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Features of different asset types and extreme risk transmission during the COVID-19 crisis

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Abstract

Unlike the current extensive literature, which discusses which assets can avoid the risks caused by the COVID-19 pandemic, this study examines whether the characteristics of different assets affect the extreme risk transmission of the COVID-19 crisis. This study explores the effects of COVID-19 pandemic–related risk factors (i.e., pandemic severity, pandemic regulations and policies, and vaccination-related variables) on the risk of extreme volatility in asset returns across eight assets. These eight assets belong to the following classes: virtual, financial, energy, commodities, and real assets. To consider the different possible aspects of the COVID-19 impact, this study adopts both empirical methods separately, considering variables related to the pandemic as exogenous shocks and endogenous factors. Using these methods, this study enabled a systematic analysis of the relationship between the features of different asset types and the effects of extreme risk transmission during the COVID-19 crisis. The results show that different types of asset markets are affected by different risk factors. Virtual and commodity assets do not exhibit extreme volatility induced by the COVID-19 pandemic. The energy market, including crude oil, is most affected by the negative impact of the severity of the pandemic, which is unfavorable for investment at the beginning of the pandemic. However, after vaccinations and pandemic regulations controlled the spread of infection, the recovery of the energy market made it more conducive to investment. In addition, this study explains the differences between the hedging characteristics of Bitcoin and gold. The findings of this study can help investors choose asset types systematically when faced with different shocks.

Keywords: Covid-19 pandemic, COVID-19 pandemic–related risk factors, Risks of extreme volatility, Risk transmission effect, Hedging characteristics

Introduction

The outbreak of the COVID-19 pandemic (hereafter referred to as "the pandemic") had an enormous impact on the global economy and resulted in steep fluctuations in financial markets. For these reasons, the pandemic is frequently referred to as the COVID-19 crisis (Fu et al. 2021; Al-Omoush et al. 2022) or the black swan event (Ahmad et al.

2021; Aslam et al. 2022).[1] A crisis or extreme event can occur for various reasons, inducing a crash in different asset markets, and causing investors to incur substantial losses. Although a growing body of literature has empirically investigated the various events that cause market crashes, an analysis that "systematically" dissects the impact of black swan events is still required.

Asset markets differ in their properties, trade behavior, and market mechanisms. Consequently, they differ in terms of market depth, width, and efficiency. Sudden market effects, including pandemic-related information pertaining to pandemic severity, pandemic regulations, and vaccination-related variables, can influence lifestyle behaviors and financial performance. However, the speed of transmission and the level of the market effect on each asset market differ depending on market properties. Therefore, some markets may experience a crash while processing the initial pandemic shock, whereas others may not. Only by dismantling the structure of risk transmission can risk spread before the next abnormal event occurs.

First, to analyze the significant possible losses caused by the pandemic, this study focuses on the extreme risks associated with various types of assets. The following three methods are then used to disassemble the impact of the COVID-19 crisis on asset return fluctuations to systematically evaluate why this black swan event exerted different effects on different assets. (1) To explore the characteristics of assets, this study selects the market by asset type (i.e., virtual, financial, energy, commodity, and real assets). (2) To analyze the sources of risk, we selected three types of COVID-19 pandemic–related factors (pandemic severity, pandemic regulations and policies, and vaccination-related variables). (3) To distinguish different impacts, the study discusses both the short-term and long-term impacts caused by the COVID-19 crisis. The former estimates the exogenous effects of the crisis, whereas the latter analyzes the structural changes in the market caused by the crisis. Using these methods, this study seeks to explain the relationship between asset characteristics and risk transmission by "systematically" dissecting the impact of the COVID-19 pandemic.

This study differs from previous studies on hedging practices that discuss whether individual asset markets are vulnerable to the impact of the pandemic. It aims to methodically analyze which COVID-19 risk factors affect the extreme risk of different types of assets. Using this method, we can examine the relationship between the characteristics of assets and risk sources, which will, in turn, will help investors to "pre-hold" assets with low-risk transmission effects when faced with different types of risk surge events in the future. Accordingly, this study investigates how factors related to the pandemic (e.g., pandemic severity, pandemic regulations and policies, and vaccination-related variables) influence extreme risks in virtual, financial, energy, commodity, and real assets. Additionally, this study explores the sources of risk spread and observes whether the characteristics of asset markets contribute to market risk or resilience.

The next section reviews the literature to justify the aim of this study: to systematically dissect the impact of this black swan event (the COVID-19 crisis) by exploring the

[1] Black swan events (Taleb 2007) describe those cases that are surprising given contemporary knowledge. Many studies use the concept to explore certain special performances in financial markets (Higgins 2014; Lin and Tsai 2019; Bhanja and Das 2021) and how to avoid risks when such events occur (Bekiros et al. 2017).

extreme risks of different types of assets affected by various COVID-19-related risk factors. In doing so, this study aimed to provide more explicit evidence of the patterns of risk transmission. Section "Empirical Model" explains the research methodology used in this study and explores the short-(exogenous) and long-term (structural) impacts of the pandemic. Section "Empirical analysis" introduces the five asset types and samples used in this study. Finally, Sect. "Conclusion" draws conclusions, illustrates the study's contributions, and provides recommendations for further studies.

Literature review

Following the outbreak of the pandemic, numerous studies have explored its effects on lifestyle behaviors (Balanzá-Martínez et al. 2020; Bentlage et al. 2020; Pan and Yue 2022; Rafique et al. 2022) and the world economy (Phan and Narayan 2020; Su et al. 2022). Some scholars have analyzed whether the performance of asset markets was influenced by the pandemic (Bouri et al. 2021). Others have examined whether the pandemic has influenced return on assets (ROA) (Ji et al. 2020), asset risks (Baker et al. 2020a), trade behaviors (Huber et al. 2021), and market efficiency (Wang and Wang 2021).

Numerous studies have explored the effect of the pandemic from the perspective of different asset markets (e.g., van Hoang and Syed 2021; Monge and Lazcano 2022). Some studies provide evidence of increased asset risk during the pandemic (Devpura and Narayan 2020; Bourghelle et al. 2021) and the spillover or contagion of negative information between assets under epidemic effects (Corbet et al. 2020; Huynh et al. 2020; Adekoya and Oliyide 2021; Farid et al. 2021). Although, there are studies showing that some assets are more resistant to the impact of the pandemic (López-Cabarcos et al. 2020; Chen et al. 2022; Khan et al. 2022) or some characteristics can make certain types of companies resilient under epidemic conditions (Anzenbacher and Wagner 2020; Cavallo et al. 2021; Al-Omoush et al. 2022),[2] studies comparing the effect of various COVID-19 risk factors on the extreme risks in various types of assets (e.g., virtual and tangible assets) are rare. However, an analysis from this perspective is important. This article reviews the relevant literature to illustrate its importance.

The importance of discussing extreme risks

Many studies on the impact of the pandemic and the risk to asset markets use different methods to observe the risks associated with different asset characteristics. For example, Yarovaya et al. (2021) assert that the black swan effect of the pandemic did not aggravate financial panic in the Bitcoin market. Le et al. (2021) indicate that because the tail distribution of Bitcoin was less associated with that of other assets, Bitcoin can be viewed as a safe haven. Mariana et al. (2021) also point out the short-term safe haven property of Bitcoin. However, Yarovaya et al. (2022) also considered the outbreak of the pandemic as a black swan event and explored the effect of the pandemic on the extreme risks in

[2] For example, the Environmental, Social, and Governance (ESG) stocks of companies with a strong record on social capital, innovation, and sustainability, investors can avoid pandemic risk (Broadstock et al. 2021; Díaz et al. 2021). Heredia et al. (2022) find that those companies with digital transformation can accelerate technological innovation during the pandemic, benefiting firm performance. Al-Omoush et al. (2022) show that companies with high social capital can maintain a high degree of innovation and improve the sustainability of the company's operations during the COVID-19 crisis.

stocks, bonds, gold, and cryptocurrencies, finding that in the long term, the pandemic had a greater effect on the extreme risks in Bitcoin than on other assets.

Most studies examine risks to the stock market during the pandemic. Specifically, scholars have explored the U.S. stock market crash in March 2020 (Dai et al. 2021; Hong et al. 2021; Mazur et al. 2021; Shu et al. 2021) and various major corrections in the Chinese stock market (Liu et al. 2021; Singh et al. 2021). Numerous studies have explored the transmission effect of the financial crisis on stock markets worldwide (Contessi and De Pace 2021; Li 2021; Zehri 2021).

Nevertheless, owing to the lack of integration, it remains unclear what causes certain markets to collapse easily when encountering unexpected events. There are also inconsistencies among the findings of different studies. For example, some studies indicate that market risk has reduced in specific asset markets during the pandemic. Diniz-Maganini et al. (2021) report that during the pandemic, gold and Bitcoin served as safe havens for investors who held instruments related to the Morgan Stanley Capital International (MSCI) World and U.S. dollar indices. However, Nedved and Kristoufek (2022) find that the volatility behaviors of stocks and Bitcoin are highly correlated, implying that a two-asset portfolio cannot be hedged.

To address these gaps in the literature, this study focuses on changes in extreme risk during the pandemic. "Extreme" risk refers to the risk exposure of assets in more extreme situations in probability allocation, that is, the tail (in the probability distribution) risk of asset returns. Some studies separately illustrate the high-extreme risk of different assets, that is, the existence of the fat tail phenomenon. Kwon (2020) reported the presence of the fat tail phenomenon in the Bitcoin, currency, gold, and stock indices. They discuss the correlation between the tail risks of various assets. Their results indicate that extreme risks in these assets increase when markets are affected by external factors. Le et al. (2021) examine the tail risks of 51 financial assets and discuss the correlations between the risks in these assets. Their results revealed that the COVID-19 pandemic considerably increased the left-tail correlation of ROA, thereby increasing the risk of a market crash.

Through the decomposition of the tail behaviors of assets, this study explores the influence of the pandemic on extreme volatility risks in various markets to identify asset markets that are more vulnerable to market crises. Due to the unprecedented severity and duration of the pandemic, studies have reported that it has induced public anxiety (Awijen et al. 2022; Wang and Liu 2022). This anxiety influences trade behavior, resulting in complex and irrational market fluctuations (Chang et al. 2020; Gao et al. 2022a, b) and unpredictable market effects. In turn, these may further exacerbate individual anxiety (Li et al. 2022) and prompt excessive selling of assets, ultimately resulting in the pandemic crisis causing a market crash or market crisis. Therefore, this study focuses on how extreme risks have been affected by the pandemic.

The importance of distinguishing asset types to explore the relationship between risk transmission and asset characteristics

Asset markets are susceptible to various influencing factors and risk sources. This study selects five types of assets for comparison: virtual, financial, energy, commodities, and real assets. Specifically, it uses Bitcoin and the Crypto Currencies Index (CCI) to represent virtual assets, the MSCI World Stock Price Index (WSPI) to represent financial assets, the West Texas Intermediate (WTI) and MSCI World Energy Price Index (WEPI) to represent energy assets, gold prices and the Standard & Poor's (S&P) 'Goldman Sachs Commodity Index' (GSCI) commodity price index to represent commodity assets, and real estate (the FTSE NAREIT All REITs) to represent real assets. These five types of assets were included because studies have examined the impact of the pandemic on each asset type. For example, Albulescu (2020) and Dutta et al. (2020) discuss crude oil price crashes. Conlon and McGee (2020) explore the risks of a stock market crash caused by the pandemic and the risk of a decrease in Bitcoin prices. The literature also discusses whether gold (Akhtaruzzaman et al. 2021) and real estate investment trusts (REITs) (Akinsomi 2021) are resistant to the pandemic.

In the aforementioned studies, various risk evaluation methods were employed to analyze the effect of the pandemic on extreme risks in asset markets; thus, the results of these studies may be inconsistent. Additionally, the properties of different asset markets and the concerns of each market regarding pandemic-related events further complicate the assessment of the pandemic's effect. Therefore, understanding and constructing investment portfolios may become difficult for investors, and evaluating the possibility of market crashes may become difficult for market regulators. The present study proposes the use of empirical evidence based on event and asset types to systematically determine the effect of the pandemic on extreme risks in various assets. To explore the effect of pandemic-related risk factors (i.e., pandemic severity, pandemic regulations, and vaccination-related variables), this study represents the properties of virtual, financial, energy, commodity, and real assets by analyzing the returns across eight assets.

The importance of exploring different sources of risk

The five types of assets studied herein range from virtual to real, and their characteristics and trading methods differ. It is necessary to systematically evaluate extreme risk behaviors in the face of external shocks; that is, to explore behaviors under different sources of risk. Information related to the development of the pandemic can be categorized into pandemic severity, pandemic regulations, and vaccination-related information.

The negative shock of the pandemic mainly comes from the severity of the pandemic and policies that restrict economic activity. Most studies have examined how the stock market has been affected by the rise in COVID-19 cases and lockdown policies. Baig et al. (2021) observed the effect of pandemic severity and lockdown implementation on the U.S. stock market and reported that an increase in the number of confirmed cases and deaths increased stock market volatility and that pandemic severity and lockdowns contributed to a reduction in market liquidity. Aggarwal et al. (2021) explored the factors that caused the global stock market crash during the pandemic and indicated that the fear of the pandemic and strict lockdown policies increased stock market risk, thereby increasing the risk premiums of assets. Gao et al. (2022a, b) compared changes in the volatility of the Chinese and U.S. stock markets and argued that different pandemic regulatory models result in different stock market reactions. The Chinese stock market was more readily influenced by pandemic-related factors and experienced an increase in volatility, whereas fluctuations in the U.S. stock market were effectively suppressed by monetary easing and low-interest policies introduced by the U.S. government. Based on the above research, this study also explores the impact of the number of confirmed cases and deaths and the strictness of regulatory policies on the market.

Studies have also employed uncertain policies as indicators to evaluate policy risks during pandemics. Wang et al. (2020) compared the effectiveness of the CBOE Volatility Index and the Economic Policy Uncertainty (EPU) index in predicting the volatility of stock indicators. Their study revealed that the EPU index effectively predicted the volatility of five of the 19 stock markets observed in their study. Jiang et al. (2021) explored the relationship between the EPU index proposed by Baker et al. (2020a) and the volatility of cryptocurrencies, and they discovered that cryptocurrencies can serve as safe havens for investors who want to offset the risks caused by pandemic policy changes. This study uses the EPU index to assess policy risks.

Studies indicate that information pertaining to changes caused by the pandemic has an asymmetrical influence. Baek and Lee (2021) explored the transfer of risk from the pandemic to the U.S. stock market. They reported that the volatility of the U.S. stock market increased with the number of deaths (negative pandemic-related news). Conversely, an increase in the recovery rate from the disease (positive pandemic-related news) reduced market volatility. In the U.S. stock market, negative news has a considerably greater influence than positive news. The research, development, launch, and administration of a vaccine increased people's hopes of ending the pandemic. Developments such as these are among the limited range of positive pandemic-related news reported during the pandemic. However, the effect of vaccines on asset market volatility requires further investigation. Chan et al. (2022) revealed that when the clinical testing of a COVID-19 vaccine was initiated, the global stock market exhibited a positive response, indicating that the stock market reacted positively to vaccines developed by China and the United States. Rouatbi et al. (2021) explored the effect of COVID-19 vaccination on global stock market volatility and reported that an increase in vaccination popularity reduced stock market volatility. Furthermore, the stabilization effect of vaccination popularity was greater in stock markets in developed economies compared to emerging economies. Therefore, this study also evaluates vaccine-related variables to observe whether the markets were affected differently by positive and negative pandemic shocks.

In summary, the aforementioned literature findings indicate that the three pandemic-related risk factors (pandemic severity, pandemic regulations, and vaccination-related variables) have different effects. Therefore, the objective of the present study is to estimate the empirical outcomes caused by the effects of each risk factor.

The importance of simultaneously exploring exogenous shocks and structural changes

Both exogenous shocks and structural changes must be observed to fully describe the impact of an abnormal financial event on a given asset. The first observation is the immediate and exogenous impact of the event on the asset (Albuquerque et al. 2020), whereas the second analyzes the extent to which the behavior of the asset undergoes structural changes after the event (Kumar et al. 2022). This study uses two approaches to estimate the impact of pandemic-related risk variables on the extreme volatility risk of an asset: exogenous shocks and endogenous factors. The first involves a univariate volatility estimation model to estimate the impact of risk factors as exogenous shocks by adding the shocks to the heterogeneous variance (volatility risk) models of asset returns, and then to evaluate extreme risks in assets (i.e., the fat-tail distribution of asset returns). The second uses a bivariate volatility estimation model, taking risk factors as endogenous variables and estimating the risk transmission effect between asset returns and the pandemic-related variables. Through these two methods of analysis, the empirical results of the present study analyze the effect of the pandemic on extreme risks in various assets and explore the sources of risk transmission.

Two methods were applied to estimate how a pandemic-related risk variable can affect an asset's extreme volatility risk. Both methods use a Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-type model, separately adding the pandemic-related variables to the model in the form of exogenous shocks (univariate GARCH-type model) and endogenous factors (multivariate GARCH-type model) to estimate the risk of assets. Based on the univariate and multivariate models introduced, this study analyzes the effect of the pandemic on extreme risks in various markets. It also explores the sources of risk transmission and identifies markets through which the risk of each pandemic-related factor is transmitted.

GARCH-type models have been widely used to analyze the risk behavior of various assets such as virtual assets (Ardia et al. 2019; Tiwari et al. 2019), financial assets (Liu and Chen 2020; Kim 2022), energy assets (Bai and Lam 2019; Robiyanto et al. 2020), commodity assets (Nargunam et al. 2021; Wang et al. 2022), and real assets (Piao et al. 2022). GARCH-type models are particularly appropriate for estimating the fat-tailed probability distributions of asset returns (Fakhfekh et al. 2021; Yong et al. 2021). From the estimation results produced by this type of model, we obtain a complete structural function of asset volatility behavior, which can be used to describe the overall return volatility risk. By further observing the tail structure in this function, we can gain insight into the return fluctuation behavior in extreme cases.

Although a substantial body of literature is using the GARCH empirical method to explore the impact of the outbreak of the COVID-19 pandemic on asset risk (Fakhfekh et al. 2021; Hung et al. 2022), most studies do not distinguish between different risk factors. By estimating the two types of models in this study, investors can obtain insight into which markets are more vulnerable to risks caused by the pandemic crisis (results of the exogenous model) and identify the markets to which pandemic-related events may transmit their risks (results of the endogenous model).

Differences in the characteristics of different types of assets and their possible impact on the shocks caused by the pandemic

To systematically analyze the effect of the pandemic on extreme risks in asset markets, we select specific assets that represent virtual, financial, energy, commodity, and real assets to explore the effects of pandemic severity, pandemic regulations and policies, and vaccination-related variables. We detail the differences in the properties of the five asset markets to determine how they influence market reactions to the pandemic.

(1) Virtual assets

This study uses Bitcoin and the Crypto Currencies Index (CCI) to represent virtual assets. Many studies state that Bitcoin is a new asset class. For example, Ram (2019) reported that Bitcoin is the most representative cryptocurrency and has the largest market share in the cryptocurrency market. Although scholars have not yet reached a consensus on the properties of Bitcoin, most consider it a new type of asset that is distinct from financial assets and general commodities. Al Mamun et al. (2020) pointed out that Bitcoin is particularly sensitive to geopolitical risk. Additionally, Kwon (2021) found that the extreme risk of Bitcoin is affected by the uncertainty of US economic policy. Notably, the total Bitcoin supply is limited (Zohar 2015). In a market climate that is quantitatively inflated by monetary easing policies, the rarity of Bitcoin is a frequently discussed topic that contributes to an increase in its value (Choi and Shin 2022).

At the beginning of the pandemic, several countries implemented monetary easing policies to induce quantitative inflation. In particular, the United States introduced unlimited monetary easing policies, which increased public concern over the price of fiat currency and increased the demand for Bitcoin. Marmora (2022) indicated that the promulgation of national currency policies increased Bitcoin demand and influenced the local trading of Bitcoin. In addition to Bitcoin, other cryptocurrencies may be considered safe haven assets. Yousaf and Ali (2020) used three cryptocurrencies–Bitcoin, Ethereum, and Litecoin–to show that they are more suited to hedging during the pandemic. Therefore, in addition to using Bitcoin, this study also discusses the CCI to analyze the risk characteristics of cryptocurrencies.

Given the uniqueness of cryptocurrency (Martínez et al. 2022), several studies show that it can be used to hedge the risks of other assets (Dyhrberg 2016; Fang et al. 2022). However, Özdemir (2022) investigated the risk transmission of eight major cryptocurrencies during the pandemic and found that Bitcoin, Ethereum, and Litecoin are covolatile, and almost all cryptocurrencies studied in the research had higher downside risks than stocks. Shahzad et al. (2021) studied 18 cryptocurrencies and found that their volatility increased after the COVID-19 outbreak.

However, Bitcoin is not a national currency and can be traded pseudonymously and used in illegal transaction activities. Thus, the investment risks associated with this asset are higher than those of other assets (Wong 2019). Bitcoin prices are often volatile (Katsiampa 2017), and Koutmos (2020) finds that these fluctuations exhibit low correlations with macroeconomic fundamentals. Other studies posit that Bitcoin prices have price discovery functions (Brandvold et al. 2015 and Bouoiyour et al. 2016). On the basis of these properties, the response time of Bitcoin to information during the pandemic was faster than that of the market, particularly when the information pertained to currency policies aimed at inducing monetary easing and stimulating the market. However, the risks resulting from a pandemic-induced economic slump may not necessarily spread to the Bitcoin market.

(2) Financial markets

This study uses the stock market (MSCI WSPI) to represent financial assets. Stocks are the most typical risky financial assets. Since the outbreak of the pandemic, there has been much research on its impact on stock market risk, many of which are based on the MSCI WSPI as the research target (O'Donnell et al. 2021) or the use of the MSCI WSPI as a representative stock market classification to explore the relationship between the stock market and other assets (Bouri et al. 2021; Naeem et al. 2021).

The literature on market structure (Madhavan 2000; O'Hara 2015) reports that transaction regulations and limitations, transaction structure, trader structure, trader emotions, irrational trader behaviors, and trading timing and patterns of the stock market can influence market returns, volatility, and efficiency. Various market properties can increase the market's vulnerability to crashes. Hong et al. (2021) provides evidence indicating that the decrease in market efficiency during the pandemic caused the U.S. stock market crash. This created an asymmetric profit opportunity for traders with access to information on pandemic severity and policies (e.g., U.S. Senate Committee members) and for opportunists, owing to information asymmetry.

Liu et al. (2020) indicate that the pandemic has substantially influenced the global stock market. Ashraf (2020, 2021) proposed that the timing of stock market crashes is determined by the stage of the pandemic outbreak. Gil-Alana and Claudio-Quiroga (2020) reported that the pandemic's negative effect on the stock market differs depending on market properties. In an empirical study, Huber et al. (2021) explored the March 2020 stock market crash caused by the pandemic and asserted that extreme events that occurred during the pandemic increased market risks. This finding is consistent with that of Ashraf (2020, 2021), who reports that countries with a higher degree of risk aversion experience more severe market crashes. Fernandez-Perez et al. (2021) explore how national culture influences stock traders' responses to financial crises and reveal that countries where traders exhibit less individualism and greater fear of uncertainty are more likely to experience stock market crashes. Additionally, the literature indicates that fear of trading can explain the stock market crisis caused by the pandemic (Lyócsa et al. 2020; Lyócsa and Molnár, 2020; Vasileiou 2021).

Based on the aforementioned findings, this study infers that the level of public aversion to risk and uncertainty and the spread of fear increase extreme risks in the stock market. During the pandemic, low stock market efficiency further increases the risk of market crashes. The uncertainty of pandemic-related information or policies transmits risk to the stock market. However, several types of information, such as vaccination popularity, can stabilize the market and reduce the extreme risks generated by stock market volatility.

(3) Energy markets

This study uses the price of crude oil and the World Energy Price Index to discuss energy assets' risk. Salisu and Obiora (2021) examined the risk of crude oil investment during the pandemic. They found that when assets are distinguished by energy and non-energy asset characteristics, assets that can act as a hedge against crude oil prices can be identified (e.g., nonenergy exchange-traded funds). Therefore, we distinguish crude oil from the general commodity market. In recent years, in response to climate change, governments in many countries have adopted energy-saving and carbon-reduction policies, which have attracted research interest regarding the characteristics of non-renewable energy (Marinakis and White 2022), as well as relationships between energy prices and other assets (Elsayed et al. 2020).

Sheth et al. (2022) discussed the effect of the pandemic on commodity markets (including oil, energy, and agricultural products) and revealed that the sudden occurrence of the pandemic resulted in a considerable decrease in commodity demand. Their study also reported that different markets reacted differently. For example, during the pandemic, the demand for gold reached a new high, whereas the demand for oil hit a new low. Furthermore, pandemic-related factors and lockdown restrictions may substantially reduce product demand, prompting price drops. This phenomenon affected oil prices the most during the start of the pandemic. Albulescu (2020) reported that pandemic-induced fear and uncertainty resulted in a 20% single-day decrease in crude oil prices and crashed the crude oil market.

(4) Commodity markets

We use gold prices and a commodity price index (S&P GSCI) to represent commodity assets. Salisu et al. (2020) revealed that during the pandemic, a global fear index (GFI) could be used to predict commodity market returns. The GFI has a negative impact on the commodity market but is positively correlated with the stock market, thereby creating different hedging attributes between the stock and commodity markets.

The trading of ordinary goods is influenced by the supply and demand of these assets. In contrast to the trading prices and volumes of virtual and financial assets, those of the commodity market are determined by factors that influence the production and consumption of commodities (e.g., climate, import and export tariffs, and consumer preference). Domanski and Heath (2007) posit that the trading volume of derivative goods is growing rapidly, particularly that of precious metals. Between 2002 and 2005, the trading volume of precious metals increased by 30 times, resulting in increased investor engagement in the commodities market. Holmes (2006) asserts that the increase in commodity prices in 2006 was caused by an increase in the diversity of financial investors and the investment strategies applied in commodity markets. This trend resulted in the sudden emergence of exogenous impact factors and changes in the properties of stable commodity markets that financialized commodities.

Gold is regarded as a safe haven (Baur and Lucey 2010; Baur and McDermott 2010). Throughout history, when events detrimental to the market occur (e.g., wars or natural disasters), the demand for gold has increased. During the pandemic, the advantage of gold as a safe haven asset has increased. Dutta et al. (2020) explored the relationship between the pandemic and crude oil market crash and proposed investing in gold instead of Bitcoin to offset the losses caused by the crude oil market crash. In addition to gold, this study uses an aggregated commodity price index (S&P GSCI) to explore the risk characteristics of other commodities, with reference to the literature (Kinateder et al. 2021). Some studies also indicate that the S&P GSCI has a fairly good hedging effect (Al-Yahyaee et al. 2019).

(5) Real asset

Real assets are another asset category that has been less explored in the research on extreme risks. The most common real asset is real estate. However, because the data frequency of real estate is relatively low, daily data cannot be obtained, and its primary use is for consumption rather than investment hedging. Therefore, existing studies tend to use real estate investment trust funds as proxies for real estate assets for investment purposes. Most of these studies use REIT data provided by NAREIT (Case et al. 2012; Doran et al. 2012).[3] Based on these studies, for this type of asset, this paper also uses the FTSE NAREIT All REITs.

Real estate is commonly viewed as an asset with low risk of price fluctuations. This is because the general housing market does not involve derivatives trading, which is common in other asset markets. Therefore, studies that explore the effect of the pandemic on the housing market have mostly focused on observing changes in housing behaviors, such as the increase in demand associated with the movement of people from city centers to the suburbs (Ramani and Bloom 2021). Given this trait, real estate may have been the least affected by the pandemic. However, the financialization of real estate has changed drastically (Sternik and Safronova 2021). Blakeley (2021) mentions that the impact of COVID-19 may accelerate the financialization of real estate. Meanwhile, van Loon and Aalbers (2017) proposed that real estate should be regarded as a special asset classification and that more research should be conducted to explore it.

Previous studies observed the effect of the pandemic on the real estate market by examining real estate–related financial assets (e.g., real estate investment trusts) as a substitute variable and analyzing their performance (Akinsomi 2021; Balemi et al. 2021; Periola-Fatunsin et al. 2021; Chong and Phillips 2022). Akinsomi (2021) reveals that the REITs related to accommodations and resorts, retail spaces, and office spaces were the most severely affected assets. This finding reflects how the pandemic changed traveling and work-from-home behaviors. Chong and Phillips (2022) estimated the effect of the pandemic on commercial real estate prices in the United States and found that government-imposed lockdowns and regulatory measures accelerated the decrease in real estate prices caused by the pandemic.

The aforementioned literature findings indicate that the basic influencing factors of the market determine whether the effect of the pandemic on different assets results in a market crash. If an asset is highly connected to the real economy, the risk of the corresponding market, which reflects the pandemic's economic effects, increases. The connectivity between financial assets can also influence changes in risk caused by the pandemic. For example, gold is generally regarded as a safe haven asset relative to other financial assets. During a stock market crash, an increase in the demand for safe haven assets benefits the gold market and helps stabilize it. Contrastingly, because REITs have the properties of a security, they are subject to high risks when the stock market is volatile.

[3] NAREIT is an organization that promotes the development of the REITs market in the United States.

Empirical model

This study explores how pandemic-related risk factors affect different types of assets and the changes that occur in terms of extreme volatility risk. We use two methods to estimate the impact of a pandemic-related risk variable on the extreme volatility risk of an asset.

The first approach is to use the GARCH model, with the inclusion of a pandemic risk factor of exogenous shocks, to estimate the volatility risk of asset returns (general fluctuations). We then perform Value at Risk (VaR) analysis to observe the returns' tail behaviors and evaluate the extreme risks in assets. The second approach involves a Vector Autoregressive (VAR)-Multivariate GARCH (MGARCH) model, taking risk factors as endogenous variables, and then estimating the risk transmission effect between asset returns and the pandemic-related variables. The detailed descriptions of the two methods are as follows across the two subsections.

Impact of the pandemic risk: The GARCH-X model estimation and VaR analysis

Numerous studies have proposed that when a black swan event such as the pandemic occurs, asset returns exhibit a fat-tail distribution. In other words, the possibility of extreme asset returns is higher when a black swan event occurs. These studies primarily use the GARCH model to estimate the volatility of asset returns (Fakhfekh et al. 2021; Yong et al. 2021). Ekinci (2021) reports that the daily growth rate of newly confirmed cases conforms to the properties of the GARCH model.

To analyze the effect of the pandemic on the volatility of asset returns, pandemic-related risk factors are considered exogenous events and their effects on changes in volatility are estimated using the GARCH-X model (Han 2015).[4] The GARCH X model is a univariate GARCH-type model. In the model, Δy_t is the return on asset price for the t th order, and the error term is $\varepsilon_t \sim N\left(0, \sigma_t^2\right)$. σ_t^2 is the conditional volatility. We express the GARCH(p, q) model as:

$$\Delta y_t = \mu + \varepsilon_t \tag{1}$$

$$\sigma_t^2 = c + \sum_i^p a_i \varepsilon_{t-i}^2 + \sum_i^q \beta_i \sigma_{t-i}^2 \tag{2}$$

This study adopts the Schwarz information criterion to determine the lag order. Subsequently, the pandemic-related risk variables were input into Eq. (2), and the GARCH-X model is employed for estimations:

$$\sigma_t^2 = c + \sum_i^p a_i \varepsilon_{t-i}^2 + \sum_i^q \beta_i \sigma_{t-i}^2 + \gamma \Delta x_{t-1} \tag{3}$$

Δx_t represents the rate of change of risk factors, which includes proxy variables related to pandemic severity (total infected cases [TC] and total deaths [TD]); proxy variables related to pandemic regulations and policy risks (stringency index [SI] and EPU); and vaccination-related variables (total number of vaccines [TV] and population vaccinated

[4] X represents exogenous variables.

$[PV]$). On the basis of the estimation results for coefficient γ, the role of the aforementioned risk factors in increasing the volatility of asset returns can be clarified.

After estimating the impact of risk factors on the volatility of returns, the volatility obtained by the GARCH-X model is used to calculate VaR. VaR is commonly used to evaluate extreme risks in a market. For example, Emenogu et al. (2020) used nine GARCH model estimates to verify the superiority of such models in estimating tail risk and to illustrate the importance of assessing VaR to represent extreme risk.

The VaR method evaluates the maximum loss in asset returns for a given confidence level and a given time period. Statistically, VaR quantifies the left tail of a return distribution:

$$Prob\left(\Delta y_{T+k} > VaR_{T+k}|\Phi_T\right) = 1 - m \tag{4}$$

where x_{T+k} represents the asset return at time point $T+k$ and Φ_T represents the information set at time point T, for the confidence level of $1-m$, VaR_{T+k} represents the maximum loss for the asset during the k th order.

According to Eq. (3), we can obtain the volatility of asset returns ($\widehat{\sigma_t^2}$) estimated by the GARCH-X model, including pandemic-related factors. From this, VaR can be computed:

$$\widehat{VaR}_{T+k} = \widehat{\mu}_T - z_{1-p}\widehat{\sigma}_T \tag{5}$$

Pandemic risk factors endogenously affect asset return volatility risk: The VAR-MGARCH model

In the second method, a VAR-MGARCH model is used to evaluate the relationships between pandemic-related risk factors with mean asset returns and volatility. The VAR-MGARCH model is a multivariate GARCH-type model. The model employs pandemic-related risk factors as endogenous variables. We estimate their relationship with asset returns and volatility. This model is suitable for estimating the transmission of volatility, and can perform a rigorous assessment to determine whether the relationship between two variables is a result of mean values or volatility (Lucheroni et al. 2019; Okorie and Lin 2020).

The VAR-MGARCH model employs two equations to obtain estimations. The first equation used to calculate the conditional mean, is as follows:

$$\begin{bmatrix} \Delta y_t \\ \Delta x_t \end{bmatrix} = \begin{bmatrix} \phi_{y,t} \\ \phi_{x,t} \end{bmatrix} + \begin{bmatrix} \sum_{i=1}^{n} \psi_{11,i}\Delta y_{t-i} \\ \sum_{i=1}^{n} \psi_{12,i}\Delta y_{t-i} \end{bmatrix} + \begin{bmatrix} \sum_{i=1}^{n} \psi_{21,i}\Delta x_{t-i} \\ \sum_{i=1}^{n} \psi_{22,i}\Delta x_{t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{y,t} \\ \varepsilon_{x,t} \end{bmatrix} \tag{6}$$

and H_t is the conditional volatility, that is:

$$H_t = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' e_{t-1}e_{t-1'} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \tag{7}$$

$$\varepsilon_t \Big| \Omega_{t-1} = \begin{bmatrix} \varepsilon_{y,t} \\ \varepsilon_{x,t} \end{bmatrix} \Bigg| \Omega_{t-1} \sim N(0, H_t) \tag{8}$$

Equation (6) determines how the risk factors influence asset returns. Equation (7) determines how risk factors influence asset volatility. An advantage of this model is that it can simultaneously estimate the return and volatility of multiple variables, thereby facilitating a rigorous analysis of the transmission effect of pandemic risk. Hence, this study uses the VAR-MGARCH model to explore the transmission of return and risk (Balcilar et al. 2018; Funke et al. 2022). Specifically, we examine the effects of volatility to assess and quantify the influence of each risk factor on asset volatility. Based on these estimations, this study depicts how each pandemic-related risk factor transmits risk to asset volatility.

Empirical analysis

Data

Data on the eight assets used in this study include the prices of Bitcoin, the CCI, the MSCI $WSPI$, the WTI, the MSCI $WEPI$, gold prices, the S&P $GSCI$, and the NAREIT $REITs$. This study uses data from the earliest point at which the daily data of all assets can be obtained for analysis of longer-term asset return behavior. The sample period spans from January 1, 2015, to October 31, 2022. Returns are calculated based on the price or index of the assets. All asset prices and index data were sourced from the Datastream database.

Six pandemic-related factors are examined as risk factors. The selection of variables is based on studies that examine pandemic-related events, which use variables of three primary types: pandemic severity (Al-Awadhi et al. 2020; Ashraf 2020), pandemic policy–related factors (e.g., lockdowns and policy changes; Baker et al. 2020b; Scherf et al. 2022), and information related to the development, launch, and administration of vaccines (Awijen et al. al., 2022; Chan et al. 2022). Hence, the risk factors include total infected cases (TC) and total deaths (TD), both of which are proxy variables for pandemic severity, and the total number of vaccines (TV) and the population vaccinated (PV), both of which are vaccination-related variables. These data were obtained from the WHO Coronavirus (COVID-19) Dashboard.[5] Finally, the variables representing pandemic regulations and policies comprise the *SI* and the *EPU* index proposed by Baker et al. (2016). Data pertaining to the *SI* are obtained from the Oxford COVID-19 Government Response Tracker: Stringency Index provided by the Blavatnik School of Government.[6] Data pertaining to the *EPU* index were obtained from the website.[7] Variables related to the pandemic are only available since the first confirmed COVID-19 case (January 22, 2020). Hence, for each risk factor, this study examined data for the period of January 22, 2020, to October 31, 2022.

Panels A and B of Table 1 separately list the basic statistics and data characteristics of the return rates for the eight assets and the rate of change of the influencing factors. Figure 1 depicts the time series of asset prices and indices. Figure 2 plots the rate of change of the influencing factors. Table 1 reveals that among the various examined assets, the two assets with the lowest returns are energy prices and the *REITs*. Cryptocurrencies,

[5] https://covid19.who.int/.

[6] For measuring the government policies of strict response, The Oxford Coronavirus Government Response Tracker (OxCGRT) project develops a Stringency Index, which is the average of nine criteria with values ranging from 0 to 100. A higher score suggests a more rigid reaction.

[7] https://www.policyuncertainty.com/us_monthly.html.

Table 1 Basic statistics and data characteristics of variables

Panel A	**Δ*CCI***	**Δ*BTC***	**Δ*WSPI***	**Δ*WTI***
Mean	0.0021	0.0020	0.0002	0.0004
Std. Dev	0.0501	0.0459	0.0099	0.0302
Skewness	− 1.1747	− 0.8621	0.8892	− 1.6540
Kurtosis	8.6066	10.9357	17.9096	52.3753
J-B	**6772.0240**	**10,428.0278**	**27,784.3584**	**234,329.0509**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Q (10)	**23.6639**	12.1512	**152.1985**	**53.7822**
	(0.0085)	(0.2751)	(0.0000)	(0.0000)
Q (20)	**52.3488**	23.1405	**188.6810**	**92.7014**
	(0.0001)	(0.2819)	(0.0000)	(0.0000)
Q^2 (10)	**88.3041**	**69.7991**	**2067.8906**	**278.1154**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Q^2 (20)	**99.5996**	**76.9885**	**2398.2340**	**325.8721**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ADF test	**− 45.9506**	**− 45.9945**	**− 13.7079**	**− 38.4509**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	Δ*WEPI*	**Δ*Gold***	**Δ*GSCI***	**Δ*REITs***
Mean	0.00001	0.0002	0.0004	0.00002
Std. Dev	0.0173	0.0086	0.0143	0.0132
Skewness	− 1.2254	− 0.3059	− 0.8246	− 2.1165
Kurtosis	22.4935	3.4374	8.9553	32.7819
J-B	**43,559.5416**	**1037.1526**	**7054.8323**	**92,959.3348**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Q (10)	**63.9861**	17.2184	12.2415	**121.3499**
	(0.0000)	(0.0697)	(0.2692)	(0.0000)
Q (20)	**91.6591**	26.3366	**32.2669**	**161.9908**
	(0.0000)	(0.1550)	(0.0405)	(0.0000)
Q^2 (10)	**977.2221**	**143.5666**	**454.1760**	**1387.6544**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Q^2 (20)	**1246.2855**	**203.8627**	**590.4677**	**1677.4876**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ADF test	**− 15.1916**	**− 44.1859**	**− 42.9641**	**− 23.4343**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Panel B	**Δ*TC***	**Δ*TD***	**Δ*SI***
Mean	0.0090	0.0059	0.0008
Std. Dev	0.0591	0.0398	0.0291
Skewness	12.1704	11.4631	14.1001
Kurtosis	176.6471	156.4033	330.5337
J-B	**2,705,367.1937**	**2,126,028.3888**	**9,363,230.6341**
	(0.0000)	(0.0000)	(0.0000)
Q (10)	**5151.3550**	**10,406.3250**	**657.3298**
	(0.0000)	(0.0000)	(0.0000)
Q (20)	**6697.3017**	**13,780.3230**	**672.1648**
	(0.0000)	(0.0000)	(0.0000)
Q^2 (10)	**1284.5730**	**3789.1230**	**684.3104**
	(0.0000)	(0.0000)	(0.0000)
Q^2 (20)	**1524.7820**	**4311.9470**	**687.0451**
	(0.0000)	(0.0000)	(0.0000)

Table 1 (continued)

Panel B	ΔTC	ΔTD	ΔSI
ADF test	**− 4.4774**	**− 13.6300**	**− 10.7406**
	(0.0002)	(0.0000)	(0.0000)
	ΔEPU	ΔTV	ΔPV
Mean	0.0001	0.0047	0.0043
Std. Dev	0.4924	0.0394	0.0407
Skewness	0.2176	17.3263	18.1483
Kurtosis	1.5258	350.2036	377.4784
J-B	**214.1810**	**10,537,003.9131**	**12,235,608.7513**
	(0.0000)	(0.0000)	(0.0000)
Q (10)	**372.4214**	**4046.8167**	**3741.1373**
	(0.0000)	(0.0000)	(0.0000)
Q (20)	**400.9224**	**4816.8866**	**4251.5144**
	(0.0000)	(0.0000)	(0.0000)
Q^2 (10)	**128.9736**	**1894.7896**	**1817.6908**
	(0.0000)	(0.0000)	(0.0000)
Q^2 (20)	**133.2240**	**1903.0918**	**1821.2716**
	(0.0000)	(0.0000)	(0.0000)
ADF test	**− 23.2077**	**− 7.8875**	**− 6.5698**
	(0.0000)	(0.0000)	(0.0000)

Panel A: This table shows the statistics, independence tests, and unit root tests of the variables. ΔCCI, ΔBTC, $\Delta WSPI$, ΔWTI, $\Delta WEPI$, $\Delta Gold$, $\Delta GSCI$, and $\Delta REITs$ respectively denote the return of cryptocurrency index, Bitcoin price, MSCI World Stock Price Index, WTI crude oil spot price, MSCI World Energy Price Index, gold spot price, S&P Goldman Sachs Commodity Index, and FTSE NAREIT All REITs index. The normality test statistics J-B stands for Jarque–Bera with null hypothesis. Q (n) is the Ljung-Box Q statistic for testing autocorrelation with null hypothesis. Q^2 (n) is the McLeod-Li Q^2 statistic for testing non-linearity with null hypothesis. Number in parentheses is *p*-value. Number in bold stands for significance at 5%

Panel B: This table shows the statistics, independence tests, and unit root tests of the risk variables. ΔTC, ΔTD, ΔSI, ΔEPU, ΔTV, and ΔPV respectively denote the return of total infected cases, total deaths, stringency index, Economic Policy Uncertainty, total number of vaccines, and population vaccinated. The normality test statistics J-B stands for Jarque–Bera with null hypothesis. Q (n) is the Ljung-Box Q statistic for testing autocorrelation with null hypothesis. Q^2 (n) is the McLeod-Li Q^2 statistic for testing non-linearity with null hypothesis. Number in parentheses is *p*-value. Number in bold stands for significance at 5%

including Bitcoin and the CCI, exhibit the highest mean return. Figure 1 uses a vertical line to represent the timeline of the pandemic, and it reveals that the prices of cryptocurrency and gold did not decrease considerably during the pandemic but increased exponentially in 2020. In comparison, the prices of other assets decreased significantly during the pandemic. Although they underwent varying degrees of correction and exhibited varying market recovery speeds, the prices of almost all five assets exceeded their pre-pandemic prices in 2021. Overall, the recovery in the energy market was slower. The price trends of the eight assets differ in terms of pattern. Relative to their pre-pandemic price trends, the price trends of the eight assets from 2020 to 2022 exhibited high volatility.

Empirical result

The unit root test results in Table 1 indicate that all asset returns and changes in the influencing factors are stationary and can be used to perform empirical model estimations. The data properties presented in Table 1 reveal that asset returns do not follow a normal distribution but instead exhibit self-correlation. Based on the estimation results

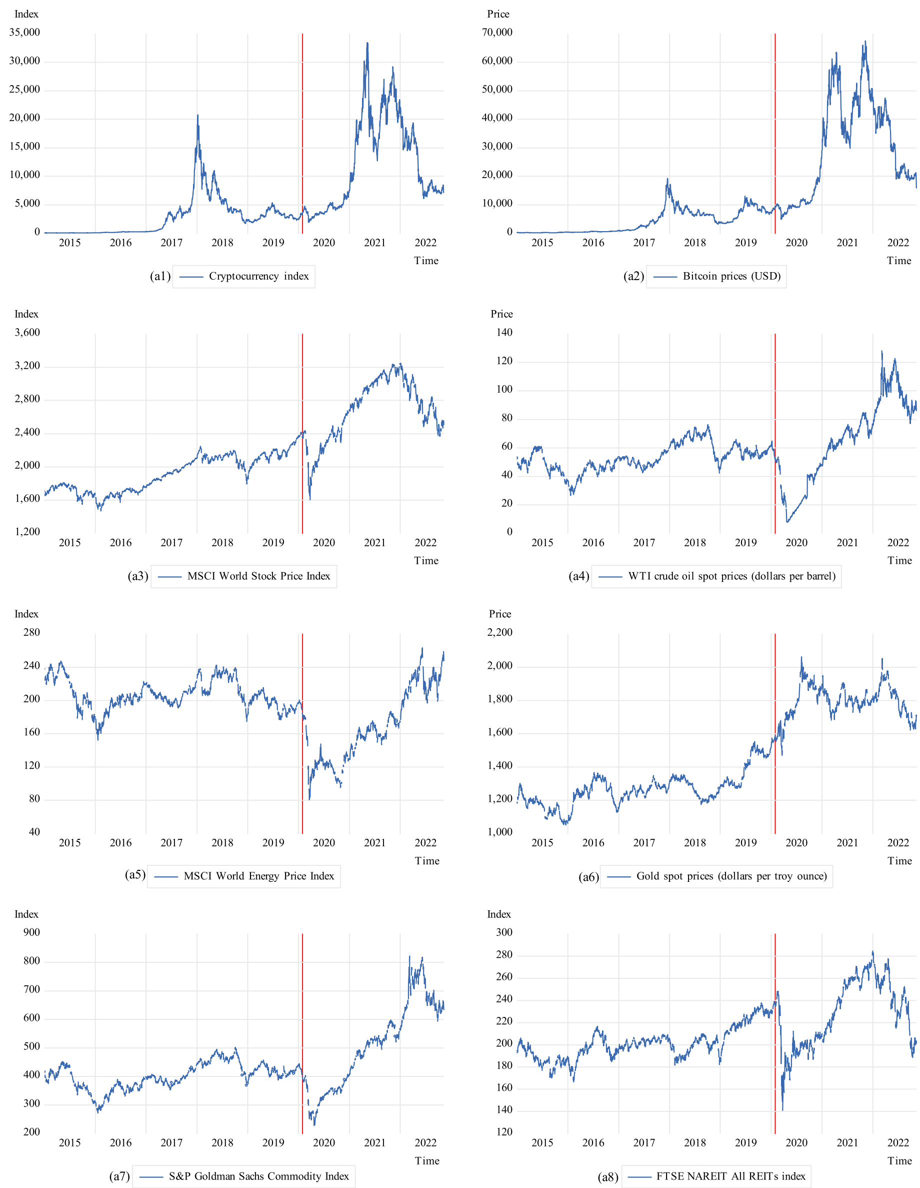

Fig. 1 Time series of eight assets

of the Jarque–Bera test, the hypothesis of normal distribution is rejected. Similarly, based on the Q and Q-squared statistics obtained using the Ljung–Box test and the McLeod–Li test, respectively, the hypothesis of self-correlation is rejected. Given the aforementioned properties of the asset returns data, the GARCH model is the most suitable for estimating the fat -tail phenomenon in these data. Therefore, this study employs the GARCH model for estimations. In Table 2, the estimation results for each asset reveal that the residual sum of squares and the conditional variables of the preceding order significantly influence the volatility of the present order. Therefore, the GARCH(1,1) model exhibits favorable fitness.

To predict the performance of asset returns under extreme conditions, numerous large-scale financial institutions use historical simulation-based methods (HSBMs)

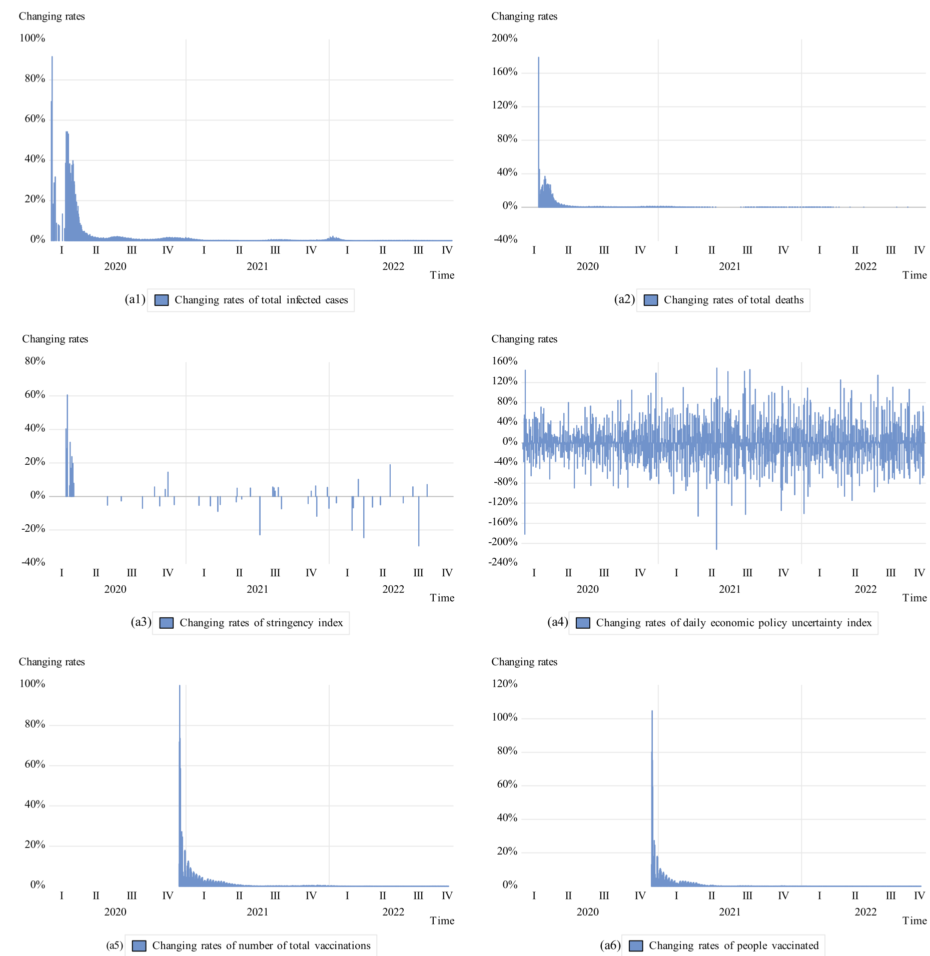

Fig. 2 The rate of change of the six influencing factors

(Boudoukh et al. 1998) to compute VaR. For a given confidence level, HSBM can estimate the maximum loss in asset investments caused by market volatility during a given time period. However, Pritsker (2006) indicated that HSBMs are unsuitable for estimating long-term and high-variance data. Figures 3 and 4 depict the VaRs[8] of the eight assets estimated using an HSBM and the GARCH(1,1) model, respectively. A comparison of Figs. 3 and 4 reveals that the GARCH model is advantageous for estimating long-term data; relative to the employed HSBM, this model can more accurately evaluate changes in VaR during periods with high market volatility. By contrast, the estimation results of the employed HSBM did not reflect changes in extreme risks during the pandemic.

As a black swan event, the pandemic has increased the severity of multiple risk factors that may influence the economy. To evaluate the effect of these factors on extreme asset risk, we employ the GARCH-X model (Eq. 3) We estimate the exogenous effect of three risk factors (pandemic severity, pandemic regulations and policies, and vaccination-related variables) based on six indices, thereby clarifying the influence of these risk factors on the volatility of asset returns. The estimation results are listed in Tables 3, 4

[8] Because HSBM is inferred using historic data and not computed through the application of a distribution model hypothesis, a rolling window is required for estimations. The present study sets the window length as 100 trading days.

Table 2 The estimations of GARCH (1,1) model $\Delta y_t = \mu + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = c + a\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$, y denotes asset return

Variables	**Δ*CCI***	**Δ*BTC***	**Δ*WSPI***	**Δ*WTI***
μ	0.0019**	0.0022**	0.0007***	0.0011**
	[2.0683]	[2.5416]	[5.0407]	[2.5435]
c	0.0001***	0.0001***	< 0.0000***	< 0.0000***
	[3.9218]	[4.7462]	[5.4204]	[4.6547]
a	0.1271***	0.1392***	0.2099***	0.2112***
	[7.3980]	[6.9799]	[8.3564]	[9.2657]
β	0.8547***	0.8204***	0.7742***	0.7819***
	[46.0244]	[35.5481]	[33.6462]	[36.4525]
	Δ*WEPI*	**Δ*Gold***	**Δ*GSCI***	**Δ*REITs***
μ	0.0003	< 0.0000	0.0006**	0.0004
	[0.9920]	[0.2220]	[2.3977]	[1.9591]
c	< 0.0000***	< 0.0000	< 0.0000***	< 0.0000***
	[2.8475]	[1.4894]	[3.9869]	[4.0186]
a	0.1119***	0.0307***	0.0790***	0.1538***
	[8.3060]	[3.3156]	[7.9166]	[7.1199]
β	0.8874***	0.9612***	0.8967***	0.8130***
	[70.5536]	[69.0150]	[67.9285]	[31.5292]

This table shows the conditional volatility estimations of the assets. ΔCCI, ΔBTC, $\Delta WSPI$, ΔWTI, $\Delta WEPI$, $\Delta Gold$, $\Delta GSCI$, and $\Delta REITs$ respectively denote the return of cryptocurrency index, Bitcoin price, MSCI World Stock Price Index, WTI crude oil spot price, MSCI World Energy Price Index, gold spot price, S&P Goldman Sachs Commodity Index, and FTSE NAREIT All REITs index. Number in brackets is *t*-statistic. The symbols ** and *** denote significance at 5% and 1% level, respectively

and 5. Table 3 lists the estimation outcomes obtained using TC and TD as proxy variables. In Table 3, the outcome of the coefficient γ indicates that only the stock market and crude oil are not significantly affected by the number of confirmed cases or deaths. For other assets, when the pandemic becomes more serious, the volatility of the returns increases correspondingly. However, the volatility of some assets has increased due to price increases. As shown in Fig. 1, after the pandemic, the cryptocurrency and gold markets experienced considerable growth, while the volatility of energy markets might rise due to market crashes.

Table 4 presents the estimated outcomes obtained using the SI and EPU index as risk factors. With the exception of the stock market and crude oil, the return volatilities of the other six types of assets are significantly influenced by lockdown policies. Stringent pandemic regulations have increased the volatility risks of these six assets. Table 4 also indicates that the asset returns of the cryptocurrency, gold, and real estate markets are positively associated with the regulations. The volatilities of these three markets are also affected by the risk of policy uncertainty. Table 5 depicts the effect of TV and PV on the volatility of asset returns. The table indicates that positive vaccination-related news influences the Cryptocurrency, stock, and crude oil markets respectively. Notably, increases in both TV and PV result in lower volatility risks in the CCI, stock, and crude oil markets. An increase in PV results in lower volatility risks in the Bitcoin market.

Tables 3 and 4 show the estimated effects of negative pandemic-related news on the markets examined in this study. Table 5 estimates the effect of positive pandemic-related news on these markets. A comparison of the results in Tables 3–5 indicates that the

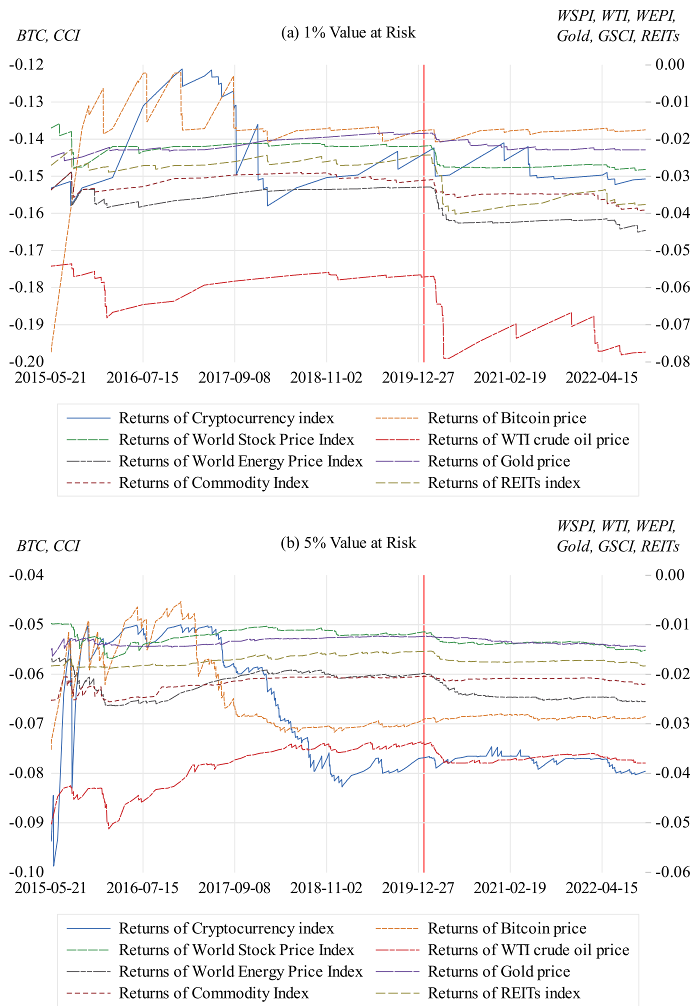

Fig. 3 The VaRs of the eight assets that are estimated using the HSBM method

effects of good and bad news are asymmetric during the pandemic. The assets influenced by positive news were mostly distinct from those influenced by negative news. Pandemic severity was found to mainly influence the Bitcoin, gold, and commodity markets, whereas vaccination-related variables exerted a largely positive impact on stock and crude oil assets. Since the onset of the pandemic can be seen as a bad news event, and vaccine-related news developed once the pandemic had expanded, the results indicate that investors should change their target market as new developments arise. In addition, across all risk factors, policy uncertainty is the least influential exogenous factor, which only increases the volatility of the three markets. Although several studies illustrate the impact of the *EPU* index on the asset market (Choi 2020), this study finds that its immediate and exogenous influences are relatively weak.

Figures 5, 6 and 7 depict the VaR estimations obtained using the models in Table 3, 4 and 5. These estimations are used to observe, examine, and infer the effect of various risk factors on the extreme risks in asset returns. Table 5 presents the estimations of the effect of positive pandemic-related factors. The distribution in Fig. 7 (i.e., the estimation outcomes of Table 5) exhibits a right-tail distribution for extreme risk performance.

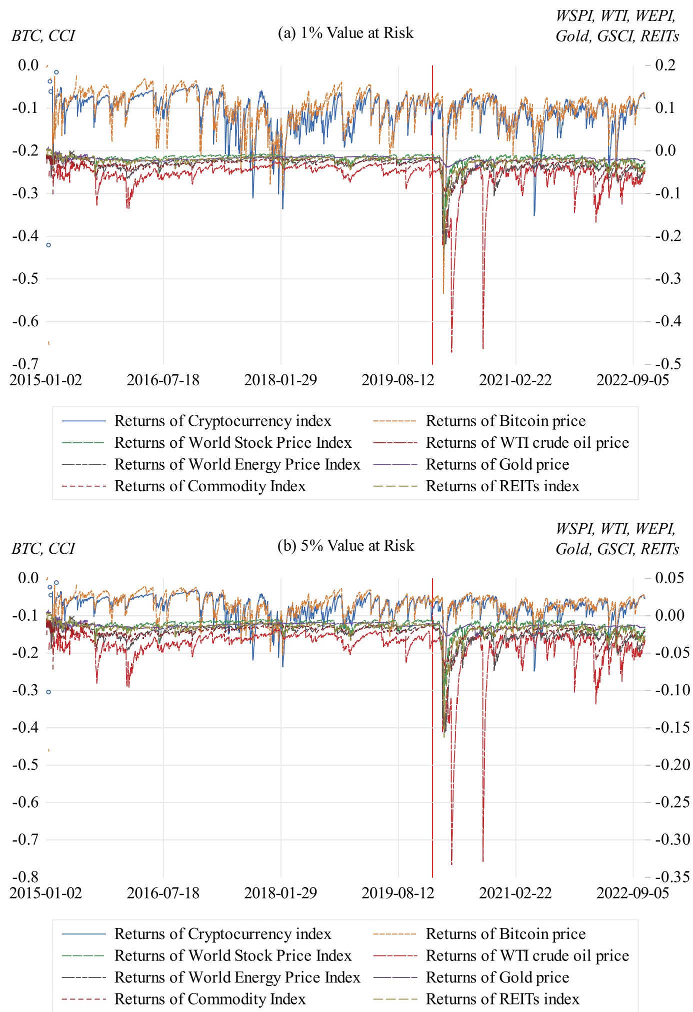

Fig. 4 The VaRs of the eight assets that are estimated using the GARCH(1,1) model

Figures 5, 6 and 7 reveal that the Bitcoin and crude oil markets exhibit the highest extreme risk variances. Furthermore, among the examined risk factors, positive vaccination-related news results in the highest volatility and the highest degree of change in the crude oil market. The above results show that although the oil market crashed at the beginning of the pandemic, this does not mean that crude oil was not a good investment opportunity during the pandemic. Indeed investment in the crude oil market became significantly more attractive when the good news about vaccines began to emerge.

Subsequently, we employed the VAR-MGARCH model to examine the relationship between asset returns and pandemic-related risk factors. As Table 5 indicates, positive vaccination-related news stabilizes volatility in several markets. The following tests discuss the long-term influence of negative information to determine if they produce structural changes in the market. The present study used the *TC* and *SI* results to estimate the effects of pandemic severity and pandemic regulations and policies, respectively. Table 6 indicates that pandemic severity has varying degrees of influence on the changes in asset

Table 3 The effect of the factors of pandemic severity on the extreme risks in assets: AR(1)-GARCH(1,1)-X model $\Delta y_t = \theta_0 + \theta_1 \Delta y_{t-1} + \theta_2 \Delta x_{t-1} + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, $\sigma_t^2 = c + a\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma \Delta x_{t-1}$, y denotes asset price, x denotes risk factor

Risk factor: Δ*TC*

Variables	Δ*CCI*	Δ*BTC*	Δ*WSPI*	Δ*WTI*	Δ*WEPI*	Δ*Gold*	Δ*GSCI*	Δ*REITs*
θ_0	0.0024	0.0014	0.0006	0.0027***	0.0009	− 0.0001***	0.0013**	0.0007
	[1.2724]	[0.8122]	[1.6875]	[2.7367]	[1.3047]	[− 97.8743]	[2.2876]	[1.5079]
θ_1	0.0139	− 0.0212	0.0338	− 0.0639	0.0592	− 0.0112***	0.0250	− 0.0305
	[0.3160]	[− 0.5319]	[0.8073]	[− 1.3953]	[1.4601]	[− 3.0975]	[0.5858]	[− 0.6969]
θ_2	− 0.0312	− 0.0154	0.0070	− 0.0017	0.0120	− 0.0067***	0.0034	− 0.0098
	[− 0.5735]	[− 0.3472]	[0.5041]	[− 0.0573]	[0.3856]	[− 31.0628]	[0.1994]	[− 0.4729]
c	0.0001	0.0002	< 0.0000***	0.0002***	< 0.0000***	0.0001***	< 0.0000***	< 0.0000***
	[1.9436]	[1.7864]	[2.9899]	[3.5583]	[2.7908]	[55.811]	[2.7366]	[2.9691]
a	0.1099***	0.0443**	0.1719***	0.7114***	0.0597***	0.0083***	0.1018***	0.1653***
	[4.0417]	[2.3538]	[4.4991]	[6.8166]	[2.6894]	[103.6327]	[3.6657]	[4.3255]
β	0.8435***	0.8302***	0.7820***	0.3861***	0.7914***	− 0.2953***	0.8435***	0.7628***
	[22.0483]	[12.3274]	[19.1468]	[5.2647]	[14.8168]	[− 1689.9098]	[21.8262]	[16.3102]
γ	0.0023**	0.0030**	0.0002	0.0018	0.0020***	0.0018***	0.0003**	0.0005**
	[2.5021]	[2.3286]	[1.7478]	[1.4287]	[2.6451]	[71.2663]	[2.1613]	[2.2087]

Risk factor: Δ*TD*

Variables	Δ*CCI*	Δ*BTC*	Δ*WSPI*	Δ*WTI*	Δ*WEPI*	Δ*Gold*	Δ*GSCI*	Δ*REITs*
θ_0	0.0021	0.0011	0.0005	0.0025***	0.0010	− 0.0001	0.0013**	0.0006
	[1.0747]	[0.6289]	[1.3801]	[2.6583]	[1.2871]	[− 0.3484]	[2.3142]	[1.2569]
θ_1	0.0141	− 0.0278	0.0311	− 0.0642	0.0589	0.0372	0.0218	− 0.0285
	[0.3011]	[− 0.6833]	[0.7449]	[− 1.5212]	[1.3693]	[0.9102]	[0.4803]	[− 0.6782]
θ_2	0.0188	0.0261	0.0259	0.0232	0.0222	0.0053	− 0.0047	0.0053
	[0.2942]	[0.4919]	[1.377]	[0.4175]	[0.5336]	[0.4989]	[− 0.1722]	[0.1519]
c	0.0002	0.0004**	< 0.0000***	0.0002***	< 0.0000***	< 0.0000***	< 0.0000***	< 0.0000***
	[1.8128]	[2.0338]	[2.8450]	[3.3421]	[2.6379]	[2.8227]	[2.8650]	[2.9743]
a	0.1277***	0.0415	0.1858***	0.6823***	0.0698***	0.0688**	0.1087***	0.1733***
	[3.6876]	[1.6825]	[4.6423]	[6.1911]	[2.8918]	[2.5658]	[3.9968]	[4.6216]
β	0.8137***	0.7211***	0.7703***	0.3902***	0.7607***	0.7338***	0.8232***	0.7472***
	[15.2335]	[6.7015]	[17.9557]	[4.7155]	[12.5501]	[9.4051]	[20.7982]	[15.6587]
γ	0.0038**	0.0087**	0.0003	0.0038	0.0032***	0.0002	0.0006**	0.0009**
	[2.0393]	[2.1886]	[1.4849]	[1.3772]	[2.6896]	[1.7899]	[2.3685]	[2.1232]

This table shows the influence of risk factors on the volatilities of assets. Δ*CCI*, Δ*BTC*, Δ*WSPI*, Δ*WTI*, Δ*WEPI*, Δ*Gold*, Δ*GSCI*, and Δ*REITs* respectively denote the return of cryptocurrency index, Bitcoin price, MSCI World Stock Price Index, WTI crude oil spot price, MSCI World Energy Price Index, gold spot price, S&P Goldman Sachs Commodity Index, and FTSE NAREIT All REITs index. Δ*TC* and Δ*TD* denote the rate of change of total infected cases and total deaths, respectively. Number in brackets is *t*-statistic. The symbols ** and *** denote significance at 5% and 1% level, respectively

returns and risks. Table 7 presents the changes in each asset's returns and risks caused by the stringency of lockdowns.

Table 6 indicates that the transmission effect of the negative asset returns of TC only exists for crude oil, because the significance of ψ_{21} is –0.04. On the contrary, ψ_{21} is significantly positive for gold, commodity ($GSCI$), and REIT markets. This shows that in terms of returns, the assets that avoid are least affected by the pandemic are those in the commodity and real asset markets. The risk transmission effect is insignificant only in the CCI, and the transmission effects of the pandemic on both returns and risk are also insignificant in the CCI. However, Bitcoin is significantly affected by the pandemic (a_{21}), which results in higher volatility. This may be because the CCI includes other types of

Table 4 The effect of the factors of pandemic regulations and policies on the extreme risks in assets: AR(1)-GARCH(1,1)-X Model $\Delta y_t = \theta_0 + \theta_1 \Delta y_{t-1} + \theta_2 \Delta x_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N\left(0, \sigma_t^2\right)$, $\sigma_t^2 = c + a\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma \Delta x_{t-1}$, *y* denotes asset price, *x* denotes risk factor

Risk factor: ΔSI

Variables	ΔCCI	ΔBTC	$\Delta WSPI$	ΔWTI	$\Delta WEPI$	$\Delta Gold$	$\Delta GSCI$	$\Delta REITs$
θ_0	0.0013	0.0016***	0.0007	0.0028***	0.0011	− 0.0002***	0.0014***	0.0003***
	[0.3620]	[19.7103]	[1.8461]	[3.0947]	[1.4468]	[− 112.3294]	[2.6150]	[82.6677]
θ_1	− 0.0496	− 0.0738***	0.0358	− 0.0612	0.0575	0.0661***	0.0210	0.0301***
	[− 0.7446]	[− 33.4822]	[0.7898]	[− 1.4709]	[1.4039]	[13.5543]	[0.4751]	[855.1747]
θ_2	0.0824***	0.0306***	0.0075	− 0.0343	− 0.0235	0.0031***	− 0.0503***	0.0236***
	[5.9802]	[55.5470]	[0.6722]	[− 1.7155]	[− 1.073]	[32.0924]	[− 19.0469]	[62.9887]
c	0.0024***	0.0019***	< 0.0000***	0.0002***	< 0.0000***	< 0.0000***	< 0.0000***	0.0001***
	[22.3893]	[100.9414]	[3.3143]	[4.1188]	[4.2876]	[156.2189]	[327.8977]	[116.3445]
a	0.0190***	0.0041***	0.1802***	0.7641***	0.0460***	0.1217***	0.1532***	0.2948***
	[680.516]	[229.3772]	[4.7773]	[7.2732]	[2.8815]	[64.8860]	[757.3872]	[1744.7736]
β	0.1854***	0.1755***	0.7896***	0.3779***	0.8981***	0.6619***	0.7905***	0.3716***
	[110.8882]	[2498.4900]	[21.1602]	[5.9501]	[39.9693]	[1099.3975]	[151.4857]	[169.9104]
γ	0.0100***	0.0077***	< 0.0000	0.0008	0.0009***	0.0003***	0.0005***	0.0005***
	[23.2134]	[101.0555]	[0.7124]	[0.9799]	[5.8619]	[170.6974]	[35.9492]	[128.8896]

Risk factor: ΔEPU

Variables	ΔCCI	ΔBTC	$\Delta WSPI$	ΔWTI	$\Delta WEPI$	$\Delta Gold$	$\Delta GSCI$	$\Delta REITs$
θ_0	0.0022	0.0014	0.0006	0.0029***	0.0012	− 0.0001	0.0013**	0.0013***
	[1.1996]	[0.7246]	[1.8383]	[3.0278]	[1.5802]	[− 0.2973]	[2.4098]	[24.7283]
θ_1	0.0104	− 0.0263	0.0379	− 0.0561	0.0626	0.0326	0.0287	0.0246
	[0.2365]	[− 0.6084]	[0.8379]	[− 1.2659]	[1.4515]	[0.7337]	[0.6432]	[0.8271]
θ_2	− 0.0012	− 0.0008	0.0000	0.0007	− 0.0002	0.0001	− 0.0009	− 0.0003
	[− 0.2398]	[− 0.1917]	[0.0192]	[0.3507]	[− 0.0994]	[0.1618]	[− 0.811]	[− 0.8502]
c	0.0001**	0.0001	< 0.0000***	0.0002***	< 0.0000**	< 0.0000**	< 0.0000***	< 0.0000***
	[2.2012]	[1.8336]	[2.9289]	[3.6934]	[2.3922]	[2.2715]	[2.6257]	[339.1972]
a	0.1203***	0.0572	0.1834***	0.7525***	0.1019***	0.0763***	0.1024***	0.3551***
	[4.1281]	[1.8964]	[4.9730]	[6.5599]	[3.1199]	[2.6447]	[3.4057]	[160.8725]
β	0.8481***	0.8862***	0.7935***	0.3821***	0.8569***	0.8402***	0.8616***	0.6369***
	[24.4995]	[17.3119]	[21.7960]	[4.9297]	[21.4657]	[14.9133]	[23.4618]	[3608.1487]
γ	0.0007**	0.0004	< − 0.0000	< 0.0000	0.0001	< 0.0000**	< 0.0000	0.0001***
	[2.0261]	[1.1692]	[− 1.1043]	[0.3394]	[1.5658]	[2.1606]	[1.1471]	[450.9683]

This table shows the influence of risk factors on the volatilities of assets. ΔCCI, ΔBTC, $\Delta WSPI$, ΔWTI, $\Delta WEPI$, $\Delta Gold$, $\Delta GSCI$, and $\Delta REITs$ respectively denote the return of cryptocurrency index, Bitcoin price, MSCI World Stock Price Index, WTI crude oil spot price, MSCI World Energy Price Index, gold spot price, S&P Goldman Sachs Commodity Index, and FTSE NAREIT All REITs index. ΔSI and ΔEPU denote the rate of change of stringency index and daily economic policy uncertainty index, respectively. Number in brackets is *t*-statistic. The symbols ** and *** denote significance at 5% and 1% level, respectively

virtual currencies, and the price changes of some virtual currencies are affected by market risk factors. Thus, the source of volatility (risk) of the *CCI* is not affected by the pandemic. However, this is not the case for Bitcoin. Bitcoin is significantly affected by the risk transmission effect of the pandemic's severity, which results in higher returns during the pandemic owing to increased risk.

In addition, the a_{21} of gold and crude oil are both significantly positive. However, the b_{21} of gold is significantly negative, indicating that the risk of transmission of the pandemic to gold can be divided into two effects. One is the shock of the pandemic, which increases the risk posed to gold, and the other is the risk of the pandemic itself, which reduces the risk posed to gold. The commodity market, as viewed by *GSCI* exhibits two

Table 5 The effect of the factors of vaccination-related variables on the extreme risks in assets: AR(1)-GARCH(1,1)-X model $\Delta y_t = \theta_0 + \theta_1 \Delta y_{t-1} + \theta_2 \Delta x_{t-1} + \varepsilon_t$, $\varepsilon_t \sim N\left(0, \sigma_t^2\right)$, $\sigma_t^2 = c + a\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma \Delta x_{t-1}$, y denotes asset price, x denotes risk factor

Risk factor: ΔTV

Variables	ΔCCI	ΔBTC	$\Delta WSPI$	ΔWTI	$\Delta WEPI$	$\Delta Gold$	$\Delta GSCI$	$\Delta REITs$
θ_0	0.0016***	0.0011	0.0006**	0.0026***	0.0015	−0.0001	0.0013**	0.0006
	[27.4399]	[0.6593]	[1.9631]	[62.0257]	[1.8582]	[−0.3211]	[2.4152]	[1.3733]
θ_1	−0.0288	−0.0997***	0.0458	−0.0569***	0.0575	0.0378	0.0276	−0.0212
	[−1.7839]	[−2.9274]	[1.0603]	[−188.3148]	[1.2824]	[0.8988]	[0.6172]	[−0.4672]
θ_2	0.0206***	0.0716***	−0.0005	0.0088***	−0.0078	0.0018	0.0048	−0.0023
	[289.5012]	[3.0278]	[−0.1906]	[48.7046]	[−0.7662]	[0.3805]	[0.8878]	[−0.4984]
c	0.0017***	<0.0000	<0.0000***	0.0003***	<0.0000**	<0.0000**	<0.0000***	<0.0000***
	[392.6338]	[0.3723]	[3.5323]	[170.0061]	[2.4139]	[2.4675]	[2.7889]	[2.8470]
a	0.0937***	−0.0026***	0.1794***	0.9490***	0.1062***	0.0893***	0.1104***	0.1799***
	[271.5141]	[−3.7399]	[4.6287]	[15.6035]	[3.1134]	[3.1950]	[3.8058]	[4.5671]
β	0.3623***	0.9997***	0.7885***	0.1596***	0.8490***	0.8103***	0.8546***	0.7784***
	[4968.7864]	[510.338]	[21.3027]	[52.0864]	[19.8301]	[14.2861]	[25.1078]	[17.8896]
γ	−0.0024***	0.0003***	<−0.0000**	−0.0004***	0.0000	<−0.0000	<−0.0000	<0.0000
	[−425.8199]	[4.4472]	[−1.9813]	[−203.1139]	[−0.8311]	[−0.2314]	[−0.3346]	[0.0230]

Risk factor: ΔPV

Variables	ΔCCI	ΔBTC	$\Delta WSPI$	ΔWTI	$\Delta WEPI$	$\Delta Gold$	$\Delta GSCI$	$\Delta REITs$
θ_0	0.0006***	−0.0004***	0.0003	0.0022***	0.0015	−0.0001	0.0013**	0.0006
	[236.0007]	[−322.7389]	[0.3474]	[65.0494]	[1.933]	[−0.3533]	[2.4296]	[1.4152]
θ_1	−0.0316***	−0.0772***	−0.0067	−0.0650***	0.0571	0.0374	0.0278	−0.0213
	[−58.7025]	[−30.2465]	[−0.0931]	[−16.7246]	[1.3278]	[0.8794]	[0.6601]	[−0.5002]
θ_2	0.0259***	0.0710***	0.0069***	0.0088***	−0.0086	0.0022	0.0041	−0.0021
	[257.9519]	[418.9184]	[13.9560]	[23470.0241]	[−0.8689]	[0.4918]	[0.7507]	[−0.3356]
c	0.0030***	0.0018***	0.0003***	0.0005***	<0.0000**	<0.0000**	<0.0000***	<0.0000***
	[8384.6107]	[183.2014]	[182.3012]	[203.9397]	[2.3964]	[2.4720]	[2.6302]	[3.0773]
a	0.0770***	0.0035***	0.0500***	0.9600***	0.1067***	0.0899***	0.1107***	0.1796***
	[579.2403]	[400.1458]	[174.0538]	[35.5704]	[3.0892]	[3.4103]	[3.9439]	[4.8998]
β	0.1133***	0.2333***	0.3327***	0.0448***	0.8485***	0.8086***	0.8544***	0.7789***
	[196.2190]	[15545.2828]	[1923.5196]	[55.5196]	[19.9778]	[14.6755]	[24.5872]	[19.5374]
γ	−0.0032***	−0.0019***	−0.0003***	−0.0005***	<−0.0000	<−0.0000	<−0.0000	<0.0000
	[−10873.5210]	[−184.1849]	[−204.0440]	[−213.3385]	[−0.8282]	[−0.3083]	[−0.2748]	[0.1190]

This table shows the influence of risk factors on the volatilities of assets. ΔCCI, ΔBTC, $\Delta WSPI$, ΔWTI, $\Delta WEPI$, $\Delta Gold$, $\Delta GSCI$, and $\Delta REITs$ respectively denote the return of cryptocurrency index, Bitcoin price, MSCI World Stock Price Index, WTI crude oil spot price, MSCI World Energy Price Index, gold spot price, S&P Goldman Sachs Commodity Index, and FTSE NAREIT All REITs index. ΔTV and ΔPV denote the rate of change of number of total vaccinations and people vaccinated, respectively. Number in brackets is *t*-statistic. The symbols ** and *** denote significance at 5% and 1% level, respectively

types of risk transmission. The severity of the pandemic does not necessarily increase the degree of risk in commodity markets, including gold. However, the pandemic positively affects the transmission of risk for crude oil. Therefore, under pandemic conditions, investment in crude oil is unfavorable. This increases the risk of crude-oil consumption, resulting in negative returns. The results indicate that commodity and real assets markets should be chosen instead of the energy market by investors who wish to avoid risk due to negative pandemic factors.

Although Fig. 1 shows that, in addition to gold, Bitcoin is also an asset that performs better when the pandemic is severe, Table 6 shows that gold benefits from pandemic severity without considering risk factors, while the high returns of Bitcoin are due

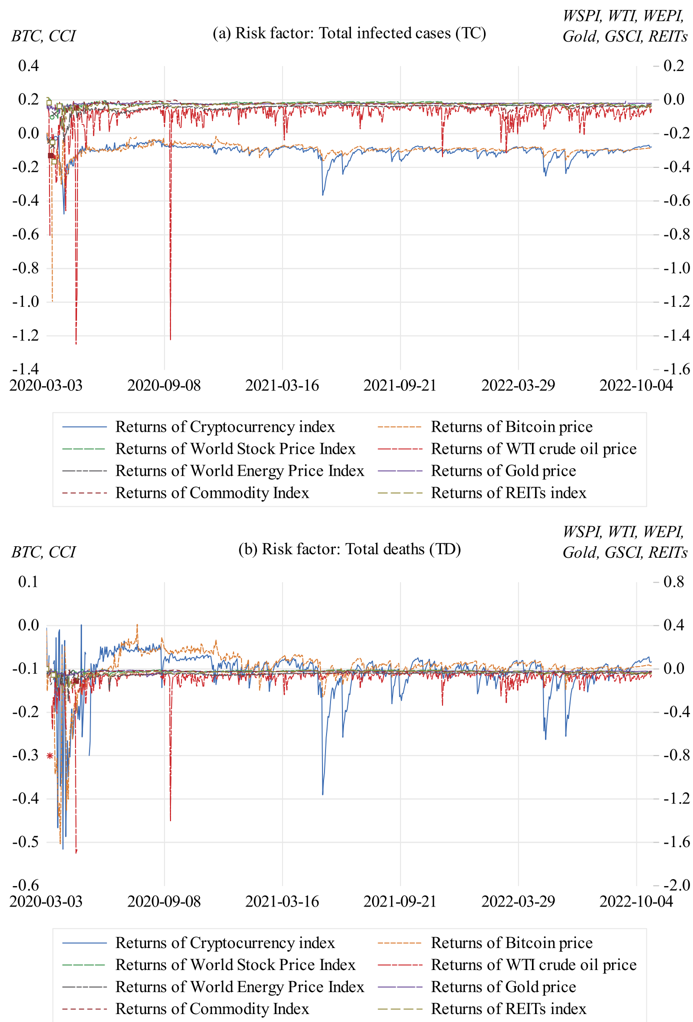

Fig. 5 The effect of pandemic severity on the extreme risks in asset returns

to this asset bearing high risks under the influence of the pandemic. Therefore, from Table 6, we obtained more detailed results than those in the past literature. Previous studies have found that both gold and Bitcoin can be used as haven assets to avoid extreme risks, and this study further distinguishes these two types of assets by their haven characteristics. As a safe haven, gold's risk-hedge features are relatively stable. This may be due to fear of the pandemic, which incentivized the holding of gold as the pandemic worsened. Although the excellent performance of Bitcoin during the pandemic suggests that it is a safe haven asset, this is because the risk premium is affected by the increase in volatility resulting from the pandemic's impact.

In addition to gold, the REIT market also exhibits the characteristics of safe haven assets during the pandemic. It benefits from people holding real assets during the pandemic; investors enjoy higher returns, while the pandemic's impact reduces the risk (a_{21} <0). Although the risk of stocks also decreases in the face of pandemic shocks (a_{21}<0), there is no positive return impact on the stock market during the pandemic.

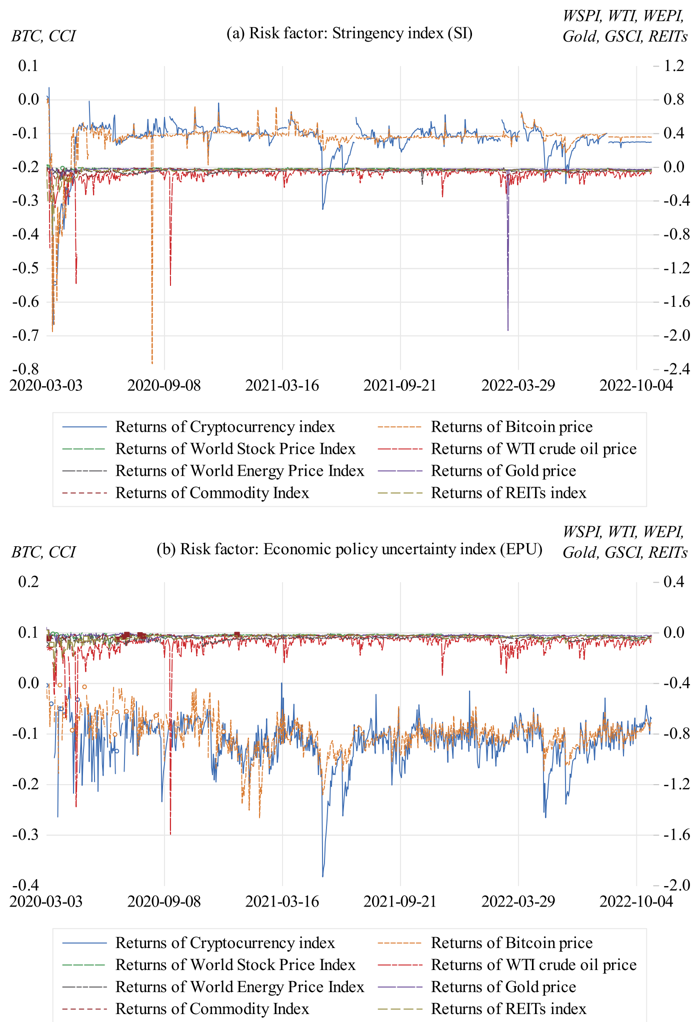

Fig. 6 The effect of pandemic regulations and policies on the extreme risks in asset returns

Table 7 indicates that the returns from the energy markets increase significantly when the stringency of lockdowns increases (ψ_{21}>0). In contrast, the severity of lockdowns had a negative effect on commodity markets. However, this control increases the volatility risk of gold and virtual currencies, and brings positive returns.

Additionally, besides the stock market and REITs, all markets have a a_{21} or b_{21} that is significant and non-zero, indicating that new information on the stringency of lockdowns or the volatility of lockdown regulations influences the volatility of asset returns in these markets. Therefore, the stringency of lockdowns has a risk transmission effect on these markets. Table 7 shows that stock markets and REITs are not influenced by the risk transmission effect associated with the stringency of lockdowns. However, Table 4 reveals that as an exogenous shock, pandemic regulations increased the volatility of the real estate market. This may be because the stringency of lockdowns did not affect the real estate market. Otherwise, we would expect an increase in real estate volatility risk. As far as stocks are concerned, the stringency of lockdowns had no significant effect on risk transmission, whether exogenous or

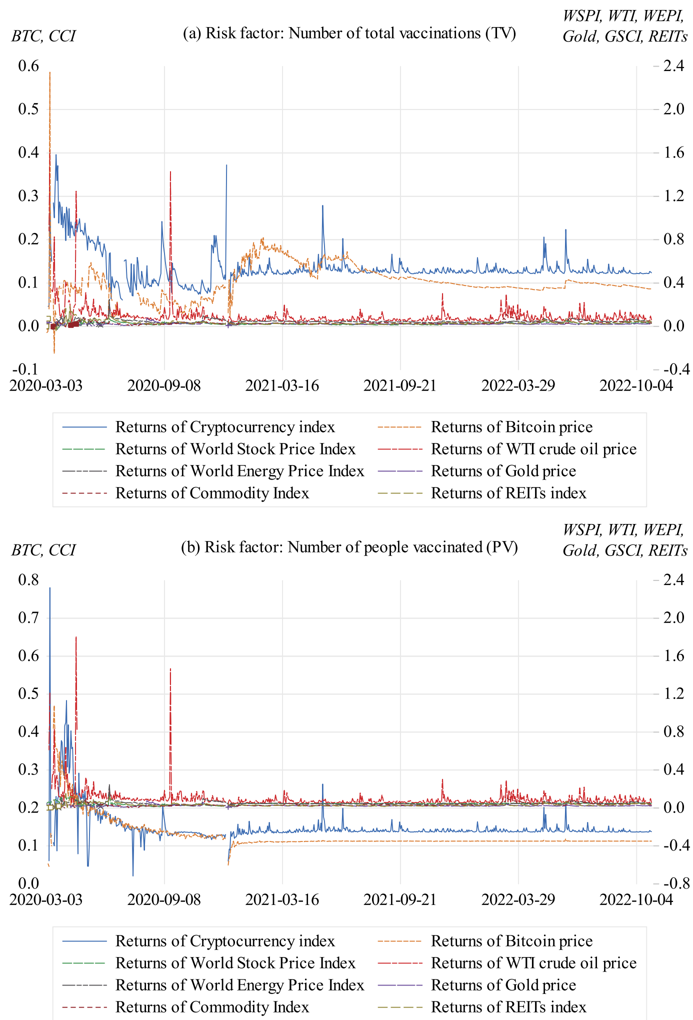

Fig. 7 The effect of vaccination-related variables on the extreme risks in asset returns

endogenous. This may be because the study used global stock market data for its analysis. The control period of each country is different; therefore, each country's stock market is affected differently, such that the stock price index constructed with the global stock market can avoid the transmission of risks.

Figure 8 depicts the estimation outcomes for the risk factors presented in Table 7 and the coefficients of asset returns. Figure 9 compares the average correlation coefficients between different assets and risk factors. Figure 8 indicates that with the development of the pandemic, the correlation between each asset and the severity of the pandemic was constantly changing. On average, crude oil exhibited the highest positive correlation. During most of the period, gold returns were negatively correlated with the stringency of the lockdowns. Except for a few periods, the correlation between Bitcoin and the stringency of lockdowns was close to 0. Figure 9 shows that, on average, gold and Bitcoin are less correlated with both risk factors, indicating that an increase in pandemic risk results in less risk transmission to gold and Bitcoin. These outcomes highlight the safe-haven properties of gold and Bitcoin.

Table 6 The relationship between asset returns and total infected cases: the VAR-MGARCH model

	ΔCCI		ΔBTC		$\Delta WSPI$		ΔWTI	
Variable	**Coefficient**	***t*-Statistic**	**Coefficient**	***t*-Statistic**	**Coefficient**	***t*-Statistic**	**Coefficient**	***t*-Statistic**
Mean model:Δy_t								
ψ_{11}	**−0.1100**	−2.8984	−0.0527	−1.4323	0.0128	0.3143	−0.0330	−0.7640
ψ_{21}	0.0116	0.3786	0.0400	1.0702	−0.0048	−0.4567	**−0.0441**	−3.1779
$\phi_{y,t}$	−0.2492	−1.1518	0.1457	0.8634	**0.0884**	3.0005	**0.2763**	2.8350
Mean model:ΔTC_t								
ψ_{12}	−0.0001	−0.1001	−0.0006	−1.0199	0.0003	0.1277	−0.0007	−0.9216
ψ_{22}	**0.1996**	22.9835	**0.7086**	25.0757	**0.7158**	25.8383	**0.6679**	25.2747
$\phi_{x,t}$	**0.1049**	16.0787	**0.0239**	6.8618	**0.0232**	6.1393	**0.0267**	7.7507
Variance model								
c_{11}	**1.3366**	5.3072	**2.4970**	6.2373	**0.1474**	5.1065	**1.6406**	8.7827
c_{21}	**0.0610**	11.5451	**0.0048**	2.1872	0.0050	1.2517	0.0004	0.1457
c_{22}	< 0.0000	0.0000	< −0.0000	−0.0001	0.0038	0.6251	0.0051	1.5030
a_{11}	**0.2637**	8.7881	**−0.1677**	−2.9413	**−0.2684**	−9.0183	**0.8518**	13.8189
a_{12}	**0.0062**	3.2664	0.0002	0.3530	−0.0014	−0.5728	0.0019	1.1112
a_{21}	−0.0146	−0.1918	**0.1969**	3.6465	**−0.0266**	−2.0085	**0.1471**	3.1291
a_{22}	**1.5113**	25.1957	**0.5201**	19.3417	**0.5282**	19.3352	**0.5115**	20.8847
b_{11}	**0.9298**	62.3234	**−0.8017**	−12.4816	**0.9539**	97.7096	**0.5618**	7.8991
b_{12}	**−0.0029**	−2.9571	0.0011	0.8920	−0.0006	−0.7255	−0.0010	−0.9735
b_{21}	−0.0402	−0.9031	−0.0202	−0.2760	−0.0039	−0.8114	**−0.0624**	−2.8858
b_{22}	**0.1703**	5.8202	**0.8830**	115.1169	**0.8835**	110.8897	**0.8913**	137.8748

Table 6 (continued)

Variable	Δ *WEPI*		Δ *Gold*		Δ *GSCI*		Δ *REITs*	
	Coefficient	***t*-Statistic**	**Coefficient**	***t*-Statistic**	**Coefficient**	***t*-Statistic**	**Coefficient**	***t*-Statistic**
Mean model:Δy_t								
ψ_{11}	**0.1522**	3.8637	− 0.0011	− 0.0278	**0.1131**	3.1478	**0.1070**	2.7823
ψ_{21}	0.0166	1.0682	**0.0219**	5.0490	**0.0407**	3.5082	**0.0238**	2.1321
$\phi_{y,t}$	**0.2141**	3.1001	− 0.0219	− 0.5714	**0.1637**	3.3290	**0.1077**	2.4120
Mean model:ΔTC_t								
ψ_{12}	**0.0042**	2.1454	0.0012	0.4414	− 0.0010	− 0.3794	0.0038	1.3847
ψ_{22}	**0.2070**	25.8571	**0.6866**	24.4510	**0.1984**	17.6438	**0.2067**	23.9408
$\phi_{x,t}$	**0.0810**	19.0021	**0.0264**	7.5898	**0.0947**	9.3057	**0.0884**	16.4561
Variance model								
c_{11}	**0.5802**	6.0520	**0.4309**	6.1878	**0.2833**	7.8666	**0.2611**	6.3818
c_{21}	**− 0.0444**	− 8.6982	− 0.0052	− 1.9107	− 0.0003	− 0.0093	0.0098	0.2579
c_{22}	< 0.0000	0.0000	< − 0.0000	− 0.0004	**− 0.0646**	− 13.1353	**0.0542**	5.5077
a_{11}	**− 0.1659**	− 4.3853	**− 0.2407**	− 4.8169	**− 0.2443**	− 10.1158	**− 0.2282**	− 7.2965
a_{12}	**− 0.0176**	− 5.2948	− 0.0021	− 0.7424	0.0023	0.3744	**− 0.0176**	− 3.5173
a_{21}	**− 0.1385**	− 2.5515	**0.0295**	3.0785	**− 0.2727**	− 8.1326	**− 0.1156**	− 2.7230
a_{22}	**1.4851**	28.0701	**0.5221**	19.4691	**1.4821**	24.8455	**1.5163**	24.9427
b_{11}	**0.9342**	48.6790	**0.8582**	20.3909	**0.9474**	122.4117	**0.9499**	91.1389
b_{12}	**0.0057**	2.5156	**0.0035**	2.7460	0.0021	0.4566	− 0.0065	− 0.9475
b_{21}	0.0146	0.4557	**− 0.0131**	− 3.1776	**0.1492**	7.7747	0.0206	0.8913
b_{22}	**0.2276**	6.5371	**0.8832**	114.0730	**0.1998**	4.4158	**0.1970**	6.1787

This table shows the relationships between risk factors and asset returns.ΔCCI,ΔBTC,$\Delta WSPI$,ΔWTI,$\Delta WEPI$,$\Delta Gold$,$\Delta GSCI$, and$\Delta REITs$respectively denote the return of cryptocurrency index, Bitcoin price, MSCI World SPI, WTI crude oil spot price, MSCI World Energy Price Index, gold spot price, S&P Goldman Sachs Commodity Index, and FTSE NAREIT All REITs index.ΔTCdenotes the rate of change of total infected cases. Number in bold stands for significance at 5%

Table 7 The Relationship between Asset Returns and Stringency Index: The VAR-MGARCH Model

	ΔCCI		ΔBTC		$\Delta WSPI$		ΔWTI	
Variable	**Coefficient**	***t*-Statistic**	**Coefficient**	***t*-Statistic**	**Coefficient**	***t*-Statistic**	**Coefficient**	***t*-Statistic**
Mean model:Δy_t								
ψ_{11}	−0.0533	−1.1621	−0.0423	−1.1576	0.0295	0.8131	0.0431	1.4585
ψ_{21}	0.0163	0.2715	−0.0921	−1.9249	−0.0087	−1.1249	**0.1501**	5.4719
$\phi_{y,t}$	0.2760	1.4423	0.2418	1.3526	0.0509	1.5514	**0.2348**	3.3055
Mean model:ΔSI_t								
ψ_{12}	−0.0296	−1.2960	−0.0072	−0.3211	**−0.1757**	−2.2958	−0.0307	−1.2171
ψ_{22}	**−0.3152**	−11.4994	**−0.2961**	−12.0099	**0.3413**	12.7230	**0.0485**	2.1521
$\phi_{x,t}$	**−0.2489**	−2.3169	**−0.2068**	−2.1177	−0.0041	−0.0373	−0.0244	−0.3608
Variance model								
c_{11}	**1.1679**	5.1402	**3.0346**	8.8474	**0.2352**	6.4751	**1.5404**	15.7764
c_{21}	**−1.0336**	−3.5236	0.0476	0.1526	**1.0976**	3.2526	0.0558	0.4194
c_{22}	< 0.0000	< 0.0000	**1.7892**	6.4882	**1.9747**	9.4298	< 0.0000	< 0.0000
a_{11}	**0.2643**	6.8182	0.0744	0.8680	**0.2983**	6.8604	**1.0955**	21.8817
a_{12}	**−0.0432**	−2.3590	−0.0118	−0.5042	**−0.5038**	−2.1890	−0.0058	−0.1240
a_{21}	−0.0389	−0.9888	**0.2942**	3.5497	0.0115	0.5505	**0.6855**	12.9573
a_{22}	**0.3554**	6.5266	**0.5825**	5.7487	**0.9085**	8.1943	0.0708	1.7190
b_{11}	**0.9399**	59.8402	**0.6678**	7.6453	**0.9243**	57.3504	−0.0415	−1.7054
b_{12}	**0.0625**	6.3790	0.1372	1.7091	0.1141	1.0714	**0.7209**	25.5754
b_{21}	0.0042	0.2552	**−0.3379**	−6.1058	**−0.0360**	−2.2198	**−0.4588**	−9.0735
b_{22}	**0.8858**	19.7042	**0.6750**	10.1659	**0.4313**	8.1905	0.0294	0.6696

Table 7 (continued)

Variable	Δ*WEPI*		Δ*Gold*		Δ*GSCI*		Δ*REITs*	
	Coefficient	***t*-Statistic**	**Coefficient**	***t*-Statistic**	**Coefficient**	***t*-Statistic**	**Coefficient**	***t*-Statistic**
Mean model:Δy_t								
ψ_{11}	**0.0978**	2.3561	−0.0058	−0.1429	−0.0315	−0.8400	−0.0094	−0.2601
ψ_{21}	**0.1455**	9.8857	**0.0248**	3.4011	**−0.1217**	−8.7510	0.0007	0.0577
$\phi_{y,t}$	**0.2515**	3.7029	0.0240	0.6404	**0.2655**	6.8881	0.0493	1.0572
Mean model:ΔSI_t								
ψ_{12}	−0.0107	−0.1916	**0.3073**	3.7971	**−0.3613**	−5.8832	**−0.1672**	−3.2748
ψ_{22}	0.0329	1.3041	**−0.3273**	−10.3493	**−0.2498**	−8.1015	**0.3362**	10.6693
$\phi_{x,t}$	−0.1742	−1.8176	**−0.5541**	−5.5983	**0.2382**	3.8242	**−0.4191**	−3.8667
Variance model								
c_{11}	−0.0099	−0.0590	**0.1952**	3.2341	**−0.2776**	−6.4074	**−0.2321**	−4.8514
c_{21}	**0.7872**	6.1823	**2.0792**	16.5220	**−0.7497**	−2.4348	0.0120	0.0258
c_{22}	**0.9233**	18.2396	−0.0928	−1.5552	**−1.0116**	−4.1215	**2.2139**	20.6657
a_{11}	**−0.1374**	−2.9882	**0.2061**	4.9505	**0.1175**	2.8674	**0.2602**	5.4771
a_{12}	**0.6948**	11.6201	**−0.7285**	−3.8955	**−1.5536**	−15.7887	**0.3813**	3.2593
a_{21}	**−0.1341**	−6.5489	−0.0409	−1.9071	**−0.2157**	−4.1920	−0.0233	−0.6120
a_{22}	**−0.0514**	−2.2188	**1.4240**	7.0544	**−1.3989**	−9.1630	**1.2935**	7.0597
b_{11}	**0.9523**	64.8906	**0.9551**	65.1453	**0.9436**	105.4076	**0.9440**	58.1046
b_{12}	**−0.2183**	−8.1438	**−0.4643**	−2.8941	−0.0285	−0.4404	−0.0056	−0.0863
b_{21}	**0.1738**	6.7792	**0.0306**	2.5923	**−0.0645**	−2.4734	−0.0135	−0.6474
b_{22}	**0.7626**	27.6339	**0.3100**	7.2032	**0.2372**	7.9817	**0.3437**	7.3629

This table shows the relationships between risk factors and asset returns.ΔCCI,ΔBTC,$\Delta WSPI$,ΔWTI,$\Delta WEPI$,$\Delta Gold$,$\Delta GSCI$, and$\Delta REITs$respectively denote the return of cryptocurrency index, Bitcoin price, MSCI World SPI, WTI crude oil spot price, MSCI World Energy Price Index, gold spot price, S&P Goldman Sachs Commodity Index, and FTSE NAREIT All REITs index.ΔTCdenotes the rate of change of total infected cases. Number in bold stands for significance at 5%

Discussion of empirical results

The empirical results show a relationship between asset type and extreme risk transmission. This study finds that gold and virtual assets perform best in terms of hedging risks associated with the COVID-19 pandemic. Among them, the return volatility of the virtual assets' portfolio (the *CCI*), which is observed in multiple virtual currencies, is mainly affected by its own market factors and has no significant correlation with the severity of the pandemic and the strictness of regulation.

Both Bitcoin and gold performed well after the outbreak of the pandemic. While other assets fell sharply during the early stage of the pandemic and then slowly rebounded, both virtual currencies and gold rose sharply during this time. Such good performance shows that from the perspective of the black swan event triggered by COVID-19, Bitcoin and gold can indeed be used as safe havens during periods of turbulence. In the past, the literature has pointed out the advantages of Bitcoin and gold in hedging (Selmi et al. 2018; Będowska-Sójka and Kliber 2021), and some studies have pointed out that these two assets can also be used during the COVID-19 pandemic to hedge against the risk of the crisis. For example, Salisu et al. (2021) found that gold is an excellent safe haven during the COVID-19 pandemic. However, Akhtaruzzaman et al. (2021) pointed out that the hedging effects of gold are not constant across different periods. However, whether gold or Bitcoin is a good hedging option has been widely debated. Chemkha et al. (2021) proposed that in the face of the COVID-19 pandemic, the hedging result of gold was better than that of Bitcoin. Bouri et al. (2020) suggested that Bitcoin has a greater hedging advantage than gold and other commodity assets based on the low correlation between Bitcoin and stocks.

The results of the present study provide valuable insights. The results showed that Bitcoin and gold differ in their safe haven characteristics during the pandemic. Gold is suitable for investors looking for a safe haven because its benefits are stable, and investors can obtain a positive premium effect brought about by the spread of the epidemic without taking additional high risks.

However, the safe-haven characteristics brought about by Bitcoin vary significantly at different points in time because its good performance during the pandemic is attributed to a substantial increase in risk. Therefore, Bitcoin is more suitable for investors willing to bear high risks, but wish to pursue high returns. By dismantling the risk sources of assets, this study not only compares hedging performance but also explains differences in hedging effects.

In contrast, the performance of crude oil was not favorable during the pandemic. It was directly affected by the pandemic and delivered negative returns. This asset also suffered from higher volatility (risk) caused by the pandemic. However, the impact of vaccines and regulations was marked by an improvement in crude oil market performance. Hence, although the energy market, including crude oil, is an extremely risky asset producing negative returns during the pandemic, signs of improvement and subsequent rebound and recovery offered a good investment opportunity for investors.

The performance of REITs is relatively close to that of commodity markets, including gold; thus, they can also be used as safe haven assets. This may be because these are tangible assets. In addition to financial factors and market panic, there are also additional impacts related to physical consumption.

The stock market's performance is sometimes similar to that of the crude oil market, although it is sometimes more consistent with REITs. When observing the impact of the pandemic's risk on the volatility of asset returns utilizing exogenous factors, the stock and crude oil markets are similar. When jointly estimating the relationship between the return on assets and the risk factors of the pandemic, we found that the stock market's performance is more consistent with that of REITs and is also unaffected by the risk transmission of the pandemic.

Because this study uses an index of the global stock market to measure its performance, the risk of a pandemic is dispersed across many countries. Therefore, the results were less affected by the transmission of pandemic risk. Other studies find that the stock

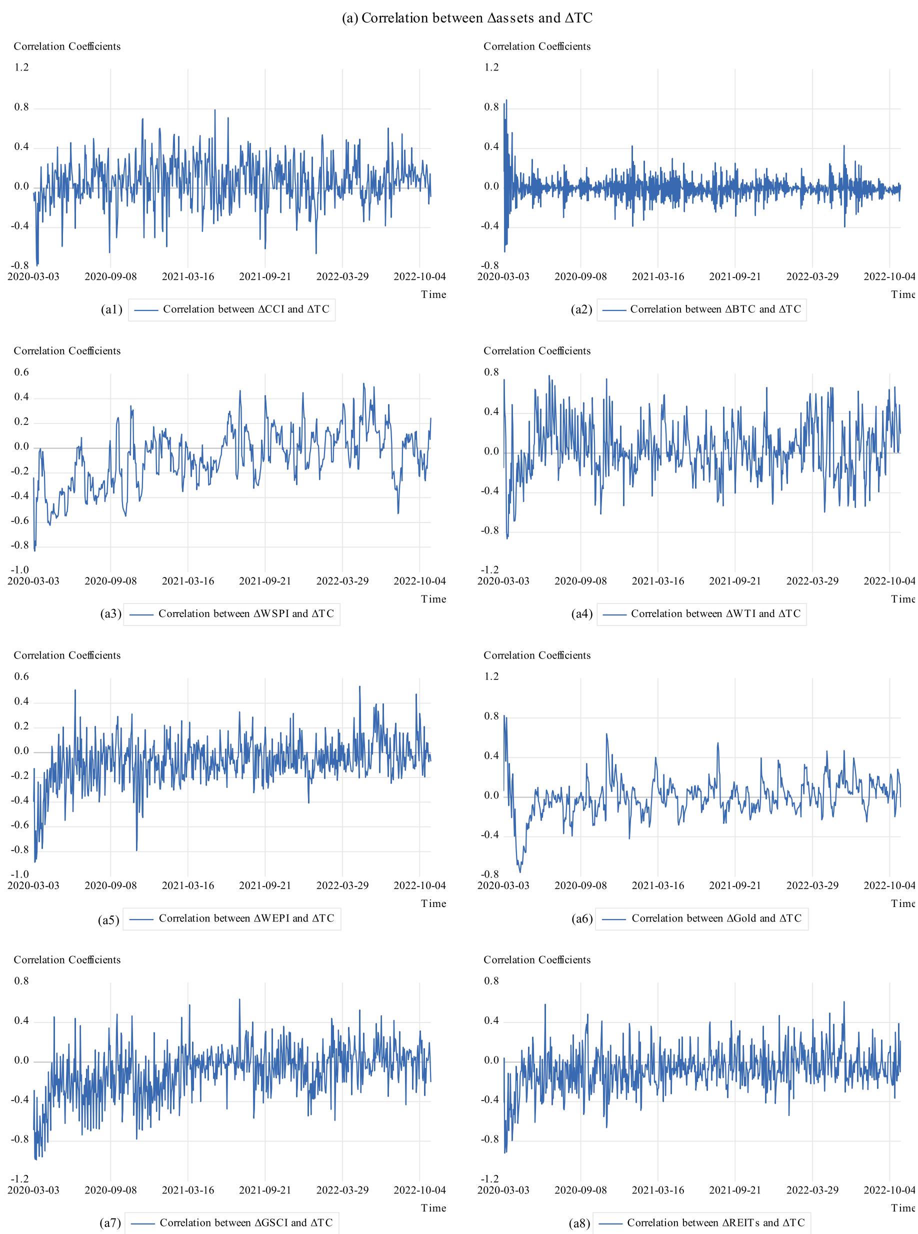

Fig. 8 Correlation coefficients between asset returns and risk factors

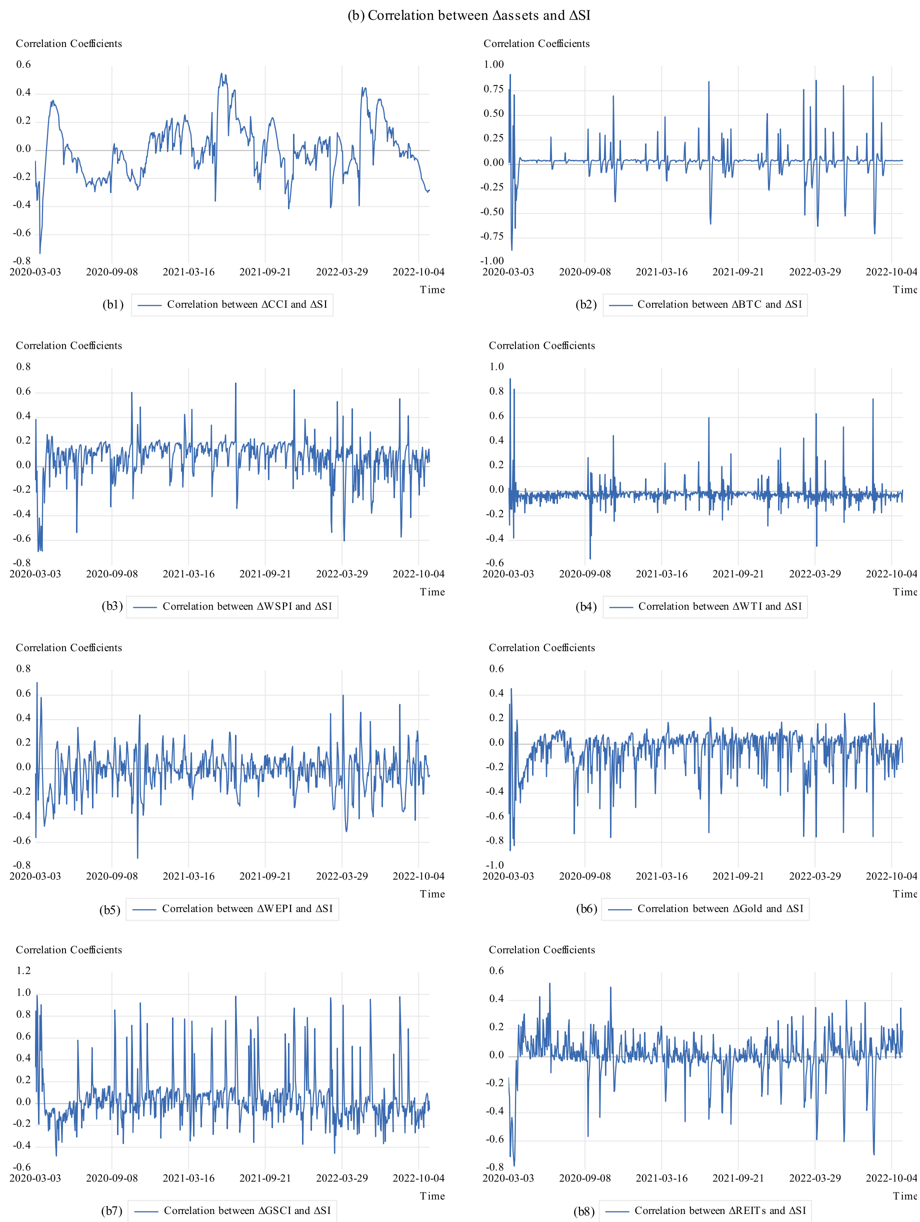

Fig. 8 continued

market is susceptible to the impact of pandemic risk transmission (Rakshit and Neog 2022) and the contagion effect of COVID-19 (Fu et al. 2021; Jebabli et al. 2022).

The results obtained in this study differ from those of other studies because most of them use the stock market of a single country. This study finds that by focusing on the risk of asset classes in terms of the global stock market, it is possible to analyze more differentiated assets. Stocks were not hit as hard as energy, but did not perform the same safe haven role as virtual currencies, commodities, and tangible assets. This compartmentalization allows investors to hold stocks as separate asset classes. When a storm occurs at different stages of a crisis, investors can change their holding assets, for example, by increasing their holdings of virtual and tangible assets. After the risk factors of

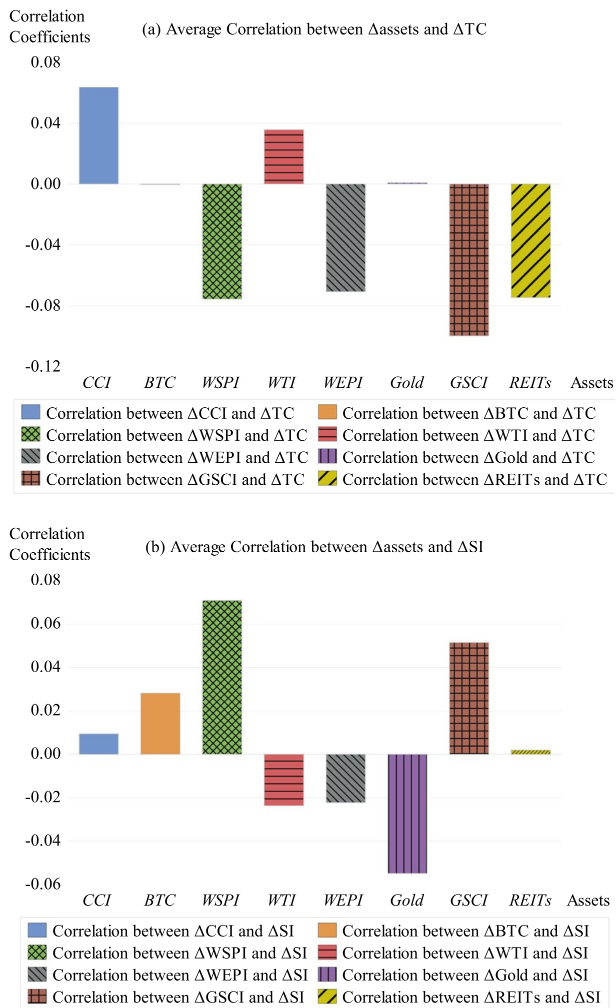

Fig. 9 Comparison of average correlation coefficients

the crisis diminish, investors can switch to holding energy and stock to obtain the benefits of an asset price rebound.

Conclusion

The goal and findings of this study

The COVID-19 pandemic imposes different effects on different asset markets, with each effect comprising multiple dimensions. To fulfill various investment demands, investors observe the dimensions and degree of influence of the real estate market. Given the diversity of investment demands, investors should first reference the dimensions of a market and the degree to which it is influenced to develop an optimal asset distribution plan. Furthermore, investors should distinguish between the various effects of each risk factor on asset returns to effectively understand how they can mitigate the losses caused by extreme risks in the market.

This study explores how six pandemic-related risk factors across three dimensions (pandemic severity, pandemic regulations, policy risks, and vaccination-related variables) influence extreme risk in asset markets. To this end, the present study examines eight assets to identify the differences in how the pandemic has influenced virtual, financial, energy, commodity, and real assets. This study focuses primarily on whether pandemic-related risk factors influence the asset market and cause changes in extreme risks. Moreover, we discuss whether the pandemic has a risk-transmission effect on the asset market.

Contributions and suggestions

Although many previous studies have explored the extent to which individual assets are susceptible to the pandemic, they have not distinguished between asset characteristics to illustrate their relationship with risk transmission. This study attempts to systematically analyze the COVID-19 risk factors that affect the extreme risk of different types of assets. The goal of this study differs from studies on hedging practices that evaluate whether individual asset markets are vulnerable to the impact of the pandemic. The intended contribution of this study is to provide a novel analysis that can "systematically" dissect the impact of a black swan event. Instead of including other macro- and micro-factors, this study explores the effects of COVID-19 pandemic–related risk factors (i.e., pandemic severity, pandemic regulations and policies, and vaccination-related variables) on the risk of extreme volatility in asset returns across eight assets belonging to different asset categories (virtual, financial, energy, commodity, and real assets).

Using this method, we can examine the relationship between asset characteristics and risk sources, which can in turn help investors prehold assets with low-risk transmission effects when faced with different types of risk surge events in the future. To develop our understanding of the avoidance of extreme risk, this study analyzes different asset categories. Future empirical studies should include additional asset types. There is a need for more theoretical research on this issue that can allow for the development of further models to explain the common factors in assets that influence the risk characteristics and hedging functions of various asset classes.

Abbreviations

ROA	Return on assets
ESG	Environmental, Social, and Governance
MSCI	Morgan Stanley Capital International
CCI	Crypto Currencies Index
WSPI	MSCI World Stock Price Index
WTI	West Texas Intermediate
WEPI	MSCI World Energy Price Index
S&P	Standard & Poor
GSCI	Goldman Sachs Commodity Index
REITs	Real estate investment trusts
EPU	Economic Policy Uncertainty
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GFI	Global fear index
VaR	Value at Risk
VAR	Vector autoregression
MGARCH	Multivariate Generalized Autoregressive Conditional Heteroskedasticity
TC	Total infected cases
TD	Total deaths
SI	Stringency index
TV	Total number of vaccines
PV	Population vaccinated
HSBM	Historical simulation-based method

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I-Chun Tsai contributed data curation, formal analysis, and writing. The author read and approved the final manuscript.

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Availability of data and materials
The datasets generated during and/or analyzed during the current study are available in the Eikon with Datastream for Office. https://www.refinitiv.com/en/products/eikon-trading-software

Declarations

Competing interest
The author have no competing interest to declare that are relevant to the content of this article.

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