ANALYSIS OF VOLATILITY AMONG THE FOREIGN EXCHANGE RATES AND CRYPTOCURRENCIES

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Abstract

A cryptocurrency is a digital asset which is gaining high impetus, as it serves as a medium of exchange designed through cryptography destined for a secured transaction and control the creation of additional units. Many national and international traders have started accepting crypto currencies since its prices are not managed or influenced by governments, rather the demand and supply determine it. Bitcoin is one of the popular crypto currencies available in the market. Now Bitcoins are not mere currencies, market participants are using it for investing, therefore, understanding the Bitcoin's is vital from the investor perspective. This paper attempts to understand the relationship between the returns of major currencies traded in India and the Bitcoin. The focus of the study is to quantify the volatility of the major exchange rates and its impact on the volatility in the Bitcoins. Data will be collected from the RBI and other reliable secondary sources. The tools used for the analysis will be Stationarity tests, Auto regressive conditional heteroskedasticity and Granger causality. The model developed would enable investors take informed decisions and the policy makers to regulate and guide them for the measures on crypto currencies.

Key words: Foreign exchange rate, volatility, Crypto currency, Econometric model

JEL Classification: B23, C32, G17

I. Introduction:

Technological advancements are helping financial markets to introduce new products; Crypto currency is one such example. Bitcoin is the first such crpto currency introduced in the market. Some argue Bitcoins are currencies and some classify this as an asset class. In 2008, Mr Satoshi Nakamoto first time discussed about possibilities of cryptocurrency, public ledger in his paper and from that idea, Bitcoin was launched and rest is history now. Some of the major attractions in trading Bitcoins are no or negligible transaction cost, much faster peer to peer transfer, security and anonymity. We can also observe some disadvantages like Irreversible transaction, very high fluctuation of prices, non-acceptability in all public places. Bitcoin trading uses blockchain technology with public and private key with the trusted third parties approve the transaction and avoid the double spending. Since its launch bitcoin started gaining greater acceptance in the market, 1300 plus crypto currencies trading in the market shows its popularity. Upward price momentum of bitcoin is attracting many traders and investors from across the world, but we need to understand the price fluctuation and volatility before taking investment decision.

Price variation of a financial asset can be measured through volatility. High volatility indicates larger fluctuation of prices. A Bitcoin price has been volatile and even now we can observe very high volatility in crypto currency market. It is commonly associated with the risk level of the instrument, a highly volatile instrument is regarded as risky and a less volatile instrument as less risky. The value of bitcoin may go up or down considerably on a given time frame make it a more risky avenue. Many factors influence the price fluctuations in the Bitcoin spot rate and it is very difficult to measure impact of all that factors. Volatility models will help us in understanding the relationship between any other asset class volatility got any impact on the volatility of bitcoin and how we can predict and take the informed decision.

II. Review Of Literature

Volatility forecast can be done with many methods; some are traditional simple methods like Standard Deviation, Random walk, Moving Average, EWMA and these have its own flaws and not consider volatility clustering. Modern time series techniques like ARMA and GARCH captures long-term mean reversion of volatility and also include near-term persistence and fluctuations in volatility. (Clark, Tamirisa, & Wei, 2004 and Kumar & Dhawan,1999).

Current regulations and information will have higher impact on the current price of any exchange rate hence the general accepted idea of that future values depend solely on past values may not yield expected results. ARCH (autoregressive conditional heteroskedasticity) and GARCH (generalized versions of ARCH) models capture no constant volatility of time-series data more effectively. (Sparks & Yurova, 2006; Wang & Barrett, 2002)

Financial time series volatility can be modelled effectively using ARCH and GARCH models since these models shows ability to capture "shocks" or "news" components, which are quite common factors in financial time series (Matei, 2009)

Exchange rates can be effectively forecasted using GARCH model. Most studied proved GARCH (p,q) models are very effective in measuring volatility particularly with the first lags GARCH (1,1) model. Previous period influence and volatility both are captured in GARCH(1,1) model and this feature of the model proves it is a better option for volatility prediction. (Pacelli , 2012; Tripathy & Gil-Alana, 2010; Floros, 2008)

Marra of Lazard asset management in his predicting volatility paper compared major volatility models and listed following GARCH features. The GARCH model specifies the dependence of the time varying nature of volatility. GARCH incorporates changes in the fluctuations in volatility and record the persistence of volatility as it fluctuates around its long-term average. More weight is given to more recent observations and observations are exponentially weighted.

III. RESEARCH DESIGN

NATURE OF THE STUDY

The study type is analytical, quantitative and historical. The study is analytical because facts and existing information is used for the analysis, quantitative as relationship is examined by expressing variables in measurable terms and also historical as the historical information is used for analysis and interpretation. The research is on the secondary data of RBI and other sources collected from September 10, 2014 to December 7, 2017.

OBJECTIVES OF THE STUDY

1. To investigate the relationship between bitcoin prices and other major currencies

2. To model the volatility of the Bitcoin returns and factors affecting the volatility of other major currencies.

SAMPLING

The current study investigates the relationships between Bitcoin prices and USD, Euro, GBP and Yen exchange rates for the period September 10, 2014 to December 7, 2017 using daily data.

HYPOTHESIS OF THE STUDY

H0= There is no significant relationship between Bitcoin prices volatility and volatility in foreign exchange of major currencies

H1= There is a significant relationship between Bitcoin prices volatility and volatility in foreign exchange of major currencies

RESEARCH METHODOLOGY

In the first phase descriptive statistics have been run to break down the collected data to understand the mean reactions, standard deviation, other applicable insights to find out the outliers and to better comprehend the information. In the second phase the collected data has been tested for unit root by applying ADF test. In the third phase a robust regression has been run and residual diagnostics test like Serial Correlation LM Test and Heteroskedasticity Test. In the fourth phase to investigate the causes of volatility in Bitcoin GARCH model have been run. In the last phase a brief discussion and conclusion have been made.

IV. DATA ANALYSIS AND INTERPRETATION

Table 1: Descriptive Statistics of Price and Return of Major currencies

	USD	*GBP*	*EURO*	*YEN*	*Bitcoin*	*RUSD*	*RGBP*	*REURO*	*RYEN*	*RBitcoin*
Mean	65.18	91.82	73.43	57.39	82783.84	0.01	-0.01	0.00	0.00	0.53
Standard Error	0.07	0.25	0.10	0.15	4582.00	0.01	0.02	0.02	0.02	0.14
S D	2.03	7.03	2.76	4.16	128050.20	0.29	0.63	0.62	0.69	4.00

Sample Variance	4.11	49.40	7.63	17.33	16396852952.22	0.09	0.39	0.38	0.48	16.03
Kurtosis	-0.92	-1.57	-0.57	-0.58	13.48	1.32	15.59	3.16	1.82	4.12
Skewness	-0.31	-0.13	-0.27	0.41	3.32	0.12	-1.36	0.18	0.33	0.61
Range	7.99	25.24	13.45	16.17	981650.59	2.22	9.27	6.38	6.11	32.80
Minimum	60.79	79.86	65.95	50.98	13417.78	-1.01	-6.55	-3.02	-3.12	-14.12
Maximum	68.78	105.10	79.39	67.15	995068.37	1.21	2.72	3.36	2.99	18.67
Sum	50904.27	71712.15	57346.75	44824.17	64654178.77	6.26	-11.31	-1.84	2.22	410.06
Count	781.00	781.00	781.00	781.00	781.00	780.00	780.00	780.00	780.00	780.00

Table 1 reports the statistical description for daily Exchange rates and daily returns of USD, EURO,GBP, YEN and Bitcoin during the period of 10-09-2014 to 7-12-2017 that contains major descriptive statistics like mean, standard deviation, Kurtosis, Skewness, Range, Minimum and Maximum. Standard deviation of Bitcoin return is 4, which indicates that return are not constant and varying too much from the mean, this argument is also supported by a huge range(32.8). In a normally distributed data series we can observe that Kurtosis is around 3 and Skewness 0, which again show data series are not normally distributed, all the above mentioned statistical analysis gives more support to the suitability of applying ARCH/GARCH model since the selected observations can be described as not normally distributed fat tailed and leptokurtic.

Graph 1: Graph showing Bitcoin price momentum and daily returns of all major currencies and Bitcoin

Figure 1.

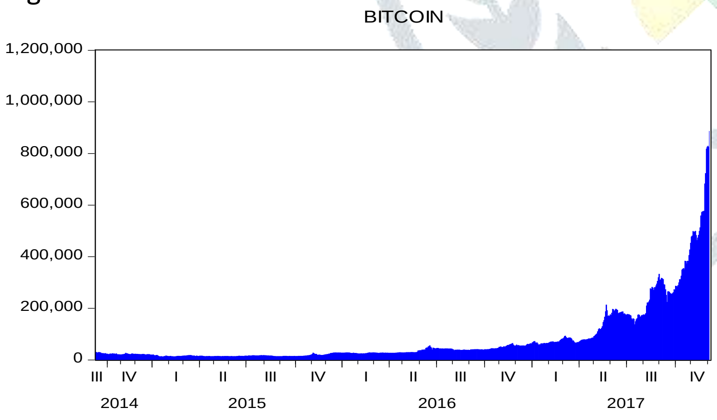
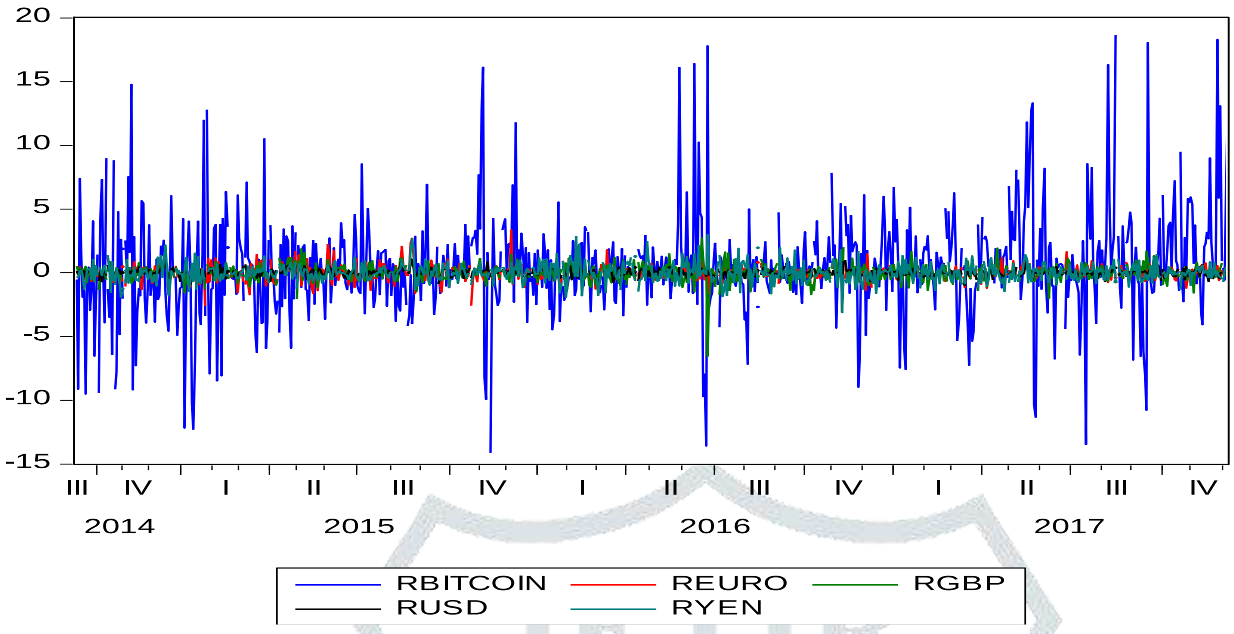


Figure 2



By visual inspection it can be observed that Bitcoin price momentum in recent days is very high. From Figure 2, it can be observed that small changes are followed by small changes and large changes tend to be followed by large changes.

Table 2 ADF Unit Root Tests

Augmented Dickey-Fuller Unit Root Test on RBITCOIN

Null Hypothesis: RBITCOIN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-24.89464	0.0000
Test critical values:	1% level	-3.438518	
	5% level	-2.865035	
	10% level	-2.568686	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RBITCOIN)
Method: Least Squares
Date: 12/08/17 Time: 10:15
Sample (adjusted): 9/12/2014 12/07/2017
Included observations: 779 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RBITCOIN(-1)	-0.892828	0.035864	-24.89464	0.0000
C	0.472323	0.143994	3.280145	0.0011

R-squared	0.443706	Mean dependent var	0.016290
Adjusted R-squared	0.442990	S.D. dependent var	5.341212
S.E. of regression	3.986313	Akaike info criterion	5.606175
Sum squared resid	12347.07	Schwarz criterion	5.618133
Log likelihood	-2181.605	Hannan-Quinn criter.	5.610774
F-statistic	619.7430	Durbin-Watson stat	1.991518
Prob(F-statistic)	0.000000		

Augmented Dickey-Fuller Unit Root Test on RUSD

Null Hypothesis: RUSD has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-27.24428	0.0000
Test critical values:	1% level	-3.438518	
	5% level	-2.865035	
	10% level	-2.568686	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RUSD)
Method: Least Squares
Date: 12/08/17 Time: 10:17
Sample (adjusted): 9/12/2014 12/07/2017
Included observations: 779 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RUSD(-1)	-0.977117	0.035865	-27.24428	0.0000
C	0.007666	0.010503	0.729896	0.4657

R-squared	0.488564	Mean dependent var	-6.28E-06
Adjusted R-squared	0.487905	S.D. dependent var	0.409493
S.E. of regression	0.293036	Akaike info criterion	0.385523
Sum squared resid	66.72118	Schwarz criterion	0.397482
Log likelihood	-148.1613	Hannan-Quinn criter.	0.390123
F-statistic	742.2507	Durbin-Watson stat	1.998028
Prob(F-statistic)	0.000000		

Augmented Dickey-Fuller Unit Root Test on RGBP

Null Hypothesis: RGBP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-26.69138	0.0000
Test critical values:	1% level	-3.438518	
	5% level	-2.865035	
	10% level	-2.568686	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RGBP)
Method: Least Squares
Date: 12/08/17 Time: 10:16
Sample (adjusted): 9/12/2014 12/07/2017
Included observations: 779 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RGBP(-1)	-0.956241	0.035826	-26.69138	0.0000
C	-0.014558	0.022472	-0.647836	0.5173

R-squared	0.478324	Mean dependent var	-0.000934
Adjusted R-squared	0.477652	S.D. dependent var	0.867581
S.E. of regression	0.627032	Akaike info criterion	1.906926
Sum squared resid	305.4926	Schwarz criterion	1.918885
Log likelihood	-740.7478	Hannan-Quinn criter.	1.911526
F-statistic	712.4296	Durbin-Watson stat	2.005198
Prob(F-statistic)	0.000000		

Augmented Dickey-Fuller Unit Root Test on REURO

Null Hypothesis: REURO has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-27.74271	0.0000
Test critical values:	1% level	-3.438518	
	5% level	-2.865035	
	10% level	-2.568686	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(REURO)
Method: Least Squares
Date: 12/08/17 Time: 10:12
Sample (adjusted): 9/12/2014 12/07/2017
Included observations: 779 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
REURO(-1)	-0.995359	0.035878	-27.74271	0.0000
C	-0.002320	0.022145	-0.104758	0.9166

R-squared	0.497626	Mean dependent var	-0.000288
Adjusted R-squared	0.496980	S.D. dependent var	0.871461
S.E. of regression	0.618075	Akaike info criterion	1.878149
Sum squared resid	296.8265	Schwarz criterion	1.890108
Log likelihood	-729.5389	Hannan-Quinn criter.	1.882749
F-statistic	769.6580	Durbin-Watson stat	2.000003
Prob(F-statistic)	0.000000		

Augmented Dickey-Fuller Unit Root Test on RYEN

Null Hypothesis: RYEN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-27.41508	0.0000
Test critical values:	1% level	-3.438518	
	5% level	-2.865035	
	10% level	-2.568686	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RYEN)
Method: Least Squares
Date: 12/08/17 Time: 10:18
Sample (adjusted): 9/12/2014 12/07/2017
Included observations: 779 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RYEN(-1)	-0.983301	0.035867	-27.41508	0.0000
C	0.003164	0.024784	0.127651	0.8985

R-squared	0.491687	Mean dependent var	0.000158
Adjusted R-squared	0.491033	S.D. dependent var	0.969597
S.E. of regression	0.691729	Akaike info criterion	2.103320
Sum squared resid	371.7861	Schwarz criterion	2.115278
Log likelihood	-817.2430	Hannan-Quinn criter.	2.107919
F-statistic	751.5868	Durbin-Watson stat	2.000365
Prob(F-statistic)	0.000000		

To examine the unit roots in the daily return series Augmented Dickey Fuller (ADF) test was used. Results show that; ADF is statistically significant at 1% level in all daily return series. This also confirms the non-existence of autocorrelation and series are mean reverting, hence we have to reject null hypothesis and accept that the returns are stationery.

Table 3 – Regression Result

Dependent Variable: RBITCOIN
Method: Least Squares
Date: 12/08/17 Time: 10:22
Sample (adjusted): 9/11/2014 12/07/2017
Included observations: 780 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.509639	0.142942	3.565342	0.0004
RUSD	1.126708	0.533038	2.113750	0.0349
REURO	0.472703	0.307311	1.538193	0.1244
RYEN	-0.384181	0.252939	-1.518869	0.1292
RGBP	-0.638291	0.265571	-2.403468	0.0165

R-squared	0.012689	Mean dependent var	0.525719
Adjusted R-squared	0.007593	S.D. dependent var	4.004180
S.E. of regression	3.988949	Akaike info criterion	5.611322
Sum squared resid	12331.58	Schwarz criterion	5.641190
Log likelihood	-2183.416	Hannan-Quinn criter.	5.622810
F-statistic	2.490035	Durbin-Watson stat	1.758338
Prob(F-statistic)	0.041981		

It is evident from the above Table, that only the USD recorded a positive Coefficient Value 1.1267 with a standard error of 0.53303 meaning that USD returns shares direct relationship with Bitcoin returns during the study period. USD returns were statistically significant at conventional levels of significance (5%) with a p value of 0.0349 indicating that there is a significance relationship between USD returns and Bitcoin returns. GBP return with the negative coefficient is also statistically significant at 5%. F-Statistic indicates that the overall fit of the model was good.

Table 4: Heteroskedasticity Test: ARCH

Heteroskedasticity Test: ARCH

F-statistic	0.002040	Prob. F(1,777)	0.9640
Obs*R-squared	0.002045	Prob. Chi-Square(1)	0.9639

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 12/08/17 Time: 10:51
Sample (adjusted): 9/12/2014 12/07/2017
Included observations: 779 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.004229	0.098061	10.24090	0.0000
WGT_RESID^2(-1)	-0.001621	0.035886	-0.045166	0.9640

R-squared	0.000003	Mean dependent var	1.002610
Adjusted R-squared	-0.001284	S.D. dependent var	2.545904
S.E. of regression	2.547538	Akaike info criterion	4.710696
Sum squared resid	5042.692	Schwarz criterion	4.722655
Log likelihood	-1832.816	Hannan-Quinn criter.	4.715296
F-statistic	0.002040	Durbin-Watson stat	1.996939
Prob(F-statistic)	0.963987		

To confirm the model fitness, we have conducted a Homoscedasticity test. It is evident from the above table since p value is greater than 5%, there is no Heteroskedasticity in the daily return data series.

GARCH Model

Generalized Autoregressive Conditional Heteroscedasticity (GARCH (1, 1)) test was conducted to understand the impact of major currencies on Bitcoin by using daily time series data covering September 10, 2014 to December 7, 2017 taking Bitcoin as a dependent variable and USD, GBP, Euro and Yen as independent variable.

Table 5– ARCH Model

Dependent Variable: RBITCOIN
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 12/08/17 Time: 10:31
Sample (adjusted): 9/11/2014 12/07/2017
Included observations: 780 after adjustments
Convergence achieved after 31 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(6) + C(7)*RESID(-1)^2 + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.291930	0.119747	2.437904	0.0148
RUSD	1.317052	0.325359	4.047989	0.0001
RGBP	-0.223883	0.207734	-1.077738	0.2812
RYEN	-0.521422	0.197561	-2.639298	0.0083
REURO	0.200242	0.204068	0.981253	0.3265
Variance Equation				
C	0.737332	0.107573	6.854230	0.0000
RESID(-1)^2	0.212146	0.026844	7.902835	0.0000
GARCH(-1)	0.770507	0.016759	45.97697	0.0000

R-squared	0.005358	Mean dependent var	0.525719
Adjusted R-squared	0.000224	S.D. dependent var	4.004180
S.E. of regression	4.003732	Akaike info criterion	5.392734
Sum squared resid	12423.15	Schwarz criterion	5.440522
Log likelihood	-2095.166	Hannan-Quinn criter.	5.411114
Durbin-Watson stat	1.757124		

It is evident from the above table that the USD shares a positive coefficient with Bitcoin. It indicates that an increase in USD prices will lead to an increase of volatility in Bitcoin.

GARCH (1, 1) Model shows that, the p value of ARCH 1 and GARCH 1 are also less than 0.0000. Hence the null hypothesis that the no volatility caused by major currencies has been rejected. We can conclude that the Currency prices were significant in the volatility of the Bitcoin. Null hypothesis rejection indicates that currency prices are significant and can affect bitcoin volatility.

V. Discussion and Conclusion

Sudden upward trend of bitcoin prices captured every ones attention and investors started showing greater investing interest in crypto currencies. Crypto currencies are not regulated in many countries and doing bitcoin transaction is not illegal in many countries. Indian government through RBI warned its investor and asked them to stay away from these crypto currencies.

This study attempted to understand the forecasting possibilities of bitcoin using other major currency exchange rates in India. The empirical study is based on the daily exchange rates of major currencies and Bitcoin prices over the sample period of 10^{th} September 2014 to 7^{th} December 2017. Collected daily exchange rate data is used to calculate daily return and first analysed with descriptive statistics to understand the distribution data. We observed bitcoin prices are fluctuating too much compared to other currencies.Unit root of the data series tested with ADF test, test revealed daily return data series are stationary and we can proceed with further analysis. Regression analysis showed USD daily return is significant and have a positive relationship with bitcoin return. Further test showed there is no Heteroskedasticity in the daily return data series. GARCH (1,1) test proved exchange rate volatility is significant in Bitcoin volatility. Therefore, the current paper establishes that fluctuations in exchange rate prices have a significant impact on Bitcoin prices and volatility.

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