



The Nexus between Russian Capital Market and Bitcoin Rouble Exchange Rate

Debesh Bhowmik

Department of Business and Accountancy, Lincoln University College, Petaling jaya 47301, Selangor D. E., Malaysia

Correspondence E-mail: debeshbhowmik269@gmail.com

Abstract

The paper endeavours to explore the nexus between Bitcoin Rouble exchange rate and the Russian capital market using cointegration and vector error correction analysis taking the capital market indicators namely US Dollar Rouble exchange rate, MOEX index, RTX index, Moscow exchange trade turn over and RUONIA of Russia using daily data from 1/11/2021 to 18/4/2022 as a consequence of post pandemic recovery and sets back from war between Russia and Ukraine. The paper found that the trend line of Bitcoin Rouble rate is cyclical with four phases whose Wavelet threshold signal curve is explosive oscillatory. There are no short run causalities from the indicators of capital market to the Bitcoin Rouble price but there is insignificant and converging cointegrating long run causalities from those indicators where the relation between Bitcoin Rouble and US Dollar Rouble rate and MOEX index are significantly negative and the relation with RTX index is significantly positive. It was evident that there is little significant influence of Bitcoin Rouble pricing on the Russian capital market in the long run.

Keywords: *Bitcoin Rouble; Dollar Rouble; MOEX index; RTX index; RUONIA*

JEL Classification Codes: C12, C22, C58, E44, E58, F30, F40, G15, G20

Introduction

The world economy has been recovering slowly after the global pandemic but the war between Russia and Ukraine sets back the global recovery. The growth of world output has reduced to -3.1% in 2020 due to the impact of covid-19 which has been revived to 6.1% in 2021 but was forecasted to be 3.6% in 2022 and 2023 due to war. The advanced economy's growth of output fell down to -4.5% in 2020 which was recovered to 5.2% in 2021 but was expected to slip down to 3.3% in 2022 and 2.4% in 2023 as forecasted by IMF. The growth of output recovery of emerging markets and

developing countries was 6.8% in 2021 from a negative growth rate of -2.0% in 2020 and the recent war may reduce the rates to 3.8% in 2022 and 4.0% in 2023 in which Russia's growth of output fell down to -2.7% due to covid-19 but recovered to 4.7% in 2021 and is forecasted to -8.5% in 2022 and -2.3% in 2023 respectively. India's recovery is more prominent even if it slipped down output growth to -6.6% in 2020 as an impact of the pandemic and recovered to 8.9% in 2021 but is expected to fall to 8.2% in 2022 and 6.9% in 2023 due to war. The recovery of growth of world trade volume is more than expected after the pandemic. The negative growth rate was observed at -7.9% in

2020 which was recovered to 10.1% in 2021 but forecasted to 5.0% in 2022 and 4.4% in 2023 for the war between Russia and Ukraine. The export growth rate of advanced countries in covid-19 period in 2020 was -9.1% which was hiked to 8.6% in 2021 but forecasted to 5.0% and 4.7% in 2022 and 2023 respectively. In the case of emerging and developing countries, the export growth rate dipped down to -4.8% in 2020 and recovered to 12.3% in 2021 and is expected to fall 4.1% in 2022 and 3.6% in 2023. The import growth rate of advanced countries fell to -8.7% due to the pandemic and rose to 9.5% in 2021 and is forecasted to dwindle to 6.1% in 2022 and 4.5% in 2023. The growth rate of imports of emerging and developing countries was -7.9% in 2020 which was recovered to 12.3% in 2021 and is expected to fall down to 4.1% in 2022 and 3.6% in 2023 due to war. Global current account balance (sum of country surpluses and absolute levels of deficits) widened for a second successive year in 2021 largely because of pandemic-related factors. It has worsened as a result of war and is forecasted worse where low-income developing countries will affect badly. The financial current account balance of advanced countries (which was positive) improved after covid-19 but it will tend to be negative in 2022 and improve marginally in 2023 as positive. A similar trend is observed in emerging markets and developing economies, but the improved positive balance will be reduced in 2023 due to war. The global industrial production including manufacturing has been increasing since 2020 but fell down after 2021 due to war according to three months moving average. In advanced economies, three months moving average inflation rate trends to rise since 2020 steeply but it is cyclically rising in emerging markets and developing economies. The international cereal price has been rising since 2022 February due to war. The deviation from pre-covid-19 average (in %) goods and services inflation in advanced and emerging markets and developing economies have been increasing since 2020 July (International Monetary Fund, 2022a).

A few studies claim that there is a correlation between crypto trading and the stock market, but the Financial Stability Board (2018) concluded that crypto assets did not pose a

material risk to global financial stability but identified several transmission channels like market capitalisation that could change its initial assessment (Bhowmik, 2017).

The Russia-Ukraine war affected the liquidity position of Rouble and Hryvnia in trading in centralised exchanges, and as a result, the liquidity declined, and more recently the large-scale transfers of value through cryptocurrency assets exchanges were observed as a result of the war, but that is less impressive (International Monetary Fund, 2022b). Yet, market capitalisation and the increased demand for crypto assets could facilitate capital outflows that can affect the foreign exchange market which has an indirect impact on the capital market.

Thus, in this paper, the author is interested in exploring the relationship between Bitcoin Rouble value and the capital market of Russia during the post-pandemic recovery and during the time of war by explaining the nature of the Bitcoin Rouble value and its cointegration and vector error correction model with the specified indicators of capital market.

Review of Literature:

The psychological behaviour of holding a digital asset like Bitcoin and other crypto currencies for higher return in the future is now a concern of central analysis on crypto investment.

Almansour and Arabyat (2017) examined the investor's rationality where the face of uncertainty of the processes of decision-making investors are generally influenced by heuristic herding, prospect and familiarities which can offer successful prediction significantly in the equity market.

Kirk and Swain (2018) explained that consumer often feels significant psychological ownership of digital technologies and that digital technologies can facilitate the emergence of psychological ownership of other non-digital targets.

Li, Wang and Li (2019) studied that people are eager to hold digital assets hoping to gain wealth through added value, and the psychological impact of public attention to hold assets through coverage of media. It is

examined that search volume has a significant linear relationship with price because according to Metcalf's law, the network value is proportional to the square of number of users participating in the network.

A concrete argument lies in the fact that some governments allow crypto trading by converting their currency and indirectly promoting money laundering and corruption.

Konowicz (2018) intended to show that Russia announced the sale of its energy to 70 Bitcoin-mining companies which clarified that Russia has initiated the development of native government-backed cryptocurrencies.

Mahdavi (2019) studied that high levels of corruption, low level of economic growth, high economic volatility, devaluation and inflation in Iran, Russia and Venezuela initiated to adopt of government-backed cryptocurrencies.

Thomson Reuters (2022) stated that in 2020, the Russian President Vladimir Putin signed a law that regulates digital financial asset transactions. Under the law, which took effect on January 1, 2021, digital currencies are recognized as a payment means and investment. Digital currency cannot be used to pay for any goods and services, because digital currencies were previously banned. Russian banks and exchanges can become exchange operators of digital financial assets if they register with the Bank of Russia. The Central Bank of Russia has also begun a pilot program to develop a digital central bank currency, the Digital Rouble. The central bank has staunchly opposed cryptos, while Russia's Ministry of Finance has pushed for regulations on cryptos. The Ministry of Finance introduced a bill "On Digital Currency" in February 2022, which creates a "mechanism for organizing the circulation of digital currencies." Despite the regulatory confusion, Russia is considered a significant player, and estimates peg Russian ownership of cryptos at approximately 12% of the international crypto economy.

Pascual (2022) clearly stated that since the war between Russia and Ukraine began, the use of cryptocurrency especially Bitcoin had risen unprecedentedly and 140 million dollars of Rouble has been converted to Bitcoin in a few days

which was announced by Crypto Compare data aggregated by Euro news. During the war, the Dollar Rouble rate had collapsed, and the Russian citizens turned to the decentralized digital currency to maintain their purchasing power while the Ukrainian government is also relying on cryptocurrency donations to finance the country's defence against Russia. In response to the government's official Twitter, 15 million Dollars in crypto especially Bitcoin and Ethereum had been transferred as donations.

A crucial debate arises regarding the impact of crypto assets trading on the capital market in recent years for considering it into a currency or an asset.

Bouri *et al.* (2017), as well as Baur *et al.* (2018), find that Bitcoin is suitable for diversification purposes as its returns are uncorrelated with those of most major assets. Interestingly, they provide empirical evidence of the predominant usage of Bitcoins as speculative assets, though this is done on the data on USD transactions only and thus likely reflects the behaviour of U.S. cryptocurrency investors mainly.

Danielsson (2018) clearly stated that a cryptocurrency or fiat money has no intrinsic value, or they are not a bond that reflects future income appropriately discounted to the present. The value of cryptocurrency is caused by scarcity, as well as the cost of mining or government promises. However, mining is sunk cost, not a promise of future income. The only reason is cryptocurrencies retain value because we expect other people in the future to value them the same, or more than we do now. Cryptocurrencies are not an investment in the same way as a stock or a bond. In the case of credibility, the value of the euro and the dollar is underpinned by the credibility of the ECB or the Fed. With cryptocurrencies, it is the credibility of some unknown entities and processes. Regarding privacy and security concerns, cryptocurrencies are only safe from theft if one is an expert and takes elaborate precautions. We are much more likely to be a victim of a crime with cryptocurrencies than cash or electronic money.

Ankenbrand *et al.* (2020) propose a taxonomy for the systematic classification of all types of

assets, be it of physical, digital, or tokenised nature by identifying 14 attributes, each of which is assigned different characteristics, that can be used to classify all types of assets in a structured manner. These attributes include the claim structure, technology, underlying, consensus-/validation mechanism, legal status, governance, information complexity, legal structure, information interface, total supply, issuance, redemption, transferability, and fungibility. With the help of a morphological box, various possible characteristics that an asset can have identified and assigned to these attributes.

Haryanto, Subroto and Ulpah (2020), in their study, remarked on the disposition effect and the herding behaviour in the cryptocurrency realm by investigating the trading behaviour at a crypto exchange. Authors find a reverse disposition effect in bullish periods where the Bitcoin price increases while a positive disposition effect is observed in bearish periods. They also find that in different market conditions herding moves along with market trend (in the bullish market a positive market return increases herding, while in the bearish market a negative market return has the same effect). The reverse disposition effect in the bullish market indicates investors exhibit more optimism and expect returns to further grow, which is consistent with the exponential price growth in a bubble in the absence of a clearly defined fundamental value. This lack of clarity regarding the fundamental value is also supported by the asymmetric herding behaviour when the price grows in a bullish market, investors look at other market participants to see whether others also think the price will continue to grow (similarly but with the opposite sign for the bearish market).

Abraham and Tao (2019) derived a theoretical portfolio model of cryptocurrencies as a single asset or as part of a multiple-asset portfolio within the framework of modern portfolio theory. The cryptocurrencies correlate poorly with the security market so the return on a cryptocurrency cannot be explained by Capital Asset Pricing Model. Consequently, cryptocurrencies are a Capital Asset Pricing Model anomaly. The prices of cryptocurrencies cannot be explained by the Fama-French

model because cryptocurrencies are not larger or have higher momentum and if it is anomalous in the traditional security return model then it would be a derivative speculative investment supported by the value of stocks for equity options, real estate for real options or currency derivatives. Rather it is supported by belief or faith in the power of blockchain to reduce transaction costs for businesses. A rational investor who seeks speedy profits is interested to buy cryptocurrency in a higher pricing process, but a less rational investor may not be interested in investing in a bubble-like speculation for cryptocurrency price setting (Basu, Saha & Maity, 2018; Henry, Murtadho & Bhaumik, 2020).

Methodology:

The semi-log non-linear trend line can be estimated through the following equation: $\log(x_i) = a + bt + ct^2 + dt^3 + ht^4 + u_i$ where x_i is variable, a , b , c , d and h are constants, t is time, u_i is random error.

The Wavelet transformation for obtaining seasonality and threshold signal curve can be found by following EViews 12.0 through the methodology of Donoho and Johnstone (1998) and Bilen and Huzurbazar (2002).

The cointegration and vector error correction model were applied by following the Johansen model (1988, 1991). The short-run causality was verified through the Wald test (1943) method and the long-run causality was verified by the cointegrating equation.

The daily data of MOEX index(x_1), RTX index(x_2), Moscow exchange trade turnover in billion Rouble (x_3), and RUONIA of Russia (x_4) (Bank of Russia, n.d) from 1/11/2021 to 18/4/2022 have been collected from the Bank of Russia. The daily data on Dollar Rouble rate(x) and Bitcoin Rouble rate (y) from 1/11/2021 to 18/4/2022 have been collected from the website of Fx-rate. (n.d) respectively.

Objective of the paper

The paper endeavours to explore whether there is any nexus between the hiking prices of the Bitcoin Rouble rate and the indicators of the

capital market in Russia, especially during the post-pandemic recovery since 1st November 2021 and the sets back for war between Russia and Ukraine since February 2022. The capital market indicators of Russia have been identified as the US Dollar Rouble exchange rate, MOEX index (Moscow Exchange Index), RTX index (Russian Traded Index), Moscow exchange trade turn over and RUONIA (Rouble Over Night Index Average) of Russia respectively. How the indicators of the Russian capital market were influenced by the growth of the renowned cryptocurrency like Bitcoin price in terms of Rouble or vice versa is the cornerstone of the analysis of the paper.

Results and Discussion:

Nature of Bitcoin Rouble exchange rate

The daily Bitcoin Rouble exchange rate from 1/11/2021 to 18/4/2022 has been plotted in Figure 1 below where it was clear that the Bitcoin Rouble price has been declining cyclically till 24th of January 2022 followed by upward and downward cycles till the war began which accelerated its price to its peak level during the second week of March followed by a cyclically downward shape. So, to compare the pandemic period and after the war, the rate is more volatile during the war period while before the war, the complete movement is downward.

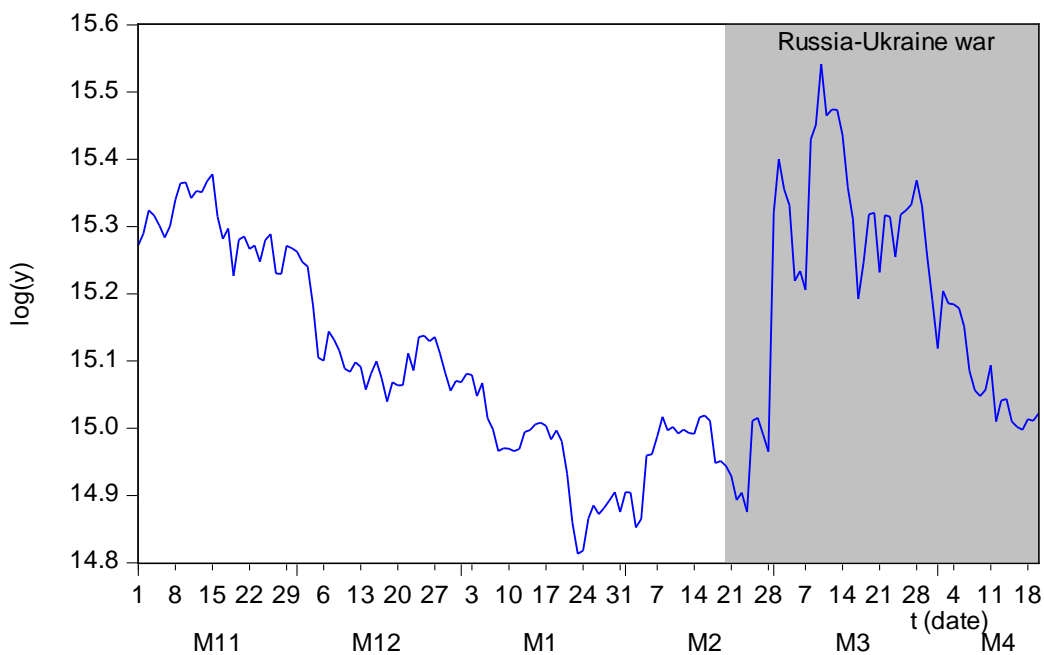


Figure 1: Bitcoin Rouble Price

In Figure 2, the daily US Dollar Rouble exchange rate from 1/11/2021 to 18/4/2022 has also been plotted where it is observed that the exchange rate is slowly upward rising till the war broke out which means the rouble is improving

against the dollar. On the other hand, the devaluation of the Rouble began after the war, and it stood at a peak level in the first week and the third week of March followed by a recovery till 18th of April, 2022. Yet it is fluctuating.

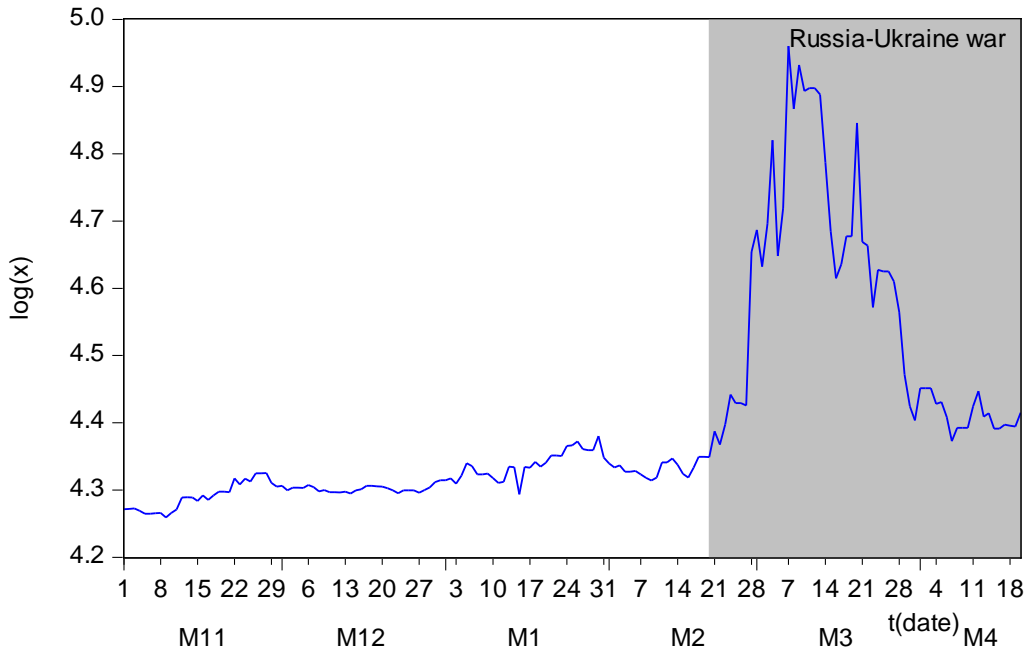


Figure 2: The US Dollar Rouble Exchange Rate

The non-linear estimated trend line of Bitcoin Rouble exchange rate (or value of Bitcoin in Rouble) is shown below where it is found a four phases cyclical trend starting with upward cycle.

$$\begin{aligned} \text{Log}(y) = & 15.2435 + 0.0135t - 0.00062t^2 \\ & (429.56)^* (4.79)^* (-9.41)^* \\ & + 6.77e^{-06}t^3 - 2.1e^{-09}t^4 + u_i \\ & (11.76)^* (-12.92)^* \end{aligned}$$

$R^2=0.71$, $F=102.23^*$, $AIC=-1.95$, $SC=-1.86$, $DW=0.314$, $n=171$, $y=\text{Bitcoin Rouble rate}$, $^*=$ significant at 5% level, $u_i=\text{random error}$.

In Figure 3, the semi-log non-linear four phases trend line has been plotted where a long declining trend in the second phase and an increasing trend in the third phase after which there is a quick declining trend, and all the coefficients of the phases are significant at 5% level.

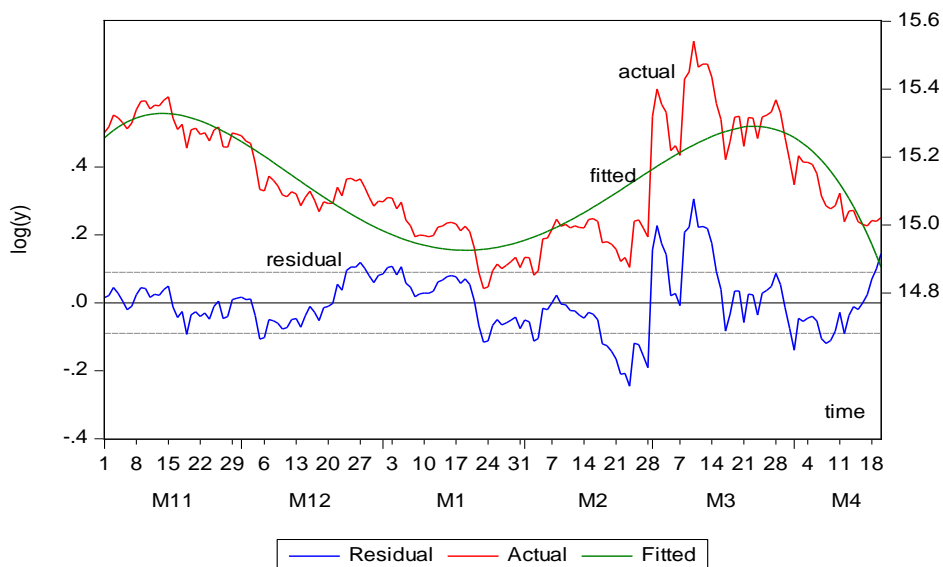


Figure 3: Non-Linear Trend of Bitcoin Rouble Rate

The Maximum Overlap Discrete Wavelet Transformation of the nonstationary Bitcoin Rouble rate during 1/11/2021-18/4/2022 in Daubechies (1992) class 4 with a maximum scale of seven revealed the seasonality whose fluctuations and amplitudes have been widening after the war while the cyclical seasonality before the war were moving around zero. Thus, its oscillation is dampening after the post-pandemic period, but it is explosive oscillatory after the war. It is shown in Figure 4 below.

the boundary in which most of them lie after the war.

In Figure 4.2 when the scale is fixed at 4, then a total of 23 coefficients (W3) have been found outside the boundary level which is seen in the figure. Similarly, in Figure 4.3, the scale is assumed at 8 units and 47 coefficients (W4) were detected outside the boundary level. Lastly in Figure 4.4, the scale is fixed at 16 units and 95 coefficients(W5) moved away from the boundary level. Thus, as scale increases the coefficients in the outside boundary level increase and the cycles decline but cyclical amplitude increases and the oscillations tended to be more explosive, especially after the war.

Figure 4.1 indicated that when the scale is fixed at 2, a total of 11 coefficients (W2) have been found outside the 5% significant level shown as

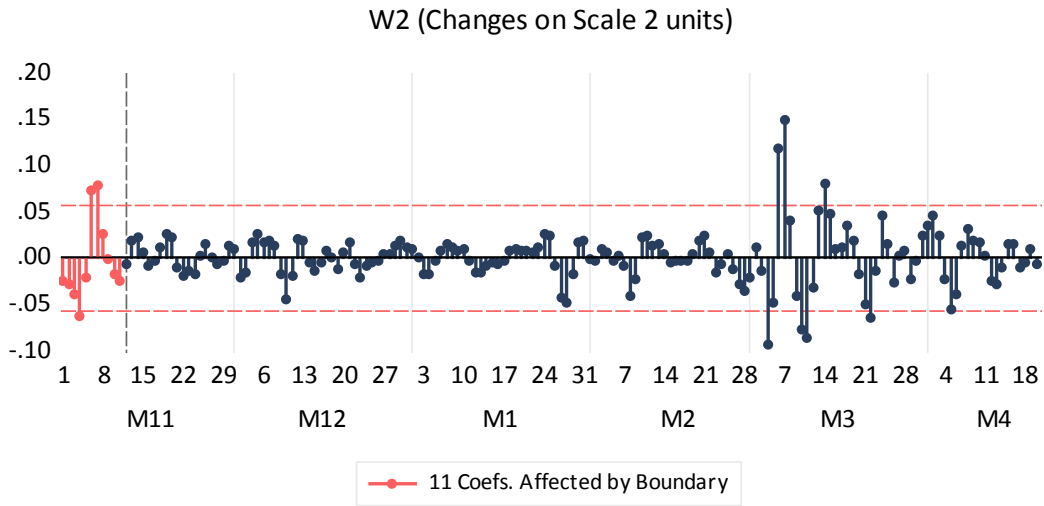


Figure 4.1: Wavelet Decomposition at W2

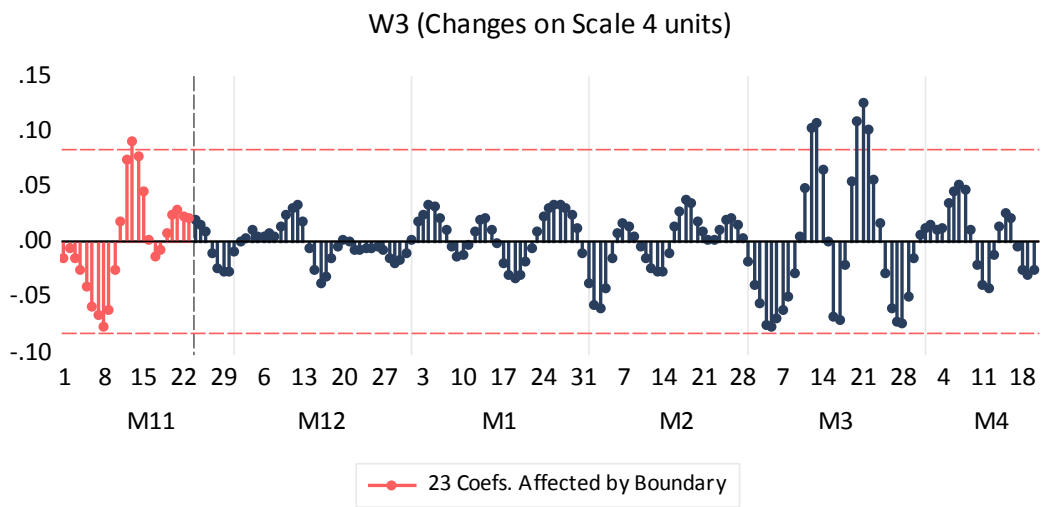


Figure 4.2: Wavelet Decomposition at W3

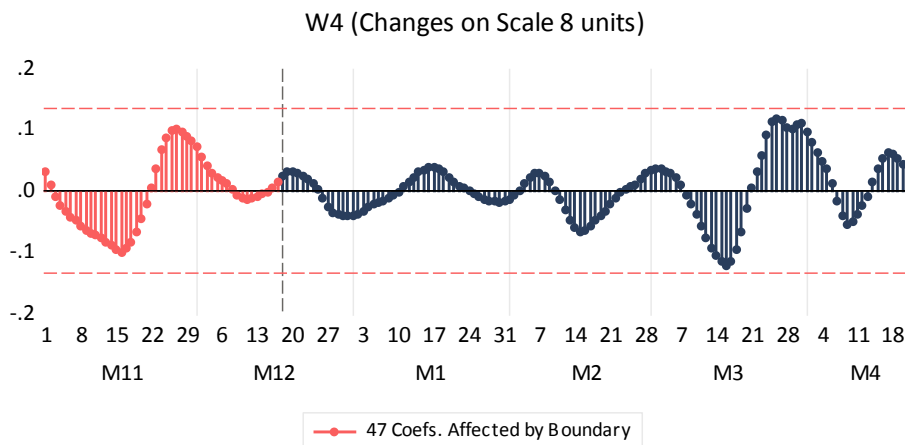


Figure 4.3: Wavelet Decomposition at W4

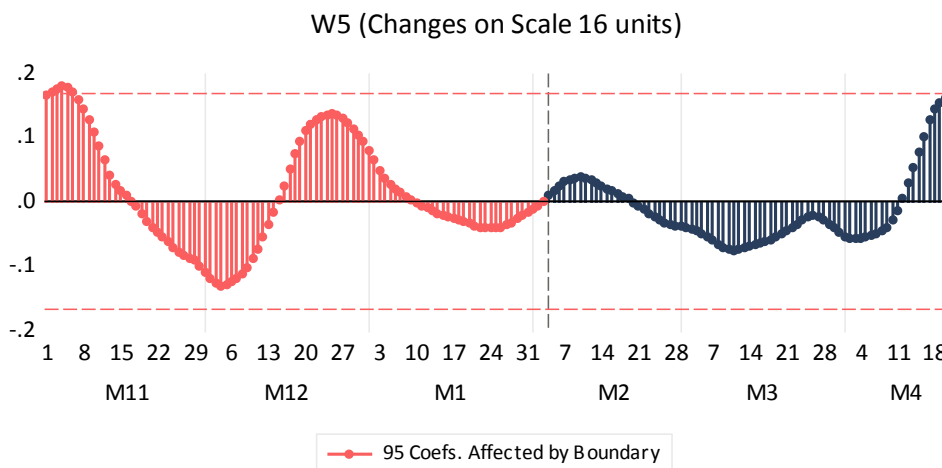


Figure 4.4: Wavelet Decomposition at W5

The Wavelet threshold noise estimator in the Maximum Overlap Discrete Wavelet Transformation assuming maximum scale seven with least asymmetric 12 of the log of Bitcoin Rouble rate assures divergent away

from equilibrium and it is cyclical which is depicted in Figure 5 in which its oscillation is explosive and nonstationary. Thus, the noise estimator is clearly seen in the figure which may be called wavelet threshold signal curve.

Wavelet Shrinkage Estimator: Noise

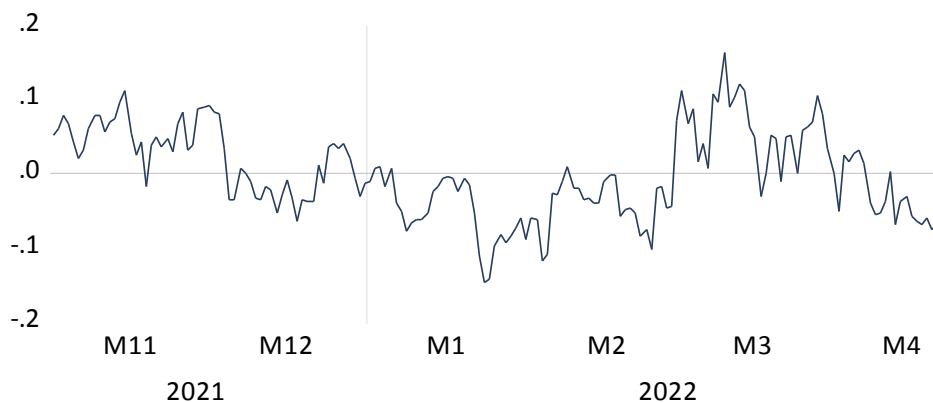


Figure 5: Wavelet Threshold Signal Curve

Therefore, the Bitcoin Rouble price is seemed to be extremely volatile and unstable. In any condition it does not tend to be a stationary process.

Cointegration and Vector Error Correction Analysis

Johansen unrestricted cointegration rank test among Bitcoin Rouble rate, Dollar Rouble rate,

MOEX index, RTX index, Moscow exchange trade turnover and RUONIA of Russia under the assumption of a linear deterministic trend from 3/11/2021 to 25/2/2022 revealed that there is one significant cointegrating equation at 5% significant level in first differences in log values. In Table 1, Eigen value, trace statistic, max-eigen statistics, critical value at 5% level with their probabilities have been arranged.

Table 1: Cointegration Test

Hypothesized No. of CE(s)	Eigenvalue	Trace statistic	Critical value at 5% level	Probabilities
None *	0.356271	107.0883	95.75366	0.0066
At most 1	0.190264	56.43341	69.81889	0.3608
At most 2	0.118628	32.16294	47.85613	0.6032
At most 3	0.093633	17.64128	29.79707	0.5926
At most 4	0.051859	6.335570	15.49471	0.6559
At most 5	0.001839	0.211630	3.841466	0.6455
		Max-Eigen statistic		
None *	0.356271	50.65492	40.07757	0.0023
At most 1	0.190264	24.27047	33.87687	0.4360
At most 2	0.118628	14.52166	27.58434	0.7850
At most 3	0.093633	11.30571	21.13162	0.6168
At most 4	0.051859	6.123940	14.26460	0.5974
At most 5	0.001839	0.211630	3.841466	0.6455

* denotes rejection of the hypothesis at the 0.05 level

** MacKinnon, Haug & Michelis (1999) p-values

The estimated vector error correction model is seen below. It was found that there was no significant impact of incremental changes of MOEX index(x1), RTX index(x2), Moscow exchange trade turn over (x3), RUONIA of Russia (x4) and Dollar Bitcoin exchange rate (x) on the incremental changes of Rouble Bitcoin exchanges (y) respectively. Rather, the

incremental change of Dollar Rouble has negatively induced to the changes in the MOEX index significantly at 5% level. The incremental changes in Dollar Rouble rate and RTX index have significantly affected positively to the change of Moscow exchange trade turn over. The other cross impacts are nil. All these results have been presented in Table 2.

Table 2: The Estimated Equations of VCEM

Error Correction:	dlog(y)	dlog(x)	dlog(x ₁)	dlog(x ₂)	dlog(x ₃)	dlog(x ₄)
CointEq1	-0.002389	0.01697	0.0090	0.019899	-0.09948	4.50e ⁻⁰⁷
t value	[-0.126]	[2.38813]*	[0.3472]	[0.6095]	[-0.6212]	[0.19326]
dlog(y) _{t-1}	0.1057	-0.0422	-0.0024	0.00041	0.87869	1.78e ⁻⁰⁵
t value	[1.043]	[-1.109]	[-0.0172]	[0.0023]	[1.0235]	[1.42835]
dlog(y) _{t-2}	-0.1058	-0.0567	0.20397	0.25911	-1.31297	1.20e ⁻⁰⁵
t value	[-1.026]	[-1.462]	[1.4310]	[1.4562]	[-1.5042]	[0.94592]
dlog(x) _{t-1}	-0.6777	0.1213	-1.34474	-1.52693	-1.87716	-1.16e ⁻⁰⁵
t value	[-1.200]	[0.571]	[-1.7223]*	[-1.5666]	[-0.3926]	[-0.16633]

dlog(x) _{t-2}	-0.2798	0.0703	0.02560	0.11244	10.0682	5.60e ⁻⁰⁵
t value	[-0.605]	[0.4048]	[0.0400]	[0.1409]	[2.5726]*	[0.98308]
dlog(x ₁) _{t-1}	-0.689	0.17651	0.49682	0.58647	4.47702	8.89e ⁻⁰⁵
t value	[-0.990]	[0.6747]	[0.5162]	[0.48815]	[0.7596]	[1.03706]
dlog(x ₁) _{t-2}	0.3186	-0.0104	-0.2311	-0.38142	-9.4696	9.54e ⁻⁰⁶
t value	[0.474]	[-0.041]	[-0.248]	[-0.329]	[-1.665]	[0.11527]
dlog(x ₂) _{t-1}	0.2198	-0.01434	-0.90062	-1.05481	-2.70021	-6.75e ⁻⁰⁵
t value	[-0.616]	[0.4706]	[-0.0536]	[0.0375]	[2.0099]*	[0.09275]
dlog(x ₂) _{t-2}	-0.349	0.10027	-0.04205	0.03673	9.64789	6.48e ⁻⁰⁶
t value	[-0.616]	[0.4706]	[-0.0536]	[0.0375]	[2.0099]*	[0.09275]
dlog(x ₃) _{t-1}	-0.0114	-0.0036	0.00308	0.00290	0.01464	2.11e ⁻⁰⁷
t value	[-1.003]	[-0.8428]	[0.1956]	[0.1474]	[0.1516]	[0.15027]
dlog(x ₃) _{t-2}	0.0163	0.00033	-0.00098	-0.00516	-0.14727	-8.90e ⁻⁰⁸
t value	[1.271]	[0.0699]	[-0.0552]	[-0.2324]	[-1.3524]	[-0.05616]
dlog(x ₄) _{t-1}	304.38	225.287	-620.988	-693.753	1156.24	0.844265
t value	[0.3880]	[0.7641]	[-0.5725]	[-0.5124]	[0.1741]	[8.73817]*
dlog(x ₄) _{t-2}	-356.85	-42.139	24.4524	-49.4087	-544.513	0.163732
t value	[-0.4434]	[-0.1393]	[0.0219]	[-0.0355]	[-0.0799]	[1.65182]*
C	0.0067	-0.03774	0.12295	0.15322	-0.11629	-8.44e ⁻⁰⁷
t value	[0.1961]	[-2.9232]*	[2.5887]*	[2.5842]*	[-0.3998]	[-0.19939]
R-squared	0.23580	0.20652	0.32637	0.33319	0.19492	0.968967
F-statistic	2.37362	2.00215	3.72693	3.84378	1.86243	240.1856
Akaike AIC	-4.12120	-6.07846	-3.47331	-3.02969	0.15090	-22.12511
Schwarz SC	-3.78518	-5.74244	-3.13728	-2.693675	0.48693	-21.78908
Log likelihood	248.908	360.472	211.9788	186.692	5.39839	1275.131

n=114, t value at 5% significant level =1.658, *=significant at 5% level.

VEC model released total 18 roots in which one root is greater than one, 5 roots are unit, 8 roots are imaginary and less than one, and remainder

one root is positive but less than one. So that the VEC model is nonstationary. In Table 3, the roots are given in details.

Table 3: The Roots (first difference lag2)

Roots	Modulus
1.004786	1.004786
1.000000	1.000000
1.000000	1.000000
1.000000	1.000000
1.000000	1.000000
1.000000	1.000000
1.000000	1.000000
-0.589452	0.589452
-0.058828 + 0.561076i	0.564152
-0.058828 - 0.561076i	0.564152
0.257093 - 0.499436i	0.561723
0.257093 + 0.499436i	0.561723
-0.287418 - 0.405236i	0.496815
-0.287418 + 0.405236i	0.496815
0.389579	0.389579
-0.330537	0.330537
0.054174 + 0.174572i	0.182785
0.054174 - 0.174572i	0.182785
0.163305	0.163305

In the unit circle, all the roots have been plotted where one root (1.004786) lies outside the unit circle and others lie inside or on the unit circle.

Thus, the model is unstable and non-stationary. It is shown in Figure 6.

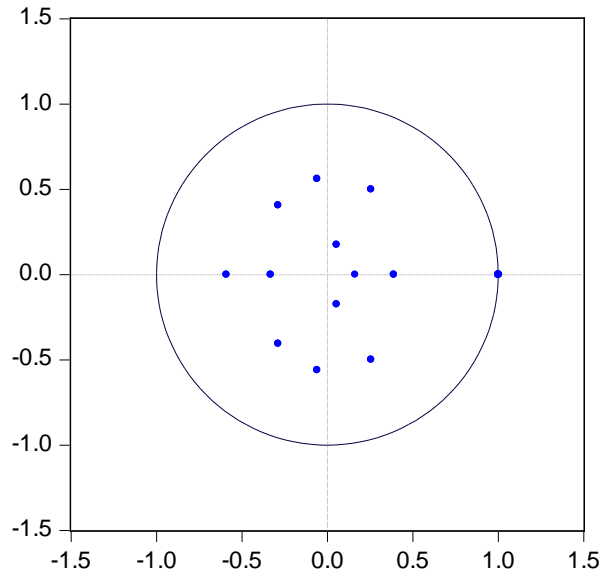


Figure 6: Unit Circle

The residual test assures that it has problem of autocorrelation, for this, it consists of seasonality which are shown by correlogram of autocorrelation functions moving from positive

to negative values continuously. In Figure 7, autocorrelations with $\pm 2\sigma$ error bounds have been plotted.

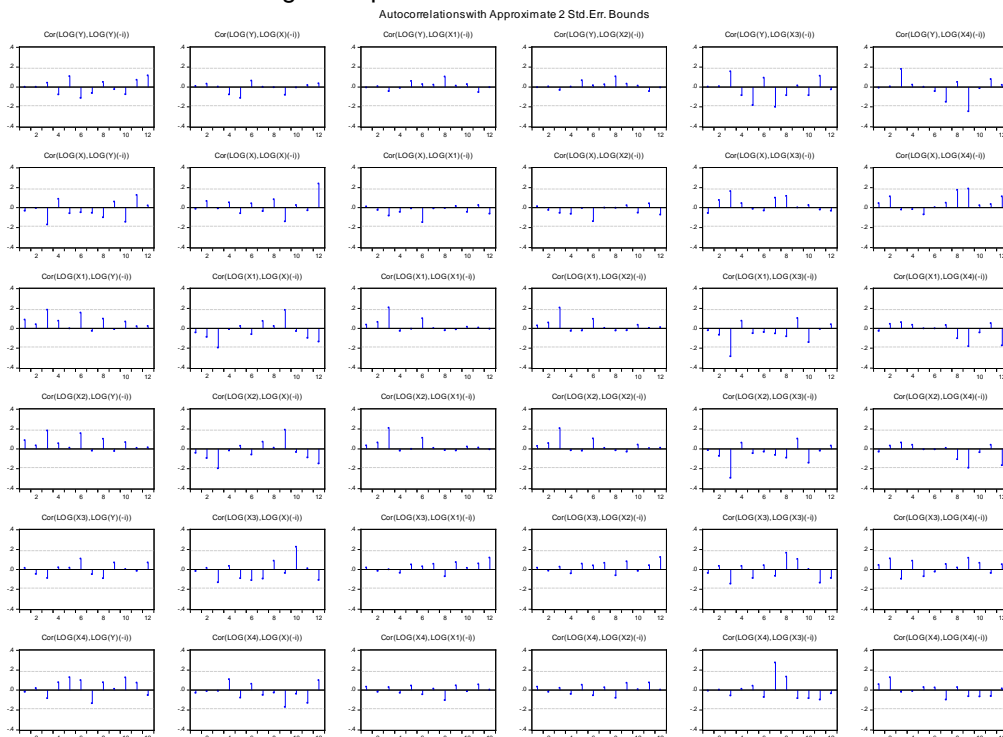


Figure 7: Autocorrelation of VECM

The following are the fundamental net results of impulse response functions as measured by

Cholesky one standard deviations innovations (Figure 8).

[i] The response of x_3 to y reaches equilibrium after the second and fifth periods then diverged

[ii] The response of x_4 to y reaches equilibrium after the second period and then diverged

[iii] The response of x_4 to x reaches equilibrium after the 3rd period and then moved away

[iv] The response of x to x_1 reaches equilibrium after 3rd and 6th periods then tend to equilibrium

[v] The response of x_4 to x_1 reaches equilibrium after 1st year and then moved away

[vi] The response of x_1 to x_2 reaches equilibrium after the 2nd, 4th and 6th periods then moved around the equilibrium

[vii] The response of x_3 to x_2 reached after the first period and then moved towards equilibrium

[viii] The response of x_4 to x_2 reaches after 1st period and then moves away

[ix] The response of y to x_3 reaches equilibrium after the 2nd and 4th periods then moves to equilibrium

[x] The response of x to x_3 reaches after the 2nd period and then diverged

[xi] The response of x_1 to x_3 , x_2 to x_3 , and x_3 to x_4 have been moving around the equilibrium.

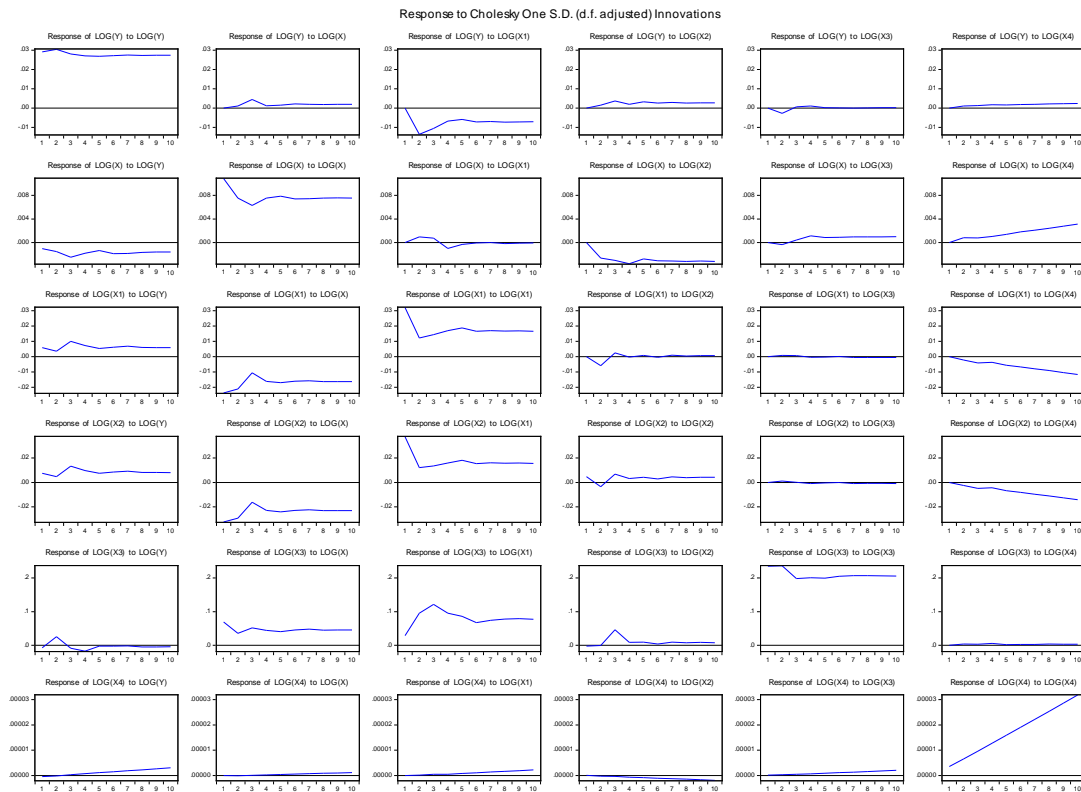


Figure 8: Impulse Response Functions

From the generalised impulse response functions, it was concluded that [i] the responses of x_4 from y , x x_2 , x_3 , and x_4 reached equilibrium in the first week of December 2021, and [ii] the response of x_4 from x_1 and x_4 from x_2 reached equilibrium in the last week of January 2022 but the response x_4 from x_3 moves to the equilibrium. Secondly, the response of x_3 from y , the response of x_2 from y , and x_1 from y reach and move around equilibrium continuously, or in other words, they

cyclically moved and crossed equilibrium repeatedly, but the response of x from y reaches equilibrium repeatedly and moves away from equilibrium. Thirdly, the responses of y from x , x_1 , x_2 , x_3 , and x_4 cyclically reached and moved to equilibrium while the response of y from x_1 and x_2 has higher cyclical amplitudes and the fluctuations, on the contrary, the response of y from x_3 and x_4 have shown very low cyclical amplitudes and fluctuations (Figure 9).

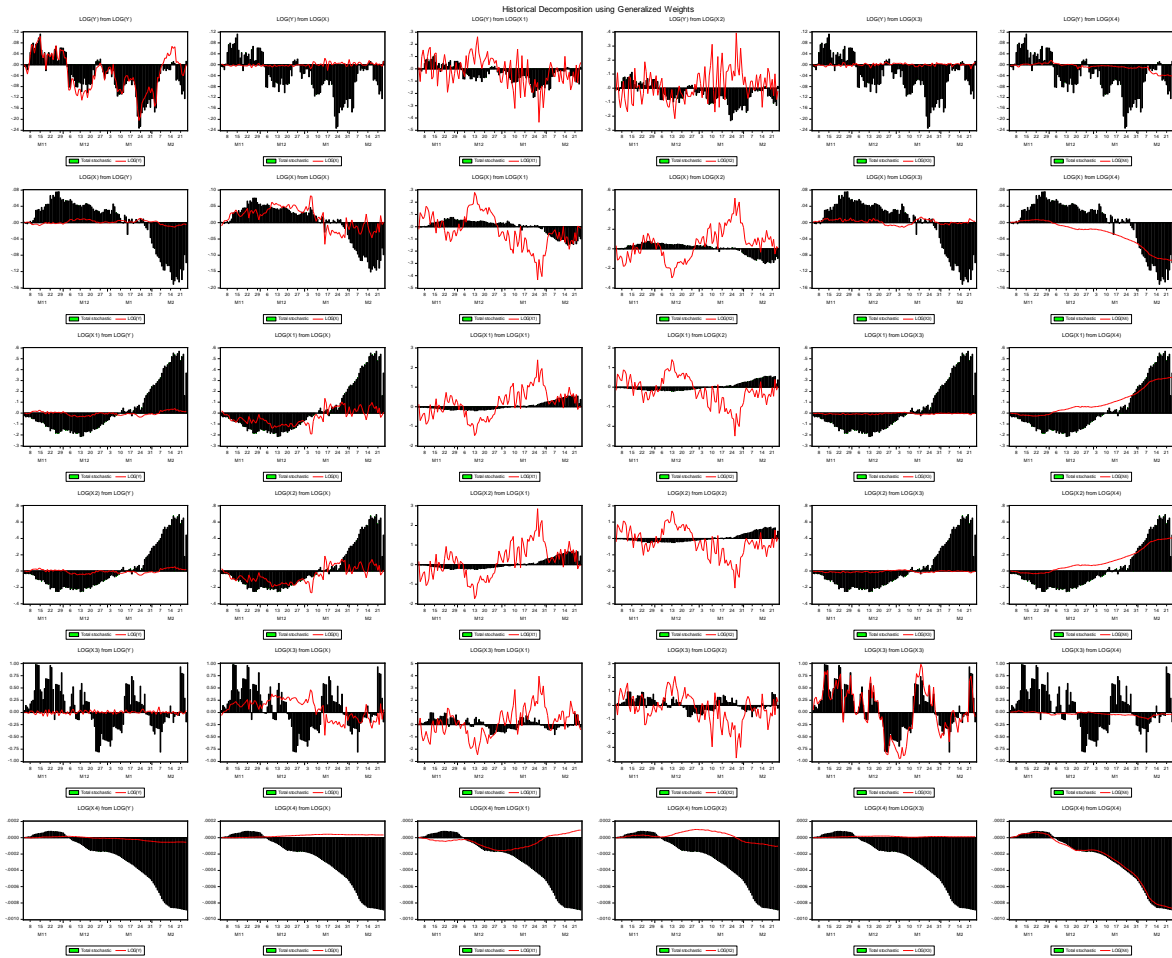


Figure 9: Generalised Impulse Response Functions

With the help of estimated system equations and the estimated equations of VECM, the

cointegrating equation has been estimated as given below.

$$\begin{aligned}
 Z_{t-1} = & -0.00189\log(y)_{t-1} - 34.399\log(x)_{t-1} + 29.5004\log(x_1)_{t-1} - 31.699\log(x_2)_{t-1} + 0.1119\log(x_3)_{t-1} \\
 & (-0.1007) \quad (-6.34)^* \quad (5.58)^* \quad (-6.11)^* \quad (1.53) \\
 & + 5.4600\log(x_4)_{t-1} + 118.86 \\
 & (0.4609)
 \end{aligned}$$

This cointegrating equation indicated that the Bitcoin Rouble rate has long run causalities with Dollar Rouble rate, MOEX index, RTX index, Moscow exchange trade turnover, RUONIA of Russia respectively where causal relations between Bitcoin Rouble rate and Dollar Rouble rate and RTX index are negatively significant at 5% level and causal relation with MOEX index is positive and significant. Other causal relations are positive but insignificant.

The cointegrating equation tends to equilibrium convergently since the coefficient of $\log(y)_{t-1}$ is negative whose t value is insignificant, thus why it is insignificantly approaching equilibrium and never stabilised on it. During the convergent period, the speed of adjustment is found to be a very slow rate of 0.189% per day. Therefore, the long-run causalities remain insignificant. In Figure 10, the cointegrating equation has been depicted neatly.

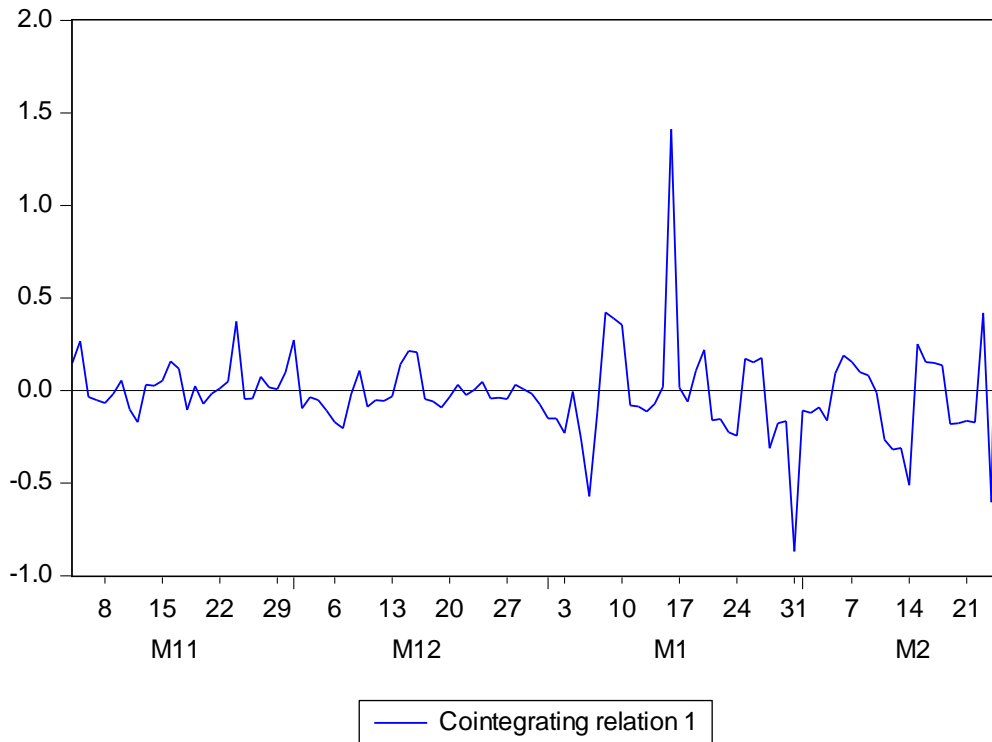


Figure 10: Cointegrating Equation

There are no short-run causalities from Dollar Rouble exchange rate, MOEX index, RTX index, Moscow exchange trade turn over and RUONIA of Russia to the Bitcoin Rouble exchange rate, but it was found that Moscow

exchange trade turnover has short-run causalities with Dollar Rouble rate and RTX index during the survey period at 6% significant level. In Table 4, it is shown below:

Table 4: Short Run Causality Ho= No causality at 5% level

Short run causality fromto.....	Chi-square (2) value	Probability	F value	Probability
Causality from dollar Rouble rate to Moscow exchange trade turnover	13.217	0.0013	6.608[df=2,100]	0.0020
Causality from RTX index to Moscow exchange trade turnover	5.557	0.021	2.778[df=2,100]	0.0669

Conclusion:

The post-pandemic scenario and Ukraine-Russia war enabled the high speed of transactions of Bitcoin, so that the Bitcoin Rouble price had been exceedingly higher, and the structural development of the Russian capital market fell in trouble, but the impact is, however, minimum because the rising Bitcoin Rouble exchange rate had no adverse effects

in the capital market in Russia. The paper concludes that the trend line of Bitcoin Rouble rate from 1/11/2021 to 18/4/2022 is cyclical with four phases and its volatility increased during the wartime where the seasonal variation of its path is oscillatory, and the wavelet threshold signal curve showed explosive oscillatory although it tried to be damped from post-pandemic to pre-war period. The Bitcoin Rouble rate had one significant cointegration with US

Dollar exchange rate, MOEX index, RTX index, Moscow exchange trade turn over and RUONIA of Russia respectively. There is no influence of incremental change of Bitcoin Ruble exchange rate on the incremental change of above capital market indicators as observed by the vector error correction model estimates. Even, though there is no short-run causality from those indicators to the Bitcoin Rouble exchange rate and vice versa. But, there is a long-run causality from US Dollar exchange rate, MOEX index, RTX index, Moscow exchange trade turn over and RUONIA of Russia respectively to the Bitcoin Rouble exchange rate during the study period from 1/11/2021 to 13/3/2022 where the cointegrating relation of Bitcoin Ruble exchange rate with US Dollar Rouble rate and RTX index is significantly negative and the relation is significantly positive with MOEX index although the long-run causality in the cointegrating equating is insignificant. Still, converging at the speed of adjustment of 0.189% per day shows instability. The Cholesky impulse response functions of Moscow exchange trade turn over and RUONIA of Russia to Bitcoin Rouble rate is imperative but the generalized impulse response function of Bitcoin Rouble rate from MOEX index and RTX index and Moscow exchange trade turn over and RUONIA of Russia are cyclically imperative towards equilibrium. So, there is little significant influence of Bitcoin Rouble pricing in the Russian capital market in the long run.

Limitations and Future Scope of Research

There are many indicators of the capital market of Russia namely, bonds, equities, securities, foreign investment in public and private and so on for which the daily data were not available to include in this model, even, the data on MOEX index, RTX index, and Moscow exchange trade turn over are limited from 1/11/2021 to 13/3/2022, so that the impact on the capital market that had revealed in this paper is not fully analysed. Therefore, the paper has a new scope of research by taking quarterly/monthly data on the indicators of capital market structure for a long period to find a nexus with the Bitcoin Rouble price that can help to prescribe remedial policies in future.

Policies to be Reconsidered

Russia has closed the stock market temporarily after the war and reopened in March 2022 which intended to flourish crypto trading. Russia has amended its law on 10th April 2022 to allow crypto mining and trading with some particular minor regulations that is invariably affected the capital market, however small.

Acknowledgement:

The author declares that no fund from government/university/NGO was received to prepare the paper.

Conflicts of Interest:

The author proclaims that the study was accomplished without interruptions of any other business organizations or associations so that no potential conflict of interest existed in this review of research.

References

- Abraham, R., & Tao, Z. (2019). The Valuation of Cryptocurrencies in Single-Asset and Multiple-Asset Models. *Theoretical Economics Letters*, 9(4), 1093-1113. <https://doi.org/10.4236/tel.2019.94071>
- Almansour, B. Y., & Arabyat, Y. A. (2017). Investment decision making among Gulf investors: behavioural finance perspective. *International Journal of Management Studies*, 24(1), 41-71.
- Ankenbrand, T., Bieri, D., Cortivo, R., Hoehener, J., & Hardjono, T. (2020, June). Proposal for a comprehensive (Crypto) asset taxonomy. In *2020 Crypto Valley Conference on Blockchain Technology (CVCBT)* (pp. 16-26). IEEE.
- Bank of Russia. (n.d). Ruonia. https://cbr.ru/eng/hd_base/Ruonia/
- Basu, S., Saha, T. R., & Maity, S. K. (2018). Implications of cryptocurrency: A new business proposition of today's entrepreneurial horizon. *International Journal on Recent Trends in Business and Tourism (IJRTBT)*, 2(3), 64-70.
- Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative

assets? *Journal of International Financial Markets, Institutions and Money*, 54, 177–189.

Bhowmik, D. (2017). Real Effective Exchange Rate of India: Patterns and Determinants. *International Journal on Recent Trends in Business and Tourism (IJRTBT)*, 1(4), 15-23.

Bilen, C., & Huzurbazar, S. (2002). Wavelet-based detection of outliers in time series. *Journal of Computational and Graphical Statistics*, 11(2), 311-327.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?. *Finance Research Letters*, 20, 192-198. <https://www.sciencedirect.com/science/article/abs/pii/S1544612316301817>

Danielsson, J. (2018). Cryptocurrencies don't make sense. *VoxEU*. <https://voxeu.org/article/cryptocurrencies-dont-make-sense>

Daubechies, I. (1992). *Ten lectures on wavelets*. Society for industrial and applied mathematics. <https://jqichina.files.wordpress.com/2012/02/ten-lectures-of-waveletsefbc88e5b08fe6b3a2e58d81e8aeb2efbc891.pdf>

Donoho, D. L., & Johnstone, I. M. (1998). Minimax estimation via wavelet shrinkage. *The Annals of Statistics*, 26(3), 879-921. <https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.184.5755&rep=rep1&type=pdf>

Financial Stability Board. (10th October 2018). Crypto-Asset Markets: Potential Channels for Future Stability Implications. <https://www.fsb.org/2018/10/crypto-asset-markets-potential-channels-for-future-financial-stability-implications/>

Fx-rate. (n.d). Find the best currency exchange. <https://fx-rate.net>

Haryanto, S., Subroto, A., & Ulpah, M. (2020). Disposition effect and herding behavior in the cryptocurrency market. *Journal of Industrial and Business Economics*, 47(1), 115-132.

Henry, E., Murtadho, A. M., & Bhaumik, A. (2020). The Relationship Between the

Exchange Rate Fluctuations and Economic Growth in Nigeria. *International Journal of Management and Human Science (IJMHS)*, 4(4), 11-18.

International Monetary Fund. (2022a, April). *World Economic Outlook-2022*. <https://www.imf.org/en/Publications/WEO>

International Monetary Fund. (2022b, April). *Global Financial Stability Report-2022*. <https://www.imf.org/en/Publications/GFSR>

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 12(2-3), 231-254. [https://doi.org/10.1016/0165-1889\(88\)90041-3](https://doi.org/10.1016/0165-1889(88)90041-3)

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica: Journal of the Econometric Society*, 1551-1580. <https://doi.org/10.2307/2938278>

Kirk, C. P., & Swain, S. D. (2018). Consumer psychological ownership of digital technology. In *Psychological Ownership and Consumer Behavior* (pp. 69-90). Springer, Cham. https://doi.org/10.1007/978-3-319-77158-8_5

Konowicz, D.R. (2018). *The New Game: Cryptocurrency Challenges US Economic Sanctions*. Naval War College, Newport United States. <https://apps.dtic.mil/sti/pdfs/AD1062142.pdf>

Li, Z., Wang, J., & Li, K. (2019). Digital assets Price forecast based on POW mining mechanism. *Open Journal of Social Sciences*, 7(2), 185-198. <https://doi.org/10.4236/jss.2019.72016>

MacKinnon, J. G., Haug, A. A., & Michelis, L. (1999). Numerical distribution functions of likelihood ratio tests for cointegration. *Journal of Applied Econometrics*, 14(5), 563-577.

Mahdavi, R. (2019). Governments' Adoption of Native Cryptocurrency: A Case Study of Iran, Russia, and Venezuela. <https://stars.library.ucf.edu/cgi/viewcontent.cgi?article=1532&context=honorstheses>

Pascual, M.G. (13th March 2022). Cryptocurrency: A lifeline for Russian oligarchs? *International*. <https://english.elpais.com/international/2022->

[03-13/cryptocurrency-a-lifeline-for-russian-oligarchs.html](https://www.thomsonreuters.com/en-us/posts/wp-content/uploads/sites/20/2022/04/Cryptos-Report-Compendium-2022.pdf)

Thomson Reuters. (2022). Cryptocurrency regulations by country. <https://www.thomsonreuters.com/en-us/posts/wp-content/uploads/sites/20/2022/04/Cryptos-Report-Compendium-2022.pdf>

Wald, A. (1943). Tests of statistical hypotheses concerning several parameters when the number of observations is large. *Transactions of the American Mathematical society*, 54(3), 426-482.

<https://www.pp.rhul.ac.uk/~cowan/stat/wald1943.pdf>