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Investor-Induced Cryptocurrency Contagion Channels: An Empirical Evidence from Five Major Economies

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Abstract: *Coupled with the global pandemic and hyperinflation, the innovation risks of cryptocurrency have led to significant price volatility. There is a significant effect of cryptocurrencies on traditional financial markets and contagion channels. Therefore, regulatory authorities should understand the contagion channels to analyze the input risks and take necessary measures. This paper adopts the copula model to study the contagion channels of cryptocurrencies in five major economies. Additionally, three hypotheses are tested to determine whether investor induction serves as the main contagion channel. The empirical results indicate that cryptocurrency market contagion is significant in all five economies, with "portfolio rebalancing" as an important channel of transmission. Moreover, some countries represent time-varying contagion channels. Lastly, cryptocurrencies are not only an indirect symbol of the country's integration into the global economy but also a risk indicator for new assets.*

Keywords: *Cryptocurrency regulation; Contagion channels; Portfolio rebalancing; Copula model*

1. Introduction

Financial innovation has given birth to a decentralized financial system which consequently has led to the rapid rise of digital assets. The transmission of traditional assets into virtual assets (such as cryptocurrencies) has become a hot topic in the present era. The contagion channel from digital assets to traditional assets is becoming increasingly complex due to changes in the investor's expected risk. Moreover, the recent global recession caused by the COVID-19 pandemic has complicated the risk of contagion from digital asset innovation. Besides, the high inflation associated with currency overshooting adversely influences traditional regulatory mechanisms. Therefore, it is essential to determine the contagion channels of cryptocurrencies to traditional financial markets.

Gai et al. (2008) indicate that financial innovation is expected to not only introduce systemic risks but also increase the financial crisis.[1] The extant literature also reveals that financial crises trigger contagion; for instance, the US subprime crisis happened to be contagious to other countries (Jiang et al. 2022; Samitas et al. 2022; Boubaker et al. 2016; Ye et al. 2012; Longstaff, 2010). [2-6]Although, there is a need to virtually explore the financial innovation-triggered transmission.

Cryptocurrency is changing the existing systems of financial payment using disruptive technology (Lipton, 2021; DeVries et al. 2016). [7,8]Malhotra and Gupta (2019) reports that there is a substantial impact of Bitcoin innovation on the future volatility of stock market returns. [9]Furthermore, Berna (2022) highlights that there exists either a one-way or two-way spillover effect between cryptocurrency and stock markets of different countries. [10]However, no study explores the contagion channels of digital assets to traditional assets triggered by financial innovation risks. The internal cumulative risk of cryptocurrency has increased significantly, owing to changes in the investor's portfolio allocation triggered by COVID-19 and hyperinflation in various countries. Hence, financial contagion is more complicated due to both internal and external factors.

The asset holdings of international investors spread the financial crisis rather than the fundamental changes (Yuan et al. 2022; Boyer et al. 2006).[11,12] Kumar et al. (2002) argue that change in the investors' risk preference is one of the major causes of financial contagion.[13] Investor-induced contagion channels can be divided into "portfolio rebalancing" and "wealth constraint" channels. Moreover, "portfolio rebalancing" is categorized into "cross-market portfolio rebalancing" and "risk aversion" channels (Wang et al. 2021; Horta et al. 2016; Boyer et al. 2006).[12,14,15] The volatility spillover of cryptocurrency is similar to the investor-induced contagion due to its decentralized nature, trading mechanism, and distinct liquidity from traditional currencies. This study focuses on the channels through which the investor-

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induced cryptocurrency returns the volatility risk, and by which the effects of external economic shocks spread to traditional assets.

Copula models primarily measure the non-linear and extreme tail correlations. These models are widely used in research studies on optimal portfolios (Naeem et al. 2021; Pho K H et al. 2021),[16,17] tail risk (Fülle et al. 2022),[18] and, contagion channels. Wang et al. (2021) apply dynamic copula theory to determine whether "wealth constraint" serves as a contagion channel in the foreign exchange market amid the subprime crisis.[14] Jayech et al. (2016), and Horta et al. (2016) adopt the copula model to highlight that the "portfolio rebalancing" channel represents the most important crisis communication mechanism in the stock market.[15,19] Presently, no research study has used the copula model to study the cryptocurrency contagion channel, therefore, this is the first study to examine the contagion channel of investor-induced cryptocurrency's market to financial markets in five major economies based on the copula model.

This study applies the copula model to analyze the non-linear correlation and extreme co-movements between cryptocurrency markets and five major economy markets. Additionally, three hypotheses proposed by Forbes & Rigobon (2002) are used to determine the investor-induced contagion channel (see Figure1).[20] The time variation and infection value of contagion channels across different countries are also analyzed to understand the integration degree of economic globalization and the ability to curb risks.

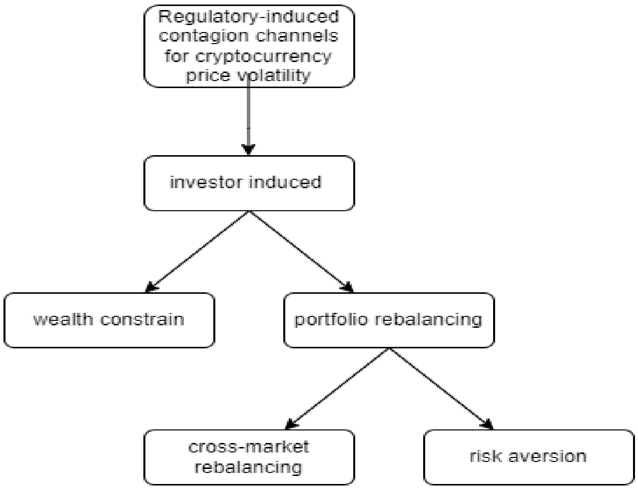

Figure 1: Contagion Channels Induced by Investors in Cryptocurrency.

2. Data

The data used in this study consists of the cryptocurrency CRIX index, national benchmark bond index, and five national stock indexes[1]: S&P 500, CSI 300, FTSE 100, Nikkei 225, Frankfurt, and Germany[2]. The time period for selected price data ranges from September 1, 2015, to December 23, 2021. In addition, the logarithmic rate of return is calculated as: $r_t = (lnp_t - lnp_{t-1}) * 100$.

Since the Chinese government termed the initial coin offering (ICO) as illegal financial activity on Sept 4, 2017, therefore, the regulatory measures for digital tokens were also released on Sept 5, 2017, in Hong Kong, where cryptocurrency trading was then active. Afterward, Japan, Singapore, South Korea, and the US also issued strict regulatory measures related to cryptocurrency in the same year. Subsequently, September 4 is marked as a major time point for the event research, as the prices of cryptocurrencies declined significantly after Sept 4, 2017. Similarly, the China Banking Association, the China Internet Finance Association, and the China payments and Clearing Association jointly announced to prevent the risk of virtual currency transactions on May 18, 2021. As a result, the CRIX index was immediately reduced to half. Hence, May 18, 2021, is taken as the time point for the second event study, owing to the strong relevance of China's regulatory policies in the market and the depth of Chinese investors' participation in cryptocurrency.

1 CRIX index are obtained from https://www.royalton-crix.com/., National stock and bond index are obtained from https://www.wind.com.

2 These five countries are currently the most dominant economies in the world and are the most frequently traded countries for cryptocurrencies.

3. Theoretical Model

This paper applies ARMA (p, q)-GARCH (1, 1) to inscribe the model marginal stepwise before the development of the copula model.

3.1. The Model for the Marginal Distribution

The mean equation is determined by the recursive volatility process in the ARMA-GARCH. This study assumes that the conditional mean adopts the ARMA (p, q) process and the conditional variance incorporates the GARCH (1,1) process (see Liu et al. 2011).[21] ARMA(p,q)-GARCH(1,1) can be modeled as below:

$$r_{jt} = \mu_{jt} + \varphi_j\left(r_{j,t-1} - \mu_{jt}\right) + \theta_j \epsilon_{j,t-1} + \epsilon_{j,t} \tag{1}$$

$$\epsilon_{j,t} = z_{jt}\sqrt{h_{jt}}, z_{jt} \sim t\ distribution \tag{2}$$

$$h_{jt} = \omega_j + \alpha_j \epsilon_{j,t-1}^2 + \beta_j h_{j,t-1} \tag{3}$$

where r_{jt} denotes the real return of asset j at moment t; j=1,2..., z_{jt} is the normalized residual, and $\omega_j > 0,\ \alpha_j \geq 0,\ \beta_j \geq 0,\ \alpha_j + \beta_j < 1,\ \varphi_j + \theta_j \neq 0$.

3.2. Copula Joint Distribution Model

The copula model estimates the correlation between different variables. The marginal distribution of X1, X2 is expressed as $F_i(x_i) = Pr(Xi \leq xi) = ui, i = 1,2$ and the joint distribution function is represented as $F(x1, x2) = Pr(X1 \leq x1, X2 \leq x2)$ for bivariate variables. Furthermore, there exists a unique copula as Sklar's (1959) theorem[22]:

$$F(x1, x2) = C[F1(x1), F2(x2)] = C(u_1, u_2) \tag{4}$$

This paper uses six classical copula functions: three Archimedes copula (Clayton, Gumbel, Frank), two elliptical copula (Gaussian and t-Student), and mixed SJC copula (Cherubini et al. 2004; Joe, 1997).[23,24]

The Gaussian copula function is as follows:

$$C(u_1, u_2, \rho) = \int_{-\infty}^{\phi^{-1}(u_1)} \int_{-\infty}^{\phi^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} exp[\frac{-(r^2-2\rho rs+s^2)}{-2(1-\rho^2)}]drds \tag{5}$$

Where $u_i = \phi(x_i); i = 1,2, \phi$ is the univariate Gaussian density function and (-1<ρ<1).

The t-Student copula function is as follows:

$$C(u_1, u_2, \rho) = \int_{-\infty}^{t_v^{-1}(u_1)} \int_{-\infty}^{t_v^{-1}(u_1)} \frac{1}{2\pi\sqrt{1-\rho^2}} exp[1 + \frac{(r^2-2\rho rs+s^2)}{2(1-\rho^2)}]drds \tag{6}$$

where $t_v^{-1}(.)$ is the quantile function of the standard t-distribution with v degrees of freedom.

The Clayton copula function is as follows:

$$C(u_1, u_2, \theta) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-1/\theta} \tag{7}$$

where θ indicates that the two variables X1, X2 correlation.

The Gumbel copula function is as follows:

$$C(u_1, u_2) = exp[-(\tilde{u}_1^{\theta} + \tilde{u}_2^{\theta})^{\frac{1}{\theta}}] \tag{8}$$

Where $\tilde{u}_i = -\ln(u_i)\,; i = 1,2, \theta \geq 1$.

The Frank copula function is as follows:

$$C(u_1, u_2, \alpha) = -\frac{1}{\alpha} ln(1 + \frac{(e^{-\alpha u_1}-1)(e^{-\alpha u_2}-1)}{e^{-\alpha}-1}) \tag{9}$$

Where $-\infty < \alpha < \infty$.

The SJC copula is as follows:

$$C_{SJC}(u, v, \tau^U, \tau^L) = 0.5[C_{JC}(u, v, \tau^U, \tau^L) + C_{JC}(1-u, 1-v, \tau^U, \tau^L) + u + v - 1] \tag{10}$$

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where C_{JC} is the Joe-Clayton copula.

Kendall's tau represents the correlation coefficients in the Copula model. The expressions of the two random variables (X1 and X2) are as follows:

$$\tau = \tau(X1, X2) = 4\int_0^1 \int_0^1 C(u_1, u_2) dC(u_1, u_2) - 1 \tag{11}$$

Lastly, the tail dependence predicts the association between two variables in extreme states. This statistical instrument consists of upper tail dependence "λ_U" and lower tail dependence "λ_L"(Frahm et al. 2005).[25] The tail dependency is mathematically derived by the given copula function:

$$\lambda^U = \lim_{u \to 1} \frac{[1-2u+C(u,u)]}{1-u} \tag{12}$$

$$\lambda^L = \lim_{u \to 0} \frac{C(u,u)}{u} \tag{13}$$

3.3. Basic Hypothesis of Contagion Channel

Hypothesis 1: The first hypothesis of this study uses the definitions of Forbes & Rigobon (2002) to examine whether there is contagion in the cryptocurrency market.[20]

$$\begin{cases} H_0: \ \tau^{crisis}(i) - \tau^{pre-crisis}(i) \le 0 \\ H_1: \tau^{crisis}(i) - \tau^{pre-crisis}(i) > 0 \end{cases} \tag{14}$$

Where $\tau^{crisis}(i)$ evaluates the correlation coefficient between CRIX and country i stock market returns during periods of severe price volatility. Similarly, $\tau^{pre-crisis}(i)$ assesses the correlation coefficient between CRIX and country i stock market returns before price volatility. The rejection of the original hypothesis confirms the contagion effect whereas the acceptance nullifies the exertion of the contagion effect.

Hypothesis 2: This hypothesis estimates whether the investors transmit risk through portfolio rebalancing or wealth constraints.

$$\begin{cases} H_0: \lambda_L^{crisis}(i) - \lambda_U^{crisis}(i) \le 0 \\ H_1: \lambda_L^{crisis}(i) - \lambda_U^{crisis}(i) > 0 \end{cases} \tag{15}$$

$\lambda_L^{crisis}(i)$ measures the lower tail dependence coefficient of CRIX and country I stock market returns during periods of sharp price fluctuations. Moreover, the upper tail dependence coefficient of CRIX and country I stock market returns is estimated through$\lambda_U^{crisis}(i)$ during periods of price fluctuations. The rejection of original hypothesis implies that the risk is transmitted through the wealth constraint channel. Conversely, the risk is transmitted through the portfolio rebalancing channel.

Hypothesis 3: This hypothesis measures whether portfolio rebalancing channels are affected by cross-market or risk aversion channels.

$$\begin{cases} H_0: \tau_{bond,stock}^{crisis}(i) - \tau_{bond,stock}^{pre-crisis}(i) < 0 \\ H_1: \tau_{bond,stock}^{crisis}(i) - \tau_{bond,stock}^{pre-crisis}(i) \ge 0 \end{cases} \tag{16}$$

The correlation coefficient between the stock and bond market in the i country is represented by$\tau_{bond,stock}(i)$. The original hypothesis is accepted when the risk aversion channel plays a major role. Contrarily, the original hypothesis is rejected when the rebalancing of the cross-market portfolio serves as the contagion channel.

4. Empirical Results

Figure 2 illustrates the time series-based returns of the CRIX Index. The Bitcoin blocks had halved in 2016 and 2020, with the CRIX index reaching historic highs in 2017 and 2021. But, the cryptocurrency prices fell sharply in a short period due to the crackdown operation under the strict regulatory policies. Consequently, there was a fluctuation in the CRIX logarithmic returns in 2017 and 2021. Prices were lower after May 2011 and during 2018-2019 than the end of 2017. The prices start falling when China compelled domestic cryptocurrency dealers to halt trading at the end of December 2021. Although, COVID-19 and inflation caused the price to rebound in late 2021. In short, the cycle of the cryptocurrency

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market is based on four years. From the perspective of two data breakpoints, this study takes Sept 2015 to Sept 2017 and Sept 2019 to May 2021 as the price-rising period in the cryptocurrency market; while, September 2017 to September 2019 and after May 2021 as the recession period in the cryptocurrency market.

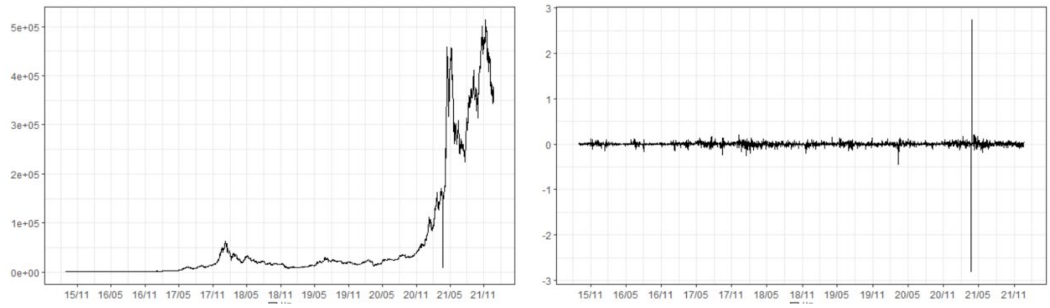

Figure 2: CRIX Index Time Series and Logarithmic Returns.

Tables 1 and 2 populates the optimal copula's[3] results for the CRIX index and the stock market as well as the stock and bond markets before and after the two price fluctuations in the cryptocurrency market during 2017 and 2021.

Clayton copula represents a better copula model than others (except Japan) before price fluctuations in 2017. The correlation between the stock market and bond market is negative for all countries except China, with correlations ranging from 3% to 21%. The correlation coefficient between CRIX and stock markets is also negative. Moreover, the country-wise order of correlation intensity between CRIX and stock markets as follows: China, Britain, US, Germany, and Japan, respectively.

The correlation between CRIX and stock markets of all countries except for China, is greater than zero during the 2017 price volatility period. Additionally, CRIX exhibits the strongest correlation with the UK and Germany. Japan and Germany demonstrate a 5% chance of rising simultaneously with the German and Japanese stock indices during the extreme boom of $\lambda_U = 0.05$. Subsequently, the correlation intensity between CRIX and stock markets is ranked as follows: Germany, Britain, US, Japan, and China.

Table 1: Optimal Copula Results in 2017.

	CRIX/SP500	CRIX/CSI300	CRIX/JP225	CRIX/FTSE	CRIX/DAX	SP500/USBond	CSI300/CNBond	JP225/JPBond	FTSE/UKBond	DAX/GEBc
Pre-price volatility										
Selected copula	Clayton	Clayton	Frank	Clayton	Clayton	t-Student	BB7	t-Student	t-Student	Gumbel
Log likehood	0	0.04	0.02	0	0	30.98	3.12	7.89	18.55	0
AIC	2.01	1.91	1.97	2	2.01	-57.95	-2.25	-11.77	-33.11	2.01
BIC	6.23	6.11	6.17	6.23	6.24	-49.5	6.13	-3.38	-24.65	6.24
Dep.parθ1	0(0.04)	0.01(0.04)	-0.05(0.28)	0(0.04)	0(0.05)	-0.32(0.04)	1.05(0.04)	-0.15(0.04)	-0.19(0.05)	1(0.02)
Dep.parθ2						6.36(2.1)	0.06(0.05)	13.1(7.4)	5.03(1.39)	
kendall τ	-0.02	-0.06	0	-0.04	-0.01	-0.21	0.03	-0.1	-0.12	-0.07
Tailλ_U						0.01	0.06	0	0.02	0
Tailλ_L	0	0		0	0	0.01	0	0	0.02	
Price volatility										
Selected copula	Clayton	Frank	Gumbel	t-Student	Gumbel	t-Student	BB7	Gaussian	Clayton	Gumbel
Log likehood	1.8	0.21	1.4	3.5	1.16	45.34	2.71	3	0	0
AIC	-1.6	1.58	-0.8	-3	-0.33	-86.68	-1.43	-4.01	2	2
BIC	2.62	5.78	3.39	5.46	3.9	-78.24	6.96	0.19	6.23	6.22
Dep.parθ1	0.08(0.04)	-0.17(0.27)	1.04(0.03)	0.1(0.05)	1.04(0.03)	-0.39(0.04)	1(0.06)	-0.11(0.04)	0(0.04)	1(0.01)
Dep.parθ2				15.6(11.35)		7.27(2.98)	0.11(0.06)			
kendall τ	0.03	-0.02	0.02	0.06	0.06	-0.24	0.07	-0.07	0	-0.09
Tailλ_U			0.05	0	0.05	0	0			0
Tailλ_L	0			0		0	0	0	0	

The 2021 pre-volatility prices reflect that there is a positive correlation between CRIX and each country's stock market except for the US, while the correlation coefficient between CRIX and the Japanese stock market is the highest, reaching 10%. In addition, the correlation between CRIX and stock markets is ranked as follows: Japan, China, the US, Germany, and Britain.

All correlation coefficients are positive after 2021 price fluctuations except for Britain. Similarly, the correlation coefficients between Chinese stocks and bond markets also become positive again.

3. Copula Goodness-of-fit Tests are Detailed in Huang, Prokhorov (2014), Wang & Wells (2000).

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Table 2: Optimal Copula Results in 2021.

	CRIX/SP500	CRIX/CSI300	CRIX/JP225	CRIX/FTSE	CRIX/DAX	SP500/USBond	CSI300/CNBond	JP225/JPBond	FTSE/UKBond	DAX/GE
Pre--price volatility										
Selected copula	Frank	t-Student	Frank	BB7	Clayton	t-Student	t-Student	Gaussian	Frank	Gaussiar
Log likehood	0.01	4.2	5.19	0.32	0	24.74	7.97	5.43	1.53	17.42
AIC	1.97	-4.41	-8.37	3.36	2	-45.48	-11.94	-8.87	-1.05	-32.83
BIC	6.03	3.61	-4.36	11.48	6.05	-37.36	-3.92	-4.86	3.01	-28.78
Dep.par$\theta 1$	0.05(0.33)	0.17(0.06)	1.1(0.34)	1.03(0.05)	0(0.05)	-0.29(0.05)	-0.03(0.06)	-0.16(0.05)	-0.56(0.32)	-0.27(0.(
Dep.par$\theta 2$		15.93(15.53)		0.01(0.05)		4.85(1.29)	4.95(1.49)			
kendall τ	-0.01	0.09	0.1	0	0.01	-0.19	-0.01	-0.09	-0.06	-0.17
Tailλ_U		0		0.05		0.02	0.05			
Tailλ_L		0		0	0	0.02	0.05			
Price volatility										
Selected copula	Gumbel	t-Student	t-Student	BB7	Gumbel	t-Student	BB7	Frank	t-Student	Frank
Log likehood	0.02	1.56	2.53	-0.03	0	-0.1	2.29	1.32	2.13	0.32
AIC	1.95	0.88	-1.06	4.07	2	4.2	-0.57	-0.65	-0.27	1.37
BIC	4.98	6.89	4.96	10.15	5.05	10.26	5.44	2.36	5.82	4.42
Dep.par$\theta 1$	1.01(0.06)	0.13(0.09)	0.18(0.08)	1(0.13)	1(0.06)	-0.09(0.17)	1.13(0.09)	-0.8(0.49)	-0.08(0.09)	-0.38(0.4
Dep.par$\theta 2$		16.19(20.18)	16.77(22.74)	0(0.1)		30	0.05(0.09)		6.39(4.1)	
kendall τ	0.04	0.09	0.13	-0.06	0.01	0.06	0.1	-0.09	-0.05	-0.04
Tailλ_U	0.02	0	0	0	0	0	0.15		0.02	
Tailλ_L		0	0	0		0	0		0.02	

Table 3 represents three hypothetical results before and after the 2017 price fluctuation of cryptocurrency and concludes that CRIX is contagious to stock markets of all countries. Besides, all four countries (except for Britain as a wealth constraint channel) serve as portfolio rebalancing channels. Lastly, Japan and China transmit risk through cross-market portfolio rebalancing channels whereas the US and Germany use risk-aversion channels.

Table 3: Three Hypothetical Results Before and After 2017 Price Fluctuations.

Index	Δτ	$\lambda_L - \lambda_U$	Hypothesis 1 conclusion	Hypothesis 2 conclusion	Hypothesis 3 conclusion
CRIX/SP500	0.05	0	Contagion detected	Portfolio rebalancing	
SP500/USBond	-0.03				Flight to quality
CRIX/CSI300	0.04	0	Contagion detected	Portfolio rebalancing	
CSI300/CNBond	0.04				Cross-market rebalancing
CRIX/JP225	0.07	-0.05	Contagion detected	Portfolio rebalancing	
JP225/JPBond	0.03				Cross-market rebalancing
CRIX/FTSE	0.1	0.01	Contagion detected	Wealth constraints	
FTSE/UKBond	0.12				
CRIX/DAX	0.07	-0.05	Contagion detected	Portfolio rebalancing	
DAX/GEBond	-0.02				Flight to quality

Table 4 shows three hypothetical results before and after the 2021 price fluctuation of cryptocurrency. The results confirm that infection is found only in the US and Japan, and both countries transmit risks through portfolio rebalancing channels, in which cross-market portfolio rebalancing plays an imperative role.

Table 4: Three Hypothetical Results Before and After 2021 Price Fluctuations.

Index	Δτ	$\lambda_L - \lambda_U$	Hypothesis 1 conclusion	Hypothesis 2 conclusion	Hypothesis 3 conclusion
CRIX/SP500	0.05	-0.02	Contagion detected	Portfolio rebalancing	
SP500/USBond	0.25				Cross-market rebalancing
CRIX/CSI300	0	-0.13	No Contagion		
CSI300/CNBond	0.11				
CRIX/JP225	0.03	-0.1	Contagion detected	Portfolio rebalancing	
JP225/JPBond	0				Cross-market rebalancing
CRIX/FTSE	-0.06	0	No Contagion		
FTSE/UKBond	0.01				
CRIX/DAX	0	0	No Contagion		
DAX/GEBond	0.13				

This paper takes Sept 30, 2020, to May 17, 2021 (due to the lack of data after May 2021) as the period before the price fluctuation of cryptocurrency to avoid errors caused by data asymmetry. Since the adjusted data excludes the first-phase period of COVID-19, therefore, it also lacks the impact of the initial outbreak on the result outcome.

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Table 5: Data-Adjusted Optimal Copula in 2021.

	CRIX/SP500	CRIX/CSI300	CRIX/JP225	CRIX/FTSE	CRIX/DAX	SP500/USBond	CSI300/CNBond	JP225/JPBond	FTSE/UKBond	DAX/GEI
Pre- price volatility										
Selected copula	BB7	t-Student	t-Student	Gumbel	Gumbel	Gumbel	BB7	BB7	Gumbel	t-Studen
Log likehood	-0.01	0.26	0.6	1.12	0	0	1.42	-0.02	1.34	10.96
AIC	4.02	3.48	2.8	-0.24	2	2	1.17	4.05	-0.68	-17.91
BIC	10.14	9.48	8.86	2.83	5.07	5.06	7.16	10.11	2.39	-11.79
Dep.parθ1	1.01(0.14)	0.06(0.11)	0.12(0.11)	1.1(0.07)	1(0.07)	1(0.04)	1.04(0.07)	1(0.08)	1.09(0.06)	-0.25(0.(
Dep.parθ2	0(0.12)	15.19(29.91)	30				0.12(0.1)	0(0.1)		3.88(1.4
kendall τ	-0.03	0.03	0.07	0.05	-0.01	-0.07	0.06	-0.04	0.09	-0.16
Tailλ_U	0.01	0		0.12	0	0	0.05	0	0.11	0.04
Tailλ_L	0	0					0	0		0.04

Table 5 presents the optimal copula results before the price fluctuations in 2021 after data adjustment. There exists a negative (4% and 16%) correlation between stock markets and bond markets in all countries except for China and Britain. Furthermore, the correlation between CRIX and Chinese, Japanese and British stock markets is positive, while that with the US and Germany is negative.

Table 6 shows 3 hypothetical results for 2021 after data adjustment. It suggests that CRIX is contagious to stock markets except for Britain. Portfolio rebalancing serves as the major channel of infection. Besides, Japanese risk aversion is better than cross-market portfolio rebalancing. Contrarily, the cross-market portfolios of Germany, China, and the US are better than risk aversion.

Table 6: Data-Adjusted for Three Hypothetical Results before and After Price Fluctuations in 2021.

Index	Δτ	$\lambda_L - \lambda_U$	Hypothesis 1 conclusion	Hypothesis 2 conclusion	Hypothesis 3 conclusion
CRIX/SP500	0.05	-0.02	Contagion detected	Portfolio rebalancing	
SP500/USBond	0.13				Cross-market rebalancing
CRIX/CSI300	0.06	-0.13	Contagion detected	Portfolio rebalancing	
CSI300/CNBond	0.04				Cross-market rebalancing
CRIX/JP225	0.06	-0.1	Contagion detected	Portfolio rebalancing	
JP225/JPBond	-0.05				Flight to quality
CRIX/FTSE	-0.11	0	No Contagion		
FTSE/UKBond	0.14				
CRIX/DAX	0.02	0	Contagion detected	Portfolio rebalancing	
DAX/GEBond	0.12				Cross-market rebalancing

The comparison of Tables 3, 4, and 6 indicates that the infection value of China expands from 0.04 in 2017 to 0.06 after adjustment in 2021, while the US is stable at 0.05 all year round. The infection value of Japan is higher than that of the US. China, and Japan. Lastly, the US observes a increase in portfolio rebalancing in the last few years whereas Germany witnesses a decline.

5. Conclusions

This is the first study to employ copula theory and hypothesize three different hypotheses to explore the investor-induced contagion channels of cryptocurrency to traditional financial markets in five different countries. The evidence suggests that financial contagion is widespread in the understudy five markets. Besides this, Britain spreads risk through "wealth constraints", while the other countries spread risk through "portfolio rebalancing". The further analysis highlights that there is a time-varying contagion channel in the US and Germany. However, the contagion channels in China and Japan have not changed over time. The changes in contagion and portfolio rebalancing values confirm that countries are not only actively integrating into the global digital economy but also enhancing their digital-risk prevention capabilities.

These findings put forward several implications for the regulatory authorities. For instance, the regulators in China and Japan should guard against cross-market rebalancing channel contagion. While the regulators in Germany and the US should focus on cross-market channels and relax control measures on risk aversion channels. Lastly, the investors should appropriately allocate their portfolios to reduce their portfolio risk.

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