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The Influences of the US Stock Market on Virtual Currency Price under US Monetary Policy Threshold

Summary: This study uses a panel smooth transition regression model to investigate the nonlinear relationship between virtual currency and the stock market under the US monetary policy threshold from 07 August 2015 to 27 October 2020. A statistical test showed a threshold effect and confirmed that the relationship between the US stock market and virtual currency is nonlinear. Furthermore, virtual currency fluctuation has asymmetric responses to the US stock market's fluctuation based on the threshold value. When the federal fund rate exceeds the threshold value, the changes in the S&P500 with a lag of one positively affect the fluctuation of virtual currency.

Keywords: Panel smooth transition regression (PSTR) model, Threshold effect, Virtual currency, US stock market, US monetary policy.

JEL: C32, C58, E52.

Technological development has motivated people to start considering the changes in payment methods. Electronic payment has significantly increased payments' effectiveness with limited costs, although people doubt the safety and stability of the most widely used currencies (Ivo Letra 2019). Under these conditions, people consider using virtual currency. Virtual currency is a digital currency designed to work as a medium of exchange. In addition to being used in payment transactions, virtual currency has recently become one of the most trending topics in the economic sector and financial issues (Cointelegraph 2013).

Bitcoin was the first virtual currency created in 2009 by a group of programmers under Satoshi Nakamoto. The success of Bitcoin as the first virtual currency has led to many other alternative virtual currencies, such as Ethereum, Ripple, and Litecoin. Approximately 5.392 virtual currencies had been traded globally, with a market capitalisation of $201 billion, as of April 2020 (Oliver Knight 2020). However, the number of people who chose virtual currency as an investment dramatically increased in 2017. The increased market capitalisation has presented more investment opportunities in virtual currency. Given the increase in investment opportunities, the price fluctuation of cryptocurrency has become a critical issue (Yhlas Sovbetov 2018).

Sovbetov (2018) pointed out a long-term close relationship between the prices of Bitcoin, Ethereum, and Litecoin with the US Stock Exchange S&P 500 index. The fluctuating price of the S&P 500 affects the price of Bitcoin, Ethereum, and Litecoin.

Junpeng Wang, Yubo Xue, and Minghao Liu (2016); Pavel Ciaian and Miroslava Rajcaniova (2018) and Arman Zhamharyan (2018) examined the influence of the stock market on the price of cryptocurrencies. However, these studies did not recognise the issues affecting the stock market. According to CBCN (2020), the changes in the US monetary policies have affected many aspects of the economy, such as bonds, the stock market, and cash. According to Michael Ehrmann and Marcel Fratzscher (2004), such changes affect the stock market, as shown by the stock market S&P 500 index's return on the day of a monetary policy decision by the Federal Reserve Bank. Therefore, this study examines the US monetary policy threshold effect between the US stock market and Bitcoin, Ethereum, and Litecoin prices.

1. Literature Review

1.1 Stock Exchange and Monetary Policy

The news of the change in monetary policy is crucial because it affects many aspects of the economy. Alex D. Patelis (1997) used long-horizon regressions and short-horizon vector autoregressions to investigate monetary policy change and stock exchange return from January 1962 to November 1994. The result showed that the shift in monetary policy could significantly predict the future return of the stock exchange. Roberto Rigobon and Brian Sack (2003) investigated the reaction of monetary policy to the stock market. The result showed monetary policy reacts significantly to stock market movement. Ehrmann and Fratzscher (2004) examined the monetary policy effect on the stock market S&P 500 index from 1994 to 2003. The results showed the US monetary policy shock's strong and significant impact on the stock market return. The monetary policy shock also strongly affected the stock market return when the Federal Open Market Committee changed the policy unexpectedly.

Hilde C. Bjørnland and Kai Leitemo (2009) investigated the US monetary policy's interdependence and the S&P 500 stock market. The result showed a great interdependence between the monetary policy and S&P 500 stock price. Konstantin Kholodilin et al. (2009) examined the effect of the European Central Bank's monetary policy on the stock market. The EURIBOR interest rate was used as the proxy for the monetary policy, and the sample data were from January 1999 to January 2008. An increase in the interest rate by 25 basis points decreased the stock market between 0.3% and 2% on the day of the monetary policy shock. Godwin Chigozie Okpara (2010) used the two-stage least squares method to investigate the effect of monetary policy on Nigeria's stock market returns from 1985 to December 2006. The results showed that the changes in monetary policy significantly impacted Nigeria's stock market, especially when the increase in interest rate decreased the stock market return.

In 2013, the rate change of Bank Indonesia (B.I.) as a monetary policy affected the stock and bond markets. The increase in the B.I. rate as Indonesia's monetary policy reduced the stock market indexes by 605 points or 11.6% (Tatang Ary Gumanti, Ayu Retsi Lestary, and Novi Puspitasari 2015). Ria Wijayaningsih, Sri Mangesti Rahayu, and Muhammad Saifi (2015) investigated the effect of the B.I. rate, Fed rate, and Indonesia exchange rate on the composite stock price index. Multiple linear regression was used to analyse the monthly data from January 2008 to December 2015. The empirical result showed that the B.I. rate, Fed rate, and Indonesia's exchange rate simultaneously affect the composite stock price index. However, the partial analysis showed that the B.I. rate and Indonesia's exchange rate have a significantly negative influence on the composite stock price index. The Fed rate does not affect the composite stock price index.

Rossanto Dwi Handoyo, Mansor Jusoh, and Mohd Azlan Shah Zaidi (2015) used a Monte Carlo algorithm for the near-SVAR model to investigate the relationship between the monetary policy and the Indonesian stock market. The results showed that monetary policy has positively affected the stock market on the short-term horizon. In the medium and long-terms, monetary policy negatively affects the stock market. Iddrisu Suhaibu, Simon K. Harvey, and Mohammed Amidu (2017) examined the effect of monetary policy on stock market performance in 12 African countries from 1997 to 2013. The panel vector autoregressive (VAR) model and two types of monetary policy, namely, real interest rate and money supply, were used in the study. The results showed that the increase in the real interest rate improves the stock market performance. In contrast, the decrease in money supply enhances the stock market performance in the 12 African countries.

According to Yang-Chao Wang, Jui-Jung Tsai, and Lanxin Lu (2019), the effect of China's monetary policy on the financial market continuously evolved from 2010 to 2017. The DCC-generalized autoregressive conditional heteroskedasticity (GARCH) model was used to investigate the monetary policy's effect from the money market on the bond and stock markets. The results showed that monetary policy mainly affected the currency and stock markets' instability. Furthermore, the money shortage incident in 2013 and the stock market crash incident in 2015 were closely related to the monetary policies.

1.2 Stock Exchange and Virtual Currency

Dennis van Wijk (2013) investigated Bitcoin's short- and long-term relationships with several financial indicators, such as stock, currency exchange rate, and oil price. The author used an error correction model (ECM), covering data from 19 July 2010 to 13 June 2013. The results showed that the stock market has a significantly positive effect on the value of Bitcoin in the long-run. In the short-run, Dow Jones has a significantly positive effect on the value of Bitcoin. Therefore, Dow Jones and Bitcoin are closely related in the short- and long-terms. Ciaian, Rajcaniova, and d'Artis Kancs (2016) used a VAR model to investigate the short- and long-term relationships between Bitcoin price and global macro-financial development, such as the Dow Jones index, exchange rate, and oil price. The research indicated that the Dow Jones index, exchange rate, and oil price only have a short-term relationship with the Bitcoin price.

Wang, Xue, and Liu (2016) used co-integration analysis and a vector ECM (VECM) to determine the relationship between Bitcoin price and the stock market. The short-term analysis showed that the stock price index considerably affects the Bitcoin price. In comparison, the long-run analysis showed that the stock price index negatively affects the Bitcoin price. Sovbetov (2018) analysed the factors influencing virtual currency prices, such as Bitcoin, Ethereum, Dash, Litecoin, and Monero. The autoregressive distributed lag was used to analyse the weekly data from 2010 to 2018.

The results showed that the stock market S&P 500 affects Bitcoin, Ethereum, and Litecoin prices in the long-run. The surge in the S&P 500 increased the virtual currency prices. However, in the short-term analysis, the S&P 500 only affects the Bitcoin price, thereby decreasing its price.

Zhamharyan (2018) applied a GARCH model to analyse the relationship between virtual currencies and macroeconomic variables. The result showed that a lagged increase in CBOE VIX is called the fear index and measures the S&P 500 index volatility in 30 days. It has a positive correlation with all virtual currencies. Other variables, such as the S&P 500 and SSE indexes, negatively correlate with both virtual currencies. Thus, when companies perform poorly, the demand and the price of Bitcoin and Ethereum may increase. The Nikkei index also has a positive correlation with Bitcoin. Christian Conrad, Anessa Custovic, and Eric Ghysels (2018) examined virtual currency's long- and short-term volatility components. They used the GARCH-MIDAS model to analyse the influences of volatility components on virtual currency in the short- and long-terms. The results showed that the S&P 500 volatility decreases and affects the long-term volatility of Bitcoin. Furthermore, the S&P 500 volatility risk premium has a significantly positive effect on the long-term volatility of Bitcoin.

Shih-Ting Hung (2018) investigated the relationship between Bitcoin and economic variables from 2013 to 2017. VECM was used to evaluate the short-term dynamic relationship. The results showed a long-run equilibrium relationship between Bitcoin and the Dow Jones index. Bitcoin price also had causality between Nikkei 225 and the S&P Global Luxury Index. Tzu-Yi Yang (2020) examined whether a nonlinear relationship exists between Bitcoin and the stock market under Taiwan's monetary policy threshold from 2 February 2012 to 31 August 2019. A STARX model with exogenous variables was used as the research model. The results showed that the effect of Taiwan's stock market's price variation on Bitcoin's price variation is nonlinear. Furthermore, the influence of the marginal effect of two transaction days is larger than that of three transaction days. Thus, potential stock market investors in Taiwan should examine the stock market transaction prices in the recent two days. Regarding monetary policy, the interbank offered rate has been used as a transformation variable. The study also showed that the interbank offered rate is affected when the government expands the money supply, influencing the transaction and liquidity in the capital market. When the offered rate is above the threshold value that can increase the stock prices, the fluctuation price of Bitcoin is affected.

The changes in monetary policy affect the stock market. Similarly, the change in the stock market affects virtual currencies. The variables, specifically monetary policy, stock market, and virtual currency, interrelate. However, whether there exists a nonlinear relationship between the variables is unclear. The panel smooth transition regression (PSTR) model proposed by Andrés González, Timo Teräsvirta, and Dick van Dijk (2005) can detect nonlinear relationships. Therefore, this study examines the nonlinear relationship between virtual currencies and the stock market under the US monetary policy by adopting the PSTR model.

1.3 Nonlinear Models

Clive W. J. Granger and Teräsvirta (1993) pointed out that, because most macroeconomic variables have nonlinear tendencies, if heterogeneity exists between variables during the empirical modelling process, specification errors will occur during estimation employing a conventional linear model, and bias will consequently occur in estimation results. In recent years, a growing number of scholars have employed nonlinear empirical models when a model's variables have heterogeneous structures to resolve this problem and achieve more precise empirical conclusions. The type and characteristics of nonlinear models most commonly seen in the empirical literature include TAR models (Howell Tong 1978) constitute nonlinear regime-switching models. However, the true state of transition variations in the models during empirical research is hard to capture because the transition process of this model is radical and discrete. The type of model consequently often cannot completely and correctly capture the transition processes of low-frequency data. The STAR model (Kim Suk Chan and Tong 1986) is composed of two nonlinear autoregressions linked by a transition function, and the transition process permits the variables to move between two different states, ensuring the smooth transition process is determined by the value of the lagged transition variable. However, this model is unsuitable for models with a cross-sectional data structure.

The chief characteristic of the PTR model proposed by Bruce E. Hansen (1999) is using a time-varying threshold variable to divide the panel data into several different intervals so that a jump will occur when the observed value data are near the transition threshold. This phenomenon is rarely seen in the real world. After changing the jump transition in this PTR model to a smooth transition, González, Teräsvirta, and van Dijk (2005) proposed the PSTR model concept and added a transition speed parameter to their model. This transition speed parameter describes the model's smooth transition phenomenon near the threshold value and ensures that the transition is not a simple jump. Furthermore, the transition variable threshold value is estimated using quantitative methods and not specified artificially. This objective estimation approach can avoid bias in the estimated model extremes owing to researchers' subjective preconceptions. Given PSTR models' features and advantages, a growing number of scholars have recently been adopting models of this type in their research (Sophie Béreau, Antonia López Villavicencio, and Valérie Mignon 2012; Po-Chin Wu, Shiao-Yen Lin, and Sheng-Chieh Pan 2013; Bi Chao, Bi, Minna Jia, and Jingjing Zend 2019; Nikolaos Giannellis and Minoas Konkouritakis 2019).

A PSTR model can capture data heterogeneity and the advantages of accurately describing the model's individual and time effects. This type of model can also avoid the common problem of collinearity in linear structural models. Furthermore, this model can provide useful information to enhance the model's estimation effectiveness when researchers are studying situations with long dependent variable lag periods.

This study uses the PSTR model to assess virtual currency price, where the model can assess the effect of nonlinear data and has a cross-sectional structure on virtual currency price, while effectively presenting the dynamic, smooth transition process of virtual currency price. Importantly, these features not only avoid the biased results that may occur when conventional linear models are employed but also enable the accurate estimation of changes in virtual currency price. Furthermore, this study uses the US monetary policy as a transition variable of the model to determine whether US monetary policy has a deferred effect on virtual currency price and investigates whether the US stock market's level of involvement in US monetary policy activities has a nonlinear influence on changes the US monetary policy.

2. Data and Methodology

2.1 Data

This study used daily data from 7 August 2015 to 27 October 2020, with the transfer and independent and dependent variables. The data regarding these variables were obtained from three sources. For instance, the transfer variable is the federal fund rate, which is the representative of the US monetary policy; the independent variable is the return rate on the stock market's closing price (S&P 500); and the dependent variable is the return rate on the closing price of virtual currencies (namely, Bitcoin, Ethereum, and Litecoin). Table 1 lists the names of variables, calculation methods, variable symbols, and data sources.

Table 1 Names of Variables, Calculation Methods, Variable Symbols and Data Sources

Names of variables	Calculation methods		Variable symbols		Data sources
Federal fund rate	Raw data		FFR		Federal Reserve Bank of St. Louis database https://www.stlouisfed.org/
Return rate on the closing price of S&P 500	$SPRL1_t = \frac{SPL1_t - SPL1_{t-1}}{SPL1_{t-1}}$		SPRL1		Yahoo! Finance database https://finance.yahoo.com/
Return rate on the closing price of virtual currencies	Bitcoin	$BTR_t = \frac{BT_t - BT_{T-1}}{BT_{t-1}}$	VCR	BTR	CoinMarketCap database https://coinmarketcap.com/
	Ethereum	$ETR_t = \frac{ET_t - ET_{t-1}}{ET_{t-1}}$		ETR	
	Litecoin	$LTR_t = \frac{LT_t - LT_{t-1}}{LT_{t-1}}$		LTR	

Source: Authors' elaboration.

This study's dependent variable is represented by the daily return rate on the closing price of virtual currencies, written as VCR_t. It is the return rate on the closing price of virtual currency fluctuation at a specific time. This study used three virtual currencies, namely, Bitcoin, Ethereum, and Litecoin. The following section describes the three dependent variables.

Bitcoin is the first and largest virtual currency based on market capitalisation. This study used the daily return rate on the closing price of Bitcoin as the dependent variable, indicated by BTR_t. BTR_t is the daily return rate on the closing price of Bitcoin in period t, BT_t is the daily closing price of Bitcoin, t denotes the time, and BT_{t-1} is the daily closing price of Bitcoin in the period $t - 1$.

Ethereum is the second-largest virtual currency based on market capitalisation after Bitcoin, released in July 2015. This study used the daily return rate on the closing price of Ethereum as the second dependent variable, indicated as ETR_t. ETR_t is the daily return rate on the closing price of Ethereum, t denotes the time, ET_t is the daily closing price of Ethereum, and ET_{t-1} is the daily closing price of Ethereum in period $t-1$.

Litecoin was released in October 2011 by Charlie Lee, a Google employee and former engineering director at Coinbase. Although nearly identical to Bitcoin, Litecoin is the seventh largest virtual currency based on market capitalisation. The present study used the daily return rate on the closing price of Litecoin as the third dependent variable, indicated by LTR_t. LTR_t is the daily return rate on the closing price of Litecoin, t denotes the time, LT_t is the daily closing price of Litecoin, and LT_{t-1} is the daily closing price of Litecoin in the period $t-1$.

The independent variable indicates the daily return rate on the closing price of the stock market. This study used the S&P 500 as the representative of the stock market, indicated by $SPRL1_t$. $SPRL1_t$ is the daily return rate on the closing price of S&P 500 with a lag of one. t denotes the time, $SPL1_t$ is the daily closing price of S&P 500 with a lag of one, and $SPL1_{t-1}$ is the daily closing price of the S&P 500 with a lag of one in the period of $t-1$.

The daily federal fund rate implies the transfer variable as the US monetary policy representative, written as FFR. The data flow was collected from 7 August 2015 to 27 October 2020. The variable used the raw data collected from the Federal Reserve Bank of St. Louis.

2.2 Methodology

2.2.1 Linear Model and PSTR Model

According to González, Teräsvirta, and van Dijk (2005), using the PSTR model has several advantages. For instance, the PSTR model assumes the series changes depending on the value of the transition variable and allows for smooth changes in cross-sectional correlations, cross-sectional heterogeneity, and time instability of the effect. Furthermore, the nonlinear relationship can be detected using this model, whereas the transition variable's threshold value can be determined using the PSTR model. To solve the nonlinear and heterogeneity problems simultaneously, the present study followed the procedures for the PSTR model by González, Teräsvirta, and van Dijk (2005). Firstly, the following were established: the linear regression model where the return rate on the closing price of virtual currency is the dependent variable, and the return rate on the closing price of S&P 500 is the independent variable, as follows:

$$VCR_{i.t} = \alpha_0 + \partial_1 SPRL1_{i.t} + \varepsilon_{it}, \tag{1}$$

where $i = 1, 2, \dots;$ N denotes the types of virtual currency; $t = 1, 2, \dots;$ T denotes the time; $VCR_{i.t}$ denotes the return rate on the closing price of virtual currency; $SPRL1_{i.t}$ denotes the return rate on the closing price of S&P 500 with a lag of one period; and ε_{it} is the residual term.

Next, in the PSTR model, there exist two extreme regimes and one single transition function, assuming that the parameters with a function of a threshold variable change smoothly. The model is written as follows:

$$VCR_{i.t} = \alpha_i + \vartheta_0 X_{i.t} + \vartheta_1 X_{i.t} G(q_{it}; y, c) + \mu_{it}, \tag{2}$$

where $i = 1, 2, \ldots, N$ denotes the types of virtual currency; $t = 1, 2, \ldots, T$ denotes the time; $VCR_{i.t}$ denotes the return rate on the closing price of virtual currency; $X_{i.t}$ is a vector of exogenous explanatory variables, $X_i = (SPRL1_{it})$; $G(q_{it;}\ y, c)$ is a transition function, with q_{it} as a transition variable, and y and c as the transition parameter and transition threshold value, respectively; and μ_{it} is a residual term.

The transition variable can be written as follows:

$$G(q_{it}; y, c) = \left(1 + exp\left(-y \prod_{j=1}^{m} (q_{it} - c_j)\right)\right)^{-1}, \tag{3}$$

where $y > 0$, and $C_1 \le C_2 \le \cdots \le C_m$. When $m = 1$ and $y \to \infty$, the PSTR model reduces to a panel transition regression model. González, Teräsvirta, and van Dijk (2005) stated that, based on the empirical perspective, the case of $m = 1$ or $m = 2$ is sufficient and can capture nonlinearities owing to regime switching. The PSTR model can be written as follows:

$$VCR_{i.t} = \alpha_i + \vartheta_0 X_{i.t} + \sum_{j=1}^{y} \vartheta_j X_{i.t} G_j\left(q_{it}; y_j, c_j\right) + \mu_{it}, \tag{4}$$

where $j = 1, 2, \ldots, r$ denotes the number of transition functions, and $(r + 1)$ is the number of regimes.

2.2.2 Estimation and Specification Test

According to González, Teräsvirta, and van Dijk (2005), one of the advantages of the PSTR model lies in detecting nonlinearity. The PSTR model is shown by Equation (4). To adopt the PSTR model in this study, a three-step procedure for estimating Equations (2) and (4) was used. Firstly, the linearity against the PSTR model constructed was used. If the null hypothesis of linearity is not rejected, transition effects exist. Next, the number of transition functions was determined. Lastly, the individual specific means were removed, and the nonlinear least squares method was applied to estimate Equations (2) and (4). To examine the linearity testing of Equation (4), the auxiliary equation is as follows:

$$VCR_{i.t} = \pi_i + \pi_1 SPRL1_{i.t} + \pi'_1 SPRL1_{i.t} q_t + \eta_{it}. \tag{5}$$

A linearity test was performed to conduct the testing of $H_0: \pi'_1 = 0$. Suppose the null hypothesis of linearity is rejected, the null hypothesis of a single threshold model is used. The testing procedure continues until the hypothesis without an additional threshold is not rejected. In this regard, $PSSR_0$ denotes the panel sum of squared residuals under the null hypothesis (the linear panel model with individual effects), whereas $PSSR_1$ denotes the panel sum of squared residuals under the alternative (the PSTR model with two regimes). The corresponding LM statistic is as follows:

$$LM_F = [(PSSR_0 - PSSR_1)/K]/[PSSR_0/(TN - N - k)], \tag{6}$$

where K is the number of explanatory variables. Under the null hypothesis, the LM statistic has an asymptotic $X^2(K)$ distribution.

3. Empirical Analysis and Results

3.1 Descriptive Statistics

Table 2 shows the descriptive statistics result for these variables during the given period, as well as the minimum, maximum, mean, and standard deviation values of these variables.

Table 2 Descriptive Statistics

Variables		Mean	Maximum	Minimum	Standard deviation
Dependent					
Return rate on the closing price of virtual currency (VCR)	Bitcoin (BTR)	0.0040330	0.2524720	−0.371695	0.0460970
	Ethereum (ETR)	0.0072366	0.6666667	−0.744243	0.0819252
	Litecoin (LTR)	0.0041450	0.7156590	−0.361742	0.0681880
Independent					
Return rate on the closing price of S&P 500 (SPRL1)		0.0004470	0.093828	−0.119841	0.0121960
Transfer					
Federal fund rate (FFR)		0.0110930	0.024500	0.000400	0.0081300

Notes: The observation period is from 7 August 2015 to 27 October 2020.

Source: Authors' elaboration based on data from the Federal Reserve Bank of St. Louis, Yahoo! Finance, CoinMarketCap.

For the dependent variable, the return rate on the closing price of Litecoin has the highest return rate (with a maximum of 0.715659) than the return rate on the closing prices of Bitcoin and Ethereum. The return rate on the closing price of Ethereum has the lowest return rate (with a minimum of −0.744243) than the other virtual currencies. Moreover, in the average return rate on the closing price of the three types of virtual currency, the average return rates on the closing prices of Bitcoin and Litecoin are almost the same, with mean return rates of 0.004033 and 0.004145. In the independent variable, the highest return rate on the closing price of the S&P 500 is 0.093828, whereas the lowest is −0.119841. In the federal fund rate, the highest rate is 0.0245, the lowest rate is 0.0004, and the average is 0.011093. In addition, the standard deviation of the federal fund rate is the lowest. The standard deviation of FFR is 0.008130. Regarding the dependent variable $VCR_{i.t}$, the value of the return rate on the closing price of a virtual currency is between 0.715659 and −0.744243. The standard deviation of those three virtual currencies includes 0.46097, 0.068188, and 0.0819252. Regarding the independent variable $SPRL1_{i.t}$, the value of return rate on closing price is from 0.093828 to −0.119841, whereas the average return rate on closing price S&P500 is 0.000447 with a standard deviation of 0.012196. The transfer variable $FFR_{i.t}$ ranges from 0.0245 to 0.0004 with an average rate of 0.011093 and a standard deviation of 0.008130.

3.2 Panel Unit Root Test

This study followed Andrew Levin, Chien-Fu Lin, and Chia-Shang James Chu's (2002) panel unit root test method to investigate the relevant variables and determine whether they are stationary or nonstationary. The hypotheses for the panel unit test are as follows.

H_0: The variable has a unit root.
H_1: The variable does not have a unit root.

In case the result of the panel unit root test shows that the *p*-value of the variable is significant, H_0 is rejected, whereas H_1 is accepted. Table 3 shows the result of the panel unit root test.

Table 3 Panel Unit Root Test

Augmented Dickey-Fuller test statistic	t-statistic	Prob.*
SPRL1	−14.77857	0.0000***
VCR	−76.29130	0.0000***
FER	−22.77350	0.0000***

Notes: *, **, and *** indicate significance at the level of 10%, 5%, and 1%, respectively.

Source: Authors' elaboration based on data from the Federal Reserve Bank of St. Louis, Yahoo! Finance, CoinMarketCap.

According to Table 3, the *p*-value is 0.0000, which indicates that the variables are significant. Thus, H_0 is rejected, whereas H_1 is accepted. Therefore, the hypothesis "the variable does not have a unit root" is accepted, showing the data are in a stationary series.

3.3 Linear Test

Based on the panel unit root test result, the variables are consistent with a stationary series. Thus, the linear test was conducted to reveal the nonlinear relationship between virtual currencies and the stock market using the PSTR model. The hypotheses of the linear test are as follows.

H_0: The linear model.
H_1: The PSTR model with at least one threshold variable (r = 1).

Suppose that the linear test result shows that the *p*-value is significant. The linear model's hypothesis is rejected, and that of a single threshold model is accepted. This study tested two cases, specifically one and two location parameters. The second test's purpose is to confirm the result of the first test and increase the trustworthiness of the test result. Table 4 shows the result of a linear test.

Table 4 Linearity Test

Test statistic	Number of location parameter (m)	
	$m = 1$	$m = 2$
Wald test (LM)	6.055 (0.014)**	10.398 (0.006)***
Fisher test (LMF)	6.058 (0.014)**	5.206 (0.006)***
LRT test (LRT)	6.059 (0.014)**	10.412 (0.000)***

Notes: Same as Table 3.

Source: Authors' elaboration based on data from the Federal Reserve Bank of St. Louis, Yahoo! Finance, CoinMarketCap.

According to Wald, Fisher, and LRT tests presented in Table 4, the *p*-value of the linear test is significant. Thus, the H_0 linear model is rejected. In the case of one and two location parameters, all test statistic results reject the null hypothesis of linearity. The test result shows that the relationship between the virtual currency and the stock market S&P 500 is nonlinear.

3.4 Optimal Number of Threshold Regime Test

The linear model test shows that the relationship between the virtual currency and the stock market S&P 500 is nonlinear. This study further examined the optimal number of threshold regimes. The hypothesis of the optimal number of the threshold regime test is as follows:

H_0: The PSTR model has $r = 1$.
H_1: The PSTR model has at least $r = 2$.

Suppose that the result of the *p*-value in the optimal number of threshold regime tests is significant. The null hypothesis of the PSTR model with $r = 1$ is rejected, whereas that of the PSTR model with at least $r = 2$ is accepted. Table 5 shows the test result.

Table 5 Test of No Remaining Nonlinearity

Test statistic	Number of location parameter (m)	
	$m = 1$	$m = 2$
Wald test (LM)	1.503 (0.220)	0.131 (0.937)
Fisher test (LMF)	1.501 (0.221)	0.065 (0.937)
LRT test (LRT)	1.503 (0.220)	0.131 (0.937)

Notes: Same as Table 3.

Source: Authors' elaboration based on data from the Federal Reserve Bank of St. Louis, Yahoo! Finance, CoinMarketCap.

According to the test result in Table 5, the optimal number of threshold regimes does not reject the null hypothesis, whether with one location parameter ($m = 1$) or two location parameters ($m = 2$). Thus, the optimal number of transitions is one.

3.5 Empirical Results

After the panel test and the linearity test, the optimal number of threshold regime test confirmed the nonlinear relationship between the virtual currency and the stock market S&P 500, the PSTR model was used to investigate the effect of the stock market S&P 500 on virtual currency price under the US monetary policy threshold. Furthermore, the linear model results were also used to present the difference between the PSTR and the traditional linear models. Table 6 shows the empirical result of the two models.

Table 6 Result of PSTR and Linear Models

Model parameter	PSTR model	Linear panel data model
C	-	0.005447 (0.001051)
ϑ_1	−0.4897 (0.0963)***	−0.192623 (0.086134)**
ϑ_1'	0.6380 (0.2272)***	-
r	7.9930e+005	-
c	0.0038	-
N	1315	3942
AIC	−5.4390	-
BIC	−5.4326	-
R-squared	-	0.001268

Notes: ϑ_1 and ϑ_1' are the return rates on closing S&P 500 with a lag of 1. $\vartheta_1 + \vartheta_1' = 0.1483$. *, **, and *** indicate significance at the level of 10%, 5%, and 1%, respectively.

Source: Authors' elaboration based on data from the Federal Reserve Bank of St. Louis, Yahoo! Finance, CoinMarketCap.

3.5.1 PSTR Model

The threshold value c in this research is 0.0038, whereas the transition variable value y is 7.9930e+005. In the PSTR model, the relationship between the price of the stock market S&P 500 and the price of virtual currency is different in regimes under and above the threshold value. In two extreme cases, $G(SPRL1_{i.t}; 7.9930e + 005, 0.0038) = 0$and $G(SPRL1_{i.t}; 7.9930e + 005, 0.0038) = 1$, the effects are $\vartheta_1(-0.4897)$ and $\vartheta_1 + \vartheta_1'(0.1483)$, respectively. Consequently, when the federal fund rates are below the threshold value, the relationship between the price of the stock market S&P 500 and the price of virtual currency is negative. The relationship between the variables is positive when the federal fund rates are above the threshold value. The equation that expresses the relationship between the virtual currency and the stock exchange can be written as follows:

$$VCR_{i.t} = \pi_i - 0.4897SPRL1_{i.t} + 0.6380SPRL1_{i.t}\, G(FFR_{i.t}; 7.9930e + 005, 0.0038) + \eta_{it}. \tag{7}$$

3.5.2 Linear Model

This section presents the result of the linear test. This section compares the results of the linear and PSTR models. In the linear model, the F-test was used to determine which model is compatible, the fixed-effect or the random-effect model. The hypotheses of the F-test are as follows:

H_0: The fixed-effect model.
H_1: The random-effect model.

If the F-test result is significant, then the null hypothesis of the fixed-effect model is rejected, and the hypothesis of the random-effect model is accepted. The result of the F-test statistic is 0.0000, which is significant and rejects the null hypothesis. The F-test results support the random-effect model and should thus be used in the empirical estimation. The linear test results in Table 6 show a negative relationship between the virtual currency and the S&P 500 price, with a coefficient of −0.192623.

Compared with the PSTR model, the empirical result provided by the linear model is biased. For example, in the linear panel data model, the effect of the S&P 500 price on the virtual currency price is fixed at −0.192623. However, in the PSTR model, the effect is based on different transition variables $G(SPRL1_{i.t}; 7.9930e + 005, 0.0038) = 0$ and $G(SPRL1_{i.t}; 7.9930e + 005, 0.0038) = 1$, with the effect of (-0.4897) and (0.1483), respectively. The linear model cannot estimate the relationship between the virtual currency price and the S&P 500 price, which is similar to the PSTR model. Therefore, the PSTR model's choice is more appropriate than the linear model to discover the effect of the S&P 500 price on the virtual currency price.

3.5.3 Estimation Results

Using the PSTR model for virtual currency and the US stock market price, this study showed only one threshold value (0.0038). The US stock market's effect on the price of virtual currency was revealed in two conditions, below and above the threshold value. In two extreme cases, $G(SPRL1_{i.t}; 7.9930e + 005, 0.0038) = 0$ and $G(SPRL1_{i.t}; 7.9930e + 005, 0.0038) = 1$, the effects are −0.4897 and 0.1483, respectively. Regarding the first case, when the federal fund rate as the proxy of US monetary policy is below the threshold value of 0.0038, every one-unit increase in the price of the US stock market will decrease the price of virtual currency by 2.0421 units, showing the negative effects. However, this relationship has an opposite tendency whenever the monetary policy, as the transition variable, exceeds the threshold value. When the federal fund rate is above the estimated threshold value of 0.0038, every one-unit increase in the price of the US stock market will increase the price of virtual currency by 6.7431 units, showing positive effects. Therefore, the influence of the US stock market price on virtual currency price is nonlinear. Similarly, the US stock market price on the virtual currency price shows the reserved tendency when the transition variable is lower or higher than the estimated threshold value.

4. Concluding Remarks

Many studies have investigated the importance of the virtual currency price on finance and the economy. However, most studies have focused on the relationship between demand and supply and financial variables, such as gold, currency rate, bonds, and the stock market. Furthermore, most studies have considered the influence of one factor on virtual currency price and not the transition variable, such as threshold value, which will influence those variables. Therefore, the relationship between the US stock market prices and virtual currency under the monetary policy threshold value should be understood. This study has three main implications. Firstly, the threshold value has proved the nonlinear relationship between the variables. Secondly, when the monetary policy is below the threshold value, the effect of the US stock market price changes, and virtual currency price is negative. Every one-unit increase in the US stock market price causes a decrease in the price of virtual currency by 2.0421 units. Thirdly, when the monetary policy is above the threshold value, the effect of the US stock market price change on the virtual currency price is positive. Every one-unit increase in the US stock market price increases the price of the virtual currency by 6.7431 units. This result has been proven by the historical price of the virtual currency and the US stock market in December 2015 and July 2020 to August 2020, when the monetary policy was under the threshold value of 0.0038, and the increase of the US stock market price caused the decrease of the virtual currency price. Similarly, the third implication was also proved in January 2017 and February 2018, when the monetary policy was above the threshold value, and the increase in the US stock market price caused the increase of the virtual currency price.

Summarising the results, when the federal fund rate is above the threshold, it belongs to the economic growth range, and its effect is to promote the increase of virtual currency products with large fluctuations and high profits in the capital market. However, when the economy is in recession, the Commonwealth Bank lowers the federal fund rate to stimulate the economy, which will indeed achieve more choices of investment targets, resulting in an unbalanced trend between the stock market and virtual currency, and the fluctuation of virtual currency. The magnitude is relatively small when the boom is hot. The investing public can use FER information to judge asset portfolio conversion and achieve profitable results.

The outcomes of this study prove the relationship between the price of the US stock market and the price of virtual currency under the monetary policy threshold value, which has not been investigated previously. This study contributes to academic research and practical situations. To investors, the study is a useful reference in predicting the price of virtual currency fluctuation owing to the changes in the stock market price. This contribution is essential for establishing good investment strategies and right decisions.

This study offers several suggestions for future research. Firstly, this study only uses three virtual currency types: Bitcoin, Ethereum, and Litecoin. Other virtual currencies should be used in future research, including Ripple, Tether, Bitcoin Cash, Bitcoin S.V., and EOS. Other types of stock markets, such as Dow Jones and Nasdaq Composite, can also be considered in future research.

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