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Unravelling Crash Risk Transmission: Cryptocurrency Impact on Stock Markets in G-7 and China

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Abstract

In this paper, we use the Empirical Bayes estimation and multiple linear regression approach to examine the impact of the top 5 cryptocurrencies' crash risks on the G-7 and China equity markets' crash risks. MATLAB was used to calculate the crash risks, while Stata software was employed for the econometric analysis. Three crash risk measures are used to validate the robustness of the results: (i) the relative frequency of the number of crash days in the market, (ii) the monthly returns' skewness, and (iii) the down-to-up volatility. Our findings indicate that overall crash risks of the top 5 cryptocurrencies are positively related with G-7 and Chinese stock markets' crash risk. This suggests that the crash risk transmits from the crypto to the equity markets and the crashes in crypto can serve as a predictor in the stock markets. Furthermore, there is a negative correlation between the historical crash risks of the G-7 stock market and the present crash risks of the same stock market. This suggests that past stock market crashes can serve as a predictive factor for assessing the current risk of a stock market crash.

Keywords: Crash risk, cryptocurrency, G-7 stock market, Bitcoin, Ethereum, Biance coins.

1. Introduction

Since the introduction of cryptocurrency by (Nakamoto, 2009), the popularity of cryptocurrencies as an alternative asset skyrocketed and has captured the attention of not only investors, but also academics and even governments globally (Atsalakis et al., 2019). Since then, numerous digital assets under the auspices of the name "cryptocurrency" have emerged and are fully functional. Their market capitalization increased astronomically from about $10 billion in January 2014 to roughly $2.8 trillion in November 2021 (CoinMarketCap, 2023). Particularly, cryptos market valuation grew explosively from $25 billion in March 2017 to about $2.8 trillion in November 2021. Nevertheless, the market capitalization plummeted by nearly 58% from $2.2 trillion in January 2022 to about $0.96 trillion in July 2022.

Decentralized financial assets like cryptocurrencies introduce additional uncertainty to an already fragile global financial system and delicate political climate. The events of the past decade, including the 2008 global financial collapse, the rise of populism and economic protectionism, epidemics, pandemics, wars, sanctions, and energy shocks, have collectively revealed the vulnerability of the international financial system and the fragility of the interconnected modern world economy (Ashraf & Goodell, 2022; Aysan et al., 2022). As a result, the implementation of decentralized cryptocurrencies further complicates the intricacies of the global financial ecosystem and raises concerns among investors and policymakers about the sustainability and stability of the global economy (Ashraf & Goodell, 2022; Muneza et al., 2022; Aysan et al., 2022). Numerous empirical studies have examined the potential benefits, drawbacks, and consequences of cryptocurrencies on various financial and economic aspects.

Researchers have explored the impact of Bitcoin prices on stock markets, specifically investigating the predictability of G7 stock returns. (Salisu et al., 2019; Babangida & Khan, 2021), concluded that Bitcoin prices can be utilized as a predictor for stock returns, especially during periods of high Bitcoin transaction activity. Also, bitcoin volatility is linked to stock markets and investor sentiment. A study by (López-Cabarcos et al., 2021) found that Bitcoin volatility is volatile during speculative periods. Another research by (Dai et al., 2023) show that cryptocurrencies are more likely to experience crashes compared to equity indices, although these crashes tend to be shorter in duration. Additionally, crash risk is shared between cryptocurrency and equity markets around 80% of the time.

On the other hand, VIX returns, S&P 500 returns, and sentiment all affect Bitcoin's volatility pattern when there is stability. Furthermore, a study by (Jalal et al., 2020) indicates that Bitcoin could be used for both diversification and profit generation, due to its similarities to gold. Additionally, (James, 2021; James et al., 2021), found that cryptocurrency prices and stock market prices were more similar during the COVID-19 pandemic than in other periods. They argued that this similarity is likely due to the fact that both assets are seen as safe havens during economic crisis. Furthermore, A study by (Koutmos, 2020), found that Bitcoin prices are not immune to market hazards, despite their independent behavior from economic factors. Thus, they are correlated with stock market prices and other financial assets. An other study by (Meegan et al., 2021), found that DAG-based digital currencies become more responsive to market shocks as they develop. This suggests that DAG-based assets have similar properties to regular blockchain-based assets.

Several studies have used different uncertainty indices to measure the volatility and unpredictability of crypto assets. For instance, (Woebbeking, 2021), used option prices to compute a volatility index (CVX) for digital assets. He found that the volatility of digital assets is often different from traditional markets, even when they share similar shocks. Similarly, (Al-Yahyaee et al., 2019), investigated the co-movements between Bitcoin and the Volatility Uncertainty Index. He found that the BTC-VIX relationship is volatile.

Nevertheless, there is limited research on how crash risk is transmitted between cryptocurrency and stock markets. It is unclear whether crash risk is transmitted from one market to the other, or in both directions. A study by (Chen & Wu, 2016), found that firms that are subsidized by the government face a higher risk of future stock price crash. He further revealed that higher information asymmetry enhances the level of crash risk. Similarly, (Luo et al., 2016), found that political affiliations can reduce the risk of stock price crashes. However, the effect of political affiliations on crash risk varies across firms and depends on the nature and degree of the political connection. (Chen et al., 2018), found that controlling corruption can reduce the risk of stock price crashes in China. They found that when corrupt officials are persecuted, investors' confidence increases and the perception of political risk decreases. This, in turn, reduces the risk of a firm's stock price crashing in the future. Another linkage is between the economic uncertainty and the stock market crash risk. A study by (Dai et al., 2021), found that economic policy uncertainty is negatively related to stock market crash risk. A research by (Uzonwanne, 2021) shows that the relationship between Bitcoin and five major stock markets is mixed. Some markets show a bi-directional relationship, while others show a unidirectional relationship. Similarly, (Dai et al., 2021), found that an increase in economic uncertainty is negatively related to Bitcoin crash risk. This suggests that investors can hedge against economic uncertainty by investing in Bitcoin. Latest research also reveals that fluctuations in cryptocurrency prices are heavily influenced by economic and political instability (Sakariyahu et al., 2024). Also, other studies that explored the potential of cryptocurrencies as tools for hedging and serving as safe havens against stock market volatility, concluded that Bitcoin's likelihood of achieving even a 10% hedging effectiveness is nearly nonexistent (Just & Echaust, 2024).

However, (Luo & Zhang, 2020) found that an increase in economic uncertainty is positively related to the probability of a stock market crash. Other studies have shown that investor sentiment, Ethereum synchronicity, and cryptocurrency uncertainty indices can all influence cryptocurrency and stock market crash risk. Investor sentiment is positively related to cryptocurrency crash risk (Anastasiou et al., 2021), Ethereum synchronicity is a positive influence on Bitcoin crash risk (Ma & Luan, 2022), whereas, cryptocurrency uncertainty indices are more appropriate for predicting co-crash phenomena compared to economic policy uncertainty (Dai et al., 2021).

Therefore, in this study, we examined the impact of cryptocurrency crash risk on stock market crash for the G-7 and China. In the literature we were unable to find the transmission direction of crash risk between cryptocurrency on stock market. This study is an attempt to address this literature gap. The aim of the study is to investigate the impact of cryptocurrency crash risk on the G-7 and China stock markets crash risks. We applied ARDL (1,1) and two other models for robustness using Empirical Bayes estimation.

The remainder of the paper is as follows. Section 2 explains the data and methodology, Section 3 describes the empirical result and their discussions, while Section 4 documents the conclusions.

2. Data and Methodology

2.1 Data

In this study, we examine the relationship between stock market crash risk and cryptocurrency market crash risks. Specifically, we focus on the G-7 (US, UK, Japan, Germany, Canada, and France) and Chinese stock markets, as well as the top 5 cryptocurrencies based on market capitalization as of July 5, 2023. Stock market data was obtained from finance.yahoo.com on the same date. The inclusion of the G-7 and China in our analysis is based on their significant role in the global economy, while Italy was excluded due to the relatively insignificant size of its stock market and inconsistent data.

The selection of the top 5 cryptocurrencies is based on their market capitalization and retrieved from www.coinmarket.com on July 5, 2023, at 14:42 (Istanbul Time). These cryptocurrencies include Bitcoin (BT), Ethereum (ET), Binance (BN), XRP (XP), and Cardano (CR). Further details can be found in Table 1.

Table 1: Cryptocurrencies and Country Stock Indices

Cryptocurrency	Abbreviation	Sample range	Country	Stock index	Sample range
Bitcoin	BT	01/01/2014-30/06/2023	US	S&P500	01/01/2014-30/06/2023
Ethereum	ET	07/08/2015-30/06/2023	UK	FTE100	01/01/2014-30/06/2023
Binance coin	BN	01/08/2017-30/06/2023	Japan	Nikkei 225	01/01/2014-30/06/2023
XRP	XP	01/01/2014-30/06/2023	Germany	DAX	01/01/2014-30/06/2023
Cardano	CR	01/10/2017-30/06/2023	France	CAC40	01/01/2014-30/06/2023
			China	CSI300	01/01/2014-30/06/2023
			Canada	TSX	01/01/2014-30/06/2023

2.2 Methodology

Three different measures are considered. Three different models and empirical Bayesian estimation are used.

2.2.1 Measuring Crash Risk

We employ three crash-risk measures from the literature, initially devised by (Chen et al., 2001), and then followed by (Kim et al., 2019, 2019; Piotroski et al., 2015).

We use the relative frequency of crash days ($RF_{i,t}$) as our first crash risk measure. ($RF_{i,t}$) is calculated by dividing the number of crash days in a month by the total number of trading days in that month. A crash day is defined as a day when the underlying firm's market's daily returns are at least two standard deviations lower than the average firm-specific daily returns for the month (Piotroski et al., 2015). The RF metric is computed as;

$$RF_{i,m} = {Count\left(R_{i,d} - \bar{R}_{i,m} \leq 2\sigma_{i,m}\right)}\Big/{(n_m)} \tag{1}$$

Where $R_{i,d}$ represents the daily return of the ith stock market on a day "d", $\bar{R}$ represents the average monthly return, d stands for the day, and "m" denotes the month. $\sigma_{i,m}$ shows the standard deviation of the ith stock market for the month. Finally, n_m denotes the total number of days in a specific month "m".

The second crash risk metric is the negative coefficient of skewness (NS). NS is calculated by taking the negative of the third moment of monthly returns, divided by the monthly standard deviation to the power of three. NS is suitable for markets with asymmetric returns, such as cryptocurrencies, which have been shown to have negative skewness(Chaim & Laurini, 2019; Urquhart & Zhang, 2019). The NS measure is calculated as:

$$NS_{i,m} = \frac{-\left((n_m((n_m-1)^{\frac{3}{2}}\sum R_{i,m}^3\right)}{\left(((n_m-1)((n_m-2)(\sum R_{i,m}^2)^{\frac{3}{2}}\right)} \quad (2)$$

Where (n_m stands for the number of days in a month "m", $R_{i,m}$ represents the daily returns of a stock or crypto market "I" in a month "m".

The third measure of crash risk is down-to-up volatility (DU). This measure of return asymmetries is quite different from the NS since the third moments are not included in it, therefore it is not probable to be significantly impacted by a few extreme monthly values. DU is calculated as:

$$DU_{\ i,m} = \log\left\{\frac{(n_u-1)\sum_{Down} R_{i,m}^2}{(n_d-1)\sum_{Up} R_{i,m}^2}\right\} \quad (3)$$

Where n_u represents the number of up days returns and n_d the number of down daily returns in a specific month. The subscripts i and m denote the stock or crypto market and month respectively. A high DU is associated with a higher stock market crash risk.

2.2.2 Model Specifications

For the robustness of the result, three different models are considered. These three models are ARDL (1,1), ARDL (1,0), and Multiple linear regression (MLR) model.

2.2.2.1 Model M1: ARDL (1,1). A general ARDL (1,1) model is considered and is specified as

$$\begin{aligned}\mathrm{RF}_{i,t} = \alpha\ &+ \beta_1\mathrm{RF}_{i,t-1} + \beta_2\mathrm{BTRF}_t + \beta_3\mathrm{ETRF}_t + \beta_4\mathrm{BNRF}_t + \beta_5\mathrm{XPRF}_t + \beta_6\mathrm{CRRF}_t \\ &+ \beta_7\mathrm{BTRF}_m + \beta_8\mathrm{ETRF}_m + \beta_9\mathrm{BNRF}_m + \beta_{10}\mathrm{XPRF}_m + \beta_{11}\mathrm{CRRF}_m \\ &+ \varepsilon_{i,t} \qquad (4)\end{aligned}$$

$$\mathrm{NS}_{i,t} = \alpha\ + \beta_1\mathrm{NS}_{i,t-1} + \beta_2\mathrm{BTNS}_t + \beta_3\mathrm{ETNS}_t + \beta_4\mathrm{BNNS}_t + \beta_5\mathrm{XPNS}_t + \beta_6\mathrm{CRNS}_t + \beta_7\mathrm{BTNS}_m + \beta_8\mathrm{ETNS}_m + \beta_9\mathrm{BNNS}_m + \beta_{10}\mathrm{XPNS}_m + \beta_{11}\mathrm{CRNS}_m + \varepsilon_{i,t} \qquad (5)$$

$$\begin{aligned}\mathrm{DU}_{i,t} = \alpha\ &+ \beta_2\mathrm{DU}_{i,t-1} + \beta_2\mathrm{BTDU}_t + \beta_3\mathrm{ETDU}_t + \beta_4\mathrm{BNDU}_t + \beta_5\mathrm{XPDU}_t + \beta_6\mathrm{CRDU}_t \\ &+ \beta_7\mathrm{BTDU}_m + \beta_8\mathrm{ETDU}_m + \beta_9\mathrm{BNDU}_m + \beta_{10}\mathrm{XPDU}_m + \beta_{11}\mathrm{CRDU}_m \\ &+ \varepsilon_{i,t} \qquad (6)\end{aligned}$$

where $\mathrm{RF}_{i,t}$, $\mathrm{NS}_{i,t}$, and $\mathrm{DU}_{i,t}$ denotes dependent variables which are the crash measures of the stock market of the seven countries i (for $i = 1, 2 \ldots..7$) at time t (for $t = 1, 2, \ldots..T$). α denotes the intercept of the model. BTNS_t, ETNS_t, BNNS_t, XPNS_t, CRNS_t, LBTNS, LETNS_t, LBNNS_t, LXPNS_t, *and* LCRNS_t are the crash risk measures of cryptocurrencies at levels and lags-1, respectively. Similarly, the variables suffixed with RF and DU represent the crash risk measured of cryptocurrencies by considering RF and DU. $\beta_1, \beta_2, \ldots\ \beta_{11}$ are the slope coefficients, and the $\varepsilon_{i,t}$ is the error term of the model. To obtain an ARDL (1,1) represented in equations (4-6), we added one period lag of both the dependent and independent variables**.**

2.2.3: Empirical Bayesian Estimation

The Bayesian approach is employed for the estimation. The general model under the Bayesian approach has the following form (Carrington & Zaman, 1994).

$$Y_{it} = \beta_i X_{it} + \varepsilon_{it}$$

where Y are the dependent variable. In our case it is the crash risk stock market, i stands for the stock and crypto market and t the number of periods. On the right-hand side, X is a vector of independent variables; in our case it is cryptocurrencies crash risk. β is the vector of slope coefficient. Equation (7) can be represented as

We apply the empirical Bayes methodology to estimate the impact of cryptocurrencies' crash risk on the stock market crash risk measures (RF, NS, and DU). The Empirical Bayes estimation method has two main advantages over the conventional time series and cross-section methods. First, Empirical Bayes considers heterogeneity for each of the stock markets. Secondly, it provides significantly lower standard errors as compared to other methodologies (Zaman, 1996).

3. Results

Table 2 demonstrates the estimation results of the seven regressions using the RF measure of crash risk. The crash risk measures of the US (SPRF), UK (SPRF), Japan (JPRF), Germany (GRRF), France (FRRF), China (CHRF), and Canada (CDRF) stock markets are the dependent variables. While the lag of each stock market's crash risk measure is the crash risk measure of Bitcoin (BTRF), Ethereum (ETRF), Binance (BNRF), XP (XPRF), Cardano (CRRF), and their lags of (LBTRF, LETRF, LBNRF, LXPRF, LCRRF) are the regressors.

At levels, Bitcoin (BT), XRP(XP), and Cardano (CR) crash risk are positively related to the stock market's crash risk. However, for some stock markets they are significantly related and for some insignificantly related, like BT crash risk is only significantly positively related to crash risks of SP, JP, and FR. Similarly, XP crash risk is significantly positively related to only SP, UK, JP, and CH crash risks. While CR crash risk is statistically insignificant despite having a positive association with the stock market's crash risks. On the other hand, ET as well as BN show a negative relation to the stock market's crash risk. However, ET depicts highly significant relationships for all the stock market's BN crash risks, while BN crash risk reports an insignificant relationship. However, in general, the lags of the dependent variable (the lag of the Stock market's crash risk) and the lags of the crash risks of the cryptocurrencies are not significantly affecting the crash risk of the stock markets with some exceptions, like the lag of BT crash risk significantly related to the US stock market crash risk.

Table 2: Empirical Bayesian Posterior Results for Model M1 With RF As a Crash Measures

Variables	SP	UK	JP	GR	FR	CH	CD
Lag	-0.03666 (0.049091)	-0.04223 (0.049149)	-0.04609 (0.048914)	-0.02746 (0.049314)	-0.02668 (0.049349)	-0.02594 (0.049478)	-0.04578 (0.048852)
BT	0.164677* (0.082811)	0.139776 (0.08369)	0.172284** (0.082454)	0.139913 (0.084049)	0.170504* (0.083937)	0.087925 (0.08514)	0.134996 (0.084618)
ET	-0.21817 *** (0.069076)	- 0.18357** (0.069824)	-0.20443*** (0.068702)	-0.19501*** (0.070257)	-0.16982** (0.070097)	0.15041** (0.070994)	- 0.15805** (0.070567)
BN	0.002729 (0.06482)	-0.05066 (0.065375)	-0.00916 (0.064326)	-0.06541 (0.065639)	-0.04055 (0.065563)	-0.04173 (0.066535)	0.027812 (0.066191)
XP	0.144589* (0.075959)	0.183571 ** (0.076781)	0.159756** (0.075647)	0.125857 (0.077256)	0.111369 (0.077041)	0.165063 ** (0.078189)	0.120721 (0.077532)
CR	0.091973 (0.084369)	0.042207 (0.085194)	0.055209 (0.083688)	0.080233 (0.08564)	0.032836 (0.085549)	0.061168 (0.086875)	0.071526 (0.086091)
LBT	-0.14631* (0.078669)	-0.11966 (0.079473)	-0.06238 (0.078269)	-0.10372 (0.079841	-0.0846 (0.079733)	-0.09184 (0.080835)	-0.12577 (0.080394)
LET	0.134993* (0.07017)	0.131526* (0.070816)	0.082572 (0.069832)	0.119865 (0.071192)	0.114496 (0.07093)	0.119385 (0.071851)	0.089371 (0.071483)
LBN	-0.07971 0.062109)	-0.04745 (0.062709)	-0.0577 (0.061744)	-0.06474 (0.062999)	-0.06149 (0.06289)	-0.07572 (0.063778)	-0.05833 (0.063473)
LXP	0.002697 (0.075955)	-0.00927 (0.077015)	-0.01936 (0.075673)	-0.02046 (0.077023)	-0.03598 (0.076853)	-0.01591 (0.078181)	0.008776 (0.077534)
LCR	0.112355 (0.088269)	0.120679 (0.08916)	0.162373* (0.087801)	0.13021 (0.089614)	0.138886 (0.089414)	0.10358 (0.09068)	0.10931 (0.090171)
Const	0.028142 *** (0.004161)	0.027528 *** (0.004192)	0.025475 *** (0.004087)	0.029203 *** (0.004265)	0.028085 *** (0.004228)	0.028299 *** (0.004263)	0.027791 *** (0.004221)

Table 3 accommodates the results of M1 when NS is considered as a measure of crash risk. At levels, Bitcoin (BT), XRP (XP), and Cardano (CR) have a positive impact on the stock market crash risks, but they are significantly related to some stock markets, while negatively related to others. For instance, BT and CR reveal significant relationships for all the stock market's crash risk except (CH) which is insignificant for CR. Also, XP reveals insignificant positive relationships for all the seven market's crash risks. On the other hand, ET and BN show negative associations with the stock market's crash risk. ET is largely insignificantly negatively related to the stock markets except for the crash risks of JP and CH which portray insignificantly positive relationships, while BN is highly significant except for the UK's crash risk. This result conforms with the RF crash risk results that are discussed previously.

Yet, in general, we document that the lags of bitcoin (LBT), Binance (LBN), RXP (LXP), and Cardano (LCR) have a positive impact on the stock market's crash risk with considerable significance except for Binance (LBN), which is insignificant for all the stock markets. In contrast, the Lag of the dependent variables and the lag of Litecoin (LET) reveal that they are significantly negatively related to stock market's crash risk.

Table 3: Empirical Bayesian Posterior Results for Model M2 With NS As a Crash Measures

Variables	SP	UK	JP	GR	FR	CH	CD
Lag	0.19237 *** (0.050418)	-0.18934 *** (0.051064)	-0.18616 *** (0.05029)	-0.20664 *** (0.050515)	-0.21376 *** (0.050411)	-0.16006 *** (0.049987)	-0.1889 *** (0.051019)
BT	0.17372*** (0.063069)	0.167169** (0.063105)	0.174959 *** (0.06170)	0.170228 ** (0.063465)	0.181185 *** (0.063602)	0.167578 ** (0.063125)	0.179347 *** (0.062774)
ET	-0.05004 (0.090446)	-0.04654 (0.090487)	0.014679 (0.08849)	-0.02027 (0.091024)	-0.03107 (0.091224)	0.033067 (0.090548)	-0.03359 (0.090012)
BN	-0.2034** (0.075082)	-0.24084 (0.075854)	-0.28191 *** (0.07348)	-0.22929 *** (0.075941)	-0.23638 *** (0.076336)	-0.28009 *** (0.074922)	-0.21332 *** (0.074891)
XP	0.023039 (0.051457)	0.027631 (0.051698)	0.003134 (0.05036)	0.004528 (0.052010)	0.006335 (0.052108)	0.015714 (0.051479)	0.011904 (0.051389)
CR	0.115305* (0.0643178)	0.130923* (0.064375)	0.116512 * (0.06294)	0.133369 ** (0.064751)	0.127193* (0.064934)	0.108876 (0.064397)	0.117128* (0.064044)
LBT	0.15322** (0.066159)	0.146223** (0.066317)	0.155152 ** (0.06471)	0.158465 ** (0.066683)	0.148692 ** (0.066983)	0.107663 (0.066319)	0.154401 ** (0.066037
LET	-0.3281*** (0.089457)	-0.35769 *** (0.0895112)	-0.35792 *** (0.08750)	-0.35439 *** (0.090012)	-0.36534 *** (0.090228)	-0.33264 *** (0.08953)	-0.33679 *** (0.089036)
LBN	0.043655 (0.068818)	0.05293 (0.069267)	0.056259 (0.06792)	0.048451 (0.069474)	0.055229 (0.06967)	0.04746 (0.069249)	0.048949 (0.068591)
LXP	0.12483** (0.051844)	0.119765 ** (0.05186)	0.139775 *** (0.05075)	0.133528 ** (0.052223)	0.137719 ** (0.05234)	0.145316 *** (0.051910)	0.12018** (0.05161)
LCR	0.206512 *** (0.062675)	0.24633 *** (0.062722)	0.21909*** (0.06133)	0.235442 *** (0.063127)	0.2455*** (0.063234)	0.216515 *** (0.062643)	0.205907 *** (0.062357)
Const	0.136198 ** (0.054561)	0.173529 *** (0.054706)	0.116325 ** (0.05333)	0.165958 *** (0.055016)	0.175385 *** (0.055186)	0.147874 ** (0.054723)	0.154059 *** (0.054352)

Down-to-up volatility (DU) is the third measure of stock market crash risk and table 3 contains the results of M1 when DU is taken into account as a measure of crash risk. The results manifest that bitcoin BT, XP, and CR have a positive effect on the stock market's crash risk. BT and CR are significantly positive, whereas XP is positively linked to stock market's crash risk but insignificant for all the regressions. On the contrary, ET and BN depict negative effects on the stock market's crash risk, where Et is insignificant for all the regressions and BN is significant negative for all the results.

In contrast, the lags of LBT, LBN, LXP, and LCR report a positive relationship with the market's crash risk. Moreover, Except for LBN, the other three cryptos are largely significant in for all the markets except the LCR which reports insignificant for US, China, and Canadian stock markets. In addition, the lag of the dependent variable (stock market crash risk measure by DU) shows significantly positive effect on its previous months' crash risk possibilities.

Table 4: Empirical Bayesian Posterior Results for Model M2 With DU as a Crash Measures

Variables	SP	UK	JP	GR	FR	CH	CD
Lag	0.15075 *** (0.051852)	0.14549 *** (0.052416)	-0.15504 *** (0.051721)	-0.16219 *** (0.051839)	-0.1585 *** (0.051888)	-0.13096 ** (0.051542)	-0.13926 ** (0.052445)
BT	0.217985 ** (0.085905)	0.182809 ** (0.085552)	0.206615 ** (0.083548)	0.207827 ** (0.086409)	0.20748 ** (0.08601)	0.19863** (0.085015)	0.200706 ** (0.08537)
ET	-0.01217 (0.103877)	-0.00011 (0.103312)	0.024463 (0.100960)	0.026181 (0.104338)	0.0176 (0.103825)	0.05622 (0.102545)	0.02192 (0.103068)
BN	0.33744 *** (0.09168)	3596*** (0.091794)	-0.39408 *** (0.089251)	-0.35755 *** (0.092252)	-0.37004 *** (0.091960)	-0.38236 *** (0.089884)	-0.34391 *** (0.091244)
XP	0.057097 (0.064671)	0.065671 (0.064559)	0.066667 (0.062912)	0.028897 (0.065128)	0.03044 (0.064802)	0.031487 (0.063991)	0.033494 (0.06436)
CR	0.143336 ** (0.069071)	0.16234** (0.068787)	0.145449 ** (0.067112)	0.161675 ** (0.069547)	0.170571 ** (0.069257)	0.158598 ** (0.068226)	0.151321 ** (0.06877)
LBT	0.20144** (0.085534)	0.204039 ** (0.08521)	0.205913 ** (0.083132)	0.208884 ** (0.086043)	0.189404 ** (0.085619)	0.186573 ** (0.084614)	0.20426** (0.08512)
LET	-0.32427 *** (0.099638)	-0.35329 *** (0.099216)	-0.35913 *** (0.096996)	-0.3399 *** (0.100242)	-0.35584 *** (0.099678)	-0.3287 *** (0.098559)	-0.31988 *** (0.099027)
LBN	0.087421 (0.084976)	0.086678 (0.085093)	0.08143 (0.083257)	0.083849 (0.085693)	0.107166 (0.085327)	0.071325 (0.084284)	0.082881 (0.084784)
LXP	0.172019 ** (0.06390)	0.160456 ** (0.063644)	0.192756 *** (0.062135)	0.174441 ** (0.064314)	0.181381 *** (0.063985)	0.178641 *** (0.06317)	0.146911 ** (0.063543)
LCR	0.118697 (0.07205)	0.137955* (0.071771)	0.132667* (0.070046)	0.137952* (0.072565)	0.144209* (0.072235)	0.110558 (0.071188)	0.110058 (0.071653)
Const	-0.01745 (0.056896)	-0.05068 (0.056674)	0.003613 (0.055349)	-0.04356 (0.05720)	-0.05201 (0.056919)	-0.03399 (0.056244)	-0.03162 (0.056546)

Table 5: Summary of the Findings from the Three Crash Risk Measures

Cryptocurrency (level) Variable	**Abbreviation**	**Measures**	**Effect and Significance**	**Overall**
Binance	BN	DU, NS RF	-ve (DU, NS, sig.) -ve (RF, insig.)	Negative significant
Bitcoin	BT	DU, NS RF	+ve (DU, NS, sig.) +ve (RF, sig.)	Positive significant
Ethereum	ET	DU, NS RF	+ve/-ve (DU/NS, insig.) -ve (RF, sig.)	Negative Insignificant
XRP	XP	DU, NS RF	+ve (DU, NS, insig.) +ve (RF, largely sig.)	Positive Insignificant
Cardano	CR	DU, NS RF	+ve (DU, NS, sig.) +ve (RF, largely insig.)	Positive Insignificant
Cryptocurrency (lag) Variable	**Abbreviation**	**Measures**	**Sign and**	**Overall**
Lag of the dependent variable	Lag	DU, NS RF	-ve (DU, NS, sig.) -ve (RF, insig.)	Negative Insignificant
Lag of Binance	LBN	DU, NS RF	+ve (DU, NS, insig.) -ve (RF, insig.)	Positive Insignificant
Lag of Bitcoin	LBT	DU, NS RF	+ve (DU, NS, sig.) -ve (RF, insig.)	Positive Significant
Lag of Ethereum	LET	DU, NS RF	-ve (DU, NS, sig.) +ve (RF, sig.)	Negative Significant
Lag of XRP	LXP	DU, NS RF	+ve (DU, NS, sig.) -ve (RF, largely insig.)	Positive Significant
Lag of Cardano	LCR	DU, NS RF	+ve (DU, NS, sig.) +ve (RF, largely insig.)	Positive Significant

* “sig.” and “insig.” mean significant and insignificant respectively

The prior estimation result of the ARDL 11 Empirical Bayes estimation contains the tables 5,6, and 7. In the RF crash risk measure the level variables BT, XP, and CR report positive results but are insignificant. Suggesting that a cryptocurrency crash leads to a stock market crash. On the other hand, ET and BN show negative relations to the stock market crash but are not significant. When comes to the lag variables LET and CR indicates positive relations to the stock market crash while LBT, LXP, LBN, and the lag of the dependent variable suggest mixed effect some positive and sometimes negative impact on the stock market crash. However, these variables are not significant at all. Thus, we can conclude the RF measure of the crash risk does not perform well in the ARDLL11 model.

Table 6: ARDL 11 Priors Measured by RF

Variables	Coeff	Var.	SE	t-value	p-value
Lag	-0.0359	0.002754	0.052475	-0.6841	0.499164
BT	0.144782	0.008024	0.089575	1.616321	0.116494
ET	-0.18338	0.005585	0.074732	-2.45381	0.02016
BN	-0.02513	0.004899	0.06999	-0.35904	0.722083
XP	0.144385	0.006757	0.082199	1.756527	0.089203
CR	0.062352	0.008319	0.09121	0.683611	0.499467
LBT	-0.10493	0.007238	0.085074	-1.23337	0.227016
LET	0.11321	0.00574	0.075766	1.494216	0.145564
LBN	-0.06373	0.004506	0.067125	-0.94946	0.349973
LXP	-0.01286	0.006753	0.082175	-0.15654	0.876654
LCR	0.12562	0.00911	0.095445	1.316147	0.198093
Const	0.027786	2.02E-05	0.00449	6.188636	0.000000824

The prior estimation of the NS result of the ARDL 11 Empirical Bayes estimation contains the table 6. In the NS crash risk measure of the level variables BT, XP, and CR report positive and statistically significant outcomes. ET and BN are also positively related to the stock market crash and largely significant, suggesting that a cryptocurrency crash exerts a stock market crash risk. On the other hand, when it comes to the lag variables all the lag variables except LET and the lag of the dependent variable suggest a positive and significant relation to the stock market crash. This tells us that a cryptocurrency crash can positively predict the stock market crash also. Hence, we can conclude the NS measure of the crash risk performs better than the RF measure in the ARDL11 model.

Table 7 ARDL 11 Prior Measured by NS

Variables	Coeff	Var.	SE	t-value	p-value
Lag	-0.19059	0.002912	0.053968	-3.53155	0.001358
BT	0.173531	0.004531	0.067314	2.577926	0.015094
ET	-0.01891	0.00932	0.096539	-0.19586	0.846043
BN	-0.24141	0.006461	0.08038	-3.0034	0.005344
XP	0.013375	0.003029	0.055041	0.243009	0.809653
CR	0.121366	0.004716	0.068676	1.767221	0.087364
LBT	0.146169	0.005002	0.070728	2.066627	0.047495
LET	-0.34729	0.009115	0.095472	-3.6376	0.001023
LBN	0.050457	0.005439	0.073749	0.684182	0.499112
LXP	0.131698	0.003065	0.055358	2.379008	0.023922
LCR	0.2247	0.004475	0.066893	3.359093	0.002142
Const	0.152357	0.003399	0.058303	2.613185	0.013887

The prior estimation of the DU result of the ARDL 11 Empirical Bayes estimation has illustrated in the tables below. The NS crash risk measure of the level variables (BT, XP, ET, BN, and CR, reports positive and statistically significant results. Only BN has two negative outcomes but is largely positive. Indicating that a crash on these digital assets exposes a stock market crash risk also. Moreover, the lag variables suggest a largely positive impact on the stock market crash and significant also. This tells us that just like the NS metric a cryptocurrency crash can positively predict the stock market crash. therefore, we can conclude the NS and DU measures of the crash risk outperforms the RF measure in the ARDL11 model.

Table 8 ARDL 11 Prior Measured by DU

Variables	Coeff	Var.	SE	t-value	p-value
Lag	-0.14855	0.00308	0.0555	-2.67661	0.011937
BT	0.203097	0.008332	0.091282	2.224941	0.033753
ET	0.019418	0.012151	0.110234	0.176149	0.861361
BN	-0.36416	0.009489	0.097413	-3.73831	0.00078
XP	0.04501	0.00473	0.068772	0.65448	0.517789
CR	0.1562	0.005388	0.073405	2.127906	0.041676
LBT	0.200088	0.008262	0.090893	2.201351	0.035543
LET	-0.34029	0.011209	0.105871	-3.21425	0.003122
LBN	0.085854	0.00821	0.090608	0.947535	0.350937
LXP	0.172572	0.00461	0.0679	2.54156	0.016441
LCR	0.127267	0.005864	0.076575	1.661996	0.10693
Const	-0.03199	0.003652	0.060436	-0.52928	0.600509

4. Discussion

Our findings reveal that cryptocurrency crashes have a significant spillover effect on equity market downturns. This observation aligns with prior research indicating that cryptocurrencies possess predictive power over equity market movements (Sakariyahu et al., 2024). The implications of this result are noteworthy: cryptocurrencies do not function as a reliable safe haven during stock market crashes, as their instability tends to propagate to other financial markets, undermining their effectiveness as a hedge. Similarly, external factors such as economic uncertainty and policy changes also contribute to cryptocurrency crashes, further intertwining the two markets (Demir et al., 2018). Consequently, cryptocurrencies do not function as reliable safe havens during stock market crashes, as their instability often propagates to other financial markets, diminishing their effectiveness as a hedge. As highlighted by Dai et al. (2023), there are varying degrees of correlation between uncertainty measures and concurrent market crashes. Specifically, uncertainties related to cryptocurrency policies and prices demonstrate significant predictive potential for the likelihood of simultaneous market crashes. This aligns with Lucey et al.'s (2022) assertion that such indices effectively capture notable fluctuations during major cryptocurrency events.

5. Conclusion

The study sheds light on the stock market and cryptocurrency crash risk transmission mechanism and reveals new evidence regarding the nexus between the crash risk measures of stock markets and the top five cryptocurrencies.

The empirical Bayes estimation framework has been employed to explore the relevance of the top five cryptocurrencies for the equity market crashes in the G-7 plus China economies. To determine crash risk, we adopted three components of crash risk metrics that were derived from previous crash risk studies. The three measures we use to gauge crash risk are the relative frequency of the number of crash days in the market (RF), the monthly returns of each stock market's negative coefficient of skewness (NS), and down-to-up volatility (DU).

Our finding highlights new evidence from crash risk mechanisms from the top five cryptocurrencies to stock markets of the G-7 plus China economies. Overall, we document that Bitcoin, Cardano, and XP on the level have positive relations with the stock markets, consistent with the contagion hypothesis (Corbet et al., 2018; Diebold & Yilmaz, 2012). Further, Bitcoin and CR point to statistical significance, but XP depicts an insignificant positive impact. Thus, the three cryptos can predict the stock market crash positively. In other words, a cryptocurrency crash translates into a stock market crash. However, Binance and Ethereum each indicate a largely negative association with the stock market crash (Baur et al., 2018; Ji et al., 2019). Therefore, we can conclude that 3 cryptos (BT, XP, and CR) out of the five-cryptocurrency utilized in this study predict stock market crash risk positively, while 2 cryptos (BN and ET) show negative links with the stock market crash. On the contrary, the lag variables have a largely positive influence on the stock market crash. Only the lag of the dependent variable and the lag of Ethereum shows overall negative significance, while the lags of all the other cryptocurrencies report significant positive prediction of the stock market crash risk.

5.1 Theoretical Contribution

This study contributes to the literature on Contagion Theory (Forbes & Rigobon, 2002) and financial integration. The positive links between Bitcoin, Cardano, and XRP with equity crashes align with contagion theory, suggesting cryptocurrencies can propagate financial shocks across markets. Conversely, the negative association of Binance Coin and Ethereum challenges earlier research portraying cryptocurrencies as homogeneous assets (Baur & McDermott, 2010). These findings underscore the heterogeneous role of individual cryptocurrencies in financial contagion, influenced by factors such as investor sentiment, market liquidity, and asset maturity. By integrating crash risk measures (RF, NS, DU), this study advances the understanding of risk metrics and systemic risk propagation over time (Barro & Ursúa, 2009). The temporal dynamics observed through lag variables further contribute to risk theory by highlighting the delayed impacts of cryptocurrency movements on equity markets.

5.2 Practical and Policy Implications

From a practical perspective, the findings offer insights for policymakers, investors, and regulators. The evidence that Bitcoin, Cardano, and XRP can predict stock market crashes underscores the importance of monitoring these cryptocurrencies as systemic risk indicators (Corbet et al., 2018; Diebold & Yilmaz, 2012). Financial regulators should consider incorporating cryptocurrency risk metrics into early warning systems to mitigate contagion effects on equity markets. For investors, the contrasting behavior of Binance Coin and Ethereum suggests potential hedging opportunities during market downturns, while Bitcoin and Cardano remain risk transmission channels (Baur & McDermott, 2010). Portfolio diversification strategies should account for these heterogeneous effects to enhance resilience against systemic crashes. Policymakers in the G-7 and China should also strengthen regulatory oversight of cryptocurrency markets to limit volatility spillovers. Targeted regulations on exchanges and trading practices, particularly for Bitcoin and Cardano, may reduce systemic risks and promote market stability.

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Appendix

Table A1: RF ARDL 101 with Empirical Bayesian Posterior

Variables	SP	UK	JP	GR	FR	CH	CD
	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff
lag	-0.03123	-0.0376	-0.04142	-0.0213	-0.01959	-0.02102	-0.04204
LBTRF	-0.05753	-0.03032	0.023166	-0.01298	-0.00105	-0.01865	-0.06144
LETRF	0.118993	0.114673	0.070937	0.100803	0.102291	0.101497	0.076851
LBNRF	-0.09942	-0.06494	-0.08103	-0.08131	-0.08539	-0.08289	-0.07315
LXPRF	-0.00665	-0.01164	-0.02397	-0.01415	-0.02885	-0.02577	-0.00685
LCRRF	0.068272	0.079368	0.111267	0.080229	0.079864	0.084818	0.083109
Constant	0.031501	0.029235	0.028835	0.029527	0.029734	0.02962	0.032107

Table A2: NS ARDL 101 with Empirical Bayesian Posterior

Variables	SP	UK	JP	GR	FR	CH	CD
	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff
lag	-0.21596	-0.22811	-0.21976	-0.2356	-0.24677	-0.19243	-0.21496
LBTRF	0.206607	0.208649	0.216448	0.215211	0.203554	0.180248	0.207841
LETRF	-0.34958	-0.37783	-0.35986	-0.37234	-0.38265	-0.33693	-0.35587
LBNRF	-0.00381	-0.00295	-0.01396	-0.00594	-0.00156	-0.02261	-0.00313
LXPRF	0.076206	0.066529	0.076108	0.080983	0.086217	0.074551	0.069515
LCRRF	0.219403	0.254829	0.224211	0.25347	0.260221	0.222367	0.221927
Constant	0.132524	0.172135	0.11893	0.167051	0.173952	0.156646	0.153031

Table A3: DU ARDL 101 with Empirical Bayesian Posterior

Variables	SP	UK	JP	GR	FR	CH	CD
	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff
lag	-0.17881	-0.18726	-0.19382	-0.19813	-0.19893	-0.16346	-0.17433
LBTRF	0.316582	0.323278	0.330535	0.319158	0.300676	0.302577	0.312257
LETRF	-0.33856	-0.3686	-0.36435	-0.35084	-0.36809	-0.33584	-0.32964
LBNRF	-0.03996	-0.04369	-0.06189	-0.05175	-0.02922	-0.06988	-0.04773
LXPRF	0.056012	0.04605	0.064056	0.061681	0.06896	0.058934	0.036256
LCRRF	0.162129	0.177906	0.172932	0.190891	0.193978	0.161486	0.158068
Constant	-0.02678	-0.0607	-0.01093	-0.05646	-0.06369	-0.0497	-0.04347

Table A4: RF OLS with Empirical Bayesian Posterior

Variables	SP	UK	JP	GR	FR	CH	CD
	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff
BTRF	0.073754	0.041227	0.079443	0.05003	0.081029	0.008945	0.05984
ETRF	-0.18899	-0.15389	-0.17431	-0.1622	-0.13681	-0.12408	-0.12682
BNRF	0.062244	0.006026	0.030457	-0.02183	0.003691	0.001068	0.07115
XPRF	0.167153	0.210276	0.190072	0.156853	0.143022	0.190764	0.142258
CRRF	0.061893	0.024178	0.047228	0.055924	0.010845	0.034957	0.040807
Constant	0.027237	0.027875	0.026361	0.029713	0.02881	0.028447	0.026616

Table A5: NS OLS with Empirical Bayesian Posterior

Variables	SP	UK	JP	GR	FR	CH	CD
	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff
BTRF	0.120277	0.114831	0.11701	0.11324	0.124754	0.128119	0.133492
ETRF	-0.09262	-0.09721	-0.04155	-0.07062	-0.08535	-0.02984	-0.08952
BNRF	-0.15642	-0.19197	-0.21868	-0.17918	-0.18521	-0.20726	-0.16658
XPRF	0.043412	0.058065	0.026318	0.036989	0.0386	0.033786	0.043779
CRRF	0.187484	0.202588	0.19002	0.204075	0.198492	0.155208	0.183049
Constant	0.077936	0.109138	0.063102	0.101966	0.109556	0.100882	0.09645

Table A6: *DU* OLS with Empirical Bayesian Posterior

Variables	SP	UK	JP	GR	FR	CH	CD
	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff
BTRF	0.079285	0.060044	0.066844	0.068072	0.066638	0.086863	0.085921
ETRF	0.0521	0.039729	0.08147	0.080331	0.066892	0.082325	0.059976
BNRF	-0.24939	-0.28106	-0.29881	-0.26896	-0.27475	-0.29252	-0.26928
XPRF	0.033615	0.066004	0.04287	0.020491	0.02155	0.028352	0.030195
CRRF	0.199248	0.210555	0.202046	0.215613	0.223314	0.193248	0.200153
Constant	0.006193	-0.02361	0.022984	-0.01759	-0.02346	-0.01713	-0.00918

Table A7: *RF* ARDL 101 with Empirical Bayesian Prior

Variables	Coeff	Var.	se	t	p
lag	-0.03054	0.002861	0.053489	-0.57097	0.57227
LBTRF	-0.02253	0.006809	0.082517	-0.27302	0.786707
LETRF	0.098097	0.005631	0.075041	1.307231	0.201065
LBNRF	-0.08142	0.004477	0.066912	-1.21678	0.233176
LXPRF	-0.01693	0.006692	0.081807	-0.20696	0.837438
LCRRF	0.08387	0.007982	0.089341	0.93876	0.355351
Constant	0.03008	1.21E-05	0.003474	8.658562	1.17E-09

Table A8: NS ARDL 101 with Empirical Bayesian Prior

Variables	Coeff	Var.	se	t	p
lag	-0.22168	0.002593	0.050918	-4.35374	0.000143
LBTRF	0.205632	0.004055	0.063679	3.229226	0.003003
LETRF	-0.36188	0.008459	0.091971	-3.93477	0.000457
LBNRF	-0.00773	0.004841	0.069576	-0.11115	0.912234
LXPRF	0.075656	0.002464	0.049643	1.523998	0.137983
LCRRF	0.236224	0.004063	0.063743	3.705849	0.000851
Constant	0.153134	0.003021	0.054962	2.78618	0.009157

Table A9: *DU* ARDL 101 with Empirical Bayesian Prior

Variables	Coeff	Var.	se	t	p
lag	-0.18474	0.002711	0.052065	-3.54825	0.001299
LBTRF	0.315182	0.007101	0.084265	3.740362	0.000775
LETRF	-0.35089	0.010682	0.103354	-3.39501	0.001949
LBNRF	-0.04921	0.007204	0.084876	-0.57977	0.566401
LXPRF	0.055979	0.00356	0.059667	0.938198	0.355635
LCRRF	0.17366	0.005094	0.071373	2.433122	0.021142
Constant	-0.04434	0.003494	0.059108	-0.75021	0.458973

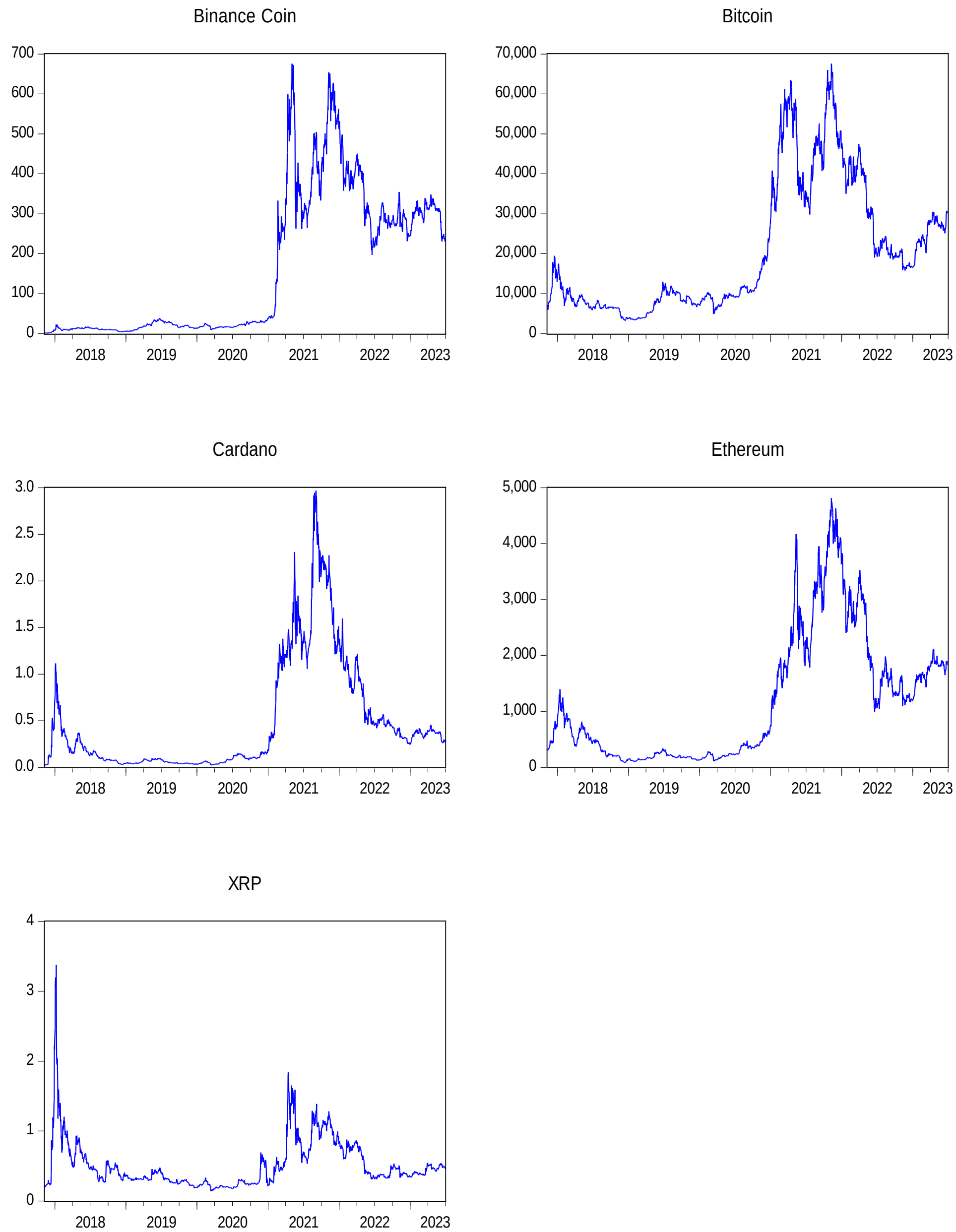

Figure A1: Bitcoin Orice Fluctuations Over Time

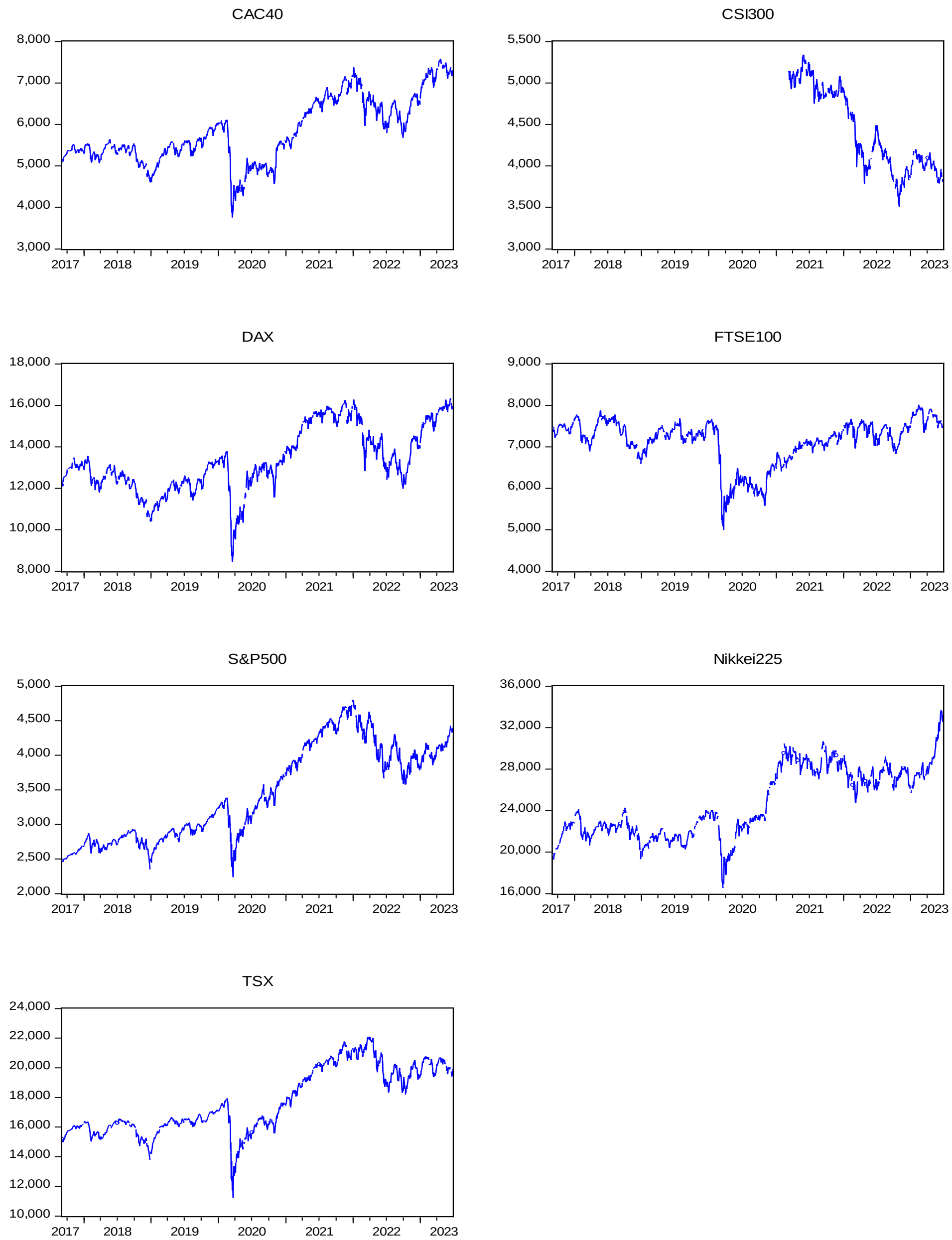

Figure A2: Stock Prices Fluctuations Over Time