risk aversion when the contagion of the coronavirus becomes widely contagious across the world. Following Corbet et al. (2020), we choose December 31, 2019, as a time point for sample splitting.[8] Hereby, there are two resulting sub-samples. The first runs from the beginning of each asset's starting date to December 30, 2019, which is identified as a pre-COVID-19 period. The second runs from December 31, 2019, through to March 31, 2021, which is identified as the pandemic period, or that representing the contagion of COVID-19.

We take the natural logarithm of daily prices, and returns series are calculated as the first differences of logarithmic prices. Table 1 presents descriptive statistics of the return series for the eleven cryptocurrencies and four traditional financial assets. The means of return series of most cryptocurrencies as to full sample are larger than those of the S&P500 index, WTI, gold and US dollar index. In addition, the mean estimates of most cryptocurrencies are positive in the full sample, except Tether. Comparing mean estimates between the pre-COVID-19 and the COVID-19 pandemic periods, we find that cryptocurrencies perform better in the pandemic period, except for EOS. This result corresponds with the phenomenon that cryptocurrency markets underwent a period of substantial growth after the COVID-19 pandemic occurred throughout late 2019 and early 2020. At the same time, the standard deviations of most presented cryptocurrencies are estimated to be significantly higher than those of the four selected traditional financial assets, particularly when we focus on the entire estimated sample. Higher risk levels are observed for cryptocurrency markets when compared to traditional assets. In addition, it is found that standard deviations of most cryptocurrency markets are larger in the pre-COVID-19 periods than they are in the COVID-19 pandemic period. Lower risk levels are observed in the cryptocurrency markets as the pandemic begins. Such observation is inverse to that identified for the traditional assets, as volatilities are significantly higher during the pandemic period for the S&P500 index, WTI and gold. Moreover, large values of skewness and kurtosis exist across the cryptocurrencies, in contrast to traditional assets that possess relatively low values. Undoubtedly, the Jarque–Bera test suggests that none of the return series follows a normal distribution. Non-normality is therefore taken into account in our selected methodological structure. Differing behaviour as to the first and second moments of return distributions from the pre-COVID-19 to the COVID-19 pandemic periods generates substantive attention when investigating the latent effects of the COVID-19 pandemic on the risk aversion behaviour of market investors.

Figures 1 and 2 present the movements of daily prices in our selected cryptocurrency and traditional asset series, respectively. Two phases of significant cryptocurrency market price

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cryptocurrency index portfolio and that in an individual constituent cryptocurrency market, the risk aversion dynamics as to some well-known cryptocurrency markets index, such as Royalton CRIX cryptocurrency index, the CME CF Bitcoin Real Time Index (BRTI) and the CME CF Bitcoin Reference Rate (BRR), is not addressed in this paper but will be left to a future study.

7 We choose January 1, 2010, as the starting point for traditional assets since all cryptocurrencies in our sample are available after 2010 and making samples all start from that time facilitates a better comparison of empirical results between cryptocurrency and traditional financial markets.

8 On December 31, 2019, the new novel coronavirus was formally recognised and confirmed by the World Health Organisation (WHO). After that date, COVID-19 was acknowledged worldwide via its incredible capacity to generate infections.

Table 1 Descriptive statistics of returns

Cryptocurrency	Sample	Mean	Median	Max	Min	SD	Skew	Kurt	Jarque–Bera
(a) Cryptocurrency markets									
Bitcoin	Full	0.0025	0.0021	0.4455	−0.6639	0.0496	−1.4166	27.5367	8.85E+04***
	Pre	0.0021	0.0019	0.4455	−0.6639	0.0505	−1.2520	26.2327	6.88E+04***
	COVID-19	0.0046	0.0039	0.1777	−0.4940	0.0435	−3.0231	40.6924	2.77E+04***
Ethereum	Full	0.0032	0.0004	0.4123	−1.3021	0.0681	−3.3498	72.8662	4.23E+05***
	Pre	0.0024	−0.0009	0.4123	−1.3021	0.0714	−3.4273	74.5780	3.46E+05***
	COVID-19	0.0058	0.0056	0.2332	−0.5507	0.0548	−2.2515	26.9502	1.13E+04***
XRP	Full	0.0011	−0.0023	1.0274	−0.6163	0.0663	1.9152	39.4275	1.48E+05***
	Pre	0.0009	−0.0032	1.0274	−0.6163	0.0663	2.4093	43.0502	1.49E+05***
	COVID-19	0.0024	0.0023	0.4496	−0.5392	0.0666	−0.4289	22.5351	7.28E+03***
Bitcoin cash	Full	0.0002	−0.0016	0.4316	−0.5614	0.0733	0.2069	12.7330	5.33E+03***
	Pre	−0.0008	−0.0034	0.4316	−0.4460	0.0794	0.6168	10.3992	2.09E+03***
	COVID-19	0.0021	0.0016	0.2780	−0.5614	0.0598	−1.6147	22.3933	7.36E+03***
Litecoin	Full	0.0014	−0.0007	0.4627	−0.4574	0.0595	0.5410	12.1895	4.93E+03***
	Pre	0.0004	−0.0035	0.4627	−0.3090	0.0613	1.2051	11.5247	3.02E+03***
	COVID-19	0.0034	0.0027	0.2087	−0.4574	0.0555	−1.2560	14.2556	2.53E+03***
Bitcoin SV	Full	0.0012	−0.0018	0.8858	−0.6236	0.0860	1.6523	29.7933	2.54E+04***
	Pre	0.0008	−0.0030	0.6204	−0.6236	0.0902	0.8633	19.8655	4.98E+03***
	COVID-19	0.0015	−0.0011	0.8858	−0.5603	0.0817	2.6965	43.7190	2.95E+04***
Tether	Full	−0.0001	0.0000	0.5005	−0.6907	0.0193	−13.2433	980.3100	8.59E+07***
	Pre	−0.0001	0.0000	0.5005	−0.6907	0.0211	−12.2698	828.6944	5.03E+07***
	COVID-19	0.0000	0.0000	0.0500	−0.0492	0.0056	0.1502	36.2542	1.79E+04***
Cardano	Full	0.0030	0.0010	0.8615	−0.5036	0.0752	2.0477	25.8853	2.80E+04***
	Pre	0.0004	−0.0023	0.8615	−0.2887	0.0792	2.9070	29.2801	2.48E+04***
	COVID-19	0.0081	0.0062	0.2523	−0.5036	0.0664	−0.7364	11.7216	1.38E+03***

Table 1 continued

Cryptocurrency	Sample	Mean	Median	Max	Min	SD	Skew	Kurt	Jarque–Bera
EOS	Full	0.0009	0.0000	0.9870	−0.5032	0.0761	1.7221	28.1033	3.59E+04***
	Pre	0.0011	−0.0018	0.9870	−0.3850	0.0827	2.2228	27.6119	2.38E+04***
	COVID-19	0.0007	0.0000	0.2082	−0.5032	0.0597	−1.4265	15.6430	3.00E+03***
Stellar	Full	0.0021	−0.0020	0.7231	−0.4100	0.0742	1.9321	19.5330	2.89E+04***
	Pre	0.0015	−0.0035	0.7231	−0.3664	0.0754	2.0082	19.5922	2.40E+04***
	COVID-19	0.0050	0.0034	0.5541	−0.4100	0.0686	1.4738	18.6962	4.57E+03***
Tezos	Full	0.0005	0.0000	0.5687	−0.6055	0.0724	−0.3390	12.7429	4.96E+03***
	Pre	−0.0004	−0.0003	0.5687	−0.4439	0.0752	0.1262	10.5279	1.94E+03***
	COVID-19	0.0023	0.0020	0.2505	−0.6055	0.0669	−1.5710	19.1024	4.82E+03***
(b) Traditional asset markets									
S&P 500	Full	0.0004	0.0004	0.0897	−0.1277	0.0108	−0.8682	19.8058	3.49E+04***
	Pre	0.0004	0.0003	0.0484	−0.0690	0.0092	−0.5002	7.8562	2.67E+03***
	COVID-19	0.0006	0.0017	0.0897	−0.1277	0.0197	−0.9292	13.5383	1.56E+03***
WTI	Full	−0.0001	0.0000	0.5812	−0.5686	0.0280	−0.3370	134.0860	2.10E+06***
	Pre	−0.0001	0.0000	0.1342	−0.1072	0.0197	−0.0295	6.6119	1.42E+03***
	COVID-19	−0.0001	0.0002	0.5812	−0.5686	0.0627	−0.2618	47.4140	2.69E+04***
Gold	Full	0.0002	0.0001	0.0578	−0.0982	0.0102	−0.6349	9.8750	5.97E+03***
	Pre	0.0001	0.0000	0.0462	−0.0982	0.0098	−0.7483	10.4447	6.26E+03***
	COVID-19	0.0004	0.0009	0.0578	−0.0511	0.0129	−0.2184	6.7827	197.554***
US dollar	Full	0.0001	0.0000	0.0245	−0.0209	0.0044	0.1084	4.9236	457.9460***
	Pre	0.0001	0.0000	0.0245	−0.0209	0.0044	0.0660	4.7441	332.1934***
	COVID-19	−0.0001	−0.0001	0.0240	−0.0165	0.0041	0.5110	6.8294	214.0318***

This table reports the descriptive statistics of return series of cryptocurrencies and traditional securities. The pre-COVID-19 denotes a sub-sample period ending on December 30, 2019. As per the WHO announcement relating to the spread of a 'mystery pneumonia,' the COVID-19 pandemic is denoted as a sub-sample period spanning December 31, 2019, through March 31, 2021. SD represents the standard deviation. Jarque–Bera denotes the test statistic of the Jarque–Bera normality test. ***Represents significance at the 1% level

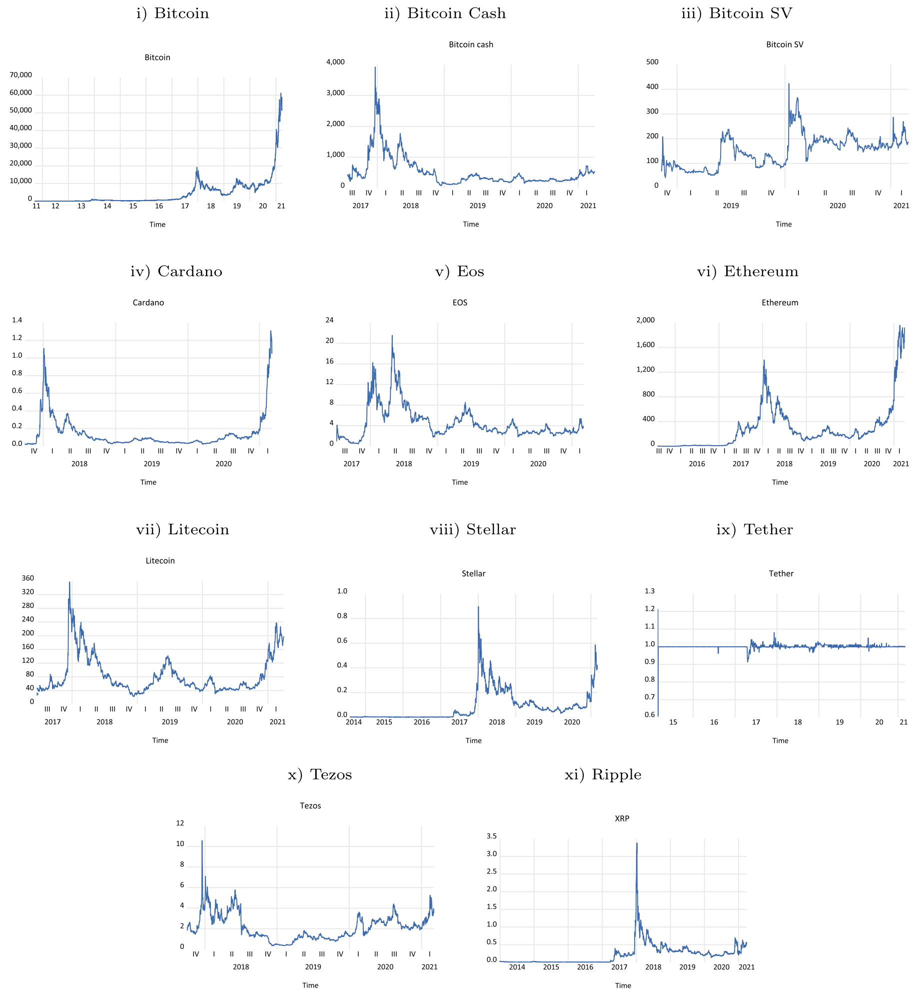

Fig. 1 Daily cryptocurrency price series. *Note*: Original daily close prices are depicted. All the data is from Refinitiv Eikon and DataStream. I, II, III and IV in the above figures represent the first through fourth quarters respectively

appreciation are observed. The first phase took place in 2017 and 2018 and is found to be present in all analysed cryptocurrencies except for Bitcoin SV and Tether. The second phase occurs following the outbreak of the COVID-19 pandemic. Furthermore, the stationarity of all the price series is examined via unit root tests of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP). All the price series are integrated at an order of one, while return series are integrated at an order of zero.[9]

[9] Results of unit root tests are omitted for brevity of presentation but are available from the authors upon request.

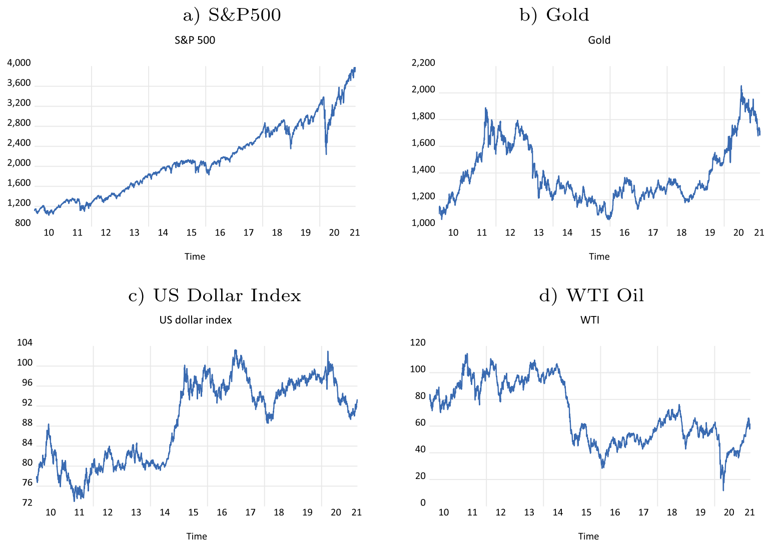

Fig. 2 Daily traditional asset price series. *Note*: Original daily close prices are depicted. All the data is from Refinitiv Eikon and DataStream. I, II, III and IV in the above figures represent the first through fourth quarters respectively

4 Methodology

4.1 A model for static risk aversion

As discussed in Shiller et al. (1984), Sentana and Wadhwani (1992) and Koutmos (1997), a decision made by an informed investor surrounding the number of holdings of a risky asset or security applies a classical risk-return trade-off principle with a purpose to maximise risk-averse utility. Further, as discussed in Chou et al. (1992), the theoretical model that prices a risk premium of a risky asset suggests that it can be obtained via individual relative risk aversion multiplying the weighted average of the variance of the risky asset and covariance between the risky asset and an unobserved portfolio. When the risky asset is a solely relevant risky one, that is, the share of the risky asset reaches 100 percent, the risk premium is determined by risk aversion times the variance of the risky asset. From this vein, it is established that the effect of variance on returns is interpreted as relative risk aversion. Alternatively, it is equivalent to the increment of the risk premium per unit of volatility, which is also called the price of the volatility of returns (Chou et al., 1992). Chou et al. (1992) further propose that a generalized autoregressive conditional heteroscedasticity (GARCH) in the mean model is a robust methodology for estimating the relative risk aversion coefficient. In this section, we follow the literature to specify the static and time-varying relative risk aversion coefficients. The ex-ante optimal quantity of holding risky securities, reflected by a fraction of shares of the market portfolio on-demand, is determined by the following equation:

$$Q_t = \left(E_{t-1}(R_t) - \alpha\right)/\theta h_t \tag{1}$$

where R_t is the ex-post rate of return at time t. $E_{t-1}(.)$ is an expectation operator based upon the information set up to time t-1. α is the rate of return on a risk-free asset, while h_t is the conditional variance of returns at time t, one of the most common proxies for risk. θ

is the coefficient of risk aversion.[10] θh_t represents a need for the required risk premium for inducing utility optimisers to hold some, or perhaps, all of the shares if utility optimisers exhibit risk-averse behaviour, corresponding with $\theta > 0$. In such a scenario, an increase in expected volatility increases the risk premium required to hold a certain fraction of shares. Assume all the investors had the same demand function following Eq. 1 that is, a market equilibrium with $Q_t = 1$. Then a dynamic Capital Asset Pricing Model proposed by Merton (1973) would be generated as:

$$E_{t-1}(R_t) - \alpha = \theta h_t \tag{2}$$

where Eq. 2 can be re-written into a model as follows:

$$R_t = \alpha + \theta h_t + \varepsilon_t \tag{3}$$

where ε_t is the forecasting errors or innovations. As illuminated by Eq. 1, a positive risk aversion coefficient refers to the extent to which an investor hates risk. The possibility of negative and zero risk aversion coefficients is discussed below. It is implied from Eq. 1 that a negative value of the risk aversion coefficient is possible, indicating that an investor may be a risk seeker who even prefers to hold a proportion of shares of a risky portfolio if its excess return is negative. Hence, a negative value of risk aversion refers to a regime of risk-seeking or gambling behaviour against risk aversion. Meanwhile, Eq. 1 also implies that risk aversion pertains to a regime of no aversion for an investor if the coefficient is zero. In such a regime, regardless of the risk level of a risky portfolio, an investor always perceives that its return is equivalent to a risk-free rate, and thus there is no excess return. Hence, a zero value of the risk aversion coefficient refers to the risk-neutral behaviour of an investor.

Further, as widely discussed and evidenced in the literature, due to market imperfection and market microstructure biases, financial return series may be affected by their own lagged values. They may also be subject to a phenomenon of volatility clustering. In such vein, Eq. 3 can be extended into a specification that facilitates empirical testing and enhances goodness of fit, that is, an autoregressive at order p (AR(p))-generalized autoregressive conditional heteroscedasticity (GARCH)-in-mean model. It should be noted that this model has been widely employed in the literature to gauge the risk aversion coefficient and control its impact (Antoniou et al., 2005; Koutmos et al., 2006; Hou & Li, 2014), The conditional mean equation of the model is specified as:

$$R_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i R_{t-i} + \theta h_t + \varepsilon_t \tag{4}$$

where $\varepsilon_t \sim F(0, h_t)$. F denotes a univariate flexible conditional distribution. Note that the lag order p of the autoregressive terms is chosen according to akaike information criterion (AIC). The conditional variance, h_t, is specified in an exponential GARCH (EGARCH) model (Nelson, 1991) as follows:

$$log(h_t) = \gamma_0 + \gamma_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma_2 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma_3 \log(h_{t-1}) \tag{5}$$

where log(.) denotes natural logarithm. γ_1 captures the effect of new shocks and γ_3 examines persistence. γ_2 refers to the asymmetric effect of past negative shocks on conditional volatility compared to the effect of past positive ones. For the stationarity of conditional volatility, $\gamma_3 < 1$. It should be noted that the EGARCH(1,1) model in Eq. 5 has an advantage

[10] Note that the risk aversion discussed in this paper is a relative term.

over alternative GARCH specifications in that the former guarantees the positivity of conditional variance without any parameter restriction in the estimation procedure, which relaxes estimation efficiency. Moreover, Eqs. 4 and 5 are modified to incorporate the effect of the COVID-19 pandemic on conditional mean and variance. To this end, we have the following equations:

$$R_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i R_{t-i} + \theta h_t + \delta d_t + \varepsilon_t \tag{6}$$

$$log(h_t) = \gamma_0 + \gamma_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma_2 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma_3 \log(h_{t-1}) + \eta d_t \tag{7}$$

where d_t is a dummy variable where it takes a value equal to unity when the sample period runs before December 31, 2019, and zero otherwise. δ and η capture how the COVID-19 pandemic affects conditional mean and volatility of returns, respectively. The estimation on the AR(p)-GARCH-in-Mean model as specified in Eqs. 6 and 7 are conducted by maximum likelihood estimation (MLE) procedure assuming the innovations ε_t follow a univariate generalised error distribution (GED). That is, $\varepsilon_t \sim GED(0, h_t, \varphi)$. φ is a shape parameter for GED. When φ equals 0.5, the GED is equivalent to the normal distribution. Hence, the normal distribution is a special case of the GED. We employ the GED to take account of the non-normality of the return series reported in Table 1. In addition, we examine whether the risk aversion changes across the outbreak of COVID-19 via the following equation:

$$R_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i R_{t-i} + \theta_1 (1 - d_t) h_t + \theta_2 d_t h_t + \delta d_t + \varepsilon_t \tag{8}$$

where θ_1 and θ_2 are the risk aversion coefficients in two sub-periods, the pre-COVID-19 period and the COVID-19 pandemic period. Note that Eqs. 6 and 8 assume that the risk aversion coefficient is time-invariant. However, the recent literature has argued that the relative risk aversion may change across time (Pålsson, 1996; Shaw, 1996; Brandt & Wang, 2003). Evidence based on the driving forces of time-varying risk aversion is mixed. Risk aversion may closely relate to personal wealth and the level of consumption (Chou et al., 1992), among a set of driving factors, leading to a hypothetical perception that the evolving pattern of risk aversion is cyclical or periodic, provided that changes in personal wealth and consumption align with the economic cycle. Joo and Park (2017) have provided interesting evidence relating to the crude oil markets where the risk aversion coefficients associating with those markets have non-linear moving patterns. In this study, we take a further step to explore the latent periodicity inherent in the risk aversion coefficients relating to cryptocurrency and traditional financial markets. The model for this purpose is illustrated in the next section.

4.2 A model for time-varying risk aversion

To examine the periodicity of the risk aversion coefficient, we employ a Flexible Fourier Form (FFF) function proposed by Park and Hahn (1999) to nest with the conditional mean equation of the AR(p)-GARCH-in-mean model. In particular, we incorporate the FFF functions into Eq. 6 to extrapolate the time-varying series of the coefficient θ. The FFF functions in Park and Hahn (1999) are originally used for modelling time-varying cointegrating coefficient concerning a cointegration test. As discussed in Park and Hahn (1999) and Park and Zhao (2010), the FFF functions have strength in the efficient and robust inference of smooth periodic time series of model parameters. Correspondingly, Eq. 6 can be modified into:

$$R_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i R_{t-i} + \theta_k(\lambda) h_t + \delta d_t + \varepsilon_t \tag{9}$$

and

$$\lambda \equiv t/n, \theta_k(\lambda) = \beta_{k,1} + \beta_{k,2}\lambda + \sum_{i=1}^{k} (\beta_{k,2i+1}, \beta_{k,2(i+1)})\varphi_i(\lambda) \tag{10}$$

where t is the order of observation in the sample, which is a positive integer, and n denotes the sample size. Hence, $\lambda \epsilon (0, 1)$. $\theta_k(\lambda)$ is a smooth function defined on (0,1], which is gauged by the FFF functions in Eq.(10). $\beta_{k,j} \epsilon R$ for j = 1, 2,…, 2(k+1) and k is some positive integer. $\varphi_i\ (\lambda) = (cos2\pi\ i\lambda, sin2\pi i\lambda)'$. Thus, the time variation of $\theta_k(\lambda)$ is gauged by trigonometric polynomial functions with 2k+2 parameters. Moreover, k is kept small enough to maintain sufficient smoothness for $\theta_k(\lambda)$. In this study, we select the best order k from a range $k\epsilon[1, 5]$ according to AIC. According to Park and Hahn (1999), k increases with the sample size n, and thus a consistent estimate of $\pi(\theta_k(\lambda))$ can be obtained. $\beta_{k,j}$ in Eq. 10 examines the periodic effects of time on the risk aversion coefficient. The conditional variance equation following Eqs. 9 and 10 is built upon the EGARCH (1,1) model specified in Eq. 7. The estimation of the AR(p)-GARCH-in-mean model nested with the FFF functions is conducted by the MLE procedure based on the univariate GED.

4.3 The effect of COVID-19, Granger causality and spillover index

Provided that the time series of risk aversion coefficient is derived, we examine how the COVID-19 pandemic affects the risk aversion coefficient associated with the cryptocurrency and traditional financial markets.[11] The following model is used to test such an effect:

$$\theta_t = a_1 + a_2\theta_{t-1} + a_3 d_t + \varepsilon_t \tag{11}$$

where $\theta_t \equiv \theta_k(\lambda)$. a_3 captures the effect of the COVID-19 pandemic on θ_t when we control the effect of the autoregressive term at an order of one in the equation.[12] Furthermore, we employ a bilateral Granger causality test to investigate the predictability between two series of risk aversion coefficients relating to two markets. Evidence sheds light on the bilateral lead-lag relationship of risk aversion behaviour. The Granger causality test is based on the following bivariate Vector Autoregressive (VAR) model:

$$X_t = c_0 + \sum_{i=1}^{p} c_{1,i} X_{t-i} + \sum_{i=1}^{p} c_{2,i} Y_{t-i} + \varepsilon_{1,t}, Y_t = d_0 + \sum_{i=1}^{p} d_{1,i} X_{t-i} + \sum_{i=1}^{p} d_{2,i} Y_{t-i} + \varepsilon_{2,t} \tag{12}$$

where X_t and Y_t represent two-time series of risk aversion coefficients in different markets. The bilateral Granger causality test is conducted based on parameter estimates in the equation. The lag order p is selected according to AIC. For the Granger causality between X_t and Y_t,

[11] Stationarity test suggests that all the derived series of risk aversion coefficients are stationary. Test results are available upon request.

[12] Note that the estimation result of Eq. 11 generates relatively high adjusted R square and low SIC and AIC values, compared to other specifications with more autoregressive terms. We also employ a multivariate VAR model to estimate the impacts of the COVID-19 pandemic on risk aversion coefficients. The results are qualitatively similar to the result of Eq. 11.

we test the following hypotheses. The null hypothesis that X_t does not Granger cause Y_t is equivalent to $H_0 : d_{1,1} = d_{1,2} = \cdots = d_{1,p} = 0$. The null hypothesis that X_t does not Granger cause Y_t is equivalent to $H_0 : c_{2,1} = c_{2,2} = \cdots = c_{2,p} = 0$. One-way Granger causality exists if either hypothesis is rejected.

Furthermore, we employ the spillover index developed by Diebold and Yilmaz (2009, 2012) to gauge the connectedness among time-varying risk aversion coefficients of the cryptocurrency and traditional financial markets. Evidence provides more insights into the between-market contagion of risk-averse behaviour of investors who apply the trade-off principle and conduct the mean-variance analysis to guide their diversification strategies and cross-border trading. As discussed in Diebold and Yilmaz (2009, 2012), the spillover index utilises the forecast error variance decomposition (FEVD) for a generalized VAR model specified for a system of covariance-stationary time series and estimates the share of the contributions made by past shocks of the other one or many series in the system toward variance of one series. In particular, the total spillover index is presented as:

$$S^g(H) = \frac{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)}{N}.100 \tag{13}$$

where $\tilde{\theta}_{ij}^g(H)$ is the normalised share of spillover from series j toward series i. N is the dimension of the variance-covariance matrix of forecast error. The index captures the contribution of spillovers of past shocks across the time series system to the total forecast error variance. Moreover, the directional spillover index received by series i from all other series is:

$$S_{i\cdot}^g(H) = \frac{\sum_{j=1}^{N} \tilde{\theta}_{ij}^g(H)}{N}.100 \tag{14}$$

Meanwhile, the directional spillover index transmitted by series i to all other series is:

$$S_{\cdot i}^g(H) = \frac{\sum_{j=1}^{N} \tilde{\theta}_{ji}^g(H)}{N}.100 \tag{15}$$

Given Eqs. 14 and 15, one may expect to know the net spillover between series i and all other series. This can be achieved using the following equation:

$$S_i^g(H) = S_{i\cdot}^g(H) - S_{\cdot i}^g(H) \tag{16}$$

The net spillover reveals the informational role of series i in a connected network with all other series in terms of its capacity for spillovers. In addition, we are interested in how much one series contributes to the variance of another one as to bilateral information transmission. The net pairwise spillover from series j to series i is shown as:

$$S_{ij}^g(H) = \left(\frac{\tilde{\theta}_{ij}^g(H) - \tilde{\theta}_{ji}^g(H)}{N}\right).100 \tag{17}$$

The net pairwise spillover running between series i and series j is the difference between the spillover effect from series j to series i and the effect of the other way around. In this study, we mainly explore the Granger causality and net pairwise spillovers between Bitcoin and the other cryptocurrency counterparts, as well as those between each cryptocurrency and four traditional financial markets. Also, the effects of the COVID-19 pandemic on the causality and spillovers are examined.

5 Empirical results

5.1 Static and time-varying risk aversion

Table 2 presents the results of static risk aversion coefficients of the analysis based on cryptocurrency and traditional financial markets.[13] The results of differing risk aversion across the COVID-19 outbreak are shown. The ARCH and Ljung–Box tests suggest that the AR(p)-GARCH-in-mean model is well specified since no heteroscedasticity is detected in the standardised innovations. Conditional volatilities are significantly driven by recent shocks and old news, evidenced for all the markets.

As can be observed in Table 2, significant risk aversion coefficients are found in seven out of eleven cryptocurrencies, excluding Bitcoin Cash, EOS, Stellar and Tezos. The magnitude of the risk aversion coefficient changes after the COVID-19 pandemic takes place. It increased from the pre-COVID-19 period to the COVID-19 pandemic as to Ethereum, XRP, Litecoin, Tether and Cardano, whereas it decreased as to Bitcoin and Bitcoin SV. It is interesting to see that the risk aversion coefficients of Bitcoin and Bitcoin SV turn negative as the COVID-19 pandemic steps in. The results in Table 2, particularly Bitcoin and Bitcoin SV, suggest changed behaviour from risk aversion to risk-seeking in these two markets as the COVID-19 pandemic occurs. In contrast, the level of risk aversion became more enhanced in the markets of Ethereum, XRP, Litecoin, Tether and Cardano during the COVID-19 pandemic. The COVID-19 pandemic exerts different impacts on cryptocurrencies, as reflected by static risk aversion. Investors sought a safe haven in Bitcoin and Bitcoin SV during the COVID-19 pandemic, differing from previous behavioural normality; however, Ethereum, XRP, Litecoin, Tether and Cardano do not appear to have exhibited the same trend.

The static coefficients of risk aversion are significant as to the S&P500 and WTI oil futures markets, as seen in Table 2. The coefficients decreased in the two markets after the outbreak of the COVID-19 pandemic. The extent of the decrease in the WTI market is substantial as the risk aversion coefficient turns null in the COVID-19 pandemic. This result suggests a reduction of risk aversion in the traders in the crude oil market in the aftermath of COVID-19. Nonetheless, we fail to detect significant static risk aversion in the gold and US dollar exchange markets. Moreover, the COVID-19 pandemic significantly affects cryptocurrency returns when static risk aversion is considered. Evidence is found for eight out of 11 cryptocurrency markets. Most evidence identifies positive estimates in the aftermath of the COVID-19 pandemic except for Tether, suggesting that cryptocurrency performance is found to become stronger during the COVID-19 pandemic. In addition, we find that conditional volatilities of Tether and S&P500 indices significantly increased during the COVID-19 pandemic.

The results of the AR(p)-GARCH-in-mean model nested with the FFF functions are shown in Table 3.[14] It should be noted that the lag order k in the FFF functions is chosen from a value range of 1–5. The optimal value of k is selected given the lowest AIC of the AR(p)-GARCH-in-mean model with that order. It is apparent from Table 3 that the coefficients of the FFF functions are significant as to all the cryptocurrency markets. Also, coefficients of the FFF functions are significant for the S&P500, WTI and Gold. Typically, the coefficients of the trigonometric functions within the FFF functions are found to be significant. This result

[13] For brevity of presentation, the estimation results of the autoregressive terms in Eq. 8 are not reported but available upon request.

[14] The estimation results of coefficients of the autoregressive terms in Eq. 9 are not reported but available upon request.

Table 2 Static risk aversion coefficients

		Conditional mean equation		Conditional variance equation									
		δ	θ_1	γ_0	γ_1	γ_2	γ_3	η	φ	ARCH test	LB2(12)	Log-like.	AIC
		(a) Cryptocurrency markets											
Bitcoin	θ_1, pre-C-19	0.0014	1.0021***	−0.3696***	0.2859***	0.0265*	0.9733***	0.0231	0.8376***	5.2076	5.2035	6897.87	−3.9653
		(0.6776)	(0.0000)	(0.0000)	(0.0000)	(0.0721)	(0.0000)	(0.5119)	(0.0000)	(0.9507)	(0.9510)		
	θ_2, C-19	0.0436***	−10.9139***	−0.3709***	0.2863***	0.0266*	0.9731***	0.0276	0.8377***				
		(0.0001)	(0.0019)	(0.0000)	(0.0000)	(0.0766)	(0.0000)	(0.4475)	(0.0000)				
Ethereum	θ_1, pre-C-19	0.0061***	0.5656**	−0.5595***	0.2885***	0.0212	0.9387***	−0.0001	0.9273***	8.1008	6.7055	3259.09	−3.1515
		(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.2981)	(0.0000)	(0.9956)	(0.0000)	(0.7772)	(0.8760)		
	θ_2, C-19	0.0056***	0.8412***	−0.5777***	0.3020***	0.0221	0.9368***	−0.0003	0.9156***				
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2677)	(0.0000)	(0.9877)	(0.0000)				
XRP	θ_1, pre-C-19	0.0053***	−0.0972	−0.9951***	0.4633***	0.0324	0.8866***	0.0162	0.7893***	2.7891	2.8009	4608.06	−3.4734
		(0.0000)	(0.5829)	(0.0000)	(0.0000)	(0.2202)	(0.0000)	(0.5927)	(0.0000)	(0.9969)	(0.9970)		
	θ_2, C-19	0.0035**	1.0199**	−0.9705***	0.4547***	0.0323	0.8894***	0.0162	0.7810***				
		(0.0121)	(0.0202)	(0.0000)	(0.0000)	(0.2123)	(0.0000)	(0.5878)	(0.0000)				
Bitcoin C.	θ_1, pre-C-19	0.0049***	−0.4446	−0.2437***	0.1646***	0.0300*	0.9757***	−0.0098	0.8176***	6.9723	6.8147	1984.93	−2.9330
		(0.0031)	(0.2172)	(0.0001)	(0.0000)	(0.0938)	(0.0000)	(0.3782)	(0.0000)	(0.8594)	(0.8700)		
	θ_2, C-19	0.0056**	−0.4548	−0.2445***	0.1645***	0.0306*	0.9755***	−0.0095	0.8178***				
		(0.0391)	(0.5397)	(0.0001)	(0.0000)	(0.0876)	(0.0000)	(0.3939)	(0.0000)				
Litecoin	θ_1, pre-C-19	0.0057***	0.7661***	−0.3655***	0.1735***	0.0174	0.9581***	−0.0081	1.0050***	10.6996	10.8820	2170.34	−3.1272
		(0.0000)	(0.0000)	(0.0023)	(0.0000)	(0.3838)	(0.0000)	(0.5068)	(0.0000)	(0.5548)	(0.5390)		
	θ_2, C-19	0.0027***	2.2016***	−0.3350***	0.1648***	0.0182	0.9623***	−0.0069	1.0002***				
		(0.0000)	(0.0000)	(0.0030)	(0.0000)	(0.3425)	(0.0000)	(0.5482)	(0.0000)				

Table 2 continued

		Conditional mean equation		Conditional variance equation									
		δ	θ_1	γ_0	γ_1	γ_2	γ_3	η	φ	ARCH test	LB2(12)	Log-like.	AIC
Bitcoin SV	θ_1, pre-C-19	−0.0018***	3.5709***	−0.5763***	0.2815***	0.0522	0.9302***	−0.0010	0.7215***	6.8268	6.9408	1297.56	−3.0853
		(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.1666)	(0.0000)	(0.9690)	(0.0000)	(0.8688)	(0.8610)		
	θ_2, C-19	0.0288***	−2.2635***	−0.5696***	0.2837***	0.0469	0.9313***	0.0001	0.7147***				
		(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.2113)	(0.0000)	(0.9955)	(0.0000)				
Tether	θ_1, pre-C-19	0.0002*	25.0953***	−1.2936***	0.1430***	0.0410***	0.8970***	−0.0937***	1.0992***	0.0172	0.0172	15439.01	−14.3337
		(0.0685)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(1.0000)	(1.0000)		
	θ_2, C-19	−0.0001***	59.9258***	−0.6132***	0.6936***	−0.1052	0.9597***	0.0787***	0.1809***				
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2067)	(0.0000)	(0.0049)	(0.0000)				
Cardano	θ_1, pre-C-19	0.0076***	−0.1032	−0.2526***	0.1775***	0.0069	0.9774***	0.0060	1.0059***	11.9460	13.0110	1761.20	−2.8174
		(0.0027)	(0.8576)	(0.0001)	(0.0000)	(0.6834)	(0.0000)	(0.5538)	(0.0000)	(0.4500)	(0.3680)		
	θ_2, C-19	0.0000	1.8804*	−0.1704***	0.1302***	0.0094	0.9863***	0.0062	1.0064***				
		(0.9988)	(0.0887)	(0.0009)	(0.0000)	(0.5104)	(0.0000)	(0.3847)	(0.0000)				
EOS	θ_1, pre-C-19	0.0026	−0.3025	−0.3305***	0.1960***	0.0113	0.9639***	−0.0057	0.8395***	7.6068	7.7344	1948.65	−2.8954
		(0.1430)	(0.4097)	(0.0005)	(0.0000)	(0.6040)	(0.0000)	(0.6685)	(0.0000)	(0.8151)	(0.8060)		
	θ_2, C-19	0.0025	−0.4643	−0.3314***	0.1959***	0.0105	0.9637***	−0.0058	0.8379***				
		(0.4757)	(0.6098)	(0.0005)	(0.0000)	(0.6306)	(0.0000)	(0.6588)	(0.0000)				
Stellar	θ_1, pre-C-19	0.0089***	0.2050	−0.7378***	0.3652***	0.0575**	0.9149***	0.0012	0.9153***	2.1771	2.1691	3611.50	−2.9979
		(0.0000)	(0.3700)	(0.0000)	(0.0000)	(0.0147)	(0.0000)	(0.9584)	(0.0000)	(0.9991)	(0.9990)		
	θ_2, C-19	0.0104***	−0.2938	−0.7336***	0.3635***	0.0575**	0.9154***	0.0010	0.9132***				
		(0.0001)	(0.6703)	(0.0000)	(0.0000)	(0.0141)	(0.0000)	(0.9639)	(0.0000)				

Table 2 continued

		Conditional mean equation		Conditional variance equation									
		δ	θ_1	γ_0	γ_1	γ_2	γ_3	η	φ	ARCH test	LB2(12)	Log-like.	AIC
Tezos	θ_1, pre-C-19	0.0042*	−0.1907	−0.6440***	0.3150***	0.0500*	0.9231***	−0.0093	1.0289***	3.0228	2.9745	1738.42	−2.7708
		(0.0919)	(0.7466)	(0.0000)	(0.0000)	(0.0795)	(0.0000)	(0.6621)	(0.0000)	(0.9954)	(0.9960)		
	θ_2, C-19	0.0041	−0.1799	−0.6431***	0.3147***	0.0499*	0.9232***	−0.0093	1.0290***				
		(0.3580)	(0.8535)	(0.0000)	(0.0000)	(0.0805)	(0.0000)	(0.6612)	(0.0000)				
		(b) Traditional markets											
S&P 500	θ_1, pre-C-19	0.0002	8.3019***	−0.7334***	0.1733***	−0.2178***	0.9387***	0.0645***	1.1546***	4.8724	4.7927	10060.22	−6.8681
		(0.6912)	(0.0027)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.9621)	(0.9650)		
	θ_2, C-19	0.0004	4.8847*	−0.7375***	0.1714***	−0.2188***	0.9382***	0.0686***	1.1571***				
		(0.4824)	(0.0571)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
WTI	θ_1, pre-C-19	0.0012	3.0087**	−0.2396***	0.1191***	−0.0977***	0.9816***	0.0101	1.2438***	39.6550	39.7160	7545.67	−5.1514
		(0.2900)	(0.0.0348)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2493)	(0.0000)	(0.1117)	(0.1100)		
	θ_2, C-19	0.0017	1.0657	−0.2401***	0.1133***	−0.1004***	0.9811***	0.0120	1.2473***				
		(0.1484)	(0.3048)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1783)	(0.0000)				
Gold	θ_1, pre-C-19	0.0010**	−1.6972	−0.1798***	0.0928***	0.0105	0.9879***	0.0092	1.0183***	19.9808	20.0470	9687.80	−6.6008
		(0.0345)	(0.6252)	(0.0001)	(0.0000)	(0.2963)	(0.0000)	(0.1086)	(0.0000)	(0.1307)	(0.1290)		
	θ_2, C-19	0.0011	−2.6758	−0.1798***	0.0928***	0.0102	0.9879***	0.0092	1.0185***				
		(0.2730)	(0.6999)	(0.0001)	(0.0000)	(0.3067)	(0.0000)	(0.1090)	(0.0000)				
US dollar	θ_1, pre-C-19	−0.0002	−2.6246	−0.1426***	0.0902***	0.0133*	0.9933***	−0.0009	1.4937***	7.1050	6.7734	11976.22	−8.1618
		(0.2301)	(0.7560)	(0.0000)	(0.0000)	(0.0805)	(0.0000)	(0.8622)	(0.0000)	(0.8506)	(0.8720)		
	θ_2, C-19	−0.0003	2.5773	−0.1418***	0.0897***	0.0138*	0.9934***	−0.0009	1.4946***				
		(0.4638)	(0.9274)	(0.0000)	(0.0000)	(0.0696)	(0.0000)	(0.8650)	(0.0000)				

This table reports the estimation results of Eqs. (6), (7) and (8), assuming the risk aversion coefficients are static. ARCH test denotes the test statistic of the ARCH Lagrange Multiplier (LM) test for the squared standardised innovations up to its 12 lags. The test static follows a Chi-square distribution. LB2(12) denotes the Ljung–Box Q test statistic on the squares of the standardised innovations up to lag order 12. AIC denotes Akaike Information Criterion. ***, ** and *Denote significance at the 1%, 5% and 10% levels, respectively

Table 3 Time varying risk aversion coefficients

	FFF functions					Conditional variance equation									
	δ	$\beta_{k,1}$	$\beta_{k,2}$	$\beta_{k,3}$	$\beta_{k,4}$	γ_0	γ_1	γ_2	γ_3	η	φ	ARCH test	LB2(12)	Log-likelihood	AIC
	(a) Cryptocurrency markets														
Bitcoin	−0.0109***	−2.1748***	6.4147***	0.5875*	2.3459***	−0.3618***	0.2830***	0.0314**	0.9739***	0.0243	0.8234***	5.7538	5.7566	6914.276	−3.9725
	(0.0095)	(0.0007)	(0.0000)	(0.0524)	(0.0000)	(0.0000)	(0.0000)	(0.0356)	(0.0000)	(0.4911)	(0.0000)	(0.9280)	(0.9280)		
Ethereum	0.0040***	−1.0378***	3.6151***	−0.2938***	0.9597***	−0.5752***	0.2923***	0.0209	0.9362***	0.0004	0.9099***	7.9921	8.0733	3268.604	−3.1588
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2898)	(0.0000)	(0.9823)	(0.0000)	(0.7857)	(0.7790)		
XRP	0.0056***	0.0502***	0.3883***	0.0562***	0.4105***	−0.9839***	0.4588***	0.0327	0.8877***	0.0158	0.7833***	2.9346	2.9525	4612.74	−3.4739
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1842)	(0.0000)	(0.5955)	(0.0000)	(0.9960)	(0.9960)		
Bitcoin Cash	0.0079***	−0.6206***	0.7667***	−0.5909***	−0.2048***	−0.2389***	0.1603***	0.0369*	0.9760***	−0.0083	0.8131***	6.7902	6.6917	1988.13	−2.9318
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0009)	(0.0000)	(0.0509)	(0.0000)	(0.4592)	(0.0000)	(0.8712)	(0.8770)		
Litecoin	0.0048***	0.8443***	1.3979***	−0.1526***	0.0183	−0.3521***	0.1697***	0.0200	0.9599***	−0.0077	1.0026***	10.4896	10.6580	2169.715	−3.1234
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.6929)	(0.0027)	(0.0000)	(0.3057)	(0.0000)	(0.5171)	(0.0000)	(0.5731)	(0.5580)		
Bitcoin SV	0.0035***	−1.8451***	2.1226***	−1.2738***	1.1871***	−0.5349***	0.2627***	0.0386	0.9354***	0.0020	0.6976***	8.2914	8.6670	1306.912	−3.0885
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.0000)	(0.2997)	(0.0000)	(0.9342)	(0.0000)	(0.7620)	(0.7310)		
Tether	0.0003***	11.0691***	−63.1957***	−14.2701***	−11.5239***	−0.3548***	0.6073***	0.5499***	0.9838***	0.0937***	0.1964***	0.0060	0.0060	14266.27	−13.2382
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(1.0000)	(1.0000)		

Table 3 continued

	FFF functions					Conditional variance equation									
	δ	$\beta_{k,1}$	$\beta_{k,2}$	$\beta_{k,3}$	$\beta_{k,4}$	γ_0	γ_1	γ_2	γ_3	η	φ	ARCH test	LB2(12)	Log-likelihood	AIC
EOS	0.0044***	0.2236***	−0.0460***	−0.8856***	−0.2985***	−0.3282***	0.1956***	0.0173	0.9642***	−0.0048	0.8215***	7.5844	7.7173	1953.181	−2.8991
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0009)	(0.0000)	(0.3792)	(0.0000)	(0.7321)	(0.0000)	(0.8167)	(0.8070)		
Stellar	0.0084***	0.0921***	−0.1849***	−0.2497***	−0.4210***	−0.7377***	0.3668***	0.0542**	0.9151***	0.0002	0.9145***	2.2119	2.2058	3612.184	−2.9968
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0163)	(0.0000)	(0.9920)	(0.0000)	(0.9990)	(0.9990)		
Tezos	0.0060***	−0.1598***	0.0806***	−0.3591***	0.1947***	−0.6325***	0.3114***	0.0507*	0.9247***	−0.0086	1.0281***	3.0851	3.0197	1738.777	−2.7681
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0016)	(0.0000)	(0.0608)	(0.0000)	(0.6981)	(0.0000)	(0.9949)	(0.9950)		
Cardano	−0.0015***	0.8918***	1.1906***	−0.1444***	−1.6583***	−0.1849**	0.1359***	0.0170	0.9844***	0.0059	0.9951***	11.1940	11.9570	1762.698	−2.8166
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0313)	(0.0052)	(0.2860)	(0.0000)	(0.4478)	(0.0000)	(0.5124)	(0.4490)		
	(b) Traditional asset markets														
S&P 500	0.0003	8.9017***	−6.4608***	3.5208***	0.1011*	−0.7160***	0.1591***	−0.2247***	0.9395***	0.0660***	1.1575***	4.5666	4.4605	10062.77	−6.8685
	(0.3438)	(0.0000)	(0.0000)	(0.0000)	(0.0877)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.9709)	(0.9740)		
WTI	−0.0094***	−11.8273**	27.0047***	1.7528	8.7622***	−0.3084***	0.1470***	−0.0808***	0.9753***	0.0392***	1.2980***	22.8113	22.8140	7462.74	−5.1056
	(0.0000)	(0.0365)	(0.0023)	(0.1734)	(0.0094)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1189)	(0.1190)		
Gold	0.0014***	7.4175***	−20.9266***	5.5787***	−5.8008***	−0.1878***	0.0954***	0.0098	0.9872***	0.0096	1.0122***	18.0938	18.0980	9695.67	−6.6048
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.3587)	(0.0000)	(0.1299)	(0.0000)	(0.1129)	(0.1130)		
US Dollar	−0.0001	−2.0522	0.1341	−4.4215	0.2607	−0.1445***	0.0908***	0.0128*	0.9932***	−0.0008	1.4904***	7.1815	6.8313	11976.51	−8.1606
	(0.6446)	(0.8861)	(0.9966)	(0.5183)	(0.9802)	(0.0000)	(0.0000)	(0.0991)	(0.0000)	(0.8784)	(0.0000)	(0.8454)	(0.8690)		

This table reports the estimation results of Eqs. (9), (10) and (7). Estimates of the FFF functions are presented. The optimal order k for the functions is chosen according to AIC. ARCH test denotes the test statistic of the ARCH Lagrange multiplier (LM) test for the squared standardised innovations up to its 12 lags. The test static follows a Chi-square distribution. LB2(12) denotes the Ljung–Box Q test statistic on the squares of the standardised innovations up to lag order 12. AIC denotes Akaike Information Criterion. ***, ** and *Denote significance at the 1%, 5% and 10% levels, respectively suggests that the risk aversion coefficients of the markets under question are significantly driven by time, and the time effects are non-linear. Further, the FFF functions well to explain the evolution of risk aversion, suggesting that periodicity exists as to its moving patterns. The result aligns with the prior studies that find the linear or non-linear time-varying evolutions of risk aversion concerning traditional risky assets. The finding that risk aversion exhibits periodic moving patterns may be attributed to Cohn et al. (2015)'s finding that emotions of fear may lead to an evolution of the relative risk aversion in a counter-cyclical pattern. Individuals' risk aversion may fluctuate against differing phases of the price collapse and growth due to varying levels of investors' fear in response to those two-time episodes. One can expect that the relative risk aversion varies periodically over time. Another reason may pertain to the first and second moments of return distribution as implied by Eq. 1, which stems from reasoning by Bordalo et al. (2012). Given a certain number of shares of a risky portfolio, Eq. 1 suggests that risk aversion can be gauged from expected return and volatility. Since the latter two variables are subject to martingale processes, it cannot be ruled out that the moving pattern of risk aversion is a martingale. Guiso et al. (2018) confirm the mechanism of the salience of changing expected distributions of returns and the channel of the emotion of fear towards evolving patterns of risk aversion. Since the risk aversion of the analysed cryptocurrencies exhibits similar moving patterns driven by time as that of traditional assets, it is signalled that, in such a sense, the cryptocurrency assets share some commonalities with the traditional risky ones concerning traders' risk perceptions.

In addition to Table 2, in Table 3 we find that the COVID-19 pandemic significantly influences returns of all the cryptocurrencies. Returns of Bitcoin and Cardano decreased while returns of the other increased as the COVID-19 pandemic started. Most cryptocurrencies have better performance under the effect of COVID-19. Evidence of traditional financial markets is also found where returns of WTI decrease, referring to worse performance, whereas returns of gold increase, referring to better performance during the COVID-19 pandemic. At the same time, the COVID-19 pandemic significantly enhances the volatilities of Tether, S&P500 index and WTI futures. Across the markets, conditional volatilities are significantly affected by recent shocks and old news. Residual diagnosis suggests that all the models are well specified.

Sample statistics of time-varying risk aversion coefficient series derived from the FFF functions are summarised in Table 4. The mean coefficients of risk aversion coefficients vary across markets. Six out of eleven cryptocurrencies have positive means of risk aversion coefficients, while the rest five have negative ones. This suggests that more than half of cryptocurrency markets are occupied by risk-averse investors, whereas risk-seeking prevails in the other. Meanwhile, risk aversion behaviour is the most volatile in the Tether market. This behaviour identified in the Bitcoin, Bitcoin SV and Cardano markets fluctuates more substantially than the rest of the cryptocurrency markets that have relatively stable risk preferences. Moreover, the S&P500 index and WTI oil markets have positive means of risk aversion coefficients with relatively large volatilities. In contrast, gold and US dollar exchange markets possess negative means of volatile risk aversion coefficients. Negative means of risk aversion as to the gold and US dollar index point to a safe-haven feature of these two assets, where investors still prefer to hold some shares of the assets even if performance is poor and the market is tumultuous. Table 4 indicates two differences in risk aversion between the cryptocurrency and traditional financial markets. First, the absolute level of risk aversion in the cryptocurrency markets is lower than that of the traditional counterparts. Second, risk aversion in traditional markets is more volatile than the cryptocurrencies. The latter possess relatively more stable risk preferences.

Table 4 Descriptive statistics of time-varying risk aversion

	Bitcoin	Ethereum	XRP	Bitcoin C	Litecoin
Mean	1.0334	0.7706	0.2445	−0.2370	1.5438
Median	0.9225	0.8828	0.2146	−0.3232	1.6963
Maximum	5.4808	2.2834	1.0742	1.5164	2.0897
Minimum	−0.9220	−1.3269	−0.4465	−1.5397	0.6929
SD	1.1973	0.6987	0.4368	0.8963	0.4080
Skewness	1.0811	−0.9931	0.2877	0.5010	−0.6536
Kurtosis	4.5692	4.2591	2.0819	2.2031	2.0818
	Bitcoin SV	**Tether**	**EOS**	**Stellar**	**Tezos**
Mean	−0.7826	−20.5434	0.2006	−0.0004	−0.1195
Median	−0.5242	−11.8572	0.1983	−0.0280	−0.1253
Maximum	0.9408	−9.1625	1.1328	0.4596	0.2828
Minimum	−4.4156	−73.4033	−0.7134	−0.4287	−0.5178
SD	1.2886	18.2790	0.6579	0.3129	0.2811
Skewness	−0.7244	−1.8392	0.0091	0.1093	0.0449
Kurtosis	2.9966	4.8622	1.4926	1.4957	1.4729
	Cardano	**S&P 500**	**WTI**	**Gold**	**US dollar**
Mean	1.4876	5.6702	1.6797	−3.0494	−1.9851
Median	1.6362	5.1527	1.4921	−4.0607	−1.9862
Maximum	3.4437	12.4206	17.7629	12.9766	2.4429
Minimum	−0.5024	1.9684	−9.1798	−9.1126	−6.4731
SD	1.4607	3.1441	4.8151	5.4963	3.1309
Skewness	−0.0328	0.7361	0.5187	1.2607	0.0008
Kurtosis	1.3739	2.4087	3.1582	3.8985	1.4994

This table reports the descriptive statistics of time-varying risk aversion coefficients of the cryptocurrency and traditional financial markets. The results of the full sample are shown. SD represents the standard deviation

The results of how the COVID-19 pandemic affects risk aversion are presented in Table 5. After controlling the autoregressive effects of risk aversion own values, the COVID-19 pandemic significantly affects risk aversion of all the markets under question except for Bitcoin Cash. It increases the risk aversion of Bitcoin, Ethereum and XRP; however, it decreases the risk aversion of the rest seven cryptocurrencies. The results suggest that investors are more cautious about moving funds into large-scale cryptocurrency assets after the COVID-19 pandemic occurs, while they are more willing to hold more shares of small- and medium-sized cryptocurrencies during the COVID-19 pandemic, given that the ratio of excess return over variance (the price of risk) holds still. It is implied a preference by investors to hold cryptocurrencies during the COVID-19 crisis. To this end, those cryptocurrencies might exhibit a safe-haven feature. Risk aversion in the S&P500 and WTI markets is levelled up by COVID-19; however, it is reduced by COVID-19 in the gold and US dollar exchange markets. It is unsurprising to see the results since funds flow from risky assets to commonly perceived safe-haven ones during the crisis period. Investors are more reluctant to hold shares of a risky equity portfolio and oil futures than holding shares of gold and the US dollar during the COVID-19 crisis, given a certain price of risk.

Table 5 The effect of the COVID-19 pandemic on risk aversion

	α_3
Bitcoin	0.0060***
	(0.0000)
Ethereum	0.0037***
	(0.0000)
XRP	0.0023***
	(0.0000)
Bitcoin Cash	−0.0015
	(0.2392)
Litecoin	−0.0003***
	(0.0001)
Bitcoin SV	−0.0156***
	(0.0000)
Tether	−0.0806***
	(0.0097)
EOS	−0.0055***
	(0.0000)
Stellar	−0.0015***
	(0.0000)
Tezos	−0.0026***
	(0.0000)
Cardano	−0.0130***
	(0.0000)
S&P 500	0.0034***
	(0.0000)
WTI	0.0555***
	(0.0000)
Gold	−0.0119***
	(0.0000)
US dollar	−0.0040***
	(0.0000)

This table reports the estimation results of Eq. (11) for the cryptocurrency and traditional financial markets. The estimates of α_3 in the equation are presented. ***Denotes significance at the 1% level

Our result on the effect of the COVID-19 pandemic on risk aversion is in line with Conlon et al. (2020), that medium- and small-scaled cryptocurrency markets exhibit a similar feature of flight-to-safe-haven during the pandemic crisis as gold and US dollar exchange markets do. This is implied by significantly decreasing effects on the risk aversion of those markets imposed by the COVID-19 pandemic.

The time-varying risk aversion coefficients derived from the FFF functions are visualised in Fig. 3 for cryptocurrencies and in Fig. 4 when considering traditional financial assets. Aligning with Table 4, we observe the non-linear cyclical, time-varying patterns of risk aversion in the cryptocurrency and traditional financial markets. Among a set of the movements of risk aversion of cryptocurrencies, Bitcoin, Ethereum, XRP, Litecoin and Cardano exhibit

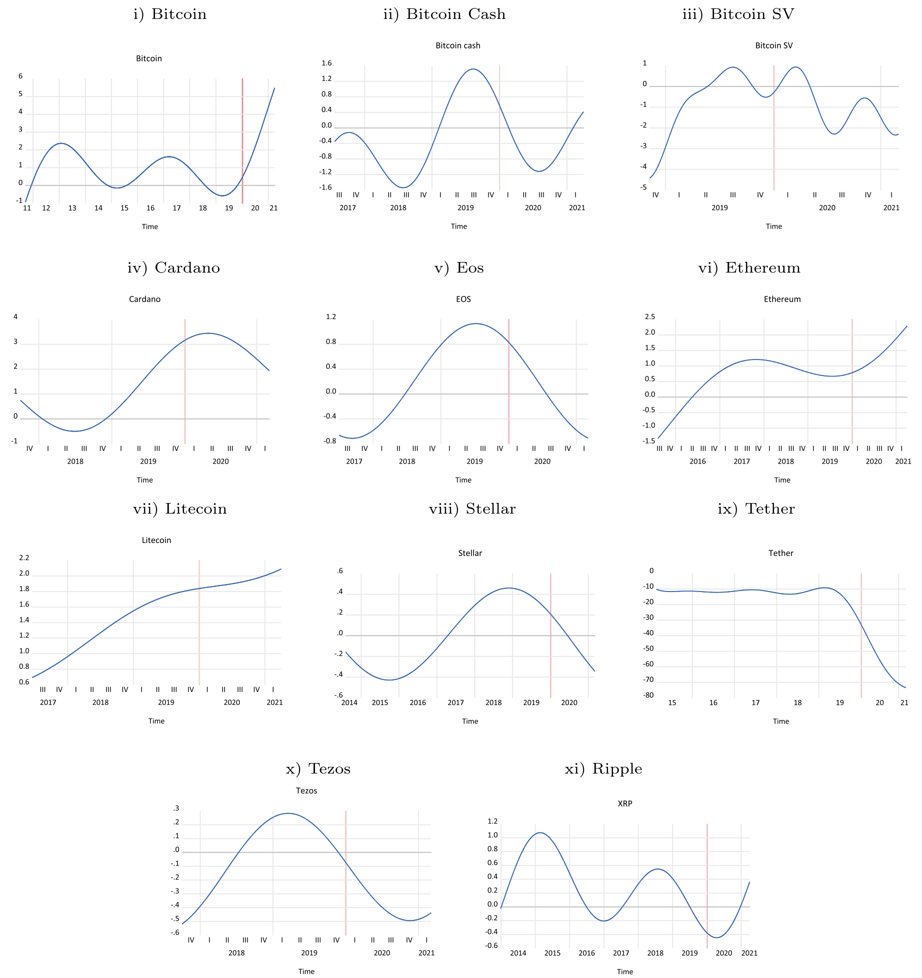

Fig. 3 Movements of time-varying risk aversion coefficients. *Note*: Time varying risk aversion coefficients are derived from the FFF functions. The red vertical line refers to the date December 31, 2019. I, II, III and IV denotes the first through to fourth quarters, respectively

risk aversion behaviour most of the time. For the rest of the cryptocurrencies, the preference for risk-seeking occupies a large proportion of the time. Typical examples are Bitcoin SV and Tether. When turning to the movements of traditional markets, investors in both S&P500 and WTI oil markets are averse to risk most of the time; however, in gold and US dollar exchange markets, risk aversion coefficients are negative for a large amount of time. According to Chou et al. (1992) and Cohn et al. (2015), negative risk aversion normally implies an investment in a risky asset even though the asset offers poor performance and high risk, pointing to risk-seeking behaviour. The risk-seeking behaviour in some cryptocurrency markets such as Bitcoin SV, as reflected by negative risk aversion coefficients in Fig. 3, aligns with the recent literature finding that the cryptocurrency markets attract market players with gambling behaviour and preference to invest in riskier assets (Mills & Nower, 2019; Hackethal et al., 2022). On the other hand, the observation that the risk aversion of gold and the US dollar

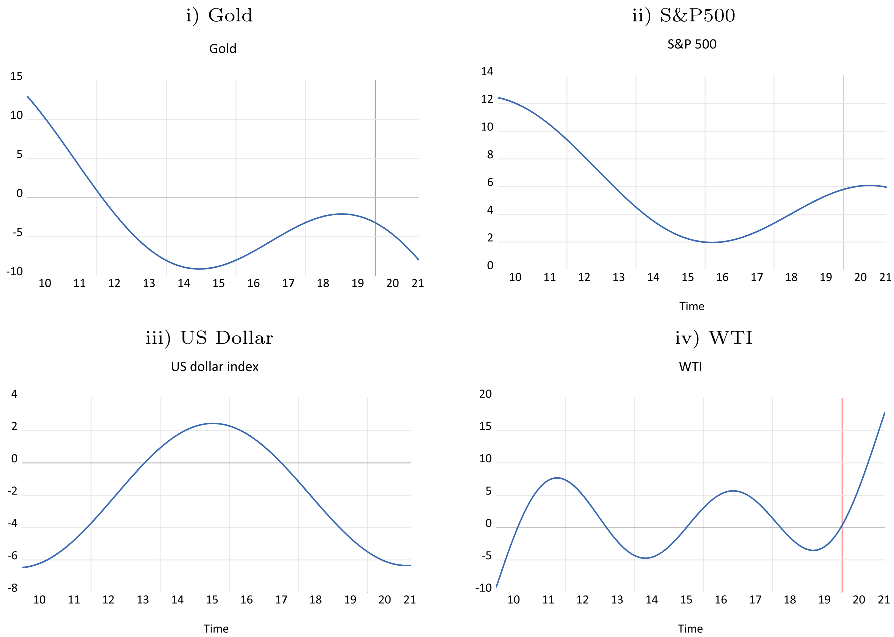

Fig. 4 Movements of time-varying risk aversion coefficients with traditional assets. *Note*: Time-varying risk aversion coefficients are derived from the FFF functions. The red vertical line refers to the date of December 31, 2019. I, II, III and IV denote the first through to fourth quarters, respectively

exchange rate presents negative for a large amount of time is worthwhile discussing. The literature has reached a solid conclusion that gold is a safe haven asset providing hedging and stabilising benefits during the financial crisis periods, as well discussed in Akhtaruzzaman et al. (2020), Bredin et al. (2015), Baur and McDermott (2010, 2016). Meanwhile, the US dollar exchange rate has also been regarded as a safe haven vehicle at both boom and bust times (Kaul & Sapp, 2006; Ranaldo & Söderlind, 2010; Cho & Han, 2021). Hence, negative risk aversion detected in both gold and US dollar exchange markets is consistent with the safe haven conclusions achieved thus far rather than revealing risk-seeking behaviour in those markets. This is because an investment in a safe haven asset may still proceed even when the asset has poor performance, where it typically makes sense for a flight-to-safe-haven strategy in tumultuous times. As visualised in Fig. 3, risk aversion of both gold and US dollar index declined subsequent to the official announcement of the global pandemic of COVID-19 by the WHO on December 31, 2019, which is consistent with the flight-to-safe-haven behaviour throughout the COVID-19 crisis discussed in Akhtaruzzaman et al. (2020). Overall, the evidence of negative risk aversion of gold and US dollar exchange markets signals a feature of haven in the two markets rather than risk-seeking relating to speculative activities in some cryptocurrency markets. Some differentials in interpreting the negative values of risk aversion are considered between the cryptocurrency and traditional financial markets. Furthermore, we observe from Fig. 3 that the trends of risk aversion during the COVID-19 pandemic differ from those in the pre-COVID-19 period. The observation corresponds with Table 5. In addition, some similarities can be observed for moving patterns of risk aversion among cryptocurrencies and traditional financial assets. Also, some coefficients move in tandem. This raises doubt about whether there are linkages of risk aversion in the markets under question. We explore the question in the next section.

5.2 Granger causality and estimated spillover indices

The results of the bilateral Granger causality test on risk aversion between Bitcoin and one other cryptocurrency are shown in Table 6. Note that we test the Granger causality of risk aversion of Bitcoin against that of the other ten cryptocurrencies. As can be seen from the table, before the COVID-19 pandemic occurred, the null hypothesis that Bitcoin risk aversion did not Granger cause that of one counterpart cryptocurrency asset to be rejected at the 0.01 level. The null hypothesis of no causality the other way around is also rejected at the same significance level. The evidence is found for all the bilateral relations. Henceforth, there is a two-way causality of risk aversion between Bitcoin and another cryptocurrency in the pre-COVID-19 period. The result enlightens strong pairwise predictability of risk preferences in the cryptocurrency markets.

The COVID-19 pandemic presents a different scenario. The bilateral causality of risk aversion turns weaker, given that the rejection of no causality is made at heightened significance levels. Still, it is found that bilateral causality is taking place in the relations of Bitcoin with eight out of eleven cryptocurrencies. Among these two-way causalities, the causalities from other cryptocurrencies to Bitcoin sound compromised. However, we find the unilateral causalities that run from Bitcoin-to-Bitcoin SV, from Litecoin to Bitcoin and from Stellar to Bitcoin. The results imply that the pairwise predictability of risk aversion among cryptocurrencies, placing Bitcoin as a focal point, is weakened by the COVID-19 pandemic.

We present the results of the bilateral Granger causality test on risk aversion between each cryptocurrency and each of the four counterpart conventional financial markets in Table 7. The null hypotheses of no Granger causalities of risk aversion running from each cryptocurrency to traditional counterparts are rejected at the 0.01 level. Meanwhile, no Granger causalities of the reverse ways are rejected at the same significance level. The results are evidenced before the COVID-19 pandemic takes place. Henceforth, there is bidirectional predictability of risk aversion between cryptocurrencies and traditional financial assets in the tranquil period. When entering the COVID-19 pandemic phase, the bilateral causality of risk aversion is evidenced in the relations of eight out of eleven cryptocurrencies with four traditional financial markets. Nonetheless, we find no causalities of risk aversion running from gold, WTI and the US dollar index to Litecoin and Stellar. And the causality from gold to Bitcoin is not significant. The results imply a strong bilateral predictability of risk aversion running between cryptocurrency and conventional financial ones. The COVID-19 pandemic can impose limited influences on predictability. Tables 6 and 7 suggest that risk behaviour and perceptions are connected within the cryptocurrency markets and cross-border to traditional, well-known financial markets. The finding stands out in the tranquil period before the COVID-19 pandemic. The outbreak of COVID-19 impairs the connections within the cryptocurrency cluster but exerts relatively small influences on the linkages of cryptocurrency cohorts with traditional financial assets. The connectedness of risk aversion is further examined by the DY spillover index below.

The DY indexes of total spillover and net spillover are shown in Table 8. The total spillover before the COVID-19 pandemic was about 84 percent which means that the cross-border spillovers of shocks of risk aversion across the 15 markets under question contribute almost 85 percent to the total forecasting error variance. The COVID-19 pandemic evidences a higher proportion of almost 91 percent contributed by the cross-market spillovers of shocks to the total forecasting error variance. This result indicates that the connectedness of risk aversion

Table 6 Granger causality among cryptocurrency markets

Pre COVID-19 period			COVID-19 pandemic		
Null hypotheses	F-statistic	*p* value	Null hypotheses	F-Statistic	*p* value
Bitcoin–Bitcoin cash					
Bitcoin cash $\neq\rightarrow$ BITCOIN	658.2410***	(0.0000)	Bitcoin Cash $\neq\rightarrow$ BITCOIN	4.5226**	(0.0342)
BITCOIN $\neq\rightarrow$ Bitcoin Cash	200.8250***	(0.0000)	BITCOIN $\neq\rightarrow$ Bitcoin Cash	782.0970***	(0.0000)
Bitcoin–Bitcoin SV					
BITCOIN SV $\neq\rightarrow$ BITCOIN	211.1460***	(0.0000)	BITCOIN SV $\neq\rightarrow$ BITCOIN	0.3099	(0.5782)
BITCOIN $\neq\rightarrow$ BITCOIN SV	73.0287***	(0.0000)	BITCOIN $\neq\rightarrow$ BITCOIN SV	4.2565**	(0.0400)
Bitcoin–Cardano					
CARDANO $\neq\rightarrow$ BITCOIN	1293.0500***	(0.0000)	CARDANO $\neq\rightarrow$ BITCOIN	3.8260*	(0.0514)
BITCOIN $\neq\rightarrow$ CARDANO	981.5110***	(0.0000)	BITCOIN $\neq\rightarrow$ CARDANO	257.0820***	(0.0000)
Bitcoin–EOS					
EOS $\neq\rightarrow$ BITCOIN	1413.2800***	(0.0000)	EOS $\neq\rightarrow$ BITCOIN	3.8802**	(0.0498)
BITCOIN $\neq\rightarrow$ EOS	1161.7000***	(0.0000)	BITCOIN $\neq\rightarrow$ EOS	26.7390***	(0.0000)
Bitcoin–Ethereum					
ETHEREUM $\neq\rightarrow$ BITCOIN	493.7410***	(0.0000)	ETHEREUM $\neq\rightarrow$ BITCOIN	4.6440**	(0.0319)
BITCOIN $\neq\rightarrow$ ETHEREUM	721.6720***	(0.0000)	BITCOIN $\neq\rightarrow$ ETHEREUM	5.4568**	(0.0201)

Table 6 continued

Pre COVID-19 period			COVID-19 pandemic		
Null hypotheses	F-statistic	p value	Null hypotheses	F-Statistic	p value
Bitcoin–Litecoin					
LITECOIN $\neq\rightarrow$ BITCOIN	1128.8800***	(0.0000)	LITECOIN $\neq\rightarrow$ BITCOIN	3.9315**	(0.0482)
BITCOIN $\neq\rightarrow$ LITECOIN	69.0041***	(0.0000)	BITCOIN $\neq\rightarrow$ LITECOIN	1.2453	(0.2653)
Bitcoin–Stellar					
STELLAR $\neq\rightarrow$ BITCOIN	292.0330***	(0.0000)	STELLAR $\neq\rightarrow$ BITCOIN	3.8726*	(0.0500)
BITCOIN $\neq\rightarrow$ STELLAR	1772.3300***	(0.0000)	BITCOIN $\neq\rightarrow$ STELLAR	2.4748	(0.1167)
Bitcoin–Tether					
TETHER $\neq\rightarrow$ BITCOIN	216.2170***	(0.0000)	TETHER $\neq\rightarrow$ BITCOIN	2.9985*	(0.0845)
BITCOIN $\neq\rightarrow$ TETHER	59.4151***	(0.0000)	BITCOIN $\neq\rightarrow$ TETHER	14.1579***	(0.0002)
Bitcoin - Tezos					
TEZOS $\neq\rightarrow$ BITCOIN	66.5521***	(0.0000)	TEZOS $\neq\rightarrow$ BITCOIN	3.8830**	(0.0497)
BITCOIN $\neq\rightarrow$ TEZOS	23.9826***	(0.0000)	BITCOIN $\neq\rightarrow$ TEZOS	177.4810***	(0.0000)
Bitcoin–XRP					
XRP $\neq\rightarrow$ BITCOIN	255.8970***	(0.0000)	XRP $\neq\rightarrow$ BITCOIN	4.6554**	(0.0317)
BITCOIN $\neq\rightarrow$ XRP	472.7030***	(0.0000)	BITCOIN $\neq\rightarrow$ XRP	126.7480***	(0.0000)

This table reports the results of the bilateral Granger causality test between bitcoin and other cryptocurrencies. The pre-COVID-19 period denotes a sub-sample period ending on December 30, 2019. The COVID-19 pandemic denotes a sub-sample period running from December 31, 2019, to March 31, 2021. The F test is used to test the null hypotheses. F-Statistic denotes the test statistic of the F test. ***, ** and *Represent significance at the 1%, 5% and 10% levels, respectively

Table 7 Granger causality between cryptocurrency and traditional financial markets

	Pre COVID-19 period				COVID-19 pandemic			
$\neq\leftarrow$	S&P500	GOLD	WTI	US DOLLAR	S&P500	GOLD	WTI	US DOLLAR
Bitcoin	450.9810***	315.8020***	1.76E+03***	154.7240***	4.8064**	0.5391	5.6220**	5.2782**
Bitcoin cash	20.1142***	149.2230***	184.1110***	18.4647***	843.3660***	758.9450***	775.5400***	800.6010***
Bitcoin SV	86.5885***	78.7516***	76.0251***	85.7920***	11.2029***	4.3564**	4.3389**	9.8814***
Cardano	788.8620***	941.0900***	970.4360***	774.5850***	259.8730***	257.9470***	261.0510***	260.9340***
EOS	105.8650***	1108.5900***	1189.7000***	90.0037***	29.6315***	22.9487***	22.4728***	30.7486***
Ethereum	413.6140***	744.5830***	827.4690***	409.4340***	5.4997**	13.7509***	9.9374***	5.8990**
Litecoin	72.9972***	106.4540***	89.0866***	59.6243***	2.8424*	0.3794	0.5824	2.3932
Stellar	2359.1900***	562.0210***	2164.5800***	512.5450***	2.6942	0.8754	0.4887	3.1688*
Tether	98.4614***	9.1178***	54.6732***	68.5064***	16.9129***	12.8782***	12.9361***	19.5747***
Tezos	98.4614***	9.1178***	54.6732***	68.5064***	191.2060***	173.9000***	174.4230***	143.5610***
Ripple	3.6004*	24.4235***	73.1141***	41.7745***	126.1230***	129.2960***	130.1170***	127.1470***
$\neq\rightarrow$	S&P500	GOLD	WTI	US DOLLAR	S&P500	GOLD	WTI	US DOLLAR
Bitcoin	419.0160***	210.7220***	1430.7700***	382.4540***	1.21E+06***	2568.5200***	1121.6200***	2.49E+05***
Bitcoin cash	763.2100***	1574.1700***	1706.8100***	773.0760***	6045.9600***	1.29E+04***	1.33E+04***	1.45E+04***
Bitcoin SV	5795.3000***	1.20E+04***	1.19E+04***	6145.6500***	41.3022***	50.0635***	45.5452***	0.9679
Cardano	1.13E+04***	2.14E+04***	2.87E+04***	1.13E+04***	5.07E+04***	8977.2500***	1.17E+04***	3.53E+04***
EOS	198.5730***	6232.1300***	1.41E+04***	162.3960***	6.67E+04***	4529.9800***	5207.3100***	6784.3500***
Ethereum	1.16E+04***	1,999.1900***	1626.0100***	9381.5500***	3.48E+06***	5,379.6800***	7.35E+04***	1.29E+06***
Litecoin	4967.5400***	3.88E+05***	2.66E+04***	2469.1100***	9.66E+04***	1,591.0400***	1860.7400***	2.64E+04***

Table 7 continued

	Pre COVID-19 period				COVID-19 pandemic			
Stellar	3637.1400***	690.6470***	1859.2900***	656.0720***	1.52E+06***	2.24E+04***	5.95E+04***	2.30E+05***
Tether	122.9070***	546.5940***	185.1990***	249.3010***	3.45E+04***	1.67E+04***	1.66E+04***	185.3700***
Tezos	9654.6000***	6023.7000***	5208.3800***	8357.6100***	1.14E+04***	4.21E+04***	6.48E+04***	3651.5600***
Ripple	504.9940***	35.7979***	76.8391***	230.1220***	3.48E+05***	3.72E+04***	7.66E+04***	2.74E+05***

This table reports the results of the bilateral Granger causality test between each cryptocurrency and the other traditional financial markets. The pre-COVID-19 period denotes a sub-sample period ending on December 30, 2019. The COVID-19 pandemic is denoted as a sub-sample period running from 31 December 2019 through 31 March 2021. The F test is used to test the null hypotheses. F-Statistic denotes the test statistic of an associated F test. E stands for scientific notation. ***, ** and *Represent significance at the 1%, 5% and 10% levels, respectively

Table 8 Total spillovers and net spillovers

Pre COVID-19 period				
Total spillovers				
84.7049				
Net spillover				
S&P 500	Gold	US Dollar	WTI	Bitcoin
−30.9861	−0.9414	−0.1749	−0.8823	1.3339
Ethereum	XRP	Bitcoin Cash	Litecoin	Bitcoin SV
1.1944	3.3849	4.4961	3.9060	4.9691
Tether	Cardano	EOS	Stellar	Tezos
2.5881	4.2315	2.3944	1.6784	2.8077
COVID-19 pandemic				
Total spillover				
90.7591				
Net spillover				
S&P 500	Gold	US Dollar	WTI	Bitcoin
−9.6638	−2.5551	−0.0008	−2.3222	0.2609
Ethereum	XRP	Bitcoin Cash	Litecoin	Bitcoin SV
0.1424	0.0499	0.6304	−0.0182	3.1710
Tether	Cardano	EOS	Stellar	Tezos
4.6535	−0.4571	0.6614	0.3565	5.0913

This table reports the results of Diebold and Yilmaz (2009, 2012) total spillover index and net spillover index as in Eqs. (13) and (16). Pre COVID-19 period denotes a sub-sample period ending at December 30, 2019. COVID-19 pandemic denotes a sub-sample period running from December 31, 2019 to March 31, 2021

among cryptocurrencies and traditional four financial markets enhanced during the COVID-19 pandemic. Concerning the net spillover of risk aversion of one market against the other counterparts, the spillovers of the four traditional financial markets exhibit dominance in the directional spillover processes in both the pre-COVID-19 period and COVID-19 pandemic period, pointing to the role of information transmitter. Among them, risk aversion in the S&P500 index shows a substantively leading role in transmitting the shocks to others. Such capacity was reduced by the COVID-19 pandemic. The spillover powers of risk aversion in the WTI, gold and US dollar exchange markets have somewhat decreased during the COVID-19 pandemic. On the other hand, despite the inferior positions of information receivers faced by risk aversion of the cryptocurrencies in transmitting shocks, it is found that their powers of spillovers are recovered by the COVID-19 pandemic. Typical examples include Litecoin and Cardano, whose net spillovers turned from positive values in the pre-COVID-19 period to negative ones in the COVID-19 pandemic. The evidence means that the role of Litecoin and Cardano turned from information receiver to information transmitter during the COVID-19 outbreak. Overall, risk perceptions in the traditional financial markets still exert influential impacts on the connectedness with cryptocurrencies, even during the COVID-19 crisis. However, those impacts are somehow weakened by the latter crisis.

Table 9 offers the one-to-one pairwise net spillover of risk aversion between Bitcoin and one other cryptocurrency. In the pre-COVID-19 period, Bitcoin played a dominant role in the spillovers with nine out of ten cryptocurrencies, as reflected by negative values of net

Table 9 Net pairwise spillovers among cryptocurrency markets

Pre COVID-19 period	
Bitcoin–Ethereum	Bitcoin–XRP
0.1149	−0.0553
Bitcoin–Litecoin	Bitcoin–Bitcoin Cash
−0.1522	−0.1255
Bitcoin-Tether	Bitcoin-Bitcoin SV
−0.5132	−0.1241
Bitcoin–EOS	Bitcoin-Cardano
−0.2720	−0.0817
Bitcoin–Tezos	Bitcoin-Stellar
−0.4950	−0.1443
COVID-19 pandemic	
Bitcoin–XRP	Bitcoin–Bitcoin Cash
0.0236	−0.0219
Bitcoin–Litecoin	Bitcoin–Bitcoin SV
0.0274	−0.2971
Bitcoin–Tether	Bitcoin–Cardano
−0.1559	0.0504
Bitcoin–EOS	Bitcoin–Stellar
−0.0408	−0.0098
Bitcoin–Ethereum	Bitcoin–Tezos
0.0118	−0.3601

This table reports the results of Diebold and Yilmaz (2009, 2012) net pairwise spillover index as in Eq. (17) running between Bitcoin and the other cryptocurrencies. Pre COVID-19 period denotes a sub-sample period ending on December 30, 2019. The COVID-19 pandemic denotes a sub-sample period running from December 31, 2019, to March 31, 2021

spillovers. An exception is that the risk aversion of Ethereum leads to that of Bitcoin, given the positive value of net spillover. There is a differing scenario regarding the pairwise lead-lag relation of risk aversion after entering the COVID-19 pandemic. The net spillovers of risk aversion between Bitcoin and four cryptocurrencies, such as XRP, Litecoin, Ethereum and Cardano, are positive, suggesting the dominant roles of the latter four cryptocurrencies in the connectedness. Meanwhile, Bitcoin leads the remaining analysed cryptocurrencies with regard to the connectedness of risk aversion during the COVID-19 pandemic. However, the strength of those net pairwise spillovers is weakened during the COVID-19 pandemic compared to those in the pre-COVID-19 period. This is indicated by lessened absolute values of net pairwise spillovers. Overall, we find the connectedness of risk aversion among cryptocurrencies, putting the Bitcoin market as a contagious core. The risk aversion of Bitcoin is an information transmitter towards the risk aversion of nine cryptocurrencies before the COVID-19 pandemic while it is an information transmitter to the risk aversion of six cryptocurrencies during the COVID-19 pandemic. The COVID-19 pandemic weakens the contagious power of risk behaviour and perceptions in the Bitcoin markets toward those in the other cryptocurrency markets.

Table 10 Net pairwise spillovers of cryptocurrencies against traditional financial markets

Pre-COVID-19 period				COVID-19 pandemic			
Bitcoin	→	S&P500	2.1848	Bitcoin	→	S&P500	0.6566
		Gold	0.3517			Gold	0.191
		WTI	0.3474			WTI	0.1751
		USD	0.2983			USD	0.0106
Ethereum	→	S&P500	2.6031	Ethereum	→	S&P500	0.6611
		Gold	0.3323			Gold	0.1836
		WTI	0.3272			WTI	0.1673
		USD	0.2695			USD	−0.0009
XRP	→	S&P500	3.0629	XRP	→	S&P500	0.6716
		Gold	0.4022			Gold	0.1769
		WTI	0.3966			WTI	0.1599
		USD	0.3346			USD	−0.0143
Bitcoin cash	→	S&P500	3.5681	Bitcoin cash	→	S&P500	0.7145
		Gold	0.3762			Gold	0.2166
		WTI	0.3704			WTI	0.1993
		USD	0.3031			USD	0.0188
Litecoin	→	S&P500	2.2206	Litecoin	→	S&P500	0.6786
		Gold	0.2932			Gold	0.1773
		WTI	0.2896			WTI	0.1601
		USD	0.2483			USD	−0.0153
Bitcoin SV	→	S&P500	2.8754	Bitcoin SV	→	S&P500	1.2595
		Gold	0.6644			Gold	0.5427
		WTI	0.6596			WTI	0.5172
		USD	0.6137			USD	0.2296
Tether	→	S&P500	0.3283	Tether	→	S&P500	0.5313
		Gold	0.1686			Gold	0.1942

Table 10 continued

Pre-COVID-19 period				COVID-19 pandemic			
		WTI	0.1682			WTI	0.1852
		USD	0.1612			USD	0.1072
Cardano	→	S&P500	2.1614	Cardano	→	S&P500	0.5855
		Gold	0.3619			Gold	0.1411
		WTI	0.3576			WTI	0.1267
		USD	0.3026			USD	−0.0161
EOS	→	S&P500	1.1165	EOS	→	S&P500	0.6325
		Gold	0.3389			Gold	0.2139
		WTI	0.3367			WTI	0.1996
		USD	0.3100			USD	0.0499
Stellar	→	S&P500	1.7995	Stellar	→	S&P500	0.6562
		Gold	0.3357			Gold	0.1982
		WTI	0.3323			WTI	0.1825
		USD	0.2924			USD	0.0204
Tezos	→	S&P500	0.4746	Tezos	→	S&P500	1.2422
		Gold	0.0843			Gold	0.5958
		WTI	0.0838			WTI	0.5755
		USD	0.0773			USD	0.3825
Pre COVID-19 period: Cryptocurrency markets net block spillover against traditional financial markets 2.9986							
COVID-19 pandemic: Cryptocurrency markets net block spillover against traditional financial markets 1.3220							
Net block spillovers differential due to the COVID-19 pandemic −1.6766							

This table reports the results of the Diebold and Yilmaz (2009, 2012) net pairwise spillover index as in Eq. (17) running from each cryptocurrency to the other traditional financial markets. Pre COVID-19 period denotes a sub-sample period ending on December 30, 2019. The COVID-19 pandemic denotes a sub-sample period from December 31, 2019, to March 31, 2021. Net pairwise block spillovers from cryptocurrency markets to traditional financial markets are calculated as block spillover from cryptocurrency markets to traditional financial markets minus block spillover the other way around. Such analysis is based on the work of Greenwood-Nimmo et al. (2016). Note that the cryptocurrency markets are treated as one block, and the traditional financial markets are treated as the other. The difference in net block spillovers between pre and post-onset of the COVID-19 pandemic is calculated as net pairwise block spillovers in the COVID-19 pandemic minus that in the pre-COVID-19 period

Further, Table 10 presents the pairwise net spillover of risk aversion between one cryptocurrency and one traditional financial asset. As can be seen from the table, the spillover processes of risk aversion between cryptocurrencies and traditional assets witnessed dominant roles of the latter before the COVID-19 pandemic, provided with positive values of the pairwise net spillovers. The result means that there exists a connectedness of risk behaviour between cryptocurrency and traditional assets during the tranquil period. Risk behaviour in the traditional markets exerts critical contagion to that in the cryptocurrency markets. In contrast, during the COVID-19 pandemic, risk aversion associated with the S&P500, WTI and gold still led to that of the cryptocurrency markets. At the same time, risk aversion of the US dollar index leads to that in the seven cryptocurrency markets. Nonetheless, the risk aversion of the US dollar index is a net information receiver from Ethereum, XRP, Litecoin and Cardano. Henceforth, the weakened strength of contagion of risk aversion from the US dollar exchange market to that in some cryptocurrencies is evidenced across the outbreak of the COVID-19 pandemic. Furthermore, we find the pairwise net spillovers running from risk aversion in the traditional financial markets to that in all the cryptocurrency markets, except for Tezos and Tether, decreased after the COVID-19 pandemic occurred. It suggests that the roles of risk behaviour in the traditional financial markets in the connectedness with that in the cryptocurrency markets are impaired by the occurrence of the COVID-19 pandemic. Block connectedness is analysed per the work of Greenwood-Nimmo et al. (2016) in the lower panel of Table 10, specifically analysing spillovers from cryptocurrency markets to traditional financial markets. Cryptocurrency markets are treated as one block, and the traditional financial markets are treated as the other, with the differential estimated as +2.99 before the onset of COVID-19 and +1.32 in the period thereafter, indicating the existence of a significant differential in block spillover transmission.

Our results on the causalities and spillovers of risk aversion imply inter-related risk behaviour of investors connecting cryptocurrency markets to the traditional financial system. The evidence aligns with and further enriches the literature regarding the interdependence of return distributions between cryptocurrency and traditional financial markets. Not only do multiple types of risk in the traditional financial markets interact with the cryptocurrency markets, but the behavioural factor critical for asset pricing is also connected with one another. We witness the dominant roles of risk perceptions in the Bitcoin and traditional financial markets in the different behavioural networks. This may provoke some hints on the understanding of the commonality of investors' behaviour running from traditional financial markets to cryptocurrency ones, which may be helpful to relevant policymakers.

5.3 Additional robustness testing procedures

In this section, we test whether our result of time-varying risk aversion coefficients is robust to differing modelling on the coefficients. Typically, for this purpose, we employ a model proposed by Chou et al. (1992) that gauges the time-varying risk aversion coefficients in the context of the state-space model nested with the GARCH-in-mean one. We further modify the model to incorporate the autoregressive effects based on the lowest AIC values as well as the effect of the COVID-19 pandemic in the conditional mean equation on returns, which better fits the data. Moreover, for the conditional variance, the EGARCH (1,1) model is chosen instead of the GARCH one for consistency with the original FFF model we use for the time-varying risk aversion. Following Chou et al. (1992), the risk aversion coefficient is assumed to follow a random walk process without a drift, which is a typical AR(1) process with the autoregressive coefficient being unity. Such a process is specified in a transition

Fig. 5 Estimated state space risk aversion dynamics. *Note*: Time-varying risk aversion coefficients are derived from the state space TVP ARCH-M model. The red vertical line refers to the date of December 31, 2019. I, II, III and IV denote the first through to fourth quarters, respectively

equation under the state space setting. The whole model is referred to as the time-varying parameter (TVP) ARCH-M model.

We estimate the modified TVP-ARCH-M model for all the samples, including cryptocurrency and traditional markets. Specifically, the estimation is conducted via the MLE procedure, where the time-varying risk aversion coefficient, also called the state variable following a random walk, is gauged via the Kalman filter. We then present the movement patterns of estimated risk aversion across the cryptocurrency markets. The result is shown in Fig. 5. As compared with Fig. 3, the random walk risk aversion coefficients exhibit a substantial number of similarities in terms of critical peaks and troughs throughout time, which is evident in all the cryptocurrency markets except Litecoin and Tezos. Furthermore, we find that the changing patterns are almost similar between the random walk coefficients and the FFF ones after the official announcement of the COVID-19 global pandemic on December 31, 2019, except for Tezos. For instance, the random walk risk aversion coefficient in the Bitcoin market presented two peaks in both the 2012–2013 and 2017–2018 periods and two

Table 11 Time varying quantity of asset holdings

	Mean	Median	Maximum	Minimum	SD	Skewness	Kurtosis
	Traditional markets						
S&P 500	0.016	0.014	0.048	0.007	0.006	1.550	6.05
WTI	0.004	0.007	5.631	−3.660	0.208	6.223	328.66
Gold	−4.49E−05	0.003	1.316	−1.204	0.043	2.804	533.29
US dollar	0.011	0.011	1.189	−3.732	0.075	−40.988	2119.22
	Cryptocurrency markets						
Bitcoin	0.004	0.014	37.161	−56.238	1.243	−19.780	1468.21
Litecoin	−0.003	−0.002	0.032	−0.475	0.015	−22.712	712.45
Stellar	0.033	0.001	55.018	−16.631	1.320	29.963	1283.14
Tether	4.64E−15	−0.062	6.927	−105.783	3.196	−25.461	739.372
Tezos	−0.009	−0.012	13.795	−3.203	0.433	25.655	839.24
XRP	0.027	−0.011	73.670	−16.130	1.576	38.223	1817.30
Ethereum	0.009	0.005	7.771	−1.293	0.178	40.072	1745.53
EOS	0.010	0.004	8.902	−2.540	0.263	28.345	986.02
Cardano	0.001	0.003	2.699	−13.842	0.419	−29.308	966.71
Bitcoin SV	0.016	0.011	2.530	−0.822	0.099	19.488	517.12
Bitcoin Cash	0.014	0.007	4.796	−1.725	0.223	15.014	312.73

The time-varying quantity of asset holding is calculated as the expected excess return divided by the multiplication of conditional variance and time-varying risk aversion coefficient. The risk-free rate is the yield of the three-month US treasury bill

troughs in the periods of 2014–2015 and 2018–2019. This is similar to the FFF risk aversion of the Bitcoin market in Fig. 3. Moreover, we observe sharp increases in both risk aversion coefficients in the Bitcoin market following the announcement of the COVID-19 global pandemic. Similar observations are for most of the other cryptocurrency markets. It should be noted that we also observe the differentials in movements between two types of risk aversion. One apparent observation is that the random walk risk aversion possesses more rugged variations across time than the FFF one. A possible reason for this phenomenon is that the differing model specification applies to estimating time-varying risk aversion. The random walk process is deemed more volatile and less stationary than the time variations governed by the trigonometric functions under the FFF model setting. The latter presents a changing behaviour of mean-reverting instead of a random walk.

Further, we explore some economic implications from our findings so far. In particular, we consider the time variations in the percentage quantity of asset holding implied from the context that conditional variance of returns and time-varying risk aversion have been estimated from the model. In this regard, the dynamic holding is calculated as a ratio of expected excess return over the multiplication of conditional variance and time-varying risk aversion, following the discussions in Chou et al. (1992). We compute the dynamic holding across both cryptocurrency and traditional markets. The descriptive statistics of the holding are presented in Table 11. As can be seen, we focus on the means of dynamic holding across time, which indicates the average buying or selling position that investors adhere to. Note that when the holding quantity is positive (negative), a buying (selling) position prevails. With respect to the cryptocurrency cohorts, we find that the long position is held by an average investor across time, except for Tezos and Litecoin, with short positions of small amounts.

Note that the mean holding of Tether is almost zero, reflecting the fact that Tether is an asset-backed cryptocurrency stablecoin where it is pegged at 1-to-1 with a matching fiat currency. Regarding the average holding of the traditional markets, the buying positions dominate, while the average holding on gold is close to null. Moreover, it is identified that the holdings on the S&P 500 and the US dollar are more favoured. Meanwhile, the holdings on XRP, Stellar, EOS, Bitcoin SV and Bitcoin Cash are more prevalent than the others. Lastly, it is observed that the holding of cryptocurrencies is more volatile than that of traditional assets, given the larger standard deviations of the latter. The result somewhat implies more active trading is taking place in the cryptocurrency markets.

Lastly, we examine whether our results of the DY spillover indices in Table 8 are robust to differential forecasting horizons. It should be noted that we selected the forecasting horizon, which is also known as h-step-ahead forecasting of the generalised forecasting error variance decomposition (FEVD) in the VMA model, to be 100 in our main analysis. It is a common selection for forecasting horizons in previous studies. We hereby choose three different forecasting horizons for estimating the DY indices, including the total spillover index and net directional spillover index, in the robustness testing. The horizons are 50, 150 and 200, respectively. The risk aversion series of 15 selected markets are involved in the estimation, and the results of both pre-COVID-19 and COVID-19 pandemic periods are presented.

The results of the associated robustness testing procedures are presented in Table 12. As observed, when the forecasting horizon is shortened to fifty, the four traditional markets take the dominant role of transmitting the information of risk preference to the counterpart cryptocurrency markets in the pre-COVID-19 period. Such a role is impaired by the COVID-19 pandemic, as evidenced by less negative values of net directional spillover indices. Meanwhile, the role of the cryptocurrency markets is enhanced in the connectedness of risk preference during the pandemic in terms of reduced values of net directional spillover indices. Despite this evidence, the traditional markets still possess influential impacts relative to their cryptocurrency counterparts during the pandemic. And the connectedness of risk aversion is tightened at the same period, given the higher total spillover index. When turning to the longer forecasting horizon of 150, similar evidence is observed in the short horizon of 50. The traditional markets take a leading role in the transmission of risk aversion, but the COVID-19 pandemic has changed such a role. A typical example is the S&P 500, which is the most influential information transmitter in both sub-periods; however, the influencing power is hugely compromised in the pandemic. The cryptocurrency markets are information receivers all the time, with their role in the transmission increased during the pandemic for most markets. And the total spillover index increases during the same period. Similar evidence regarding the forecasting horizon of 200 is presented as the forecasting horizon of 150, which is consistent with evidence derived from the shorter horizon length of 50 and 100. Overall, the results of Table 12 are similar to Table 8, suggesting that the roles of the selected markets in the connectedness of risk aversion as well as the dynamics due to the COVID-19 pandemic rarely differ across the differential forecasting horizons, chosen for the DY spillover indices. Hence, our results as to the total spillover and the directional spillover indices are robust to the choice on the forecasting horizon.

Table 12 Total spillovers and net spillovers with different forecasting horizons

Forecasting horizon: 50 Pre-COVID-19 period				
Total spillover		80.2162		
Net spillovers				
S&P 500	Gold	US Dollar	Bitcoin	Ethereum
−14.5686	−2.1645	−1.9473	0.5872	0.6200
XRP	Bitcoin C	Litecoin	Bitcoin SV	Tether
2.2669	2.7008	2.5145	4.9855	1.2595
Cardano	EOS	Stellar	Tezos	WTI
2.4590	1.1681	0.7566	1.5093	−2.1472
COVID-19 pandemic				
Total spillover		88.6502		
Net spillovers				
S&P 500	Gold	US Dollar	Bitcoin	Ethereum
−1.1722	−0.8406	−0.6022	−0.5250	−0.5828
XRP	Bitcoin C	Litecoin	Bitcoin SV	Tether
−0.6341	−0.4710	−0.6541	0.9131	2.8459
Cardano	EOS	Stellar	Tezos	WTI
−0.0862	−0.2746	−0.4685	3.3782	−0.8259
Forecasting horizon: 150 Pre-COVID-19 period				
Total spillover		87.7035		
Net spillovers				
S&P 500	Gold	US.dollar	Bitcoin	Ethereum
−43.0199	−0.1729	0.7771	2.4085	1.9611
XRP	Bitcoin C	Litecoin	Bitcoin SV	Tether
4.0272	4.9646	4.8324	4.3834	4.0715
Cardano	EOS	Stellar	Tezos	WTI
5.1493	3.4886	2.9652	4.2627	−0.0987

This table reports the results of Diebold and Yilmaz (2009); David et al. (2021) total spillover index and net spillover index as in Eqs. (13) and (16). The pre-COVID-19 period denotes a sub-sample period ending on 30 December 2019. The COVID-19 pandemic is denoted as a sub-sample period spanning 31 December 2019 through 31 March 2021

Table 12 continued

Forecasting horizon: 150 Pre-COVID-19 period				
COVID-19 pandemic				
Total spillover		93.2833		
Net spillovers				
S&P 500	Gold	US Dollar	Bitcoin	Ethereum
−11.2614	−3.8194	−0.9829	0.1508	0.0642
XRP	Bitcoin C	Litecoin	Bitcoin SV	Tether
0.0668	1.0204	0.0035	6.2858	6.5658
Cardano	EOS	Stellar	Tezos	WTI
−1.6537	0.4473	0.2353	6.4292	−3.5517
Forecasting horizon: 200 Pre-COVID-19 period				
Total spillover		90.0018		
Net spillovers				
S&P 500	Gold	US Dollar	Bitcoin	Ethereum
−44.9211	0.6353	1.4865	3.6900	3.0833
XRP	Bitcoin C	Litecoin	Bitcoin SV	Tether
4.2893	1.4276	5.2543	−0.8184	5.3007
Cardano	EOS	Stellar	Tezos	WTI
5.4486	4.7321	4.2438	5.4446	0.7033
COVID-19 pandemic				
Total spillover		93.3691		
Net spillovers				
S&P 500	Gold	US Dollar	Bitcoin	Ethereum
−12.9095	−3.9801	−0.7032	0.3746	0.2850
XRP	Bitcoin C	Litecoin	Bitcoin SV	Tether
0.2922	1.3022	0.2206	6.1750	6.6127
Cardano	EOS	Stellar	Tezos	WTI
−1.6115	0.6707	0.4592	6.4813	−3.6690

This table reports the results of Diebold and Yilmaz (2009); David et al. (2021) total spillover index and net spillover index as in Eqs. (13) and (16). The pre-COVID-19 period denotes a sub-sample period ending on 30 December 2019. The COVID-19 pandemic is denoted as a sub-sample period spanning 31 December 2019 through 31 March 2021

6 Conclusions

This research investigates the periodicity of time variations with regard to the risk aversion of eleven major cryptocurrency markets and four commonly known traditional markets. We compare the time-variation of risk aversion between analysed cryptocurrency and traditional financial markets, along with the connectedness of risk aversion in terms of predictability and spillover index. Moreover, we examine whether and how the international outbreak of the COVID-19 pandemic affects time variations of risk aversion and connectedness of risk aversion. Results indicate that the risk aversion coefficients of all the cryptocurrency markets and most traditional financial markets, including the S&P500, WTI and gold futures, are significantly driven by time. The FFF functions significantly explain the evolution of risk aversion, suggesting that periodicity exists in the moving patterns of risk aversion. This result aligns with the prior studies that support the existence of linear and non-linear time effects on risk aversion concerning traditional risky assets. Further, moving patterns of risk aversion in the cryptocurrency markets differ from those in the traditional markets in two ways. First, the absolute level of mean risk aversion in the cryptocurrency markets is lower than that of the traditional counterparts, while risk aversion in the traditional markets is estimated to be more volatile than that of cryptocurrencies. Besides Bitcoin, each of Ethereum, XRP, Litecoin and Cardano exhibit risk aversion behaviour across time. For the other cryptocurrencies, risk-seeking behaviour occupies a large proportion of the estimation based on time variation. Similar moving patterns of risk aversion are evident between cryptocurrencies and traditional financial assets.

Further, two-way Granger causalities of risk aversion running between Bitcoin and the other cryptocurrencies are identified, along with strong bilateral Granger causalities of risk aversion running between cryptocurrency markets and conventional, traditional financial markets. At the same time, the risk aversion of the four traditional financial markets exhibits dominance in the directional spillover processes against all the other counterparts, presenting evidence that the market possesses a role as an information transmitter. The risk aversion of the S&P500 index has the most influential impact on all others. Concerning one-to-one pairwise spillover processes, the risk aversion of Bitcoin is found to be an information transmitter towards that of most other cryptocurrencies. Risk aversion in the traditional markets exerts critical strength in the connectedness to that in the examined cryptocurrency markets.

Finally, the COVID-19 pandemic significantly affects the risk aversion of all the markets except that of Bitcoin Cash. Specifically, evidence suggests a decrease in the level of risk aversion of most cryptocurrencies except for some large-scale cryptocurrency assets. Investors are found to be more cautious when holding large-scale cryptocurrency assets after the COVID-19 pandemic occurs, while they are more inclined to hold small- and medium-sized cryptocurrencies during the COVID-19 pandemic. The extent to which investors are averse to holding the S&P500 index and WTI oil futures increased during the COVID-19 pandemic. Henceforth, investors prefer to hold cryptocurrencies during the COVID-19 crisis. Besides, the outbreak of COVID-19 impairs the causalities of risk aversion within the cryptocurrency cluster, to which Bitcoin is found to be the core of the network, whereas it imposes relatively small influences on the cross-border predictability of risk aversion running between cryptocurrency cohorts and traditional financial assets. Finally, concerning directional spillover processes, the influence of the traditional financial markets against that of cryptocurrencies has weakened during the COVID-19 crisis. The one-to-one pairwise net spillovers are found to present an impaired role of risk aversion, particularly with regard to

Bitcoin and its connectedness with the other cryptocurrencies after the COVID-19 pandemic occurred.

Further, we discuss the economic implications derived from our main findings. Specifically, it illuminated the dynamics of asset holding as to trading of both cryptocurrency and traditional financial assets. In sum, it is calibrated that cryptocurrency investors take long positions on average towards multiple cryptocurrency assets except for Tezos and Litecoin. Meanwhile, the average investors in the traditional markets take long positions in most of the markets examined in this paper while their mean holdings on gold are close to zero. Moreover, it is revealed that trading on the S&P 500 and the US dollar is more favoured. The trading of XRP, Stellar, EOS, Bitcoin SV and Bitcoin Cash is more popular than the other cryptocurrency counterparts. Lastly, the extent to which the popularity of trading cryptocurrencies varies across time is more substantial than trading traditional financial assets.

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