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Cointegration and Dynamic Spillovers between Cryptocurrencies and Other Financial Assets

Watcharaporn Kantaphayao

School of Development Economics, National Institute of Development Administration, Bangkok, Thailand.

Corresponding Author: makwang.kanta@gmail.com

Sorasart Sukcharoensin

School of Development Economics, National Institute of Development Administration, Bangkok, Thailand

Abstract

This paper investigates the long-term relationships and dynamic spillovers between cryptocurrencies and other financial assets by using cointegration, causality tests, impulse response functions, and volatility spillovers. The results reveal that there are long-term relationships between cryptocurrencies, stocks, fixed income, and commodity markets. For short-term spillovers, coin returns cause token, stock, and gold returns. Meanwhile, stock returns cause token returns. Coin and token returns respond immediately to each other's shocks by the first period. The responses of coin and token returns to shocks in other markets are not significant. Shocks to traditional assets do not affect cryptocurrency volatility. Therefore, cryptocurrencies might be of benefit to portfolio diversification due to their minor linkages with other financial assets.

Keywords: cryptocurrency, cointegration, causality, impulse response, volatility, spillovers

1. Introduction

At present, the structure of the economy and financial industry have become more complicated because of digital technology development. There are numerous innovative financial products which have attracted many investors to search for higher yields under uncertainty in the economy. Many investors have focused their attention on investing in cryptocurrency, which is a new investment asset class, and have realized high rates of return compared to other traditional assets (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018).

Cryptocurrency is a subclass of digital currencies mainly used as a medium of exchange (Rose, 2015). However, cryptocurrency does not meet the three functions of fiat money (medium of exchange, unit of account, and store of value) because its price fluctuates too much to be used as a store of wealth, although it is widely used as a medium of exchange (Bank of Thailand, 2019). Bitcoin is the first and the most popular cryptocurrency created by Satoshi Nakamoto in 2008. It accounts for over 60% of the cryptocurrency market in 2020. Currently, cryptocurrency is used for investment and speculative purposes. It is a good diversifier and is used as a hedge for investment (See, e.g., Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017; Zwick & Syed, 2019) because it has a very low correlation with the other traditional asset classes (See, e.g., Burniske & White, 2016; Chuen, David, Guo, & Wang, 2017; Liu & Tsyvinski, 2018; Sontakke & Ghaisas, 2017).

Cryptocurrency can be explained in terms of coin and token. Both coin and token have different characteristics. Coin is a stand-alone cryptocurrency that operates on its own blockchain and is mainly used as a medium of exchange. Meanwhile, token requires an existing blockchain or platform to operate (See, e.g., Amsden & Schweizer, 2018; Wu, Wheatley, & Sornette, 2018) and usually has been sold to the public through an Initial Coin Offering (ICOs) in order to raise funds for blockchain technology (Howell, Niessner, & Yermack, 2018).

As a new asset class, most investors lack information about cryptocurrencies. Crypto-asset investment information is limited and is mostly disseminated via news, internet communities, and social media. Negative news affects investors who use cryptocurrency for speculation. They might re-evaluate utility from their expectations and eventually sell their cryptocurrency (Glaser, Zimmermann, Haferkorn, Weber, & Siering, 2014). This might be a significant factor that makes cryptocurrency prices become volatile. Although the cryptocurrency price is quite volatile, the intrinsic value is difficult to evaluate (See, e.g., Alam, 2017; Sontakke & Ghaisas, 2017).

The cryptocurrency market is in an early stage (Alam, 2017). Most people's perception of cryptocurrency investment is currently limited. Target investors are risk lovers who have good financial and digital technology literacy. Although cryptocurrency is in an early stage and it is difficult to evaluate its intrinsic value, demand for cryptocurrency for investment and speculative purposes has increased continuously. Therefore, the short-term and long-term linkages between cryptocurrencies and other financial assets is important to analyze to evaluate investment opportunities in the cryptocurrency market.

Despite the importance of cryptocurrency for investment, research on token is still deficient. Therefore, the main contributions of this paper to the existing literature are twofold. First, it puts token analysis in the spotlight, whereas previous studies mainly focus on Bitcoin. Second, this paper constructs a price index—a composite indicator—by using market capitalization of major coins and tokens to represent the cryptocurrency market. The separate analysis of coin and token may uncover different linkages to other financial assets. Coin and token is expected to have different fundamental movements, which can impact investment planning. Furthermore, the generation of coin and token indices would limit the unsystematic risk from selecting only one coin or token to represent the cryptocurrency market.

This paper has two main objectives. First, it investigates mean and variance spillovers in the short-term period between cryptocurrency and other financial assets. It applies a Vector Autocorrelation (VAR) model to test the direction of the causality and analyze the impulse response functions to measure the impacts of the shocks from the main financial asset returns to the coin and token returns. The variance spillover approach is applied to study the volatility linkages of the coin and token markets in the short-term when any shock occurs.

Second, this paper examines the long-term relationships among coin, token, and other financial assets to analyze the fundamental characters of both coin and token. The analysis uses a cointegration method to examine long-term fundamental relationships. The results from the long-term and short-term linkages among coin and token and other financial assets could be important information for investors making decisions on whether to invest in the cryptocurrency market. Both investors and speculators could gain investment opportunities from a new asset class and hedging risks. Furthermore, the results will benefit readers by elucidating linkage movements between cryptocurrencies and other financial assets, which can help guide portfolio allocation.

The rest of the paper is organized as follows: Section 2 reviews existing literature and builds a constructive framework related to cryptocurrency issues. Section 3 describes the data and methodology utilized in the study. In Section 4, we report the findings of the study. The last section concludes.

2. Literature Review

Theoretically, it is difficult to establish intrinsic valuation of cryptocurrency. Many recent studies have therefore attempted to investigate the short-term and long-term relationships between cryptocurrency and other financial assets, as well as other macroeconomic indicators, by using various methodologies. The results of each paper have some differences depending on selected explanatory variables as well as the sample period. However, most of the recent papers still focus on Bitcoin, which has the largest market capitalization, and find that Bitcoin price has a significant long-term relationships with some financial assets.

One strand of research employs the Vector Error Correction Model (VECM) to examine the long-term relationship between Bitcoin price and the number of Bitcoins, as well as between Bitcoin price and the S&P 500 index (See, e.g., Georgoula, Pournarakis, Bilanakos, Sotiropoulos, & Giaglis, 2015). The number of Bitcoins has a positive long-term impact on their own prices, while the S&P 500 index has a negative long-term impact on Bitcoin price. It implies that the investors would sell their stocks and replace them for Bitcoin. That result seems consistent with Conrad, Custovic, and Ghysels (2018), who show long-term Bitcoin volatility and other financial asset volatility by using GARCH-Mixed Data Sampling (MIDAS). S&P 500 volatility has a negative and significant effect on long-term Bitcoin volatility.

Zwick and Syed (2019) investigate a two-regime long-term relationship between Bitcoin and gold prices by using a threshold regression model, which is concerned with non-linear variables. They find that, before the turning point of October 2017, there is a weak negative impact of gold on Bitcoin prices in the long run. However, after October 2017, gold has a significant positive impact on Bitcoin prices in the long run. This indicates that an increase in demand for gold raises the demand for Bitcoin as well. Meanwhile, some papers use an Error Correction Model (ECM) to analyze the short-term and long-term effects of traditional financial assets on Bitcoin prices and find that many financial assets, including Dow Jones, West Texas Intermediate (WTI) crude oil price, and the Euro to U.S. Dollar exchange rate, significantly influence Bitcoin prices in the long term (van Wijk, 2013).

There are several studies on short-term dynamic linkages between cryptocurrencies (as digital assets) and traditional assets published between

2017 and 2019. Most of the recent papers have also shown that there are weak relationships between cryptocurrencies and other traditional assets, while cryptocurrencies have highly dynamic linkages with each other (see, e.g., Baur, Hong, & Lee, 2018; Bianchi, 2020; Chuen et al., 2017; Corbet et al., 2018; Yi, Xu, & Wang, 2018). Meanwhile, volatility among cryptocurrencies could be connected to one another (Yi et al., 2018).

Corbet et al. (2018) select three popular coins for analysis, including Bitcoin, Ripple, and Litecoin, to explore the dynamic relationships between those coins and other financial assets consisting of bonds (Markit ITTR110 index), stocks (S&P 500 index), gold (COMEX closing gold price), currencies (U.S. broad index), commodities (MSC GSCI Total Return Index), and the volatility index from S&P 500. They employ the Diebold and Yilmaz (2012) method to measure and analyze spillover effects across assets. The spillovers for both asset prices and volatility imply a dynamic relationship among assets. As a result, they find that Bitcoin's price affects both Ripple and Litecoin's prices. In contrast, Ripple's and Litecoin's prices mildly affect Bitcoin's price. In cases of volatility spillover, they find that Bitcoin volatility has fewer effects on Ripple and Litecoin volatility than price spillover effects. However, the volatility spillover value from Litecoin to Ripple and Bitcoin are quite high. It means that both Ripple and Bitcoin are sensitive to volatility shocks transmitted from Litecoin. Furthermore, Corbet et al. (2018) also find that linkages between selected cryptocurrencies and other financial assets are very low.

Trimborn and Härdle (2018) create an index for the cryptocurrency market, referred to as CRIX. The CRIX index is constructed by modelling a selection method that reacts to structural market changes. Although CRIX captures the market well, CRIX does not include tokens in constructing the index. This study creates two separate indices for coin and token according to market capitalization in a similar fashion to CRIX. These modified indices are subsequently reviewed every three months by using the average of the top five market capitalization rankings in the last three months to avoid the bias found in the previous study.

3. Research Methodology

3.1 Data

This paper uses daily data from coin and token market capitalization collected from the CoinMarketCap website. For other financial assets, we use three main asset classes: the MSCI international world price index represents the developed stock market; the gold index represents the commodity market; and the United States' (U.S.) 10-year government bond index represents the fixed-income asset class. All data are collected from 1 January 2017 to 31 December 2019. The top-five coin and top-five token indices are generated according to the concept of a market capitalization-weighted index. These indices are reviewed every three months by using the average of the top five market capitalization rankings in the last three months. Index review every three months is consistent with the CRyptocurrency IndeX (CRIX) concept presented by Trimborn and Härdle (2018).

During the sample period, token and coin have high average daily returns of 0.25% and 0.31%, respectively. Meanwhile, all traditional assets offer a modest positive average daily return. According to the preliminary volatility analysis, token and coin have high standard deviations of 5.35% and 5.67%, respectively. The standard deviation of the other traditional assets is in a range of 0.35% to 1.41%. The returns of the U.S. 10-year government bond have the lowest standard deviation of 0.35%, while gold has the highest standard deviation of 1.41%. This implies that the returns of cryptocurrency as a new asset class are volatile compared to other traditional assets.

For the data distribution, the returns of the token, gold, and U.S. 10-year government bonds are positively skewed. Meanwhile, all asset returns have high kurtosis, which exhibits fat tails with higher peaks compared to a normal distribution. Furthermore, the Augmented Dickey-Fuller test has been applied to examine a unit root process. All asset returns are stationary and do not have a unit root process.

3.2 Short-term Dynamic Spillover Analysis Between Cryptocurrencies and Other Financial Assets

3.2.1 Mean Spillover Using the Granger Causality Test

Granger causality is generally applied for testing the causality between variables. The value movement of one variable in the past can explain the current value movement of another variable. The causality implies a spillover effect from one variable to another through the mean equation. It offers significant information to better explain the directions of causes and effects among the variables. It benefits investors and speculators to use this information as indicators for forecasting. However, it is appropriate for explaining the casual relationship in the short run only.

The causality between two assets is specified as follows:

$$Y_t = \beta_0 + \sum_{i=1}^{n} \beta_{1i} Y_{t-i} + \sum_{i=1}^{m} \beta_{2i} X_{t-i} + \varepsilon_{1t} \tag{1}$$

$$X_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} X_{t-i} + \sum_{i=1}^{m} \alpha_{2i} Y_{t-i} + \varepsilon_{2t} \tag{2}$$

The null hypothesis (H_o), $\beta_{21} = \beta_{22} = \ldots = \beta_{2m} = 0$, means that asset X's return does not cause asset Y's return. β_{1i} is the causation scale of asset Y's return at t-i, while β_{2i} is the causation scale of asset X's return at t-i. The null hypothesis (H_o), $\alpha_{21} = \alpha_{22} = \ldots = \alpha_{2m} = 0$, means that asset Y's return does not cause asset X's return. is the causation scale of asset X's return at t-i, while is the causation scale of asset Y's return at t-i. To test for causality between coin and token, asset X represents the token return (TR), while asset Y represents the coin return (CR). To test for the causality between coin (or token) and other financial assets, asset Y represents either the coin return (CR) or the token return (TR), while asset X represents the stock return (WD), gold return (GD), or government bond return (GOV).

3.2.2 Spillovers by Using the Impulse Response Function

The impulse response function is usually applied to a VAR model to measure the impact of the shock of one variable to another in the system. In other words, it is also used to explain the short-run dynamic interaction between the time-series variables in a system when the shock occurs. Most papers also usually use the impulse response function together with cointegration and causality tests to analyze the spillover effects between time-series variables in a system (See, e.g., Chang, Fang, & Wen, 2001; Chevallier, 2010; Granger, Huangb, & Yang, 2000).

The results can be of use for cryptocurrency investment strategy. The impulse response function procedure starts with the unit root process. All sample variables should be stationary. The VAR model and the impulse response function are then estimated. There are five variables in the system including coin returns (CR), token returns (TR), stock returns (WD), gold returns (GD), and government bond returns (GOV). The VAR models are written as below:

$$y_{1,t}=\mu_1+\varphi_{11}y_{t-1,1}+\varphi_{12}y_{t-1,2}+\ldots+\varphi_{15}y_{t-1,5}+\varepsilon_{1,t} \quad (3)$$

$$Y_{2,t}=\mu_2+\varphi_{21}y_{t-1,1}+\varphi_{22}y_{t-1,2}+\ldots+\varphi_{25}y_{t-1,5}+\varepsilon_{2,t} \quad (4)$$

$$\vdots \quad \vdots \quad \ldots \quad \ldots \quad \ldots \quad \vdots$$

$$y_{5,t}=\mu_5+\varphi_{51}y_{t-1,1}+\varphi_{52}y_{t-1,2}+\ldots+\varphi_{55}y_{t-1,5}+\varepsilon_{5,t} \quad (5)$$

where $y_{i,t}$ represents the endogenous variable at time t, φ_{ij} (L) represents the matrix in the backshift operator (L), μ_i represents the constant value, and $\varepsilon_{i,t}$ represent the error term. Since the impulse response function is the coefficient of the vector moving average in the VAR model, the VAR model has to be transformed as the vector moving average as below.

$$y_t= \mu + \textstyle\sum_{i=0}^{\infty} \varphi_i \varepsilon_{t-i} \quad (6)$$

where y_t represents the vector of the time-series variables in the system, μ represents the mean of y_t, φ_i represents the impulse response function or impact spillover, and ε_t represents the vector of the error terms. Therefore, y_t consists of variables as follow and the φ_i will be estimated and plotted.

$$y_t = \begin{bmatrix} CR \\ TR \\ WD \\ GD \\ GOV \end{bmatrix} = \begin{bmatrix} \overline{CR} \\ \overline{TR} \\ \overline{WD} \\ \overline{GD} \\ \overline{GOV} \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} \varphi_i^{11} & \varphi_i^{12} & \cdots & \varphi_i^{15} \\ \varphi_i^{21} & \varphi_i^{22} & \cdots & \varphi_i^{25} \\ \vdots & \vdots & & \vdots \\ \varphi_i^{51} & \varphi_i^{52} & \cdots & \varphi_i^{55} \end{bmatrix} \begin{bmatrix} \varepsilon_{CR,t-i} \\ \varepsilon_{TR,t-i} \\ \vdots \\ \varepsilon_{GOV,t-i} \end{bmatrix} \quad (7)$$

3.2.3 The Volatility Spillover Model

The volatility spillover model is one of the dynamic linkage analysis models. It describes the a shock's impact of one variable to another through the error terms. Most recent financial papers use volatility spillover to analyze the volatility linkages among the variances of asset returns in various markets such as stocks, bonds, oil, etc. The volatility spillover is applied based on the GARCH (1,1) model.

This paper applies the concept of the volatility spillover model, which follows Ng (2000), to investigate the dynamic impact from the main financial assets to the cryptocurrency market, as well as coin or token to each other, through the error terms. In other words, the shock of the main traditional assets might influence the volatility of coin and token returns. Meanwhile, the shock of coin or token might affect the volatility of each other. The volatility spillover model for the volatility of asset returns i, $\sigma_{i,t}^2$, is specified as follows:

Conditional return with AR(1):

$$R_{i,t} = \beta_{i,0} + \beta_i R_{i,t-1} + \delta_{i,\,t-1} R_{j,t-1} + \varepsilon_{i,t} \quad (8)$$

$$\varepsilon_{i,t} = e_{i,t} + \varphi_{i,t-1} e_{j,t} \quad (9)$$

$$e_{i,t} \sim N(0, \sigma_{i,t}^2) \quad (10)$$

Conditional variance with GARCH (1,1):

$$\sigma_{i,t}^2 = c_{i,0} + c_{i,1}\sigma_{i,t-1}^2 + c_{i,2}e_{i,t-1}^2 \quad (11)$$

where $e_{i,t}$ represents a purely idiosyncratic shock which has a conditional normal distribution with mean zero, and is assumed to be uncorrelated with the shocks of asset j's return, $e_{j,t}$.

All sample variables in the model should be stationary, so we must first test for a unit root process. After that, the conditional variance with a GARCH (1,1) model is estimated for the endogenous variables in each model.

Volatility spillover linkages between two assets is estimated as follows:

$$\sigma^2_{Y,t} = c_{Y,0} + c_{Y,1}\sigma^2_{Y,t-1} + c_{Y,2}e^2_{Y,t-1} + \gamma_1\sigma^2_{X,t-1} \quad (12)$$

$$\sigma^2_{X,t} = c_{X,0} + c_{X,1}\sigma^2_{X,t-1} + c_{X,2}e^2_{X,t-1} + \gamma_2\sigma^2_{Y,t-1} \quad (13)$$

The null hypothesis (H_o) $\gamma_1 = 0$ means there is no variance spillover. It implies that the volatility of asset X does not affect the volatility of the asset Y's return. The null hypothesis (H_o) $\gamma_2 = 0$ also means there is no variance spillover. It implies that the volatility of asset Y does not affect the volatility of asset X's return. To investigate the volatility linkages between coin return (CR) and token return (TR), $\sigma^2_{X,t-1}$ represents the volatility of token return at time t-1, while $\sigma^2_{Y,t}$ represents the volatility of coin return at time t. $\sigma^2_{Y,t-1}$represents the volatility of coin return at time t-1, while $\sigma^2_{X,t}$ represent the token return at time t. To investigate the volatility linkages among coin return (CR), token return (TR), and other financial assets, $\sigma^2_{X,t-1}$ represents the volatility of the main financial assets at time t-1, including MSCI international world return (WD), gold return (GD), and government bond return (GOV). Meanwhile, $\sigma^2_{Y,t}$ represents the volatility of coin return or token return at time t.

3.3 Long-Run Relationship Between Cryptocurrencies and Other Financial Assets by Using the Johansen Cointegration Method

The Johansen cointegration method proposed by Johansen (1988, 1995) is often applied to examine the long-run relationship among time-series variables based on the Vector Autoregressive (VAR) model proposed by Sims

(1980). It develops from a cointegration test proposed Engle and Granger (1987). The long-run relationship implies the fundamental characteristics or movement of the time-series variables.

This paper focuses on applying Johansen cointegration to test the long-run relationship between cryptocurrencies and the main financial assets. The Johansen cointegration test has the advantage that it can be applied to the full system, which has more than two variables, with a maximum likelihood method to estimate the number of cointegration vectors. However, the full system of the VAR model is well specified (Ericsson & MacKinnon, 2002). Meanwhile, the Engle and Granger cointegration is proper for examining cointegration vectors when there are endogenous variables in the cointegrating relationship. Furthermore, it has two procedures, which are the long-run equilibrium estimation by testing for a unit root process in the estimated error term, and the estimation of a short-run relationship by using an error-correction model (ECM) for adjustment towards the long-run equilibrium. This leads to disequilibrium in the short run when the shocks occur.

The procedures of the Johansen cointegration test include three steps. First, the unit root process has to be checked for stationary and all the variables must be non-stationary. Second, the cointegration test has to be explored for possible cointegration between the variables in the equation. The trace and maximum eigenvalue tests are applied to find out the number of cointegrating vectors. The null hypothesis of the trace test is that there are k cointegrating vectors at most. Meanwhile, the null hypothesis of the maximum eigenvalue is that there are cointegrating vectors not less than k. Third, the cointegration is estimated by using the least squares method to estimate the long-run coefficients in each equation. The cointegration between two assets can simultaneously be investigated by the persistence of cointegrating vectors.

The cointegration between two assets is:

$$Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t \qquad (14)$$

To investigate the long-term relationship between coin and token, asset X is the top-five coin index (COIN), while asset Y is the top-five token index (TOKEN). To investigate the long-term relationship among cryptocurrencies and other financial assets, asset X is the MSCI international world price index (WORLD), the gold index (GOLD), or the U.S. government bond index (GOVBOND). Meanwhile, asset Y is either COIN or TOKEN.

4. Empirical Results

Based on the causality tests (see Tables 1 and 2), this paper finds that the movement of coin returns can cause the direction of token, stock, and gold returns in the short term at the 5% level. This implies that coin return movements might determine the cryptocurrency market in terms of token, as well as the stock market and commodity markets. However, coin return movements do not cause the direction of movements for U.S. 10-year government bond returns. It means that coin return movements cannot determine the bond market in the short term. Meanwhile, the movements of all the main financial assets do not cause the movement direction of coin returns in the short-term period.

In terms of causality of token returns, stock return movements can affect token return movements in the short term, estimated at a 10% significance level. Meanwhile, the returns of gold and U.S. 10-year government bonds do not affect the movement of token returns in the short term. Furthermore, token returns do not cause movements in coin and all other main financial assets in the short term.

Table 1: Causality Direction between Coin and Main Financial Assets

Causality between CR and TR			
Dependent Variable: CR		Dependent Variable: TR	
Chi-Sq	1.8979	Chi-Sq	7.8284
Prob.	0.3871	Prob.	0.0200**
Causality between CR and WD			
Dependent Variable: CR		Dependent Variable: WD	
Chi-Sq	1.7327	Chi-Sq	6.3900
Prob.	0.1881	Prob.	0.0115**
Causality between CR and GD			
Dependent Variable: CR		Dependent Variable: GD	
Chi-Sq	5.5755	Chi-Sq	11.9071
Prob.	0.2332	Prob.	0.0181**
Causality between CR and GOV			
Dependent Variable: CR		Dependent Variable: GOV	
Chi-Sq	2.4744	Chi-Sq	2.9069
Prob.	0.2902	Prob.	0.2338

Notes: * Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

Source: Authors' calculations.

Table 2: Causality Direction between Token and Main Financial Assets

Causality between TR and WD			
Dependent Variable: TR		Dependent Variable: WD	
Chi-Sq	2.8757	Chi-Sq	0.7084
Prob.	0.0899*	Prob.	0.4000
Causality between TR and GD			
Dependent Variable: TR		Dependent Variable: GD	
Chi-Sq	1.4592	Chi-Sq	1.7317
Prob.	0.2271	Prob.	0.1882
Causality between TR and GOV			
Dependent Variable: TR		Dependent Variable: GOV	
Chi-Sq	0.4217	Chi-Sq	2.4962
Prob.	0.5161	Prob.	0.1141

Notes: * Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level

Source: Authors' calculations.

We illustrate the results of the impulse response functions in Figures A.1 – A.3 in the appendix. The results show that coin returns and token returns immediately respond to their own shocks by the first period in a positive direction. Those own shock responses are of higher values compared to shocks from other assets. Coin returns and token returns are quite high and positively respond to each other's shocks by the first period as well. Then, coin returns are back to equilibrium by the third period, but token returns are back to equilibrium by the fourth period. This result is consistent with the causality test that shows that coin return movements can affect token return movements. Furthermore, it implies that both coin returns and token returns are rapidly adaptable although there is a shock transmission to each other.

Furthermore, the impulse responses of coin returns and token returns from the shocks in traditional markets are quite small. This implies that the impulse response functions of coin returns and token returns from the shocks of other traditional markets are not significant. In other words, the shocks in traditional markets, including stocks, commodities, and bond markets, do not affect the movements of cryptocurrency returns. Meanwhile, the impulse responses of traditional assets from shocks of coin and token returns are not significant. It means that shocks to the cryptocurrency market do not affect movements of traditional asset returns.

Next, we compute the Diebold-Yilmaz pairwise spillover index. These figures can quantify the degree of spillover between each asset. The results show that coin and token have a high degree of connectedness with each other compared to those with the main traditional assets. Coin returns affect token returns at around 26.8%, while token returns influence coin returns at 27.4%. Furthermore, the returns of all main traditional assets have an extremely small influence on coin returns and token returns in the range of 0.5% to 1.0%. Moreover, the results from Table 3 show that spillover effects from cryptocurrencies to the main traditional assets are still small. Both coin returns and token returns have extremely small effects on traditional assets in range of 1.1% to 1.7%.

Table 3: Diebold-Yilmaz Index of Spillover (Connectedness)

Asset Return	CR	TR	WD	GD	GOV	From Others
CR	69.9	27.4	0.9	1.0	0.8	30.1
TR	26.8	71.2	0.5	0.7	0.8	28.8
WD	1.2	1.7	86.7	1.7	8.7	13.3
GD	1.6	2.0	0.9	82.7	12.7	17.3
GOV	1.1	1.2	8.5	11.4	77.8	22.2
Contribution to others	30.7	32.3	10.8	14.9	23.0	111.6
Contribution including own	100.6	103.5	97.5	97.6	100.8	22.3

Source: Authors' calculations.

As for the results for volatility spillovers, this paper finds that there is volatility spillover from token return volatility to coin return volatility at the 1 percent level. A shock to token returns affects the volatility of coin returns with one and two optimal lags. Meanwhile, a shock from coin returns affects token return volatility with one optimal lag at the 10 percent level. Furthermore, there is no volatility spillover from all traditional asset returns to both coin and token returns. This implies that shocks in the traditional asset markets do not affect the volatility of the cryptocurrency market.

Table 4: Volatility Spillover (Dependent Variable = CR)

	TR	WD	GD	GOV
Wald Test: Lag = 1				
F-Statistic	7.6319	0.0013	0.0453	1.9353
Prob.	(0.0059)***	(0.9710)	(0.8315)	(0.1647)
Wald Test: Lag = 2				
F-Statistic	4.8295	1.2230	0.7018	1.6049
Prob.	(0.0083)***	(0.2951)	(0.4961)	(0.2018)

Notes: * Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Source: Authors' calculations.

Table 5: Volatility Spillover (Dependent Variable = TR)

	CR	WD	GD	GOV
Wald Test: Lag = 1				
F-Statistic	3.4631	1.2572	0.0183	0.7327
Prob.	(0.0632)*	(0.2626)	(0.8925)	(0.3923)
Wald Test: Lag = 2				
F-Statistic	2.2309	1.0222	0.4093	0.4764
Prob.	(0.1083)	(0.3604)	(0.6643)	(0.6213)

Notes: * Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Source: Authors' calculations.

The empirical results of the cointegration relationship between cryptocurrencies and other financial assets are shown as Tables 6 and 7.

According to the probability of the Trace and Max-Eigen statistics, this paper finds that, in the sample period, there are long-term relationships of some financial assets to the top-five coin index and top-five token index. There are six pairs of cointegration relationships between the two assets. The top-five coin index has a long-term relationship with the top-five token index at a 1% level. The top-five coin index has the long-term relationship with the MSCI international world price index and U.S. 10-year government bonds at the 10% and 5% levels, respectively. Furthermore, the top-five token index has the long-term relationship with the MSCI international world price index and U.S. 10-year government bonds at the 5% level. Meanwhile, it has a long-term relationship with gold at the 10% level.

Table 6: Cointegration between Coin and Main Financial Assets

Cointegration between Coin and Token				
Cointegration	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.
None	18.1455	0.0048***	17.4174	0.0037***
At most 1	0.7280	0.4519	0.7280	0.4519
Cointegration between Coin and MSCI international world index				
Cointegration	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.
None	19.3177	0.0670*	15.3401	0.0609*
At most 1	3.9776	0.4155	3.9776	0.4155
Cointegration between Coin and Gold				
Cointegration	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.
None	14.7666	0.2400	13.6705	0.1083
At most 1	1.0961	0.9386	1.0961	0.9386
Cointegration between Coin and U.S. 10-year government bond				
Cointegration	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.
None	17.8391	0.1042	17.4101	0.0287**
At most 1	0.4290	0.9972	0.4290	0.9972

Notes: * Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level

Source: Authors' calculations.

Table 7: Cointegration between Token and Main Traditional Assets

Cointegration between Token and MSCI international world index				
Cointegration	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.
None	21.0564	0.0388**	16.1024	0.0464**
At most 1	4.9540	0.2885	4.9540	0.2885
Cointegration between Token and Gold				
Cointegration	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.
None	17.3517	0.1199	15.7593	0.0524*
At most 1	1.5924	0.8566	1.5924	0.8566
Cointegration between Token and U.S. 10-year government bond				
Cointegration	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.
None	17.7403	0.1072	17.1794	0.0313**
At most 1	0.5609	0.9919	0.5609	0.9919

Notes: * Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level

Source: Authors' calculations.

Analyzing the cointegrating relationship, it could be interpreted that the top-five token index has a positive impact on the top-five coin index in the long-term period. Meanwhile, the MSCI international world index has a negative impact on the top-five coin index, but it has a positive impact on the top-five token index. The U.S. 10-year government bond index has a positive impact on the top-five coin and top-five token indices. Furthermore, the gold index has a positive impact on the top-five token index.

Table 8: Normalized Cointegrating Coefficients

Cointegration between two assets	Cointegrating Equation (t-statistic)
Cointegration between Coin and Token	$COIN_t = 1.8482 TOKEN_t$ (15.2519)
Cointegration between Coin and MSCI International world index	$COIN_t = 73.3854 - 8.4032 WORLD_t$ (1.9628) (1.7173)
Cointegration between Coin and U.S. 10-year government bond	$COIN_t = 2.1692 GOVBOND_t$ (0.7170)
Cointegration between Token and MSCI international world index	$TOKEN_t = -10.5508 + 2.4736 WORLD_t$ (0.8958) (1.6047)
Cointegration between Token and gold	$TOKEN_t = 0.7715 GOLD_t$ (0.8831)
Cointegration between Token and U.S. 10-year government bond	$TOKEN_t = 2.0879 GOVBOND_t$ (0.1385)

Source: Authors' calculations.

In the case of the speed of adjustment in the error correction process, we first consider the movements between coin and token. The results imply that token adjusts towards the cointegrating vector, but not vice versa. The speed of adjustment in token is significant and exhibits a quick adjustment (11% per day). For the case of the relationship between coin and other traditional assets, the results show that coin adjusts towards a long-term equilibrium with the stock and bond markets. Meanwhile, token adjusts along with traditional financial markets, including stocks, gold, and bonds. The error correction coefficients show that the speed of adjustment in tokens are quicker than those of coins. Lastly, the error correction process of token towards a long-term equilibrium with coin is quicker than the adjustments between token and other traditional assets.

Table 9: Adjustment Coefficient

Cointegration between two assets	Adjustment Coefficient (t-statistic)			
Cointegration between Coin and Token	COIN	0.1112 (1.1139)	TOKEN	0.1112 (3.9086)
Cointegration between Coin and MSCI International world index	COIN	-0.0087 (3.7857)	WORLD	-0.0003 (1.2778)
Cointegration between Coin and U.S. 10-year government bond	COIN	-0.0144 (3.5401)	GOVBOND	-0.0003 (1.2560)
Cointegration between Token and MSCI international world index	TOKEN	-0.0267 (4.0189)	WORLD	-0.0006 (0.6482)
Cointegration between Token and gold	TOKEN	-0.0210 (3.7418)	GOLD	0.0010 (0.6757)
Cointegration between Token and U.S. 10-year government bond	TOKEN	-0.0201 (3.6495)	GOVBOND	-0.0004 (1.1833)

Source: Authors' calculations.

5. Conclusion

Due to unpredictable intrinsic values of cryptocurrencies with high volatility, this paper attempts to study fundamental movements by cointegration and dynamic linkages between cryptocurrencies (coin and token) and traditional financial assets. The empirical results in this paper conclude that coin and token are positively related to each other in the long run. The developed stock market has a negative long-term relationship with coin, while it has a positive long-term relationship with token. Fixed income assets have a positive long-term relationship with coin and token. Meanwhile, commodity assets have a positive long-term relationship with token. The analysis finds that coin and token prices adjust quickly during high volatility periods. Therefore, cryptocurrencies, including coin and token, might have some fundamental movement characteristics. The fundamental movements of the developed stock, fixed income, and commodity markets could be indicators of coin and token fundamental movements over the long term.

In terms of short-term dynamic spillovers, coin returns can cause token returns. This implies that the expected returns of coin could transfer to the token returns. Furthermore, there is some causality between cryptocurrencies and other traditional financial assets; for instance, coin returns and developed stock market returns, coin returns and gold returns, as well as token returns and developed stock market returns. Coin returns can cause the developed stock market returns and gold returns. Meanwhile, the developed stock market returns can cause token returns. This implies that the expectation, especially expected returns on investment, could transmit from the coin market to the developed stock and gold markets, as well as from the developed stock markets to token market.

This paper also shows that coin returns and token returns have immediately positive responses to their own shocks in the first period. They are quite high and positively respond to each other's shocks by the first period, and then move back to equilibrium within two to three periods. This means that cryptocurrency returns are rapidly adaptable when shocks occur. Meanwhile, the impulse response functions of coin returns and token returns from shocks to other financial markets are not significant. This implies that shocks of other financial markets do not affect the movements of cryptocurrency returns.

In terms of short-term volatility spillovers between cryptocurrencies and other traditional assets, there is variance spillover between coin and token. This implies that the volatility of coin returns and token returns can influence each other. The token market can transmit investment risks to the coin market, while the coin market can transmit the investment risks to the token market as well. Meanwhile, shocks to traditional assets do not affect cryptocurrency volatility. This is consistent with the empirical results of the impulse response functions as mentioned above.

In sum, these results show the potential for cryptocurrencies in portfolio risk management. The average return of coins and token are higher than those of traditional assets, which implies that inclusion of cryptocurrencies in asset allocations could provide higher portfolio returns. However, the volatility in coin and token require diversification of the portfolio. The low degree of linkages, spillovers and slow adjustment processes between cryptocurrency and traditional assets also provide the opportunity for diversification benefits. These issues are possibly subjects for future research.

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Appendices

Table A.1: Variable Explanations

No.	Variable	Asset Class	Explanation
1	TOKEN	Digital Asset	TOKEN represents the top 5-token index.
2	TR	Digital Asset	TR represents daily return of the top 5-token index.
3	COIN	Digital Asset	COIN represents the top 5-coin index.
4	CR	Digital Asset	CR represents the daily return of the top 5-coin index.
5	WORLD	Equity	WORLD represents the MSCI International World Index, which describes the large and middle market capitalization of 23 developed markets countries.
6	WD	Equity	WD represents the daily return of the MSCI International World Index
7	GOLD	Commodity	GOLD represents the Global Gold Index generated by Thomson Reuters.
8	GD	Commodity	GD represents the daily return of the Global Gold Index.
9	GOVBOND	Fixed Income	GOVBOND represents the U.S. 10 Year Government Benchmark Index generated by Thomson Reuters.
10	GOV	Fixed Income	GOV represents the daily return of the U.S. 10 Year Government Benchmark Index.

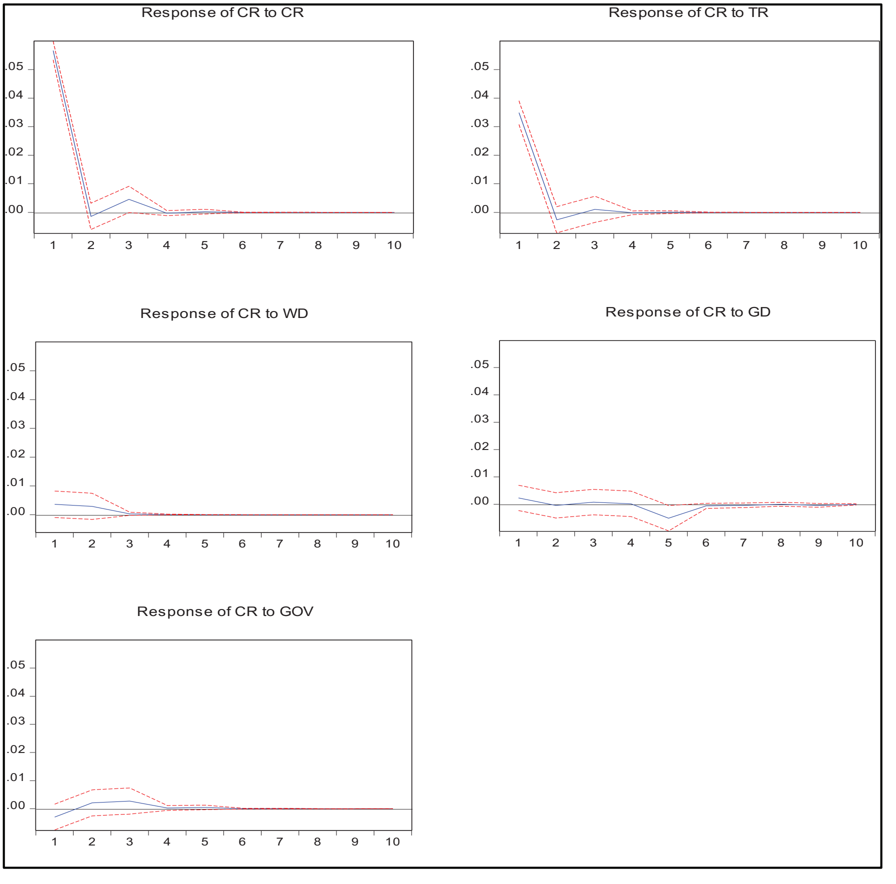
Notes: The developed markets countries consist of Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom and United States.

Table A.2: Descriptive Statistics and Unit Root Tests

Asset	Mean	Max	Min	Standard Deviation	Skewness	Kurtosis	ADF Test
TR	0.0025	0.3141	-0.2447	0.0535	0.2398	9.2471	-26.2425 (0.0000)
CR	0.0031	0.2919	-0.2603	0.0567	-0.2203	6.8635	-25.2070 (0.0000)
WD	0.0004	0.0185	-0.0318	0.0068	-0.8706	5.6587	-21.6433 (0.0000)
GD	0.0004	0.0620	-0.0525	0.0141	0.1191	4.3566	-21.3231 (0.0000)
GOV	0.0002	0.0145	-0.0122	0.0035	0.0961	4.0332	-24.7441 (0.0000)

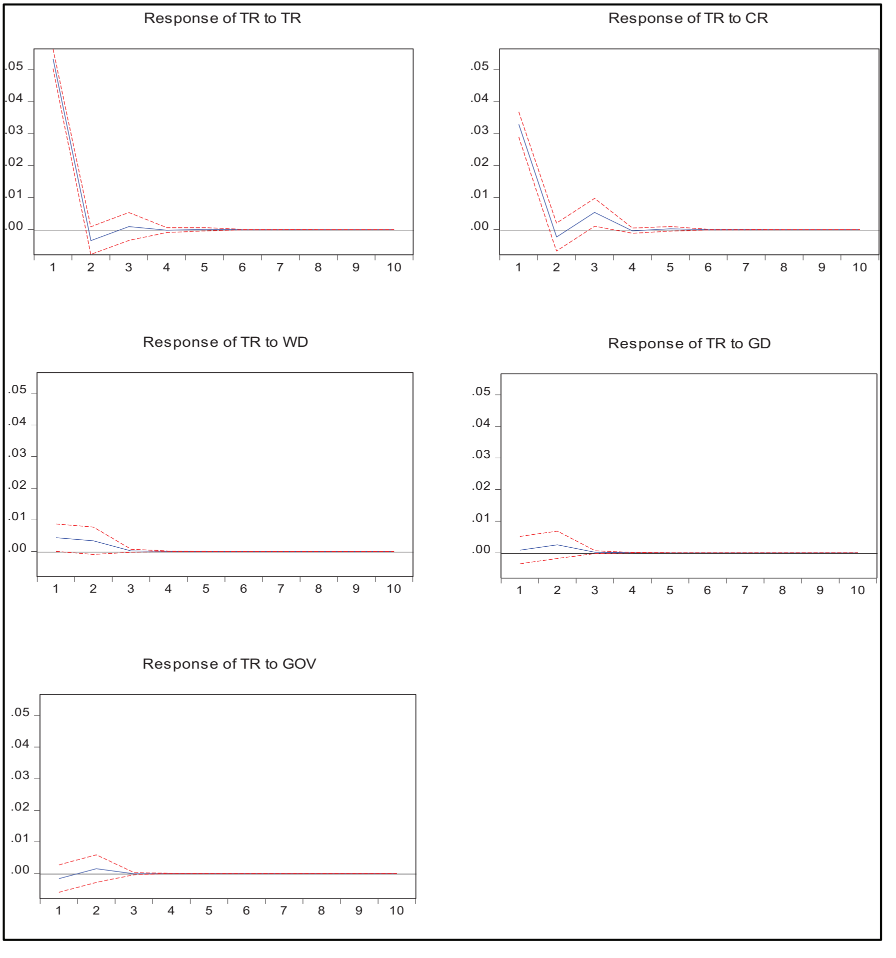
Notes: All variables analyzed in terms of daily data.
Source: Authors' calculations.

Figure A.1: Impulse Response Functions for Coin Returns



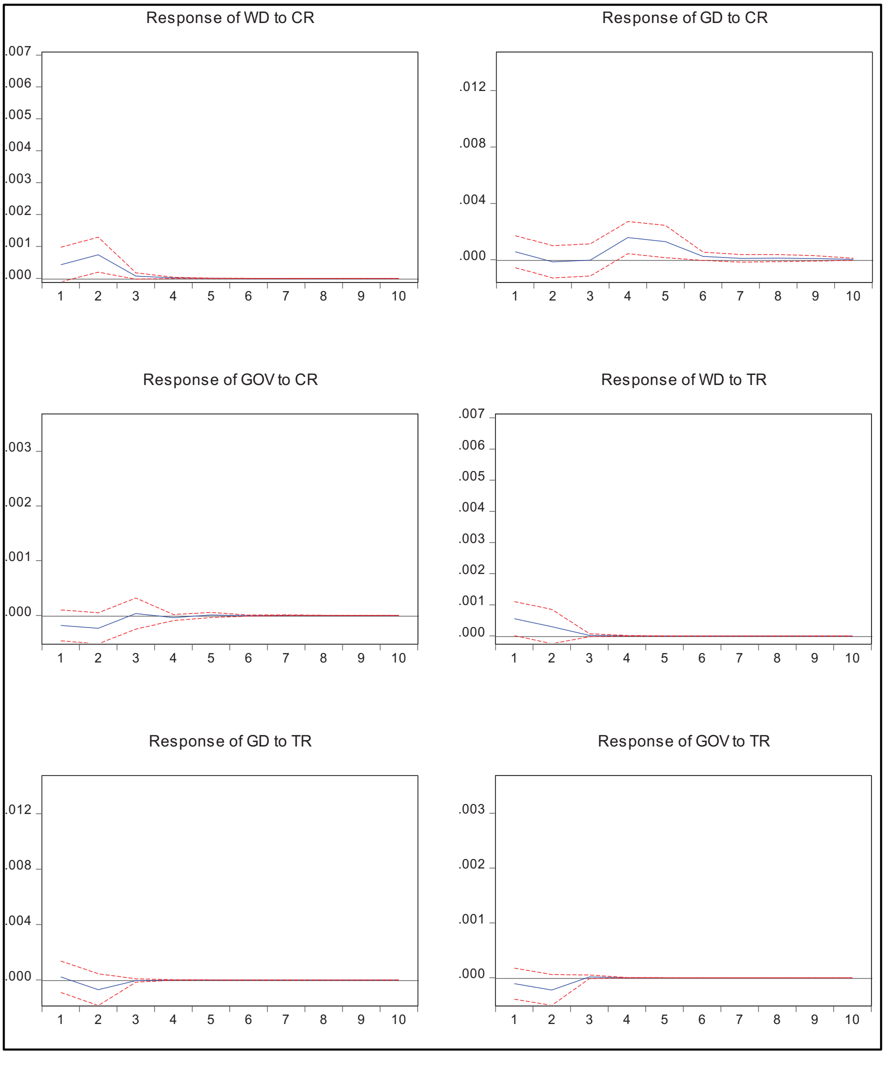
Source: Authors' calculations.

Figure A.2: Impulse Response Functions for Token Returns



Source: Authors' calculations.

Figure A.3: Impulse Response Functions for Other Financial Asset Returns



Source: Authors' calculations.