Stock market tumble sparks crypto chaos: A crash risk spillover analysis

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The study employs an empirical Bayesian estimation approach to examine how the crash risk of the G-7 (United States [US], United Kingdom [UK], Japan, Germany, Canada, and France excluding Italy) and Chinese equity markets affects the crash risk of the top 11 cryptocurrencies. Two crash risk measures were adopted to determine the monthly crash risk of the two types of markets, which are the most appropriate for skewed returns. Four separate models were estimated using the empirical Bayes estimation method because it considers heterogeneity, is more efficient than least squares, and facilitates more accurate coefficient estimation. The results reveal that the German stock market's crash risks are significantly and contemporaneously associated with the crash risk of all 11 cryptocurrencies, indicating that the German equity market is not a reliable diversifier for cryptocurrencies. The crash risks of the US, UK, and Japanese (German and Canadian) equity markets have a positive (negative) impact on the crash risk of cryptocurrency markets with a one-month lag. Generally, lagged crash risks have a more substantial influence on cryptocurrency crash risk, suggesting that historical crashes in equity markets are better predictors of cryptocurrency crashes. The one-month significant delay effect may present arbitrage opportunities because the risk of crashes in stock markets may signal potential crashes in cryptocurrencies one month in advance. A series of robustness checks confirmed the results of the analysis and the validity of our conclusions. These findings suggest that crypto investors and policy-makers should pay attention to historical events in equity markets. Investors and portfolio managers in the cryptocurrency market should monitor unexpected fluctuations in the stock market, particularly significant declines that could result in significant losses in the future.

Keywords:
Bayesian estimation,
crash risk,
cryptocurrency,
spillover,
stock market

Introduction

Since its inception approximately 12 years ago, Bitcoin has attracted considerable interest from both individual and institutional investors, leading to the development of other digital currencies and the emergence of a new market known as the cryptocurrency market. In recent years, this volatile market has attracted the attention of researchers, resulting in a growing body of academic literature that examines various aspects of the cryptocurrency market (Corbet et al. 2019). The primary areas of interest have been its high returns, volatility, bubbles, and crashes (Feng et al. 2018; Katsiampa 2017, Fruehwirt et al. 2020, Fry 2018). Additionally, there has been a growing interest in the relationship between the cryptocurrency market and traditional markets such as the equity market (see, for example, Kumah–Odei-Mensah 2021, Lahmiri–Bekiros 2020, Nguyen 2022, Stensås et al. 2019, Ünvan 2021, Wang et al. 2020, 2022).

The instability of the stock market can potentially spread to the cryptocurrency market, as evidenced by the downturn in the cryptocurrency market following the downturn in the equity market in 2018 (Matkovskyy–Jalan 2019). News events, such as public health emergencies, can also prompt investors to rapidly shift funds between the two markets, increasing the likelihood of risk contagion (Lahmiri–Bekiros 2020). Lahmiri–Bekiros (2020) argued that during the pandemic, the cryptocurrency market exhibited greater instability than the equity market. Unlike the stock market, the cryptocurrency market lacks a safety mechanism to prevent excessive price declines (Wang et al. 2022), which could result in a market crash if prices continue to fall.

The global economy and financial systems have become more interconnected than ever before. However, recent economic turmoil, exacerbated by the Covid-19 pandemic, has rendered global financial systems more fragile (Ashraf–Goodell 2022). For instance, Hung (2023) asserted that Covid-19 had a dramatic impact on stock markets. The Russia–Ukraine conflict and global sanctions against Russia, a significant energy supplier (Dai et al. 2022), have further destabilized global financial systems. New threats to worldwide military conflict, food supplies, and atomic warfare have also emerged, all of which have negative impacts on domestic economies (Boubaker et al. 2022). Consequently, economic downturns are inevitable and lead to stock market downturns.

Additionally, financial market integration creates opportunities for reserve portfolio managers and global financial investors. Market integration influences potential opportunities for diversification worldwide. Profoundly integrated or comoved markets provide limited benefits for global diversification. However, portfolio managers can diversify and profit from segmented markets (Kumar Tiwari et al. 2013, Mensah–Premaratne 2018). Policy-makers are also interested in financial market integration because events in one market can significantly affect other markets as each market becomes an integral part of a single global market (Angelidis–Koulakiotis 2022, Kumar Tiwari et al. 2013, Mensah–Premaratne 2018). Therefore, investors must examine portfolio diversification and possible asset allocation changes since most financial markets continue to experience large swings and are likely interconnected (Hung 2022, 2023).

Furthermore, concerns have been raised regarding the impact of cryptocurrencies on financial stability and investor-related portfolio issues (Dai et al. 2022). While the use of cryptocurrencies by investors as a means of diversifying or hedging their portfolios has increased (Mba et al. 2018), broader concerns have been expressed about the role of cryptocurrencies and their potential to exacerbate instability in equity markets and the financial system (Iyer 2022). The role and rapid expansion of cryptocurrencies in the financial system have attracted significant attention from both investors and policy-makers. As such, a body of literature has emerged that examines the link between risk and volatility contagion in cryptocurrencies and traditional assets, such as equity markets (Kumah–Odei-Mensah 2021, Lahmiri–Bekiros 2020, Nguyen 2022, Stensås et al. 2019, Ünvan 2021, Wang et al. 2020, 2022) and precious metals (Hassan et al. 2021, Mensi et al. 2019, Rehman 2020). This study contributes to the literature by establishing a link between crash risk in traditional stock markets and digital currency crash risk. This implies that the current study investigates the impact of regular stock market crash risks on cryptocurrency market crash risks using data for the top 11 cryptocurrencies and stock markets from G-7 countries (excluding Italy) and China. Understanding how crises in traditional equity markets affect other financial markets, such as cryptocurrency markets, which may share some of their investor bases, is crucial for explaining the fluctuations and crash risks in cryptocurrency markets that have puzzled both academics and investors.

While Dai et al. (2022) demonstrated that crashes in the cryptocurrency market are short-lived, they occur frequently and pose a risk to the equity market. In contrast to Dai et al. (2022), this study focuses on the transmission of equity market crashes to cryptocurrency market crashes. Additionally, this study diverges from Dai et al. (2022) by measuring crash risk using the negative coefficient of skewness (NS) and the "down-to-up" volatility (DU), which were introduced by Chen et al. (2001). These measures are appropriate for asymmetric returns, making them well-suited for the cryptocurrency market, as cryptocurrency returns are skewed (Chaim–Laurini 2019, Urquhart 2017). Furthermore, a broader range of cryptocurrencies is employed to represent the cryptocurrency market more accurately. The study utilizes daily data for the top 11 cryptocurrencies, selected based on market capitalization as of July 5, 2022, and stock markets from G-7 countries (excluding Italy) and China, considering China's emerging position in the global market. The top 11 cryptocurrencies selected constitute approximately 66.5% of the overall cryptocurrency market capitalization.

This study makes several contributions to the literature. It provides novel insights into the crash risks associated with cryptocurrencies. While there are a few published studies that have examined the determinants of cryptocurrency market crash risk (Anastasiou et al. 2021, Dai et al. 2022, Kalyvas et al. 2020, Ma–Luan 2022), no prior research has directly linked stock market crash risk with cryptocurrency market crash risk. This study presents evidence that the crash risk of conventional stock markets can be utilized to predict cryptocurrency market crashes, which constitutes a significant addition to traditional explanations for asset price crash risk. Furthermore, the study underscores the predictive power of equity market crash histories in forecasting cryptocurrency market crashes. As such, it offers a more comprehensive explanation for the fluctuations and crash risks in cryptocurrency markets, which have confounded both academics and investors.

The remainder of this paper is structured as follows. The first section briefly reviews the relevant literature, then the next one discusses the data, the crash risk measures, the model specification and the estimation method. After these the empirical results will be presented and discussed, while the last section provides concluding remarks.

Literature review

The literature on crash risk in the cryptocurrency market is still evolving. Few studies have been conducted on crash risk in the cryptocurrency market. The behavioral factors' associations with crashes in the crypto market are among the few issues discussed in the literature. Anastasiou et al. (2021) showed that the FEARS index is positively related to cryptocurrency price crash risk, indicating that a higher crisis sentiment by investors increases cryptocurrency price crash risk. Kalyvas et al. (2020) noted that investors can hedge economic policy uncertainty with Bitcoin since they conclude a negative association between the former and the latter. Similar to Anastasiou et al. (2021), Kalyvas et al. (2020) also noted an association between behavioral factors and Bitcoin crash risk but in a weak form. In a similar study, Smales (2022) found that the association between investor attention and cryptocurrency crash risk is positive below the median quartile and negative above the median quartile. Smales (2022) also observed seasonality in crash risk, with a higher crash risk during the June–August period and a lower crash risk during the Halloween period (November to April). Corbet et al. (2020) discovered that investors seeing cryptocurrencies as a store of value led to an increase in returns and trading volumes in the Covid-19 pandemic era.

Bubbles and structural breaks in cryptocurrency market pricing can result in crashes. Fruehwirt et al. (2020) demonstrated that structural breaks in market pricing are a direct cause of cryptocurrency crashes. Fry (2018) argues that in the absence of regulation, cryptocurrency markets are likely to experience crashes because empirical evidence indicates bubbles in the Ethereum and Bitcoin markets.

Ma–Luan (2022) study the synchrony between Bitcoin and Ethereum under the assumption that Bitcoin's volatility will increase as a stand-in for concerns over rising Bitcoin prices. According to Ma–Luan's (2022) empirical findings, Ethereum synchronization significantly reduces the likelihood of a Bitcoin crash when upside volatility is severe. Dai et al. (2022) indicated that cryptocurrency markets have a higher likelihood of crashing than equity markets. Further evidence shows that although crashes in the cryptocurrency market occur in a shorter period, they could be passed to equity market crashes. Further investigation shows that the commonality between crash risk in cryptocurrency and the equity market is 80% in the considered period.

Wang et al. (2022) show that cryptocurrency and the US stock market have a nonlinear causal relationship, concluding that lower tail dependencies are more significant than upper tail dependencies. Wang et al. (2020) find that the S&P 500 weakly impacted the cryptocurrency market. Further investigation by the authors shows that the mean and standard deviation of the S&P 500 and the mean of the Dow Jones indices have a strong effect on the mean of Bitcoin, and the standard deviation of the S&P 500 significantly affects Bitcoin's standard deviation. Iyer (2022) also observed a bidirectional spillover effect between the S&P 500, the MSCI emerging market index, and Bitcoin and Tether, noting that the spillover effects between the two markets increased in the Covid-19 era. In contrast, Wang et al. (2022), Iyer (2022), and Wang et al. (2020) studies, Ünvan (2021) examine Bitcoin correlation with US, Japanese, and Turkish stock markets and no significant impact of Bitcoin on US and Japan stock markets was observed. Bitcoin, however, significantly impacted the Turkish stock market, and two-way causality was observed between the two markets.

Some studies also provide compelling evidence of a time-varying relationship between the price fluctuations of major cryptocurrencies and those of US stock indices. For instance, Corbet et al. (2018), Tiwari et al. (2019), and Gil-Alana et al. (2020) found that cryptocurrencies have a low correlation with stock indices, so they can be added to the portfolios to diversify the risks. In contrast, Kristjanpoller et al. (2020) show that cryptocurrency does not act as a good instrument for hedging in stock markets because of the positive correlations found in most cases.

Data and crash risk measurements

Data for the top 11 cryptocurrencies and six G-7 (US, UK, Japan, Germany, Canada, and France excluding Italy) countries and China stock indices are used to investigate the relationship between crash risks. Italy was excluded from the analysis due to the diminutive nature of its market capitalization and the high probability of a strong correlation with the stock markets of Germany and France, thereby mitigating the incidence of multicollinearity. Table 1 delineates the specifics of the initial daily data for cryptocurrencies utilized in the computation of monthly crash risks. The top 11 cryptocurrencies encompass Bitcoin (BT), Ethereum (ET), Binance (BN), XRP (XP), Cardano (CR), Dogecoin (DG), Litecoin (LT), Chainlink (CL), Stellar (ST), Bitcoin Cash (BC), and EOS (ES), which were selected based on their market capitalization, as accessed from https://coinmarketcap.com/on July 7, 2022 at 14:05 Istanbul time. Additionally, the daily data for the benchmark stock indices of the US (S&P 500), UK (FTSE 100), Japan (Nikkei 225), Germany (DAX), France (CAC40), China (CSI 300), and Canada (TSX) are used to compute the monthly stock market crash risk. Stock market data were retrieved from Yahoo Finance (finance.yahoo.com). The samples range between January 1, 2014, and June 30, 2022, due to data availability for the various cryptocurrencies.

Table 1

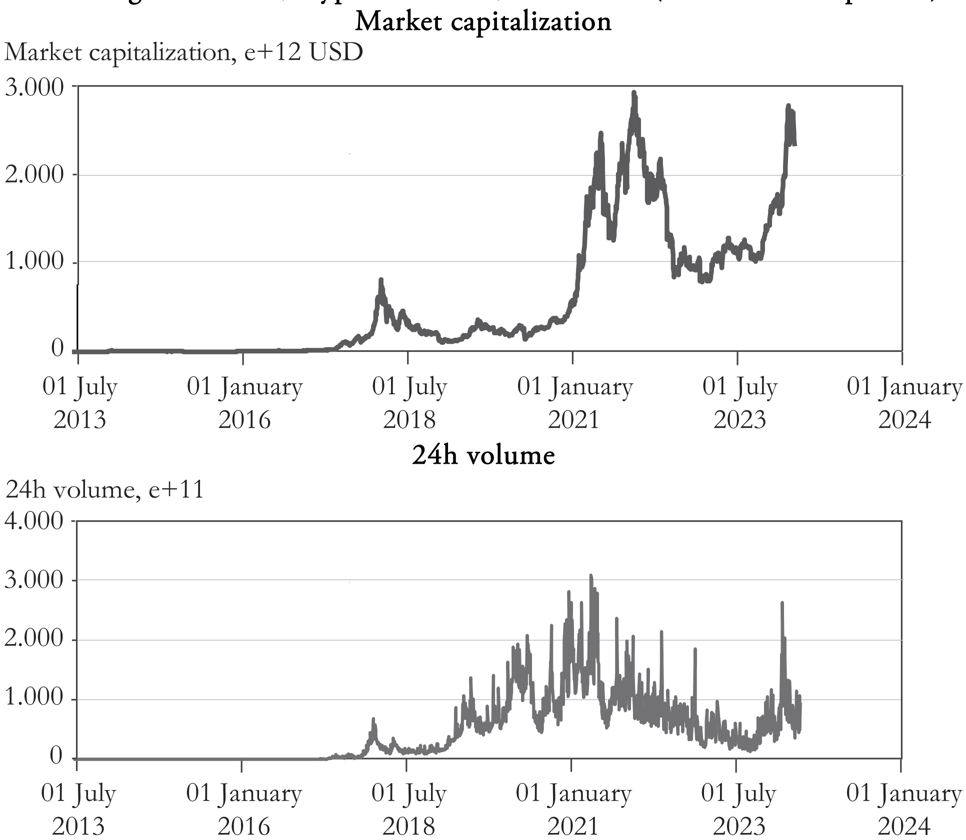
Details of cryptocurrency and country stock indices of the initial daily data

No.	Cryptocurrency	Abbreviation	Sample range
1	Bitcoin	BT	January 1, 2014– June 30, 2022
2	Ethereum	ET	August 7, 2015– June 30, 2022
3	Binance	BN	August 1, 2017– June 30, 2022
4	XRP	XP	January 1, 2014– June 30, 2022
5	Cardano	CR	October 1, 2017– June 30, 2022
6	Dogecoin	DG	January 1, 2014– June 30, 2022
7	Litecoin	LT	January 1, 2014– June 30, 2022
8	Chainlink	CL	October 1, 2017– June 30, 2022
9	Stellar	ST	August 9, 2014– June 30, 2022
10	Bitcoin Cash	BC	August 1, 2017– June 30, 2022
11	EOS	ES	July 4, 2017– June 30, 2022

The total market capitalization of crypto assets, as represented in Figure 1, has increased exponentially, from less than USD 20 billion in January 2017 to more than USD 2.8 trillion in November 2021. As of September 2021, Bitcoin and Ether are among the top 20 traded assets in the world, competing with the market value of some of the world's largest companies (Iyer 2022). However, within the last year, market capitalization decreased from USD 2.2 trillion in January 2022 to USD 0.93 trillion in July 2022, amounting to an approximately 58% decrease in market capitalization.

Figure 1

The market capitalization and trading volume of all crypto assets, including stablecoins, cryptocurrencies, and tokens (CoinMarketCap 2022)



The price of Bitcoin, the world's largest cryptocurrency, dropped by 74% from peak to trough at one point, which closely resembles the 83% collapse experienced in 2018. It must be remembered that the market is now substantially larger and has a much wider investor base than in 2018 (Tham 2022).

The crash risks of cryptocurrencies and stock market prices were computed on a monthly basis utilizing the initial daily data. Two measures of crash risk, namely, the "negative coefficient of skewness" and "down-to-up volatility", denoted by "NS" and "DU", respectively, were adopted from the crash risk literature (see Chen et al. 2001). Owing to the nature of the computational process required to measure crash risk, the final data could not be obtained at daily or weekly frequencies, as the initial data were procured at a daily frequency.

The first crash risk measure is the NS, which is the negative coefficient of skewness of cryptocurrency and stock market monthly returns and considers the third moment. This measure is appropriate when the returns are asymmetric. Therefore, it fits the cryptocurrency market, as several researchers, such as Chaim–Laurini (2019) and Urquhart (2017), show that cryptocurrency returns are skewed. In addition, Fry–Cheah (2016) provided evidence of negative bubbles in the cryptocurrency market. In this regard, standard deviation and other traditional measures of volatility may not best capture skewness and hence are not appropriate for this type of data.

The NS is calculated for a cryptocurrency and stock market i over any month period t by:

$$NS_{i,t} = {-\left(n(n-1)^{\frac{3}{2}} \sum R_{i,t}^3\right)} \Bigg/ {\left((n-1)(n-2)\left(\sum R_{i,t}^2\right)^{\frac{3}{2}}\right)} \tag{1}$$

where $R_{i,t}$ denotes daily market i returns for one month period t, *and* n is the number of trading days in a given month. Daily returns are calculated as the log differences of daily prices.

A second measure, DU, is used in addition to NS, which is less susceptible to being excessively impacted by extremely abnormal days, as it does not use the third moment. The DU measure is calculated for a cryptocurrency and stock market i over any month period t as follows:

$$DU_{i,t} = \log\left\{ (n_u - 1) \sum_{Down} R_{i,t}^2 \Big/ (n_d - 1) \sum_{Up} R_{i,t}^2 \right\} \tag{2}$$

where n_u and n_d are the number of upward and downward daily returns within a month, respectively. In addition, the subscripts i and t represent cryptocurrency/stock market and time, respectively. For each month, all daily returns are below (above) the monthly mean return, classifying each day as a "down" ("up") day. The standard deviations for the down and up days were then calculated separately. Finally, the log ratio of the standard deviation of down days to the standard deviation of up days was computed.

After obtaining the monthly crash risk measures (NS and DU), the descriptive statistics, the correlation matrix, and the variance inflation factor (VIF) were tabulated in Tables A1 and A2 in the Internet appendix. The results presented in Table A1 indicate that Litecoin has the highest standard deviation and maximum values and the lowest minimum value among NS crash risk measures. Table A2 shows that all equity market crash risks are positively related to each other, implying crash risk comovement. The VIF in Table A2 shows the unlikelihood of encountering the problem of multicollinearity with the DU measures of crash risk, as the calculated VIF is below the threshold of 5. The VIF calculation for the NS measure of the independent variables indicates Germany and France crash risk measures have a VIF negligibly above 5. Alin (2010) suggests that the threshold value for distinguishing between small and large is usually set at 10. Farrar–Glauber (1967) noted that multicollinearity is not always an issue unless it is significantly high compared to the overall degree of multiple correlation. Additionally, the correlation matrix for NS and DU between crash risk measures of cryptos and the stock markets are reported in Tables A3 and A4 in the Internet appendix.

Figure 2

Graphical representation of the NS crash risk measure of the top 11 cryptocurrencies

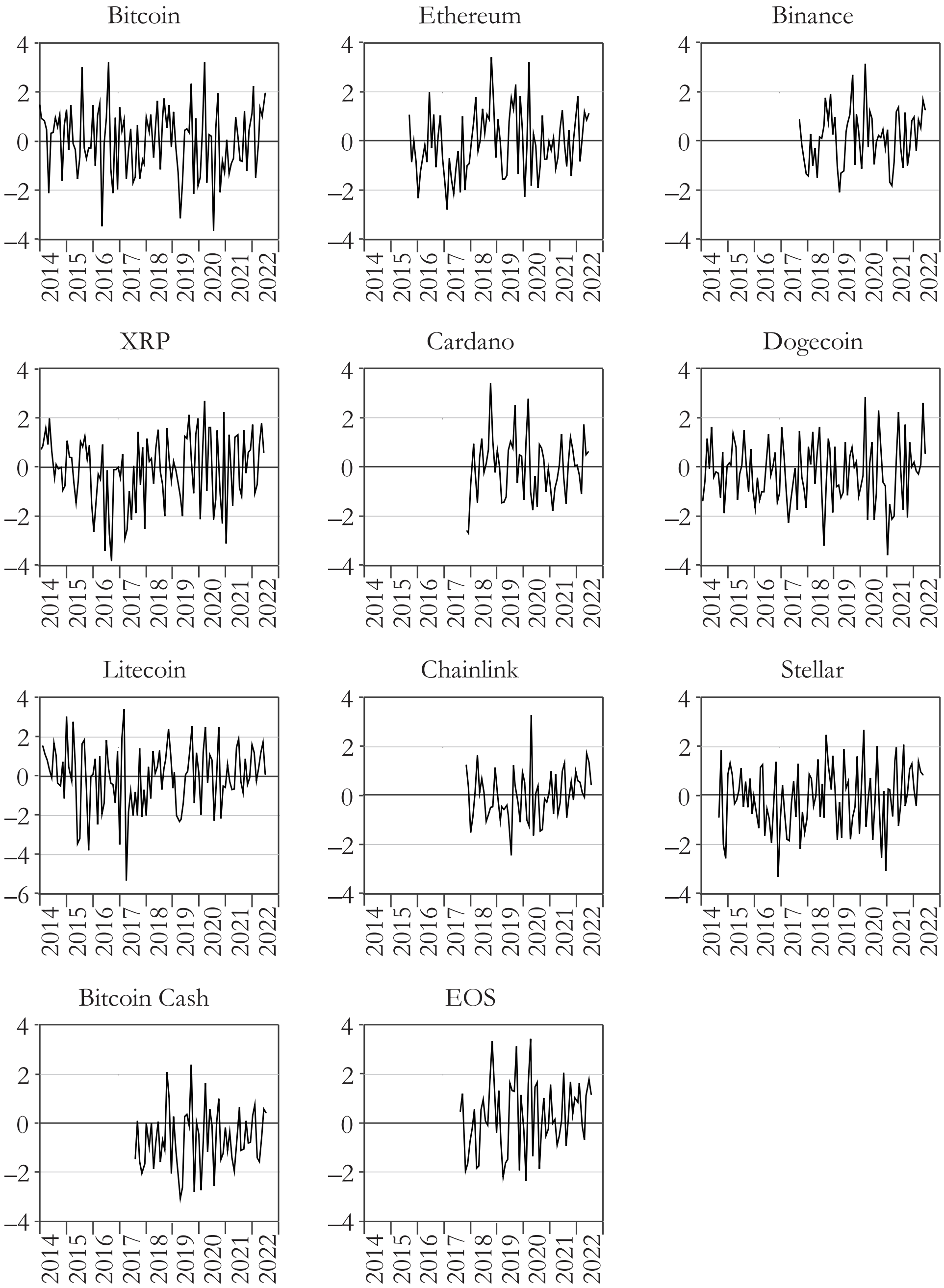


Figure 3

Graphical representation of the DU crash risk measure of the top 11 cryptocurrencies

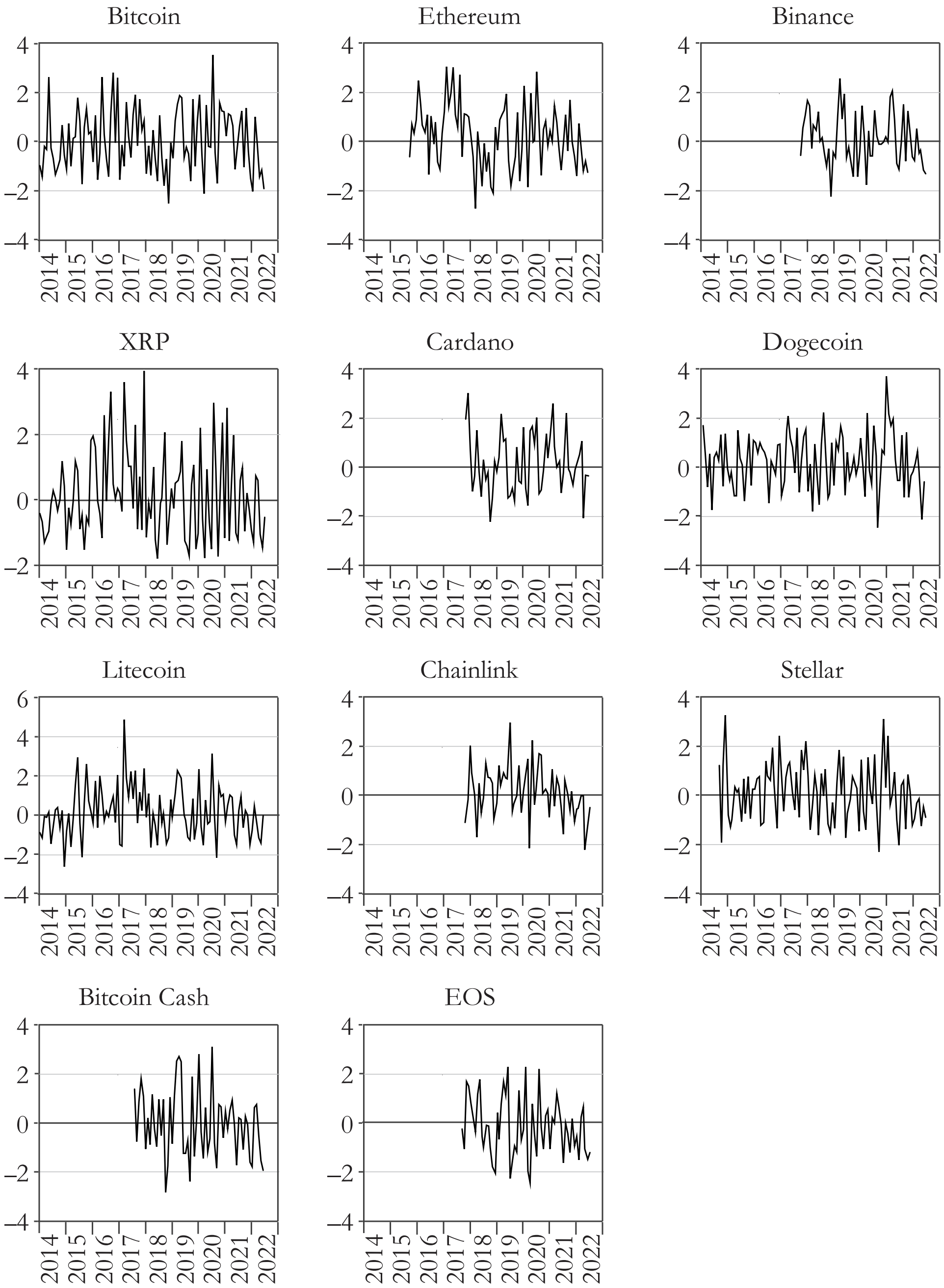


Figure 4

The plots of the NS monthly crash risk measure of the seven stock markets in the analysis

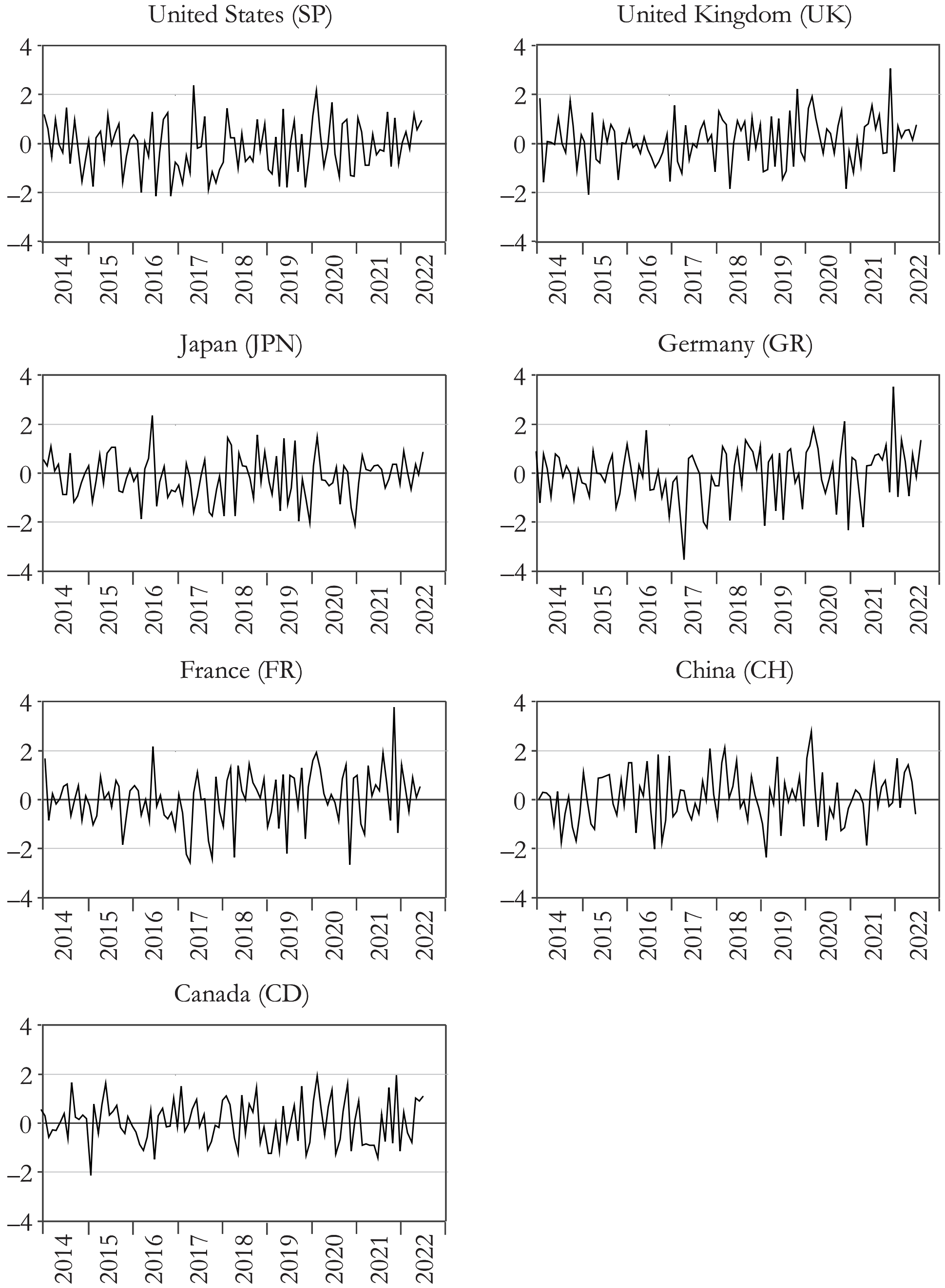
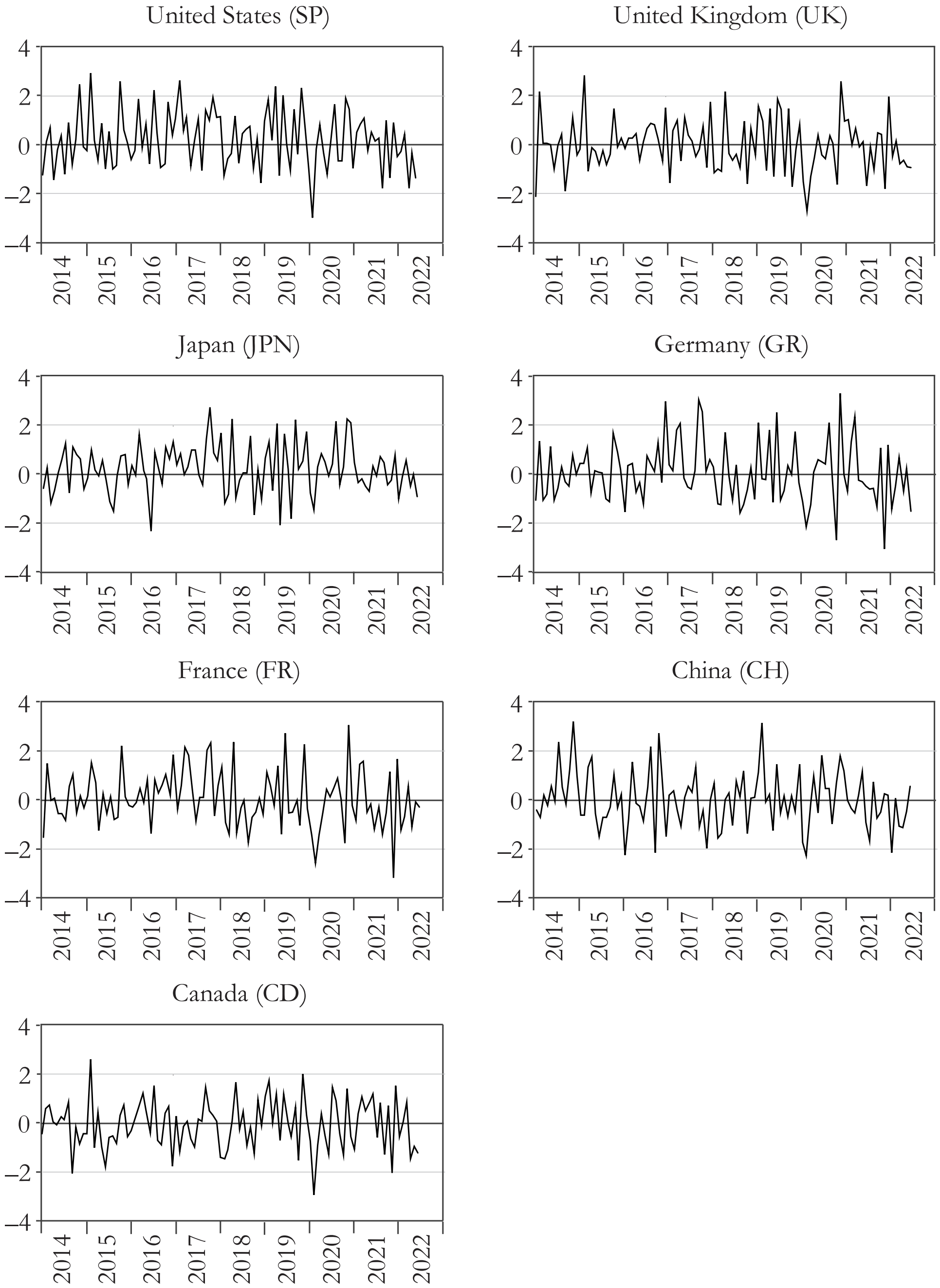


Figure 5

The plots of the DU monthly crash risk measure of the seven stock markets in the analysis



Figures 2, 3, 4, and 5 display the graphs of monthly crash risk measures of NS and DU for the 11 cryptocurrencies and the 7 stock markets. Figures 2 and 3 show the NS and DU crash risk measures of cryptocurrencies, respectively, which indicate that the highest crash risk observations are generally observed between 2018 and 2022. This reflects the crypto winters in 2018 and the impact of Covid-19 from 2019 through 2022, resulting in an approximately 58% decrease in total market capitalization. Figures 4 and 5 present NS and DU crash risk measures for the 7 stock markets. Again, the impact of Covid-19 on stock market crash risk measures is evident. Comparatively, the stock market crash risk of China and the two EU countries (Germany and France) were more affected by Covid-19 than their counterparts.

Model specification and the Bayesian estimation

The model specification commences with a general autoregressive distributed lag (ARDL) model, which applies to stationary time series. The ARDL model regresses the dependent variable as a function of both current and past values of explanatory variables. The equation for this model is as follows:

$$CM_{i,t} = \alpha + \sum_{j=0}^{1} \beta_j R_{t-j} + \varepsilon_{i,t} \tag{3}$$

where $CM_{i,t}$ represents the crash risk measure (NS and DU) of the 11 cryptocurrencies (i=1,2,----11) in the current period. α is the intercept of the model. $R_{i,t}$ is the matrix of the crash risk measures of the 7 stock markets in the current period, i.e.,

$$R_t = [SPCM_t \;\; UKCM_t \;\; JPCM_t \;\; GRCM_t \;\; FRCM_t \;\; CHCM_t \;\; CDCM_t]$$

and β_j is the coefficient vector of R_t, which measures the marginal effect of stock market crash risk on the crypto crash risk per unit change. $SPCM_t$, $UKCM_t$, $JPCM_t$, $GRCM_t$, $FRCM_t$, $CHCM_t, and\ CDCM_t$ are the crash risk measures for the US, UK, Japan, Germany, France, China, and Canada, respectively, at time t. $R_{i,t-1}$ denotes the values of $R_{i,t}$ in the previous period. $\varepsilon_{i,t}$ is the random component of the model. Equation 3 is referred to as a distributed lag (DL) model due to the inclusion of lagged effects of the independent variable.

Equation 3 can be extended to include the lagged dependent variable as one of the explanatory variables, resulting in a dynamic model with lagged values of both dependent and independent variables. This will result in an autoregressive distributed lag model, the ARDL (1,1) model:

$$CM_{i,t} = \alpha + \theta_1 CM_{i,t-1} + \sum_{j=0}^{1} \beta_j R_{t-j} + \varepsilon_{i,t} \tag{4}$$

where the lagged dependent variable ($CM_{i,t-1}$) represents the autoregressive component. Such models are referred to as autoregressive distributed lag models (ARDL) because they comprise both an autoregressive component, where the dependent variable is regressed on one or more of its past values, and a distributed lag component, which includes the independent variable and one or more of its lagged components.

We then generalized the ARDL (1,1) model in Equation 4 to include control variables[1], which takes the following form:

$$CM_{i,t} = \alpha + \theta_1 CM_{i,t-1} + \sum_{j=0}^{1} \beta_j R_{t-j} + \sum_{s=0}^{1} \gamma_k S_{t-k} + \varepsilon_{i,t} \quad (5)$$

where S_t is the matrix of control variables, i.e.,

$$S_t = [GDCM_t\ GDR_t\ GDV_t\ OLCM_t\ OLR_t\ OLV_t\ MSCI_t\ MSCIV_t\ CPR_t\ CPV_t\ CPTV_t]$$

and γ_k is the coefficient vector of the control variable. The definitions of the control variables are provided in the Supplementary file.

A special case of the generalized ARDL (1,1) model, Equation 5, in the form of ARDL (1,0,1) is considered as:

$$CM_{i,t} = \alpha + \theta_1 CM_{i,t-1} + \sum \delta_i R_{t-1} + \varepsilon_{i,t} \quad (6)$$

Model (6) contains only one time-period lag for both dependent and independent variables.

Finally, a static multiple linear regression model is considered for further robustness assessment, which is also a special case of the general model. The model is expressed as:

$$CM_{i,t} = \alpha + \beta_1 SPCM_t + \beta_2 UKCM_t + \beta_3 JPCM_t + \beta_4 GRCM_t + \beta_5 FRCM_t + \beta_6 CHCM_t + \beta_7 CDCM_t + \varepsilon_{i,t} \quad (7)$$

Then, an empirical Bayesian approach is employed for the estimation. The general model under the empirical Bayesian approach has the following form, which was used by Carrington–Zaman (1994):

$$Y_{it} = \beta_i X_{it} + \varepsilon_{it} \quad (8)$$

where Y is the dependent variable; X is the independent variable; t is the number of periods; i is the number of cryptocurrencies; and β is the coefficient of each stock market's crash risk. Equation (8) can be explained as

$$Y_i = \begin{bmatrix} y_{i1} \\ y_{i2} \\ . \\ y_{it} \\ . \\ y_{iT} \end{bmatrix}_{Tx1}, \quad X_{it} = \begin{bmatrix} x_{i1} \\ x_{i2} \\ . \\ x_{it} \\ . \\ x_{iT} \end{bmatrix}_{TxK}, \quad e_{it} = \begin{bmatrix} e_{i1} \\ e_{i2} \\ . \\ e_{it} \\ . \\ e_{iT} \end{bmatrix}_{Tx1}$$ and where

$X_{it} = \left[X_{it}^1\ X_{it}^2 \ldots\ldots X_{it}^k \right]_{k-Regressors}$ is a vector of K regressors. $e_{it} \sim N\left(0, \delta_i^2\right)$ is the stochastic error term.

The data density is $\hat{\beta}_i / \beta \sim N(\beta, \Omega_i)$

and the prior density is $\beta \sim N(\mu, \Lambda)$

[1] Definitions of control variables see in the Internet appendix.

Therefore, the posterior density becomes $\beta \big/ \hat{\beta}_i \sim N\left(m_i,\ \mathrm{V}_i\right)$ (9)

where the values of the parameters in Equation 9 are

$$m_i = V_i\left(\Omega_i^{-1}\hat{\beta}_i + \Lambda^{-1}\mu\right) \ \ and \ \ V_i = \left(\Omega_i^{-1} + \Lambda^{-1}\right)^{-1} \tag{10}$$

The Bayes estimator represents the mean of the posterior. Therefore, Equation 10 becomes $\hat{\beta}_{i(B)} = V_i(\hat{\Omega}_i^{-1}\hat{\beta}_i + \Lambda^{-1}\mu)$ and its variance-covariance matrix is

$$V_i = \left(\hat{\Omega}_i^{-1} + \Lambda^{-1}\right)^{-1} \tag{11}$$

The two hyperparameters, that is, μ and Λ are unknown in Equation 11, and if their values are used from any source other than the data at hand, then the Bayes estimator is the classical Bayes estimator. However, if these two (μ and Λ) are estimated from the data, then $\hat{\beta}_{i(B)}$ will be termed the empirical Bayes (EB) estimator, and Equation 11 becomes

$$\hat{\beta}_{i(EB)} = \hat{V}_i\left(\hat{\Omega}_i^{-1}\hat{\beta}_i + \hat{\Lambda}^{-1}\hat{\mu}\right) \tag{12}$$

where the values of ($\hat{\mu}$ and $\hat{\Lambda}$) in Equation 12 are

$$\hat{\Lambda} = \left(\sum_{i=1}^{n}\Omega_i^{-1}\right)^{-1} \text{ and } \ \hat{\mu} = \hat{\Lambda}\left(\sum_{i=1}^{n}\hat{\Omega}_i^{-1}\hat{\beta}_i\right) \tag{13}$$

The advantage of the empirical Bayes technique is that it carefully considers heterogeneity and has much lower standard errors than other techniques, such as ordinary least squares (OLS) and conventional Bayesian methods (Zaman 1996). Muradoglu et al. (2005) showed that using empirical Bayes estimates with sector information as the prior instead of ordinary least squares (OLS) improves price forecasts significantly, and thus, betas can be estimated with greater precision. They also contended that in the empirical Bayes method, priors can be assigned to the dataset itself, which alleviates the problem of prior determination. The empirical Bayes method also uses additional information provided by the dataset.

Results and discussions

Table 2 presents the findings of the 11 regression models for the DU monthly crash risk measures of the top 11 cryptocurrencies, utilizing the ARDL (1,1) Equation 4. In general, the crash risk measures of the US (SPCM), Japan (JPCM), Germany (GRCM), China (CHCM), and Canada (CDCM) exhibit a positive relationship with the crash risk measures of the cryptocurrency market at the variable level. Conversely, the crash risk measures of the UK (UKCM) and France (FRCM) exert a negative impact on cryptocurrency crash risk. Notably, the German stock market is the only one that significantly influences cryptocurrency market crash risk contemporaneously. The crash risk measure of the German stock market (GRMC) exerts a statistically significant positive impact on all 11 cryptocurrency markets at a 5% level threshold. In terms of economic significance, on average, a one-unit change in the crash risk of the German stock market is associated with a 0.23-unit increase in cryptocurrency crash risk. These results imply that a meltdown in the German stock market during economic downturns will adversely affect the cryptocurrency market, indicating that the two markets are contemporaneously related. As such, the cryptocurrency market cannot serve as a diversifier or hedge asset for German stock market investors due to the significant positive association between the crash risks of the two markets. This is because an increase in correlations between asset classes during economic downturns undermines portfolio diversification strategies (Bekaert et al. 2009). The crash risks of the remaining six stock markets (the US, UK, Japan, France, China, and Canada) do not significantly influence cryptocurrency markets' crash risks contemporaneously.

Table 2

Empirical Bayesian posterior results for the ARDL (1,1) model (Model-4) with DU as the crash risk measure

Variables	[1] BT	[2] ET	[3] BN	[4] XP	[5] CR	[6] DG
LAG	0.027 (0.034)	0.045 (0.034)	0.043 (0.034)	0.023 (0.034)	0.042 (0.034)	0.034 (0.034)
SPCM	0.005 (0.056)	0.012 (0.057)	0.023 (0.057)	0.007 (0.056)	–0.004 (0.058)	0.020 (0.055)
SPCM(–1)	0.246*** (0.058)	0.283*** (0.059)	0.281*** (0.060)	0.306*** (0.059)	0.293*** (0.060)	0.256*** (0.058)
UKCM	–0.021 (0.055)	–0.026 (0.056)	–0.034 (0.056)	0.013 (0.056)	–0.022 (0.056)	0.002 (0.055)
UKCM(–1)	0.103* (0.056)	0.109* (0.057)	0.127** (0.056)	0.099* (0.056)	0.125** (0.057)	0.094* (0.056)
JPCM	0.072 (0.059)	0.081 (0.059)	0.055 (0.059)	0.069 (0.059)	0.078 (0.060)	0.069 (0.058)
JPCM(–1)	0.187*** (0.058)	0.175*** (0.059)	0.179*** (0.058)	0.165*** (0.058)	0.182*** (0.059)	0.191*** (0.057)
GRCM	0.240*** (0.077)	0.213** (0.078)	0.241*** (0.078)	0.242*** (0.077)	0.238*** (0.079)	0.190** (0.076)
GRCM(–1)	–0.178** (0.076)	–0.154* (0.077)	–0.158** (0.077)	–0.153* (0.076)	–0.147* (0.078)	–0.163** (0.075)
FRCM	–0.092 (0.084)	–0.073 (0.085)	–0.099 (0.084)	–0.121 (0.084)	–0.095 (0.086)	–0.068 (0.083)
FRCM(–1)	0.058 (0.083)	0.026 (0.085)	0.025 (0.084)	0.018 (0.083)	–0.006 (0.085)	0.035 (0.082)
CHCM	0.029 (0.041)	0.030 (0.041)	0.027 (0.041)	0.025 (0.041)	0.037 (0.042)	0.025 (0.040)
CHCM(–1)	–0.040 (0.041)	–0.046 (0.041)	–0.050 (0.041)	–0.030 (0.041)	–0.043 (0.042)	–0.027 (0.040)
CDCM	0.047 (0.060)	0.049 (0.061)	0.048 (0.062)	0.043 (0.061)	0.065 (0.062)	0.045 (0.0600
CDCM(–1)	–0.100* (0.058)	–0.128** (0.059)	–0.114* (0.059)	–0.151** (0.058)	–0.138** (0.060)	–0.108* (0.057)

(Table continues on the next page.)

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Variables	[7] LT	[8] CL	[9] ST	[10] BC	[11] ES
LAG	0.035 (0.034)	0.026 (0.034)	0.012 (0.034)	0.032 (0.035)	0.032 (0.035)
SPCM	0.008 (0.056)	0.018 (0.058)	0.021 (0.055)	0.008 (0.058)	0.008 (0.058)
SPCM(–1)	0.271*** (0.059)	0.292*** (0.060)	0.302*** (0.058)	0.293*** (0.061)	0.293*** (0.061)
UKCM	–0.012 (0.056)	–0.028 (0.056)	0.004 (0.055)	–0.028 (0.057)	–0.033 (0.057)
UKCM(–1)	0.101* (0.056)	0.099* (0.057)	0.128** (0.056)	0.101* (0.058)	0.104* (0.057)
JPCM	0.078 (0.059)	0.065 (0.060)	0.070 (0.058)	0.073 (0.060)	0.072 (0.060)
JPCM(–1)	0.185*** (0.058)	0.159** (0.059)	0.148** (0.057)	0.181 (0.060)	0.182 (0.059)
GRCM	0.199** (0.077)	0.248*** (0.079)	0.275*** (0.076)	0.230*** (0.080)	0.226*** (0.079)
GRCM(–1)	–0.205** (0.076)	–0.148* (0.078)	–0.126 (0.076)	–0.160* (0.079)	–0.154* (0.078)
FRCM	–0.054 (0.084)	–0.095 (0.085)	–0.141 (0.083)	–0.098 (0.086)	–0.081 (0.086)
FRCM(–1)	0.084 (0.083)	0.004 (0.084)	–0.010 (0.083)	0.027 (0.086)	0.022 (0.085)
CHCM	0.023 (0.041)	0.043 (0.041)	0.029 (0.040)	0.037 (0.042)	0.029 (0.042)
CHCM(–1)	–0.041 (0.041)	–0.037 (0.042)	–0.022 (0.040)	–0.042 (0.042)	–0.042 (0.042)
CDCM	0.043 (0.061)	0.034 (0.062)	0.015 (0.060)	0.061 (0.063)	0.063 (0.063)
CDCM(–1)	–0.119** (0.058)	–0.113* (0.060)	–0.163*** (0.057)	–0.125** (0.060)	–0.126** (0.060)

Note: *, **, and*** indicate the significance of coefficients at 10, 5, and 1%. Numbers in (.) are the standard errors. Numbers in [.] denote the ARDL (1,1) regression model in the columns for each cryptocurrency DU crash risk measure.

For the lagged stock market crash risk variables, it is indicated that the lag one period of the US stock market crash risk (SPCM(–1)), UK stock market crash risk, (UKCM(–1)) and Japan stock market crash risk (JPCM(–1)) are positive and significant drivers of all 11 crypto markets' crash risks (except Japan in models [10] and [11]). A unit change in US, UK, and Japan stock market crash risks significantly caused an increase in cryptocurrency market crash risk by 0.28, 0.11, and 0.18 units on average, respectively. Conversely, the lag one period of the stock market crash risks of Germany and Canada, GRCM(–1) and CDCM(–1), are negatively and significantly associated with the crash risk of the 11 top crypto markets (except Germany in the model [9]). A unit change in one period lag of German and Canadian stock market crash risk significantly causes a decrease in cryptocurrency market crash risk by –0.16 and –0.13 units on average, respectively. The one-month statistically significant lag effects may present arbitrage opportunities, as a unit change in stock market crash risks can signal crypto investors and analysts about future cryptocurrencies' crash risks. Thus, investors and analysts can move funds to alternative assets to profit and avoid losses. These findings also imply that past information about crashes in the stock markets of the US, UK, Canada, Japan, and Germany could be useful in predicting potential one-month-ahead crash tendencies in cryptocurrency markets.

Table 3

Empirical Bayesian posterior results for the ARDL (1,1) model (Model-4) with NS as the crash risk measure

Variables	[1] BT	[2] ET	[3] BN	[4] XP	[5] CR	[6] DG
LAG	0.017 (0.033)	0.036 (0.034)	0.045 (0.034)	0.029 (0.033)	0.035 (0.034)	0.025 (0.033)
SPCM	–0.026 (0.066)	–0.022 (0.066)	0.021 (0.067)	–0.018 (0.066)	–0.014 (0.068)	–0.002 (0.065)
SPCM(–1)	0.100 (0.068)	0.108 (0.068)	0.118* (0.069)	0.146** (0.068)	0.137 (0.070)	0.124* (0.067)
UKCM	0.028 (0.058)	0.015 (0.058)	0.014 (0.058)	0.062 (0.058)	0.026 (0.059)	0.063 (0.058)
UKCM(–1)	0.051 (0.058)	0.051 (0.059)	0.080 (0.058)	0.054 (0.059)	0.060 (0.060)	0.049 (0.058)
JPCM	–0.075 (0.066)	–0.057 (0.066)	–0.116* (0.066)	–0.088 (0.066)	–0.079 (0.067)	–0.075 (0.065)
JPCM(–1)	0.282 (0.065)	0.292*** (0.066)	0.278*** (0.066)	0.258*** (0.065)	0.275*** (0.067)	0.275*** (0.064)
GRCM	0.258** (0.098)	0.265** (0.098)	0.261** (0.098)	0.288*** (0.098)	0.298*** (0.099)	0.256** (0.097)
GRCM(–1)	–0.171* (0.095)	–0.147 (0.095)	–0.158 (0.094)	–0.170* (0.0950	–0.133 (0.096)	–0.154 (0.094)
FRCM	–0.026 (0.097)	–0.032 (0.097)	–0.038 (0.096)	–0.085 (0.097)	–0.068 (0.098)	–0.058 (0.096)
FRCM(–1)	0.117 (0.094)	0.091 (0.094)	0.098 (0.094)	0.096 (0.095)	0.057 (0.095)	0.094 (0.093)
CHCM	0.054 (0.047)	0.061 (0.047)	0.056 (0.047)	0.062 (0.047)	0.060 (0.047)	0.053 (0.046)
CHCM(–1)	–0.045 (0.049)	–0.046 (0.049)	–0.056 (0.049)	–0.021 (0.049)	–0.041 (0.050)	–0.026 (0.049)
CDCM	0.095 (0.071)	0.085 (0.071)	0.087 (0.071)	0.079 (0.071)	0.098 (0.073)	0.084 (0.070)
CDCM(–1)	0.088 (0.072)	0.084 (0.072)	0.087 (0.072)	0.052 (0.072)	0.073 (0.073)	0.073 (0.071)

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Variables	[7] LT	[8] CL	[9] ST	[10] BC	[11] ES
LAG	0.024 (0.033)	0.025 (0.034)	0.011 (0.034)	0.027 (0.034)	0.032 (0.034)
SPCM	–0.013 (0.067)	0.030 (0.067)	–0.008 (0.065)	–0.006 (0.068)	–0.004 (0.060)
SPCM(–1)	0.121* (0.068)	0.134* (0.069)	0.162** (0.067)	0.127* (0.070)	0.129* (0.070)
UKCM	0.053 (0.059)	0.024 (0.059)	0.055 (0.058)	0.023 (0.060)	0.019 (0.060)
UKCM(–1)	0.061 (0.059)	0.040 (0.059)	0.064 (0.058)	0.045 (0.060)	0.044 (0.060)
JPCM	–0.084 (0.066)	–0.111 (0.066)	–0.063 (0.066)	–0.093 (0.068)	–0.092 (0.068)
JPCM(–1)	0.290*** (0.066)	0.265*** (0.066)	0.236*** (0.065)	0.294*** (0.067)	0.286*** (0.067)
GRCM	0.246** (0.099)	0.273*** (0.097)	0.325*** (0.098)	0.278*** (0.100)	0.271** (0.100)
GRCM(–1)	–0.198** (0.096)	–0.162* (0.094)	–0.143 (0.094)	–0.154 (0.097)	–0.163 (0.097)
FRCM	–0.017 (0.097)	–0.032 (0.096)	–0.109 (0.096)	–0.056 (0.099)	–0.040 (0.098)
FRCM(–1)	0.135 (0.095)	0.083 (0.094)	0.085 (0.094)	0.089 (0.097)	0.099 (0.096)
CHCM	0.054 (0.047)	0.079 (0.047)	0.047 (0.046)	0.066 (0.048)	0.061 (0.048)
CHCM(–1)	–0.047 (0.050)	–0.039 (0.049)	–0.012 (0.049)	–0.051 (0.051)	–0.049 (0.050)
CDCM	0.077 (0.072)	0.039 (0.071)	0.057 (0.070)	0.093 (0.073)	0.094 (0.073)
CDCM(–1)	0.076 (0.072)	0.092 (0.072)	0.024 (0.071)	0.087 (0.074)	0.092 (0.074)

Notes: *, **, and*** indicate the significance of coefficients at 10, 5, and 1%. Numbers in (.) are the standard errors. Numbers in [.] denote the ARDL (1,1) regression model in the columns for each cryptocurrency NS crash risk measure.

The results for the second crash risk measure, i.e., the negative coefficient of skewness (NS), estimated using Equation 4 are reported in Table 3. The results confirm the robustness of the estimates reported for the DU crash risk measure. Again, the German stock market yields a positive significant coefficient in all 11 models in the level variables, which indicates an extremely strong association between German stock index crash risk and cryptocurrency market crash risks. In terms of economic magnitude, a one-unit change in crash risk in the German stock market is associated with an average of 0.27-fold increase in cryptocurrency crash risk. Our argument that the crash risks of the German stock index and the cryptocurrency market comove holds and are also robust, as the NS results are similar to the results of the DU crash risk measure. The crash risks of the rest of the stock indices do not have a contemporaneous significant impact on cryptocurrency crash risks, except for the Japanese stock market crash risk in model [3], which significantly impacts the crash risk of Binance at the 10% level. A change in Japan's stock market crash risk adversely affects the crash risk of Binance by 0.12 times.

Turning to the lag one period variables of the stock market NS crash risk measure, the lag of the US crash risk measure, SPCM(–1), positively and significantly impacts the crypto crash risk measures in eight out of the 11 models, except for regressions [1], [2], and [5]. Japan stock market crash risk lag one period, JPCM(–1), has a significant positive impact on the crash risk of all crypto markets, except for regression [1], and Germany crash risk lag one period, GRCM(–1), significantly impacts the crash risk of four crypto market crash risks with a negative sign in regressions [1], [4], [7], and [8]. All other things remaining the same, a unit change in Japanese stock market crash risk causes an increase in crypto market crash risk by 0.28 units in one period lag on average. Additionally, a one-period lag of the German stock market crash risk induces a decrease in Bitcoin (BT), XRP (XP), Litecoin (LT), and Chainlink (CL) by –0.17, –0.17, –0.20, and –0.16 units, respectively. This suggests that the crash risk histories of equity markets are significant determinants of cryptocurrency market crash risks. As such, meltdowns and crashes in equity markets could serve as a gauge for predicting the crash risks of cryptocurrency markets at monthly intervals. Our findings are consistent with studies that indicate a growing interconnectedness between virtual assets and financial markets, which presents new risks for investors (Liu–Tsyvinski 2021, Dai et al. 2022).

Interestingly, the DU crash risk measure is more responsive to equity market crash histories, which might be because it does not consider the third moment; that is, it is less sensitive to extreme returns, unlike the NS measure. Our research emphasizes the significance of comprehending the connection between cryptocurrency and stock markets to effectively manage risk and make rational investment choices. In general, our results suggest that the delayed crash risk of stock markets has a significant influence on the crash risk of the crypto market, with the magnitude and direction of the impact varying depending on the stock market. This may be attributed to the distinct structure and investor base of stock markets. These results strongly suggest that historical stock market crash risk data can aid investors in assessing the crash risk of the crypto market. Our findings are consistent with Hong–Stein's (1999) gradual information diffusion theory, indicating that investors may underreact to crashes in traditional stock markets.

We employ an empirical Bayesian Priors estimation strategy to estimate Equation 4 for robustness, and the results are reported in Table A11 in the Internet appendix. Furthermore, we conduct additional robustness assessments by utilizing an empirical Bayesian estimation for Equations 5, 6, and 7. The results of these assessments are presented in Tables A5–A10 in the Internet appendix and are consistent with our principal findings.

Conclusions and policy implications

Crypto assets have gained popularity among investors and researchers, emerging as one of the top-traded assets by both retail and institutional investors worldwide in 2021. The role and rapid expansion of cryptocurrencies within the financial system have attracted significant attention from investors and policy-makers alike. Recent literature has linked the crash risk of the cryptocurrency market with factors such as market sentiment, economic policy uncertainty, and market bubbles. This study sought to investigate the impact of equity market crash risk on cryptocurrency market crash risk, attempting to establish a link between crypto market crash risk and regular stock market crash risk using data from G-7 countries (excluding Italy) and China. Two monthly crash risk measures were employed: the negative coefficient of skewness (NS) and the down-to-up volatility (DU), calculated from the daily returns of the two markets. These measures were selected due to the asymmetric and skewed nature of crypto-market returns. Additionally, NS depends on the third moment, while DU does not, rendering it less sensitive to extreme returns and thus serving the purpose of robustness. Four different models were estimated using empirical Bayes estimation, which considers heterogeneity, yields much lower standard errors, and ensures a more precise estimation of coefficients.

The results indicate that the German stock index crash risk exhibits a robust positive association with the top 11 cryptocurrency crash risks, thereby undermining its diversification capabilities for crypto investors. This is because portfolio diversification strategies are compromised by increased correlations among asset classes during downturns. The positive impact of the German stock index crash risk may also undermine the hedging capability of crypto assets for investors in the German stock market. Consequently, it can be argued that the German stock market crash risk represents a significant risk factor for crypto market investors. In contrast, Japan's stock market crash risk has a negative impact on Binance's crash risk when measured using the NS measure. Additionally, crash risks in the equity markets of the US, UK, and Japan (Germany and Canada) exhibit a statistically significant positive (negative) one-month lag effect on the crash risk of cryptocurrencies. Surprisingly, the lagged stock market crash risk variables exert a greater influence than the level variables, underscoring the importance of historical events in the stock market for cryptocurrency crashes. The statistically significant one-month lag effect may also present arbitrage opportunities, as current crash risks in equity markets convey signaling information about the crash risk of cryptocurrencies one month in advance. Overall, the results suggest that crashes in regular stock markets can be used to predict future cryptocurrency market crashes. The findings are robust to the inclusion of control variables and the use of alternative crash risk measures. Therefore, it is recommended that investors and portfolio managers in the crypto market pay close attention to sudden fluctuations in equity markets, particularly sharp drops that can result in significant future losses. Incorporating the impact of the Covid-19 pandemic and utilizing higher-frequency crash risk measures would provide an interesting avenue for future research. Additionally, investigating associations between emerging markets' stock market crash risks and cryptocurrencies' crash risks would also provide an interesting avenue for future research for interested researchers.

INTERNET APPENDIX

Definitions of control variables

GDCM: Monthly crash risk measure (NS or DU) of gold price returns.
LGDCM: Lag of Monthly crash risk measure (NS or DU) of gold price returns.
GDR: Gold average price returns
LGDR: Lag of gold average price returns
GDV: Monthly volatility of gold price returns
LGDV: Lag of monthly volatility of gold returns
OLCM: Monthly crash risk measure (NS or DU) of oil price returns
LOLCM: Lag of Monthly crash risk measure (NS or DU) of oil price returns
OLR: Average monthly price returns of oil
LOLR: Lag of average monthly price returns of oil
OLV: Oil price returns volatility
LOLV: Lag of oil price returns volatility

MSCI: Monthly average of the logs of the MSCI world stock index
LMSCI: Lag of Monthly average of the logs of the MSCI world stock index
MSCIV: Volatility of MSCI world stock index
LMSCIV: Lag of volatility of MSCI world stock index
LCPCM: Lag of the specific crypto (CP) monthly average of logs of market capitalization
CPR: Specific crypto monthly average of daily price returns
LCPR: Lag of specific crypto monthly average of daily price returns
CPV: Specific crypto monthly volatility of returns
LCPV: Specific crypto monthly volatility of returns
CPTV: Specific crypto monthly average of the log of daily trading volumes.

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