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Abstract

This study presents stylized facts of the fungible tokens/currencies (MANA/USD and SAND/USD) in the Metaverses (*Decentraland* and *The Sandbox*). Metaverse currency exchange rate market exhibits very high conditional volatility, albeit no leverage effect, less impact of the real-world crisis (Global Lockdown due to COVID 19 pandemic) and low correlation with either cryptocurrency index (CCi30) or real-world equity index (S&P 500). Surprisingly, MANA and SAND – fungible tokens/ currencies in different Metaverses exhibit significant and increasing correlation between each other. The relative market efficiency of Metaverse currency market is comparable to that observed in the cryptocurrency and equity markets in the real-world.

Keywords: Metanomics, Metaverse, Fungible Tokens, Cryptocurrency, Non-Fungible Tokens (NFTs), Blockchain, Adaptive Market Hypothesis, Dynamic Conditional Correlation

JEL codes: G01, G11, G14, G32

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[3] *The findings, interpretations, and conclusions expressed in this study are entirely those of the authors. They do not necessarily represent the views of Tata Consultancy Services (TCS), India.*

[4] *Other articles on Metaverse from TCS; authors: Ashok Maharaj, Parthasarathi V and Nita Sarang*
https://www.tata.com/newsroom/careers/unbearable-lightness-metaverse-tcs
https://community.nasscom.in/communities/digital-transformation/why-metaverse-matters-navigating-trends-and-future-disruptions

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1. Introduction

"In the beginning God created the heaven and the earth. And the earth was without form, and void; and darkness was upon the face of the deep. And the Spirit of God moved upon the face of the waters. And God said, Let there be light: and there was light." ***Book of Genesis***

Metaverse is a virtual universe with its own physical laws created by its creator, barring the regulations set on the creator of Metaverse by the real world. A ponderous question remains – would Metaverse evolve into the biblical paradise or into the bittersweet image of our real world?

The current Metaverses rely on Web 3.0 components – Cryptocurrencies, Augmented Reality/ Virtual Reality (AR/VR), Blockchain, both Fungible and Non-Fungible Tokens (NFTs) and Decentralized Autonomous Organizations (DAO) (Lee et. al., 2021; Moy and Gadgil, 2022; Vidal-Tomás, 2022). There are three competing visions of Metaverse today, first a single private Metaverse – a result of network effect that makes user participation in the other Metaverses, were they to exist, minimal: second a single public Metaverse – a result of regulations mandating the use of only public Metaverse and third a loose network of public and private Metaverses – like different countries in the real world, each with its culture, laws and economic systems.

We focus on the two evolving Metaverses in this study, *Decentraland* and *The Sandbox*. Fungible tokens MANA and SAND are the main medium of exchanges in these Metaverses respectively. MANA and SAND represents high Market capitalization in Metaverse "sector" that includes ~ more than 160 tokens (Vidal-Tomás, 2022a). *Decentraland* metaverse, built on public blockchain and smart contract infrastructure, features 90,601 virtual land parcels. Each plot admeasures 16 x 16 meters and has a unique location that can be represented in two dimensional cartesian co-ordinates. The land parcels are represented by corresponding unique NFT created on the Ethereum blockchain (Chalmers et. al., 2022; Momtaz, 2022). These NFTs can be bought or sold using the fungible tokens - MANA. Participants of metaverse can create their own Avatars and interact with the Avatars of other participants. Investors can build virtual structures and applications on the bought land parcels and offer products and services and organize events for the participants. *The Sandbox* is a Metaverse where users can build, own, and monetize their experiences on Ethereum blockchain. A user can generate the content using an Editor; and the content can then be traded on the marketplace as NFT assets. Sandbox also provides a game maker for the users to build games[6]. MANA was introduced on in October 2017 and SAND started trading in August 2020.

[6] https://medium.com/sandbox-game/what-is-the-sandbox-850de68d893e

Decentraland has witnessed significant transactions; JP Morgan has created Onyx lounge in Decentraland[7]. In November 2021, a subsidiary of Tokens.com, bought 116 land parcels in the Fashion Street District of Decentraland for 618,000 MANA (~ USD 2.43 million)[8]. But sale price and volumes witnessed a downturn in July 2022; the average price of land parcels dropped to ~ USD 4,000 from an average of ~ USD 17,700 in July 2020[9]. Thus, the Metaverses seem to exhibit business cycles like those in the real world. Goldberg, Kugler and Schär (2022) analysed *Decentraland* and found strong evidence that despite negligible transportation costs, location did matter. Investors tend to pay higher prices for the land parcels closer to popular landmarks and with memorable addresses. Dowling (2022a) found low volatility transmission between cryptocurrencies and the land parcel NFT prices. Land parcel NFT prices were not efficient and exhibited a steady rise in value (Dowling; 2022b). *Decentraland* can provide quasi – infinite supply of land parcels, driving the prices lower but by limiting the supply of available land parcels, the creators have made the metaverse demand driven (Kaynes; 1937) - mimicking the real-world.

Market efficiency and Volatility behaviour of the fungible tokens in Metaverse are important determinants of the Metaverse adoption and success of fungible tokens as an investment asset. Higher platform adoption would result in greater investment returns from fungible tokens (Shah 2022). The objective of this study is quite mundane – We test if the fungible tokens (the currency) used to trade the digital assets (Non-Fungible Tokens - NFT) in the budding Metaverses - *Decentraland* and *Sandbox* exhibit random walk behaviour like that exhibited in the equity and FX markets and compare fungible token's exchange rate's (MANA/USD and SAND/USD) volatility behaviour with that of S&P 500 and Cryptocurrency index (CCi30). We use Lo-MacKinlay and Chow Denning variance ratio tests and Dynamic Conditional Correlation (DCC) framework for this analysis. We do not focus on non-Fungible tokens (NFT) in this study because each digital asset represented by its NFT could exhibit unique stylized facts like the uniqueness exhibited by every physical asset. For example, Gold, Crude oil, equity, fixed income etc may exhibit unique stylized facts. Similarly, every NFT may exhibit unique stylized fact and risk – return behaviour. We also investigate the effect of the recent Global Lockdown crisis due to COVID-19 pandemic (1st January 2020 to 31st October 2020) and Facebook rebranding its company name as "Meta" (27th October 2021 to 29th October 2021)[10] on the conditional volatility and dynamic correlation behaviour of MANA/USD and SAND/USD exchange rates.

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[7] https://www.ndtv.com/business/decentraland-here-s-all-you-need-to-know-about-the-digital-real-estate-world-2778793#:~:text=In%20November%202021%2C%20a%20report,individual%20land parcels%20of%20virtual%20land.

[8] https://nypost.com/2021/11/25/digital-land-in-the-metaverse-sells-for-record-2-43m/

[9] https://cryptonews.com/news/virtual-land-sales-take-plunge-amid-broader-crypto-downturn.htm

[10] *These dates are events based, we did not use statistical techniques to decide on the start and the end dates of the events. For the Global Lockdown Crisis due to COVID -19 pandemic, we considered 1st January 2020 as the start date*

2. Data and stylized facts of MANA/USD and SAND/USD

The stock return data used in this study is summarized under table 1 below:

Table 1: Data[11]

Indices	Period	Frequency
S&P 500	1. January 2018 - 31. May 2022	Daily
CCi30 Index	1. January 2018 - 31. May 2022	Daily
MANA/USD Exchange Rate	1. January 2018 - 31. May 2022	Daily
SAND/USD Exchnage Rate	1. September 2020 - 31. May 2022	Daily

The Annexure 1 presents the daily indices in level for the period stated under table 1. Due to non-stationarity in the level series, we used the log returns of the data series in this study. The plots of the daily log returns (Annexure 2) show the evidence of the volatility clustering. Table 2 below provides the descriptive statistics and the results of the Jarque-Bera (JB) test of normality for the empirical log return distributions.

Table 2: Descriptive statistics and *t* test results

Descriptive Statistics of Returns

Daily Log returns	S&P 500	CCi30	MANA	SAND
Mean	0.00039	-0.00028	0.00145	0.00474
Median	0.00102	0.00302	0.00150	-0.00283
Maximum	0.08968	0.19568	0.92290	0.71306
Minimum	-0.12765	-0.48448	-0.65357	-0.46742
Stdev	0.01365	0.04653	0.08058	0.09536
Skewness	-0.95787	-1.39819	1.11258	1.02991
Excess Kurtosis	15.28897	10.93327	17.78470	8.42132
Mean/Stdev	0.029	-0.006	0.018	0.050
J-B	11,018.08	8,575.19	21,599.26	2,011.54
P-value	0	0	0	0
Obs	1109	1611	1609	637

t tests for mean, skewness and Kurtosis

Daily Log returns	S&P 500	CCi30	MANA	SAND
t-value mean	0.954	-0.242	0.723	1.255
	0.340	*0.809*	*0.470*	*0.210*
t-value skewness	-13.040	-22.932	18.236	10.637
	-	-	-	-
t-value Excess kurtosis	83.761	65.139	121.267	28.115
	-	-	-	-

and 31^{th} October 2020, - the announcement of launch of COVID 19 vaccines as the end date. Note: multiple waves of COVID-19 continue to plague various nations of the world. Thus, the crisis is currently ongoing. The rebranding of Facebook name as "Meta" was announced on 28^{th} October 2021 (Issac, 2021), we consider that the impact of the announcement could be felt in the small window from 27^{th} October to 29^{th} October 2021.

[11] MANA/USD and SAND/USD exchange rate data are obtained from CoinGecko website (Vidal-Tom´as; 2022b); CCi30 index is cryptocurrency market capitalization weighted benchmark. CCi30 index tracks 30 largest cryptocurrencies by market capitalization but excludes stablecoins. Thus, the index serves as a benchmark for both investment managers and passive investors. The index was launched on 1^{st} January 2017 (https://cci30.com).

The JB test indicates that, the normality assumption is strongly rejected for all the log return distributions. The null hypothesis of zero mean cannot be rejected and all the log return distributions exhibit pronounced skewness and excess kurtosis.

The return predictability or the random walk hypothesis is traditionally tested by applying various tests such as the Ljung-Box, variance ratio tests etc. to the complete dataset. Annexure 3 shows the autocorrelation (ACF) and partial autocorrelation (PACF) functions of the daily log returns series. If the return series $\{r_t\}_{t=1}^{T}$ follows a random walk, then all its autocorrelations should be zero, Ljung and Box (1978) proposed the following Q statistic that sums the squared autocorrelations $\rho^2(k)$and detects the departure from zero autocorrelations in either direction for the given number of *m* lags. The statistic $Q(m)$ incorporates the finite sample correction and is chi-square distributed with *m* degree of freedom (Campbell, Lo and MacKinlay, 1997).

$$Q(m) = T(T+2)\sum_{k=1}^{m}\frac{\rho^2(k)}{T-k} \tag{1}$$

Table 3 provides the results of Ljung – Box and two unit-root tests. The Ljung-Box test for the lags up till 1, 5, 12, and 20 indicates significant serial-correlation for S&P 500 and CCi30 for all the lags (*p – values* below 0.05, reported in *italics* below the main row in table 3). Surprisingly, MANA/USD exchange rate does not exhibit significant serial correlation, but SAND/USD exchange rate does, except for the lag = 1. These results indicate that while of S&P 500 and CCi30 indices exhibit return predictability, the MANA/USD exchange rate does not. The null hypothesis of existence of unit root is rejected for all the log return series.

Table 3: The unit Root tests and the Ljung-Box tests for daily log returns

Ljung-Box and Unit Root tests

Daily Log returns

	S&P 500	CCi30	MANA	SAND
ADF Stat. nc (no constant)	-8.84	-10.75	-11.37	-6.93
	0.01	*0.01*	*0.01*	*0.01*
ADF Stat. c (only contant)	-8.89	-10.75	-11.39	-7.08
	0.01	*0.01*	*0.01*	*0.01*
Ljung- Box, Q stat lag=1	51.60	12.37	1.04	1.04
	0.00	*0.00*	*0.31*	*0.31*
Ljung- Box, Q stat lags=5	87.29	23.15	5.35	34.17
	-	*0.00*	*0.37*	*0.00*
Ljung- Box, Q stat lags=12	283.13	33.24	17.12	39.95
	-	*0.00*	*0.15*	*0.00*
Ljung- Box, Q stat lags=20	346.28	41.33	23.39	47.38
	-	*0.00*	*0.27*	*0.00*

Annexure 4 shows the autocorrelation (ACF) and the partial autocorrelation (PACF) functions of the daily squared log returns. There are many significant lags indicating presence of volatility clustering/ conditional heteroscedasticity. The Ljung Box statistics for the squared log returns are also significant (table 4).

Table 4: The Ljung-Box test for the squared log returns

Summary of Ljung Box Tests for squared return series

Squared Log returns	S&P 500	CCi30	MANA	SAND
Ljung- Box, Q stat lag=1	275.07	8.83	95.43	10.85
	-	*0.00*	-	*0.00*
Ljung- Box, Q stat lags=5	972.21	42.47	104.24	37.58
	-	*0.00*	-	*0.00*
Ljung- Box, Q stat lags=12	1,549.13	61.99	105.39	38.58
	-	*0.00*	-	*0.00*
Ljung- Box, Q stat lags=20	1,691.11	67.43	110.50	44.40
	-	*0.00*	*0.00*	*0.00*

A simple unconditional correlation analysis (Table 5) indicates that there is significant correlation between S&P 500 and CCi30 indices and between MANA/USD and SAND/USD exchange rates. Surprisingly, we observed significant correlation between an equity and cryptocurrency index but none between a cryptocurrency and the fungible token exchange rates.

Table 5: Unconditional Correlation Analysis[12]

Correlation Probability	S&P 500	cci30	MANA	SAND
S&P 500	1.00000			
	-----			
cci30	0.34578	1.00000		
	0.00	-----		
MANA	0.01846	0.01925	1.00000	
	0.70	*0.69*	-----	
SAND	0.02860	0.05197	0.65292	1.00000
	0.55	*0.28*	-	-----

[12] This Pearson correlation is calculated for the log returns from 2nd September 2020 to 31st May 2022.

3. Adaptive Market Hypothesis

One of the objectives of this study is to explore if the exchange rate markets of fungible tokens – MANA/USD and SAND/USD exhibit efficient market behaviour. The "Efficient Market Hypothesis" (EMH) proposed by Fama (1970, 1991) - "Security prices fully reflect all available information", is quite onerous. EMH in its weak form says that the security prices follow random walk i.e. past security returns cannot be used to predict the future security returns. Thus, a weak form of EMH implies the impossibility of excess returns using technical/ trading rules. The semi-strong form of EMH states that the security prices reflect all the publicly available information for example annual reports, stock splits etc. Thus, excess returns cannot be obtained by using the fundamental analysis and trading rules based on any publicly available information. If the fungible tokens i.e. the currencies markets of the nascent Metaverses, were not efficient, an investor could achieve abnormal returns by using simple investing strategies in MANA and/or SAND.

As any test of EMH is a joint test of EMH and the equilibrium pricing model, testing of EMH is a challenge (Lo 2005). Many studies have found that the markets do not follow a random walk and that there is some predictability to the market returns - Lo and MacKinlay (1988), De Bondt and Thaler (1985), and Jegadeesh and Titman (1993) to name a few. EMH assumes that market participants are rational, their actions are based on the self-interest and they maximize utility by trading, costs against the future benefits weighted by true probabilities. Behaviour economists have questioned this assumption of rationality and have highlighted many behavioural biases that plague the human decision making (Lo 2005). Attempts have been made to incorporate the behavioural aspects into the classical finance theories such as the utility theory by Kahneman and Tversky (1979), the portfolio theory by Shefrin and Statman (2000) etc. These attempts are not widely accepted by both the behaviour economists and the practitioners alike. Lo argues that the impediment to the acceptance is an improper axiomatic structure underlying these theories. He cites the example of the prospect theory by Kahneman and Tversky's (1979) that can generate the market participant behaviour consistent with the loss aversion but cannot explain the biases such as the overconfidence and the regret at the same time. As the behavioural economics has its root in psychology it does not possess the axiomatic structure as required under the traditional economics. Thus Lo (2004) proposed the Adaptive Market Hypothesis (AMH) to reconcile the behavioural biases with EMH. Lo argued that the competition, reproduction, natural selection and mutation – the classical principles of the evolutionary biology determine the market efficiency.

Since 2004, the AMH has been tested for different markets, assets classes and with subsamples of varying sizes. Lim, Brooks and Kim (2008), Ito and Sugiyama (2009) to name a few who have found evidence of the AMH. Kim, Lim and Shamsuddin (2011) tested the AMH for a century long US data for two-year window (daily data) and five-year window (weekly data) and found a strong support for AMH. Stock market crashes were not associated with significant return predictability, but economic and political crisis were. Smith (2012) found that the global financial crisis of 2008 coincided with the high return predictability in UK and the emerging European stock markets, thus substantiating the AMH. Verheyden, Bossche and Moor (2013) tested AMH using the rolling variance ratio test for the US and the Belgian stock market on six monthly and yearly subsamples and found the evidence for time variant market efficiency. Urquhart and Hudson (2013) questioned the market efficiency in US, UK and Japanese markets and tested the AMH on yearly subsamples and found the evidence of the AMH. Urquhart and McGroarty (2016) examined the AMH in US, Europe and Japanese markets. They tested the return predictability in these markets by applying various tests on the fixed length moving subsample windows and found the evidence of the statistically significant return predictability. Shah and Bahri (2019) tested AMH in US, Hong Kong and Indian equity markets and found evidence of changing return predictability in the daily data.

In this study, we juxtapose the market efficiency of US stock market (S&P 500), cryptocurrency market (CCi30 index), exchange rate markets of MANA/ USD and SAND/USD. We applied the Ljung – Box test (1978), Lo and MacKinlay variance ratio test (1988) and Chow – Denning test (1993) to the fixed length rolling subsample windows, to test for the varying degree of market efficiency. Testing for the uncorrelated increments using a portmanteau test such as the Ljung-Box test, provides the weakest evidence for the random walk hypothesis and return predictability because uncorrelated increments do not imply independence. Lo and MacKinlay (1988) stated that tests such as variance ratio test served as a better test for the random walk hypothesis. The random walk hypothesis implies that the variance of the increments that follow a random walk must be linear function of the time interval between the increments. Hence the variance ratio, $VR(k)$ of variance of k^{th} holding period return and k $\times$ variance of one holding period return should be unity. For example, for a stationary time series, the ratio of the variances $VR(2)$ of the two period log returns $r_t(2) = r_t + r_{t-1}$ to twice the variance of one period return r_t is given as (equation 2, Lo MacKinlay 1988, Campbell et. al. 1997):

$$VR(2) = \frac{Var[r_t(2)]}{2Var[r_t]} = \frac{Var[r_t + r_{t-1}]}{2Var[r_t]} = \frac{Var[r_t] + 2Cov[r_t, r_{t-1}]}{2Var[r_t]} \tag{2}$$

$$VR(2) = 1 + \rho(1)$$

Where $\rho(1)$ is the first order autocorrelation. If the log returns are IID i.e. independent and identically distributed, then all autocorrelations are zero and $VR(2) = 1$. If the first order autocorrelation is positive then $VR(2) > 1$ and if negative, $VR(2) < 1$. Lo and MacKinlay (1988) extend the two period variance ratio to a general k period variance ratio as follows:

$$VR(k) = \frac{Var[r_t(k)]}{k\,Var[r_t]} = 1 + 2\sum_{q=1}^{k-1}\left(1 - \frac{q}{k}\right)\rho(q) \tag{3}$$

Where $\rho(q)$ is the *qth* autocorrelation of r_t and $r_t(q) = r_t + r_{t-1} + \cdots + r_{t-q+1}$. Thus $VR(k)$ is a linear combination of auto – correlations of r_t with declining weights. For all $q \geq 1$, if $\rho(q) = 0$, then $VR(q) = 1$. Lo MacKinlay (1988) showed that this variance ratio was biased and thus proposed a statistic based on, the biased corrected variance ratio[13], $\overline{VR(k)}$. They standardized this corrected ratio to get an asymptotically standard normal test statistic $\psi(k)$ (equation 4).

$$\psi(k) = \sqrt{nk}(\overline{VR}(k) - 1)\left[\frac{2(2k-1)(k-1)}{3k}\right]^{-\frac{1}{2}} \sim N(0,1) \tag{4}$$

But the tests based on $\overline{VR(k)}$ has one limitation, these tests reject the null hypothesis of the random walk even due to the presence of heteroscedasticity. As the presence of heteroscedasticity is evident in all the data series (annexure 2 and 4), we adopted the heteroscedasticity consistent approach proposed by Lo and MacKinlay (1988). Under this approach, the bias corrected variance ratio $\overline{VR}(k)$ still approaches 1 under the null hypothesis and the estimator of $\overline{VR}(k)$'s asymptotic variance is computed as follows (equation 5):

$$\hat{\theta}(k) = 4\sum_{q=1}^{k-1}\left(1 - \frac{q}{k}\right)^2 \widehat{\delta_q} \tag{5}$$

Where $\widehat{\delta_q}$ is the heteroscedasticity consistent estimator of the asymptotic variance of each of the autocorrelation coefficients defined as (Lo MacKinlay 1988, Campbell et. al. 1997):

[13] For a log price process p_t, continuously compounded returns $r_t = p_t - p_{t-1}$, given a sample of size $(nk+1)$ i.e. p_0 *to* p_{nk}, mean estimator $\hat{\mu}$,one period unbiased variance estimator $\bar{\sigma}_a^2$ and k period unbiased variance estimator $\bar{\sigma}_c^2$ are given as (Lo and MacKinlay 1988):

$$\hat{\mu}, = \frac{1}{nk}(p_{nk} - p_0)$$

$$\bar{\sigma}_a^2 = \frac{1}{nk-1}\sum_{q=1}^{nk}(p_q - p_{q-1} - \hat{\mu})^2$$

$$\bar{\sigma}_c^2(k) = \frac{1}{m}\sum_{q=k}^{nk}(p_q - p_{q-k} - k\hat{\mu})^2$$

Where $m = k(nk - k + 1)\left(1 - \frac{k}{nk}\right)$

And $\overline{VR}(k) = \frac{\bar{\sigma}_c^2(k)}{\bar{\sigma}_a^2}$

$$\widehat{\delta_q} = \frac{nk \sum_{j=q+1}^{nk} \left(p_q - p_{q-1} - \hat{\mu}\right)^2 \left(p_q - p_{q-1} - \hat{\mu}\right)^2}{\left[\sum_{q=1}^{nk} \left(p_q - p_{q-1} - \hat{\mu}\right)^2\right]^2} \quad (6)$$

Thus, despite the presence of heteroscedasticity, the asymptotically standard normal test statistic $\psi^*(k)$ is given as below (Lo MacKinlay 1988, Campbell et. al. 1997):

$$\psi^*(k) = \sqrt{nk}(\overline{VR}(k) - 1)\hat{\theta}^{-\frac{1}{2}} \qquad \sim N(0,1) \quad (7)$$

Table 6 tabulates the homoskedasticity consistent variance ratio test statistic, $\psi(k)$ and the heteroscedasticity consistent variance ratio test statistic, $\psi^*(k)$ for the daily log returns. In the table, $\psi(k)$ are reported in the main row and $\psi^*(k)$ are reported in the parentheses below the main row. Given the presence of heteroscedasticity in the data (Table 4 and Annexure 4), we focused on $\psi^*(k)$ in this study, but also presented $\psi(k)$ to highlight the impact of heteroscedasticity on the test. To improve the small sample property of variance ratio tests, the probabilities in the tables were computed using the wild bootstrap method for the variance ratio tests as proposed by Kim (2006).

Table 6: Lo – MacKinlay variance ratio test statistics for the daily log returns[14]

		Number k of base observations aggregated to form variance ratio		
Index	Number nk of base observations	2	5	10
S&P 500	1109	-7.22*	-3.22*	-2.12*
		(-2.34)*	(-1.05)	(-0.73)
cci30	1611	-3.56*	-0.9	-0.12
		(-2.54)*	(-0.67)	(-0.09)
MANA	1609	-1.04	-1.8*	-1.76*
		(-0.43)	(-0.91)	(-1.05)
SAND	637	-1.09	0.37	0.85
		(-0.71)	0.25	0.6

[14] *Test statistic marked with asterisks indicate significance (p – value 0.05).*

As table 6 shows, the Random walk hypothesis for uncorrelated increments using the heteroscedasticity consistent variance ratio test statistic, is rejected for S&P 500 and CCi30 indices for the aggregation values/ holding period of. k = 2 ($\psi^*(k)$ = -2.34 and $\psi^*(k)$ = -2.54 respectively). $\psi^*(k)$ for the other data series for tested holding periods are not significant, indicating that the random walk hypothesis cannot be rejected.

A shortcoming of the Lo -MacKinlay variance test is that the variance ratios for each aggregation value k is tested separately. But the test for random walk hypothesis requires variance ratios for all the aggregation values to be unity. Hence such individual test requires sequential testing of the random walk hypothesis. Such a testing introduces, size distortions and ignores the joint nature of the random walk. Thus, Chow Denning (1993) proposed a methodology that tested if the multiple variance ratios over many aggregation-values k were jointly 1. The Chow-Denning (CD) test statistic under the assumption of homoscedasticity (equation 8) and heteroscedasticity (equation 9) are defined as under (Chow and Denning 1993):

$$Z = max|\psi(k)_{1 \le k \le l}| \tag{8}$$

$$Z^* = max|\psi^*(k)_{1 \le k \le l}| \tag{9}$$

The test statistics follow asymptotically the studentized maximum modulus (SMM) distribution with l and T degrees of freedom, where T is the sample size. The random walk hypothesis is rejected if the test statistic is greater than the SMM critical value at the chosen significance level.

Table 7 tabulates the homoskedasticity consistent CD variance ratio test statistic, Z and heteroscedasticity consistent CD variance ratio test statistic, Z^* for the daily log returns. As in the table 6, Z statistic is reported in the main row and Z^* statistic is reported in the parentheses below the main row. The test statistic Z^* is significant for the daily log return of CCi30 and S&P 500, albeit at the p value of 0.1, and consequently the random walk hypothesis is rejected. Surprisingly, random walk hypothesis is not rejected for MANA and SAND.

Table 7: Chow – Denning variance ratio test statistics for the daily log returns[15]

Index	Number *nk* of base observations	*k = 2, 5, 10*
S&P 500	1109	7.22*
		(2.34)
cci30	1611	3.56*
		(2.54)*
MANA	1609	1.80
		(1.05)
SAND	637	1.09
		(0.71)

4. ADCC/ DCC - GARCH Modelling

The second objective of the study was to estimate the conditional volatility and time-varying correlation in the exchange rate markets of MANA/ USD and SAND/USD. The ponderous question was if various stylized facts observed in the real world were also observable in the metaverse; such as an increase in correlations during bear markets or "crisis" and decrease during bull markets (Bekaert and Harvey, 1995; De Santis and Gerard, 1997; Ang and Bekaert, 1999; Das and Uppal, 2001, Login and Solnik, 2001, Cappiello, Engle and Sheppard, 2006). Furthermore, both the volatility and correlation could exhibit asymmetric impact of negative shocks, i.e. volatility and correlation could both increase more after a negative shock than a positive shock of the same magnitude (Glosten, Jagannathan and Runkle, 1993; Bekaert and Wu, 2000; Cappiello, Engle and Sheppard, 2006). Such behaviours have hitherto not been investigated for the fungible tokens of Metaverses such as MANA and SAND, especially during crisis or major events. We performed this analysis using DCC-GARCH (Engle and Sheppard, 2001; Engle, 2002) and ADCC-GARCH (Cappiello, Engle and Sheppard, 2006) models. The appropriate univariate Generalized Autoregressive Conditional Heteroskedasticity - GARCH models – sGARCH (Bollerslev 1986) or GJR-GARCH (Glosten, Jagannathan and Runkle, 1993) and the appropriate Dynamic Conditional Correlation model - DCC or Asymmetric Dynamic Conditional Correlation model - ADCC were selected based on the BIC information criterion. The effects of Global Lockdown Crisis due to COVID-19 pandemic and rebranding of *Facebeook* to *Meta* were investigated by introducing the corresponding dummy variables in both the mean and the variance models under DCC/ADCC-GARCH framework. We also investigated the asymmetric volatility

[15] *Test statistic marked with asterisks indicate significance (p – value 0.05).*

impact of an innovation using news impact curves (Engle and Ng, 1993). ADCC/DCC-GARCH models have been used to investigate the correlation dynamics and impact of financial crisis on the correlations.

Hyde, Nguyen and Bredin (2007) investigated the correlation dynamics in 13 Asia-Pacific countries, Europe and US using AG-DCC-GARCH framework and found significant temporal variation in correlation between the equity markets. The stocks exhibited asymmetric effect both in correlation and volatility. Naoui, Liouane and Brahim (2010) analysed the effect of financial contagion following the sub-prime crisis on the correlation dynamics between the equity markets of six developed and ten emerging countries using DCC-GARCH model. They found that the conditional correlation between the equity markets of the developed countries increased substantially during the crisis. Min and Hwang (2012) analysed dynamic correlation between four OECD stock markets and US under DCC-GARCH framework and found evidence of increasing correlation during the Global Financial Crisis. Gjika and Horvath (2013) examined the time-varying co-movements of central European equity markets using ADCC-GARCH model and found evidence of increasing correlation over time indicating greater market integration. Klaus and Koser (2020) analysed correlation dynamics between Apple, Microsoft, Amazon and Google stocks employing DCC-GARCH model and found that correlations were high and increased further during market downturns. Shah and Bahri (2021) investigated the volatility and dynamic correlation behaviour in the New Age Technology (Industry 4.0) Sectoral Indices and found evidence of increased volatility and correlation during Global Lockdown Crisis due to COVID 19 pandemic.

Exploratory analysis in the section 2 showed that the daily log returns of all the data series exhibited the stylized facts of non-normal empirical distribution, fat tails, skewness, and the volatility clustering. GARCH models are known to explain many of these stylized facts. A GARCH model consists of a separate conditional mean and a conditional volatility model (Alexander 2008). The conditional mean could be a constant or a low order Autoregressive Moving Average (ARMA) model. A typical conditional volatility model consists of lagged squared residuals (i.e. Autoregressive Conditional Heteroskedasticity - ARCH terms) and lagged conditional variance (GARCH terms) terms. Usually, a GARCH(1,1) model wherein the conditional volatility model has only one lagged squared residual term and one lagged conditional variance term is adequate to obtain a good fit for many financial time series (Zivot 2009). Hansen and Lunde (2004) provide the evidence that the GARCH(1,1) model almost always outperforms the complex GARCH model with many lags.

As the empirical distribution of daily log return of all the indices exhibited skewness and high excess kurtosis, we included skew student *t* distributed error terms in the GARCH models (Zivot 2009). Since the conditional volatility model incorporates a squared residual term, the sign of residuals does not affect the conditional volatility. One of the stylized facts of the conditional volatility is that bad news tends to have a larger effect on the volatility than good news. This asymmetric impact of bad news on the volatility is called the leverage effect. The common asymmetric GARCH models that incorporate the leverage effect are TGARCH (Zakoin 1994), GJR-GARCH, EGARCH and APARCH. In this study we used GJR-GARCH model proposed by Glosten, Jagannathan and Runkle (1993) to test for leverage effect.

The general univariate conditional mean and the conditional volatility model that used in this study are given below:

The mean model:

$$r_t = \mu_t + a_t \tag{10}$$

$$\mu_t = \mu_0 + \sum_{j=1}^{2} \varphi_j d_{jt} + \sum_{j=1}^{p} \phi_j r_{t-p} + \sum_{j=1}^{q} \varsigma_j a_{t-q} \tag{11}$$

$$a_t = \sigma_t \epsilon_t \qquad \epsilon_t \sim t_\vartheta^*(\kappa)$$

Here the error term, ϵ_t is standardized skew student *t* distributed ~ $t_\vartheta^*(\kappa)$ with ϑ degree of freedom and κ - skew parameter. In the conditional mean model, r_{t-p} and a_{t-q} are the AR and MA terms with p and q lags. These lags for each sectoral log return time series are determined using the Extended Autocorrelation Function, EACF (Tsay 2010). The conditional mean model (equation 10 and 11) is same for both sGRACH and GJR-GARCH models. Both in the conditional mean and the variance models, we introduced dummy variables, d_{1t} and d_{2t} to investigate the impact of Global Lockdown Crisis due to COVID-19 pandemic (January 2020 to October 2020) and the rebranding of Facebook name as “Meta” (27th October to 29th October 2021) respectively. The dummy variable, d_{jt} = 1 during the event period and 0 otherwise.

The volatility model (sGARCH):

$$\sigma_t^2 = \left(\omega + \sum_{j=1}^{2} \psi_j d_{jt} \right) + \alpha a_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{12}$$

The volatility model (GJR-GARCH):

$$\sigma_t^2 = \left(\omega + \sum_{j=1}^{2} \psi_j d_{jt} \right) + (\alpha a_{t-1}^2 + \gamma I_{t-1} a_{t-1}^2) + \beta \sigma_{t-1}^2 \tag{13}$$

We considered only one ARCH and one GARCH terms largely for a parsimonious representation (equation 12 and 13). In the GJR-GARCH volatility model, as per the convention, the parameter γ captures the leverage effect. *I* is an indicator function that has value 1 for $a_t \leq 0$ and 0 otherwise. Thus a_{t-1}^2 now has a different impact on the conditional variance σ_t^2. When $a_{t-1} > 0$, the total effect is αa_{t-1}^2 ,and when $a_{t-1} \leq 0$, the total effect is $(\alpha a_{t-1}^2 + \gamma a_{t-1}^2)$. Hence, we should find, $\gamma > 0$ if bad news were to a have larger impact on the conditional volatility as proposed under the leverage effect (Zivot 2009; Alexios Ghalanos 2022a).

The above representation is for univariate series, a *k* dimensional multivariate return series $\{\boldsymbol{r_t}\}$ can be written as:

$$\boldsymbol{r_t} = \boldsymbol{\mu_t} + \boldsymbol{a_t} \tag{14}$$

Where $\boldsymbol{\mu_t} = E(\boldsymbol{r_t}|\boldsymbol{F_{t-1}})$ is the conditional expectation of $\boldsymbol{r_t}$ given the past information $\boldsymbol{F_{t-1}}$, and $\boldsymbol{\mu_t}$ could follow a vector autoregressive process of lag *p*, ***VAR(p)***. $\boldsymbol{a_t} = (a_{it}, \dots \dots a_{kt})'$ is the innovation vector. The innovation $\boldsymbol{a_t}$ is written as**:**

$$\boldsymbol{a_t} = \boldsymbol{\Sigma_t^{1/2}} \boldsymbol{\epsilon_t} \tag{15}$$

Where $\boldsymbol{\Sigma_t} = Cov(\boldsymbol{a_t}|\boldsymbol{F_{t-1}})$**,** is *k* x *k* positive-definite conditional covariance matrix of $\boldsymbol{a_t}$ given the past information $\boldsymbol{F_{t-1}}$**.** Like σ_t^2, in the univariate volatility modelling above, multivariate volatility modelling, pertains to the time evolution of $\boldsymbol{\Sigma_t}$**.** In this study**,** we assumed that $\boldsymbol{\epsilon_t}$ follows a standardized multivariate student *t* distribution with υ degrees of freedom**.**

There are many methods proposed to model the time evolution of $\boldsymbol{\Sigma_t}$**.** Both Exponentially Weighted Moving Average (EWMA) and Diagonal Vectorization Model (VEC) by Bollerslev, Engle and Wooldridge (1988) does not guarantee that $\boldsymbol{\Sigma_t}$ is positive definite for all ***t*.** Baba-Engle-Kraft-Kroner (BEKK) model of Engle and Kroner (1995) does produce a positive definite $\boldsymbol{\Sigma_t}$**,** but is not parsimonious; for *k* = 3, the BEKK(1,1) model requires estimation of 24 parameters. Furthermore, these parameters are not directly linked to the components of $\boldsymbol{\Sigma_t}$ (Tsey 2007, 2010, 2014). Thus, we preferred parsimonious models - Dynamic Conditional Correlation (DCC) by Engle (2002)**,** and Asymmetric Dynamic Conditional Correlation (ADCC) model by Cappiello et.al. (2006).

Under the Dynamic Conditional Correlation model (DCC), $\boldsymbol{\Sigma_t}$ is reparametrized as follows:

$$\boldsymbol{\Sigma_t} = [\sigma_{ij,t}] = \boldsymbol{D_t \rho_t D_t} \tag{16}$$

Where $\boldsymbol{\rho_t}$ is the conditional correlation matrix of $\boldsymbol{a_t}$ and $\boldsymbol{D_t}$ is a *k* x *k* diagonal matrix consisting of volatilities of elements of $\boldsymbol{a_t}$**,** i.e. $\boldsymbol{D_t} = diag[\sigma_{11,t}^{1/2} \dots \dots \sigma_{kk,t}^{1/2}]$. Hence the time evolution of $\boldsymbol{\Sigma_t}$**,** is now governed separately by elements of $\boldsymbol{D_t}$ **-** univariate variances $\sigma_{ii,t}$ i.e. $\sigma_{i,t}^2$ in equation 12 or 13 and elements of $\boldsymbol{\rho_t}$, $\rho_{ij,t}$. Engle (2002) standardized the innovation vector $\boldsymbol{a_t}$ as $\boldsymbol{\eta_t} = (\eta_{1t,} \dots \dots \eta_{kt,})'$, where $\eta_{it} = a_{it}/\sqrt{\sigma_{ii,t}}$ and proposed (Engle 2002, Tsey 2007, 2010, 2014):

$$\boldsymbol{\rho_t} = \boldsymbol{J_t Q_t J_t}$$

$$\boldsymbol{Q_t} = (1 - \theta_1 - \theta_2)\boldsymbol{\overline{Q}} + \theta_1 \boldsymbol{Q_{t-1}} + \theta_2 \boldsymbol{\eta_{t-1}\eta'_{t-1}} \tag{17}$$

In the equation above, $\boldsymbol{\overline{Q}}$ is the unconditional covariance matrix of $\boldsymbol{\eta_t}$, θ_1 and θ_2 and non-negative real numbers such that $0 < \theta_1 + \theta_2 < 1$. And $\boldsymbol{J_t}$ is defined as $diag\left[q_{11,t}^{-1/2} \dots \dots q_{kk,t}^{-1/2}\right]$ and $q_{ii,t}$ is the *(i, i)*th element of $\boldsymbol{Q_t}$.

Model parsimony is evident from equation 17, as only two parameters θ_1 and θ_2 are used to govern the evolution of the conditional correlation, irrespective of number of log return series, *k*. This makes the model easy to estimate albeit at a cost - all log return series may not exhibit the same evolution of the conditional correlation (Cappiello, Engle and Sheppard 2006; Tsey 2010, 2014).

To capture the asymmetric behaviour or leverage effect in conditional correlation, we used the ADCC model proposed by Cappiello et.al. (2006).

$$\boldsymbol{Q_t} = (1 - \theta_1 - \theta_2)\boldsymbol{\overline{Q}} + \theta_3 \boldsymbol{\overline{N}} + \theta_1 \boldsymbol{Q_{t-1}} + \theta_2 \boldsymbol{\eta_{t-1}\eta'_{t-1}} + \theta_3 \boldsymbol{\xi_{t-1}\xi'_{t-1}} \tag{18}$$

Where for each element of $\boldsymbol{\xi_t}$, $\xi_{i,t} = I(\eta_{i,t} < 0).\eta_{i,t}^2$. $I(\eta_{i,t} < 0)$ is an indicator function that takes value of 1 if $\eta_{i,t} < 0$. $\boldsymbol{\overline{N}}$ is the unconditional covariance matrix of $\boldsymbol{\xi_t}$. Hence these terms capture the asymmetries in the conditional correlation (Hyde, Nguyen and Bredin, 2007, Alexios Ghalanos 2022b).

Following is the methodology we used for building ADCC/DCC – GARCH models:

1. Estimate the conditional mean $\widehat{\mu_t}$ of log return series $\{r_t\}$ of each log return series using an autoregressive moving average (ARMA) model with lags *p* and *q*. Determine the appropriate AR and MA lags using EACF.
2. Fit ARMA(*p*,*q*) + sGARCH and ARMA(*p*,*q*) + GJR-GARCH models with mean and variance dummy variables representing each crisis, to the log return series $\{r_t\}$ of each log return series and select the model with the lower BIC value. The selected model provides the estimate of $\widehat{\sigma_{ii,t}}$.

3. Estimate the standardized innovations, $\widehat{\eta_{\iota t}} = \widehat{a_{\iota t}}/\sqrt{\widehat{\sigma_{\iota\iota,t}}}$, then fit both the ADCC and DCC models to the estimated standardized innovations. Select the model with the smallest BIC value.

As correlation between only S&P 500 - CCi30, and MANA - SAND were significant (table 5), we selected $k = 2$, and fitted the ADCC/ DCC model to S&P 500 - CCi30 and MANA – SAND bivariate log return series.

5. Results

First, we present results pertaining to the Adaptive Market Hypothesis. To test for the time varying market efficiency, we applied the moving sub-sample window of fixed length (100 and 200 days) over the daily log returns of various data series (Kim, Lim and Shamsuddin, 2011; Urquhart and Hudson, 2013; Urquhart and McGroarty, 2016; Shah and Bahri, 2018). For example, for a rolling window of 100 days, the test statistics were first computed for the log returns, $\{r_t\}_{t=1}^{100}$ then the window was advanced by one data point i.e a day, and the test statistics were computed for log returns $\{r_t\}_{t=2}^{101}$. This process was repeated up till the last data point. Ito, Noda and Wada (2014, 2016) measured the degree of varying market efficiency using a time varying autoregressive model. Tran and Leirvik (2018) proposed a variant of the measure by Ito et.al. In this study, we used the boot strapped *p-values* (Kim, 2006) of the Chow Denning statistic as a measure of market efficiency for a given stock market.

Figure 1 below depict the lag 1 autocorrelations and the corresponding *p - values* for the daily log returns. The periods of inefficiency (*p values* < 0.05, rejection of the null hypothesis of no serial correlation) do seem to coincide during the Lockdown Crisis due to COVID-19 pandemic for all the data series.

Figure 1 Rolling lag =1, Autocorrelation and *p*-values of various daily log returns

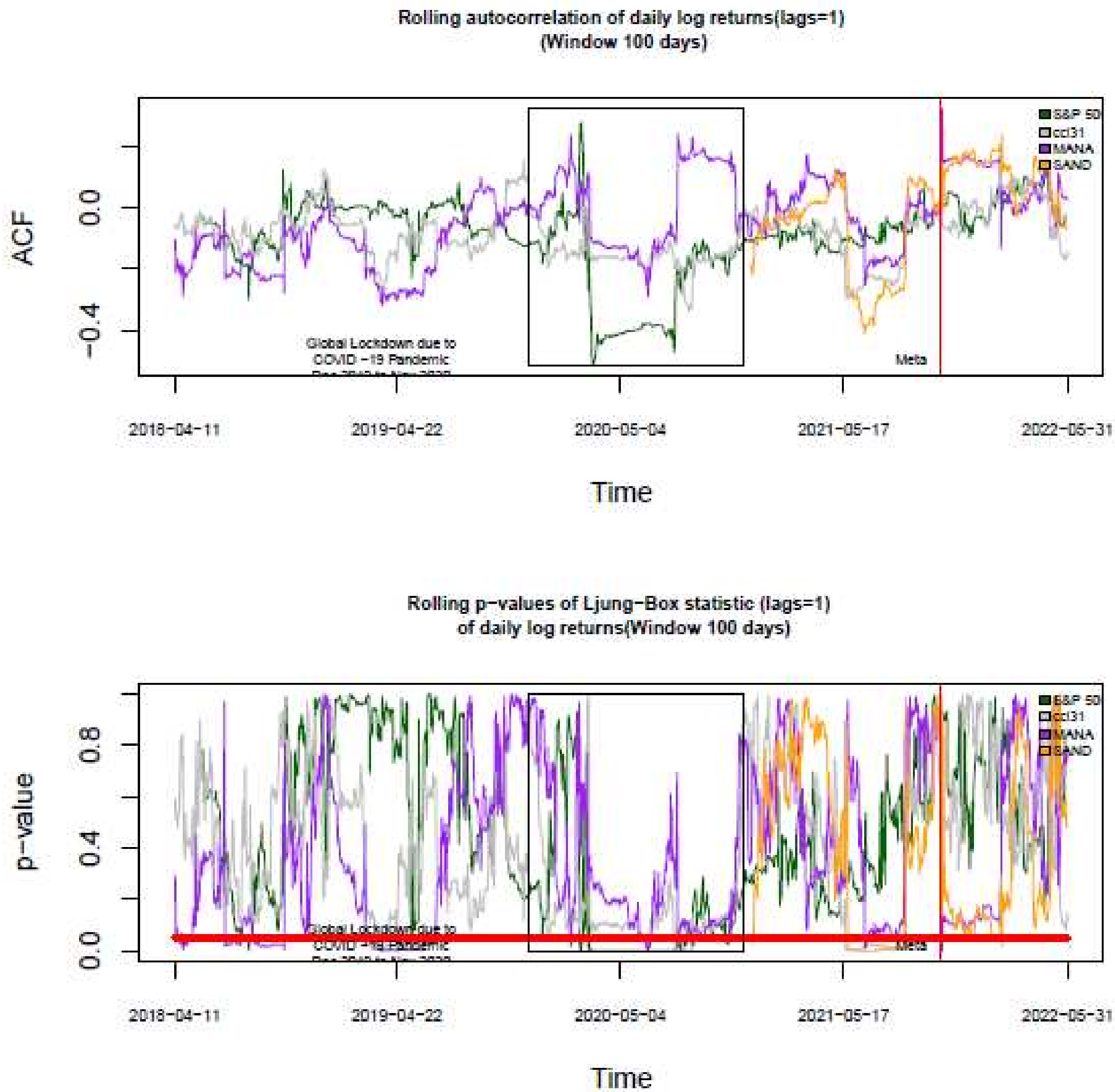
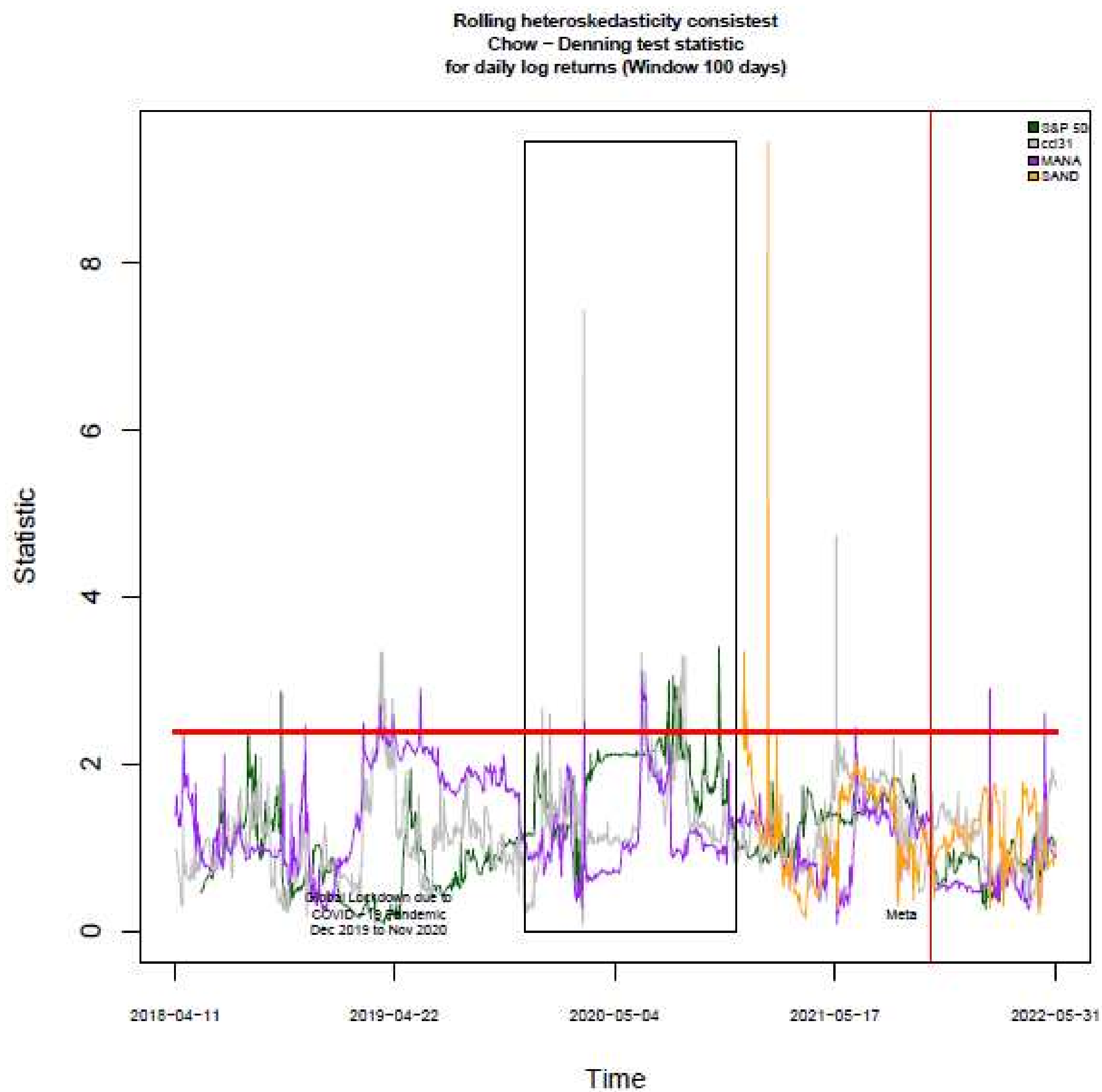


Figure 2 shows the heteroscedasticity consistent Chow - Denning statistic of the daily log returns. Contrary to that observed in the figure 1, there is no distinct period of market inefficiency during the Lockdown crisis due to COVID 19 pandemic.

Figure 2 Rolling heteroscedasticity consistent Chow Denning statistic of various daily log returns



Next, we compare the relative efficiency between various markets (Table 8). The table shows the percentage of Ljung Box statistic (lag = 1) and Chow Denning statistic (k = 2, 5, 10) that does not reject the null hypothesis of random walk at 5% significance level (Smith, 2012, Urquhart and McGroarty, 2016). Both the Ljung – Box statistic and the Lo – MacKinlay variance ratio have the inherent ambiguity in the lag length selection, thus the heteroscedasticity consistent Chow - Denning statistic is a better measure to compare the relative efficiency between the stock markets.

As evident from the results (Table 8), while the Ljung-Box statistic indicates lower market efficiency, heteroskedasticity consistent Chow Denning statistic indicates all the markets are efficient. Surprisingly, market efficiency of the MANA and SAND exchange rates is comparable to that of the S&P 500.

Table 8: Comparison of the relative market efficiency between various markets

Relative market efficiency (Window, 100 Days)

	Ljung - Box statistic (Lag = 1)	Heteroskedasticity consistent Chow Denning Statistic (k = 2, 5, 10)
S&P 500	87%	99%
cci30	90%	97%
MANA	84%	98%
SAND	81%	99%

Annexures 5 and 6, depict the results of the rolling Ljung-Box (lag 1) and the rolling Chow Denning tests for 200 days window respectively. The results are qualitatively like those for the rolling window of 100 days (Figure 1 and 2).

Now we present results for the DCC-GARCH analysis. First, we selected the appropriate ARMA + sGARCH or ARMA + GJR-GARCH model for each data series based on EACF and BIC criterion. This corresponds to the step 1 and 2 outlined in the tree step methodology in the earlier section. Table 9 presents the results of ARMA + sGARCH /GJR-GARCH models for the four data series. Only for S&P 500, $\gamma\ (gamma1) > 0$ and significant, indicating that bad news has a larger impact on the conditional volatility. Both the dummy variables *(mxreg1 and mxreg2)* were not significant for all the data series. But in the variance model, the dummy variable *(vxreg1)* for the Global Lockdown Crisis due to COVID 19 pandemic was significant for S&P 500.

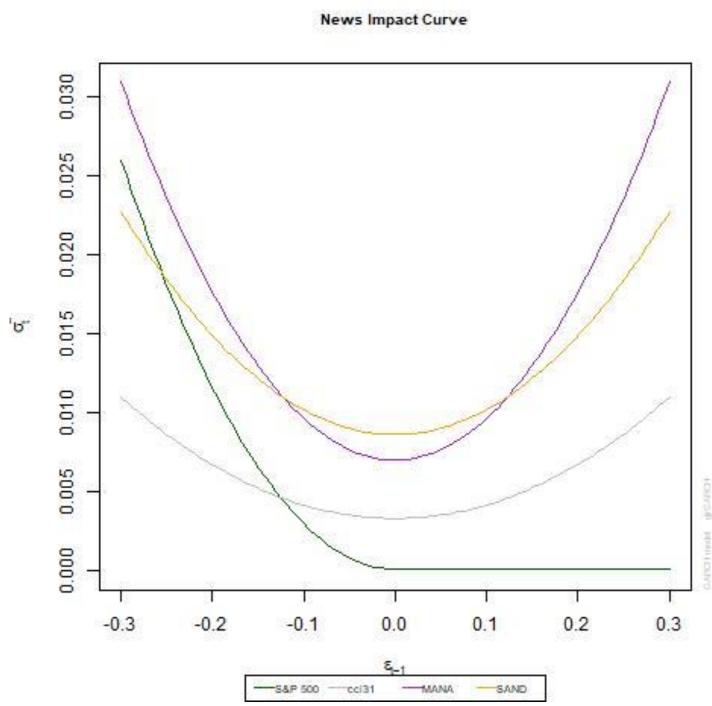
As depicted in figure 3, the news impact curves for CCi30, MANA/USD and SAND/USD are symmetric, the increase in volatility post a positive innovations ("good news") is same as the increase in volatility post a negative innovation ("bad news"). This is expected as sGARCH model was selected for these three data series. For S&P 500, the volatility impact is negligible post "good news".

Table 9: Univariate ARMA + s/GJR-GARCH models[16]

	S&P 500	cci30	MANA	SAND
Mean model	ARMA(0,2)	ARMA(0,2)	ARMA(0,0)	ARMA(0,0)
Variance Model	gjrGARCH(1,1)	sGARCH(1,1)	sGARCH(1,1)	sGARCH(1,1)
Distribution	Skew-Student t	Skew-Student t	Skew-Student t	Skew-Student t
Parameters				
mu	0.00043	-0.00073	-0.00039	0.00124
	0.49	*0.51*	*0.81*	*0.69*
ma1	-0.06317	-0.09447	-	-
	0.06	*0.00*	-	-
ma2	-0.02171	0.03988	-	-
	0.50	*0.07*	-	-
Dummy variable in Mean model, Covid - 19 Crisis(mxreg1)	0.00003	0.00258	0.00325	
	0.97	*0.15*	*0.27*	
Dummy variable in Mean model, Meta (mxreg2)	0.00160	0.02478	-0.01295	*0.04019*
	0.50	*0.43*	*0.77*	*0.64*
Omega	0.00000	0.00007	0.00061	0.00064
	0.64	*0.03*	*0.01*	*0.10*
alpha1	0.00002	0.08737	0.26219	0.09757
	1.00	*0.07*	*0.00*	*0.04*
beta1	0.83727	0.89464	0.67528	0.82483
	-	-	-	-
gamma1	0.26394	-	-	-
	-	-	-	-
Dummy variable in Variance model, Covid - 19 Crisis (vxreg1)	0.00001	0.00000	0.00000	
	0.00	*1.00*	*1.00*	
Dummy variable in Variance model, Meta (vxreg2)	0.00000	0.00000	0.00000	0.02581
	1.00	*1.00*	*1.00*	*0.23*
skew	0.71601	0.86040	0.99689	1.10684
	-	-	-	-
shape	8.27528	3.39045	3.79851	3.55595
	0.00	*0.00*	-	*0.00*
persistence	0.95573	0.98201	0.93746	0.92240
AIC	-6.51962	-3.59592	-2.64472	-2.20961
BIC	-6.46088	-3.55581	-2.61126	-2.15364
Weighted Ljung-Box Test on Standardized Residuals				
Lag	1	1	1	1
Statistic	1.83200	4.13800	0.16390	0.00221
	0.18	*0.04*	*0.69*	*0.96*
Lag	5	5	2	2
Statistic	2.89000	7.80700	0.16950	1.44415
	0.54	*0.00*	*0.87*	*0.37*
Lag	9	9	5	5
Statistic	5.46800	9.49400	0.52400	6.44338
	0.35	*0.02*	*0.95*	*0.07*
Weighted Ljung-Box Test on Standardized Squared Residuals				
	1	1	1	1
Lag	0.14120	0.42930	0.18520	0.20700
Statistic	*0.71*	*0.51*	*0.67*	*0.65*
	5	5	5	5
Lag	1.74390	3.51890	1.00390	0.52610
Statistic	*0.68*	*0.32*	*0.86*	*0.95*
	9	9	9	9
Lag	3.75250	5.42120	1.86440	0.87460
Statistic	*0.63*	*0.37*	*0.92*	*0.99*

[16] Global Lockdown Crisis dummy variable is not included in the ARMA + sGARCH model fitted to SAND/USD log return series. ACFs of standardized residuals, squared standardized residuals and QQ plots are provided in Annexures 7 and 8 respectively.

Figure 3: News Impact Curves



Next, we present two ADCC/ DCC models, one for S&P500 and CCi30 and second for MANA/USD and SAND/USD bivariate log return series (Table 10). The choice of the selected model, i.e. ADCC or DCC was based on the minimum BIC values. In both the cases DCC was selected, indicating that there were no asymmetries in the conditional correlation.

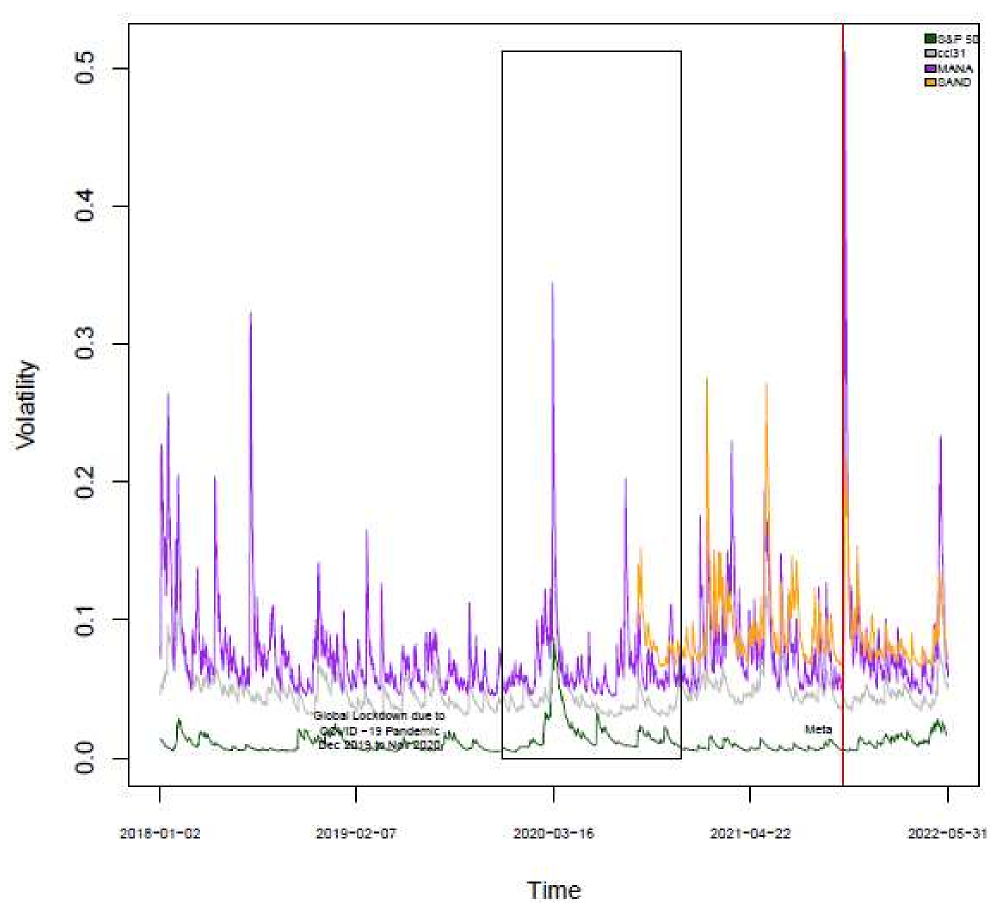
Table 10: ADCC/ DCC modelling for S&P500 and CCi30, and MANA/USD and SAND/USD exchange rates

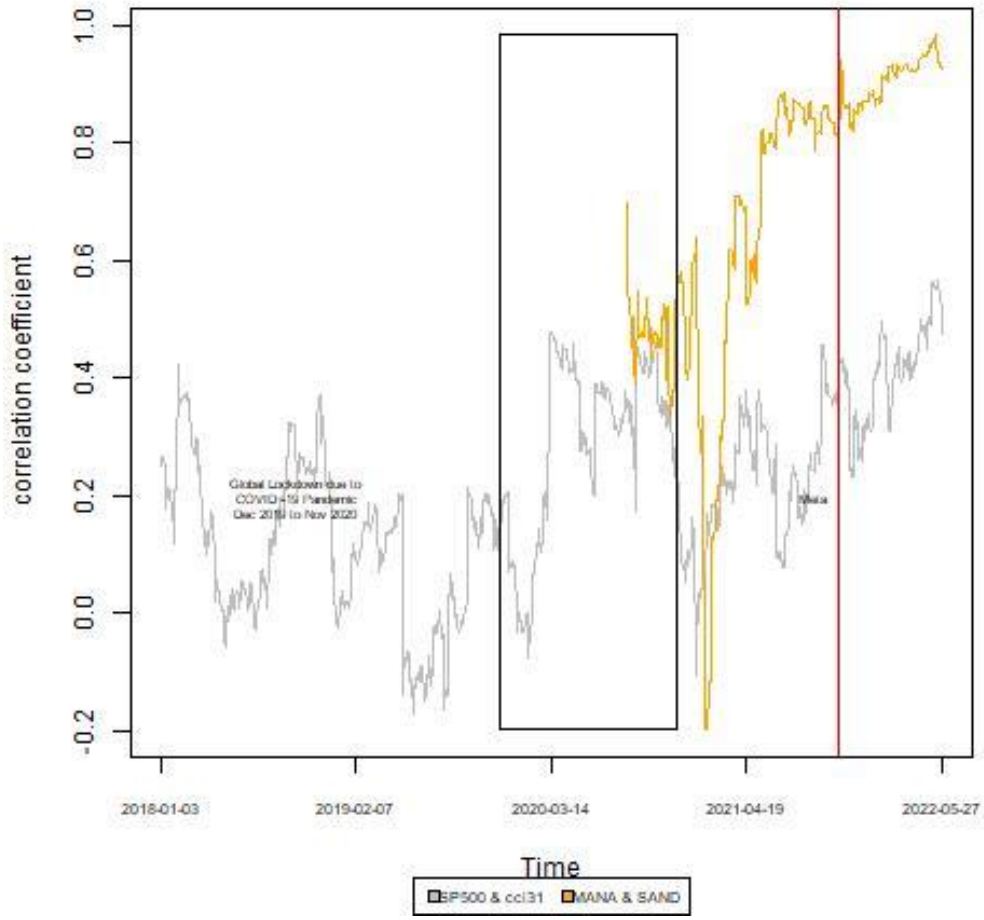
		Parameters			
Index	Selected Model	Theta 1	Theta 2	Theta 3	Shape parameter (*)
cci30	DCC(1,1)	0.954	0.032	-	5.45
		-	0.006	-	-
SAND	DCC(1,1)	0.93	0.07	-	4.00
		-	*0.000*	-	*0.020*

Figure 4 depicts volatility and dynamic correlation behaviour of the log returns of the data series. Global Lockdown Crisis related increase in volatility is visible only for S&P 500. Volatility exhibited by MANA/USD and SAND/USD exchange rates is higher than that exhibited by S&P

500 and CCi30. Crytocurrencies tend to exhibit higher conditional volatility than equity indices (Shah and Bahri, 2018), but surprisingly, fungible tokens of Metaverse, tend to exhibit even higher volatilities than the cryptocurrency index (CCi30). There was an increase in MANA/USD volatility during the rebranding of Facebook to "Meta". While the correlation between CCi30 and MANA/USD was not significant, the correlation between S&P500 and CCi30 was significant and showed an increasing trend after the Global Lockdown Crisis due to COVID 19 pandemic. There was a significant and increasing correlation between the log return of MANA/USD and SAND/USD – fungible tokens of two different Metaverses. The dynamic correlation behaviour of CCi30 and fungible tokens (currencies) in Metaverses suggests a potential for diversification benefits by pursuing investment strategy in the Metaverse currencies.

Figure 4: Volatility and Dynamic Correlation behaviour





6. Conclusion

This study presents stylized facts of the fungible tokens/currencies (MANA/USD and SAND/USD) in the Metaverses (*Decentraland* and *The Sandbox*). Metaverse currency exchange rate market exhibits very high conditional volatility, albeit no leverage effect, less impact of the real-world crisis (Global Lockdown due to COVID 19 pandemic) and low correlation with either cryptocurrency index (CCi30) or real-world equity index (S&P 500). Surprisingly, MANA and SAND – fungible tokens/ currencies in different Metaverses exhibit significant and increasing correlation between each other. The relative market efficiency of Metaverse currency market is comparable to that observed in the cryptocurrency and equity markets in the real-world.

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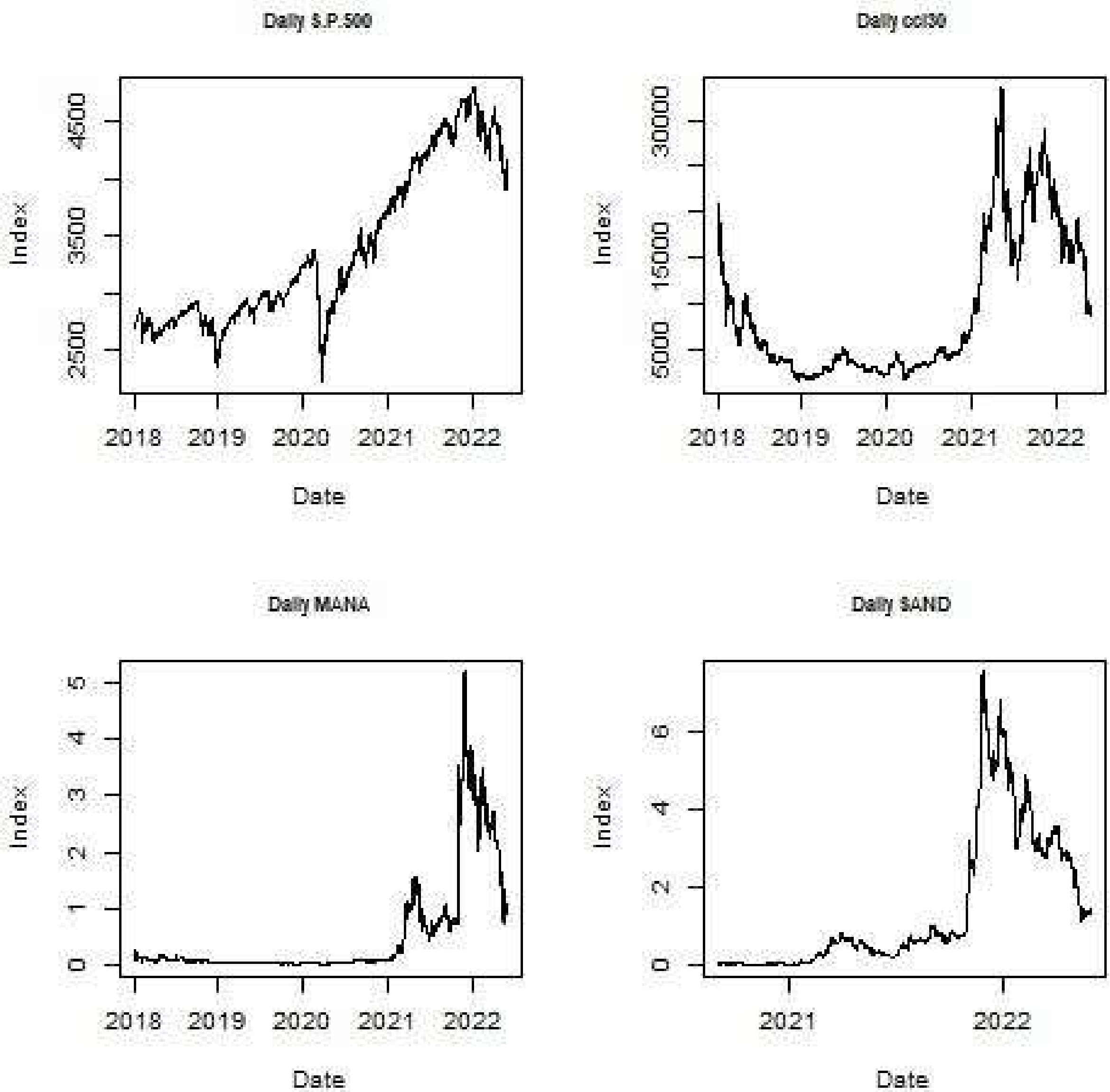
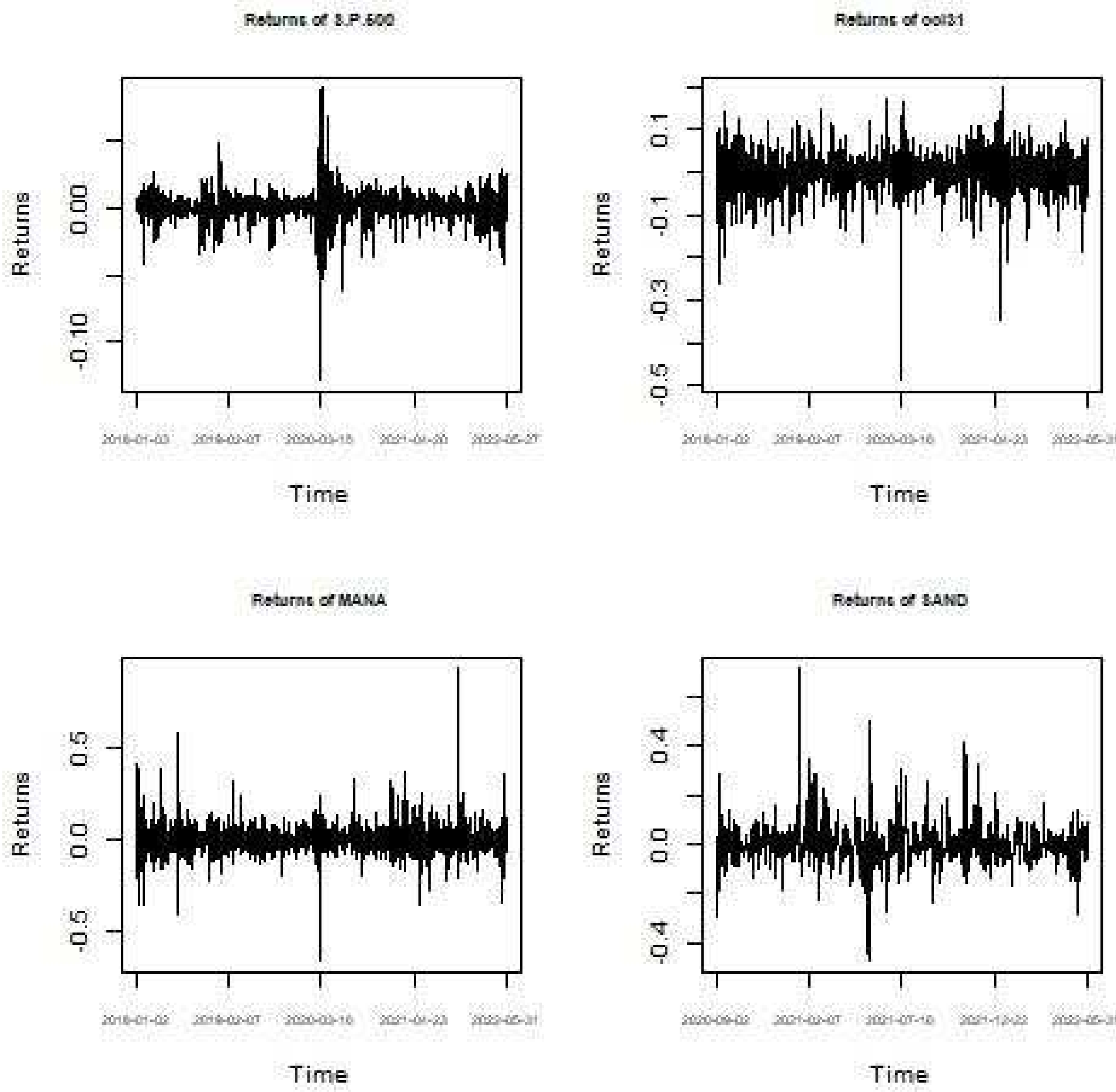
Annexures:

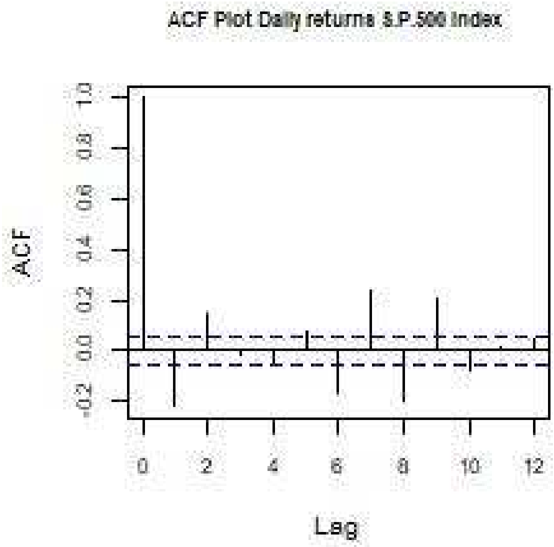
Annexure 1: Daily time series in level

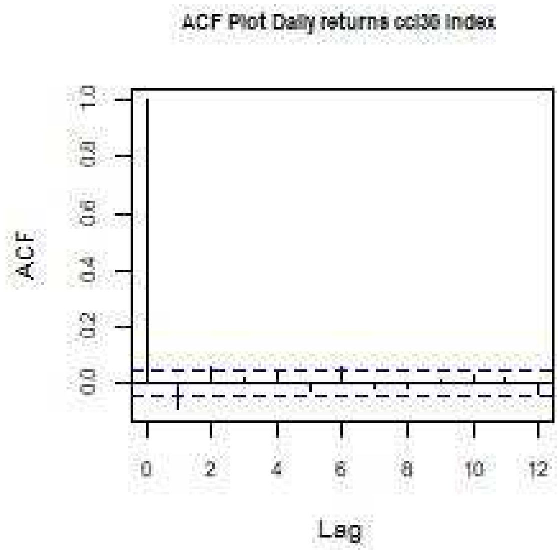


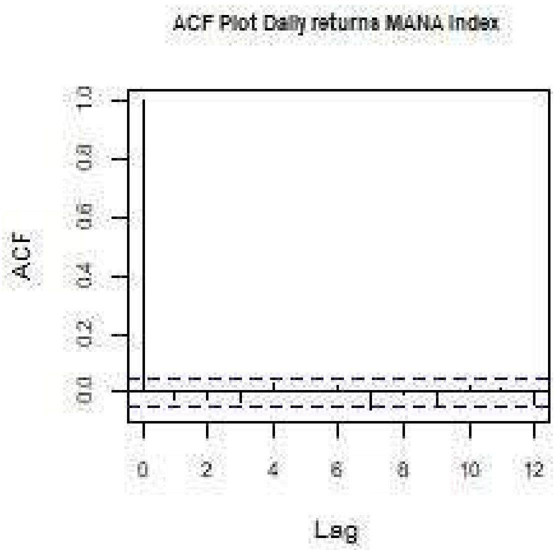
Annexure 2: Log returns of daily time series

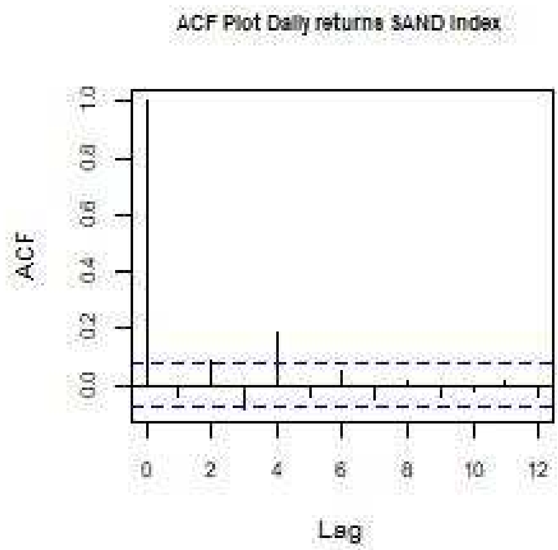


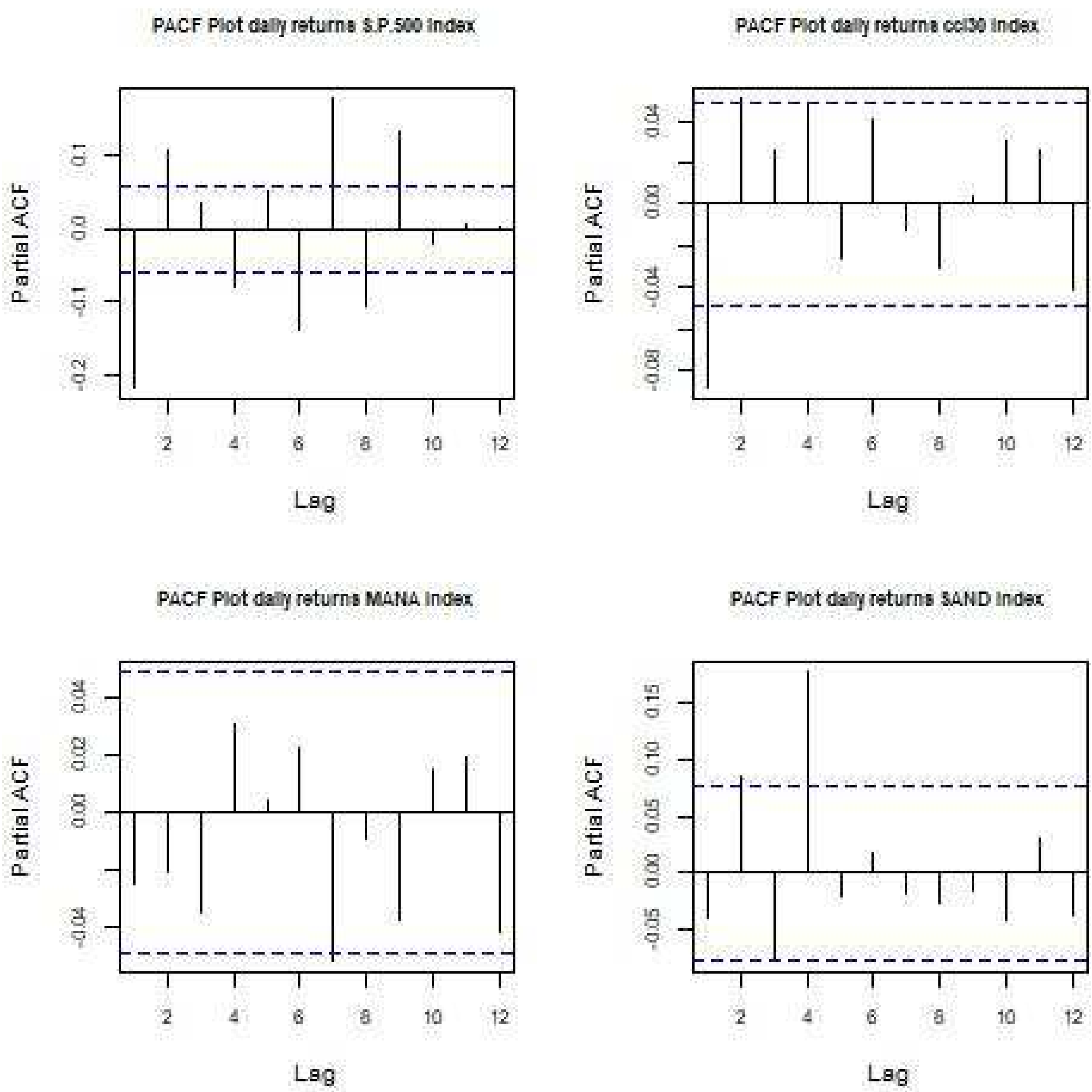
Annexure 3: ACF and PACF plots of log return series



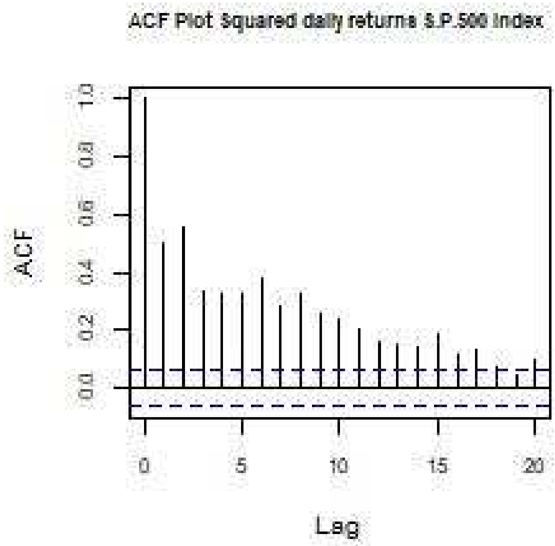


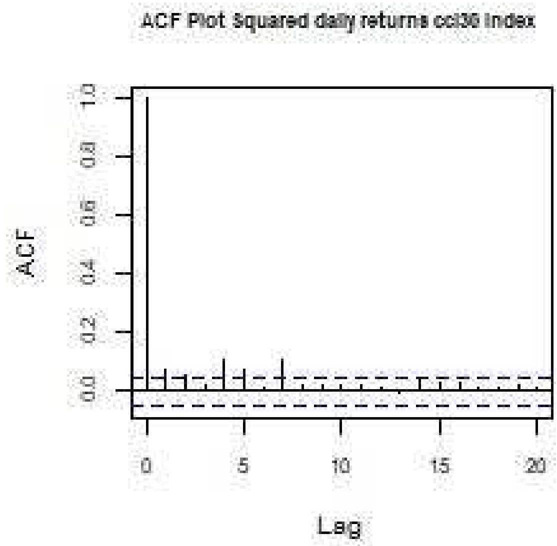


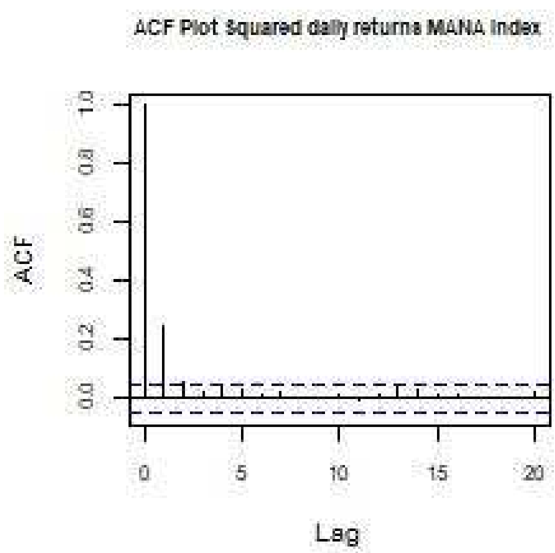


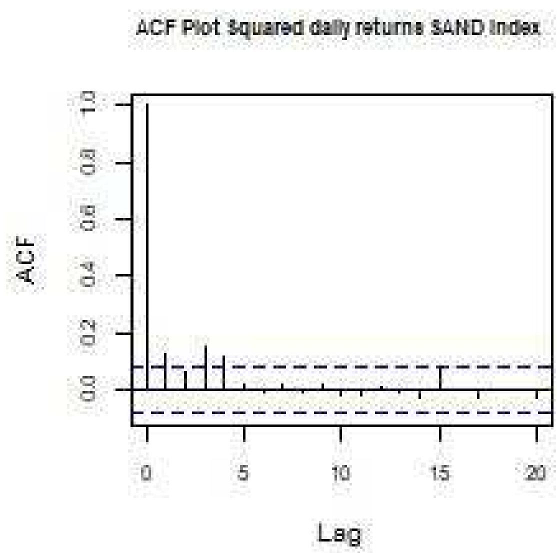

PACF Plot daily returns S.P.500 index
PACF Plot daily returns cci30 index
PACF Plot daily returns MANA index
PACF Plot daily returns SAND index
Partial ACF
Lag

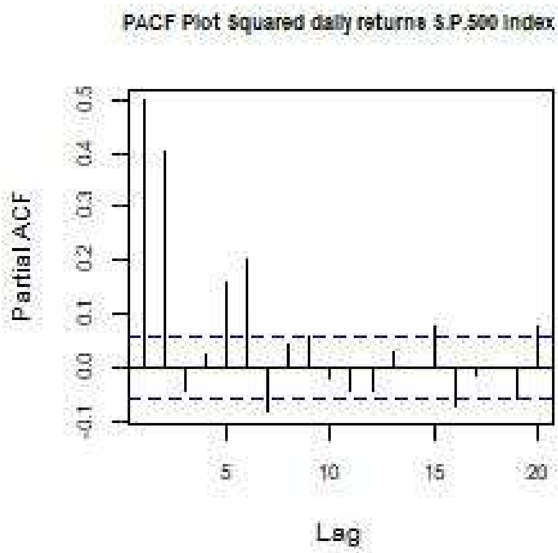
Annexure 4: ACF and PACF plots of squared log return series

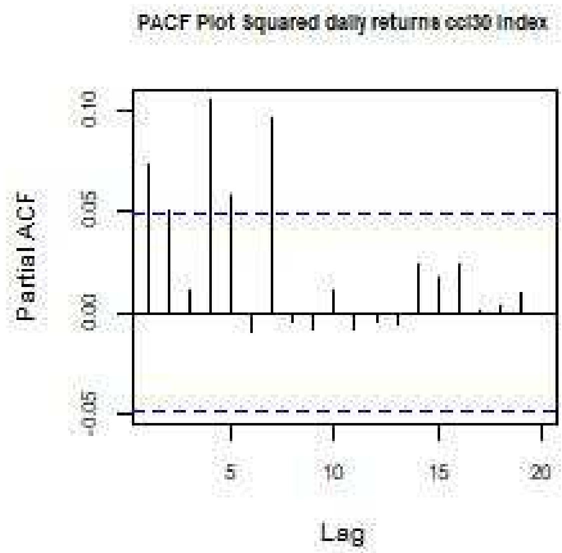


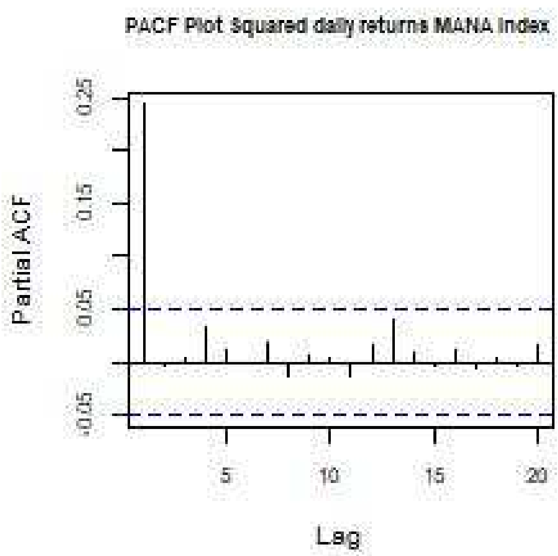


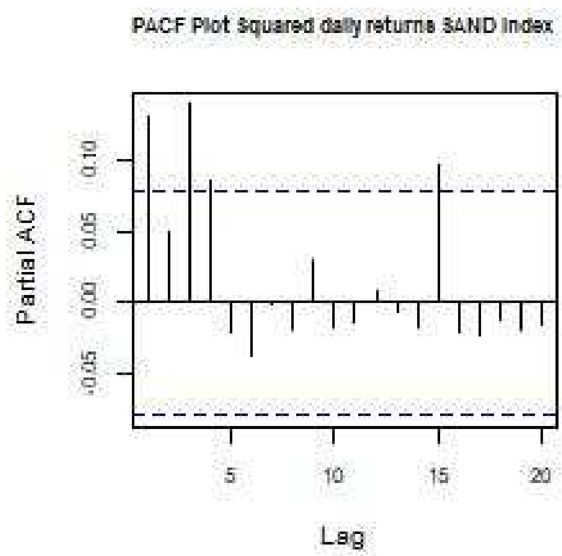




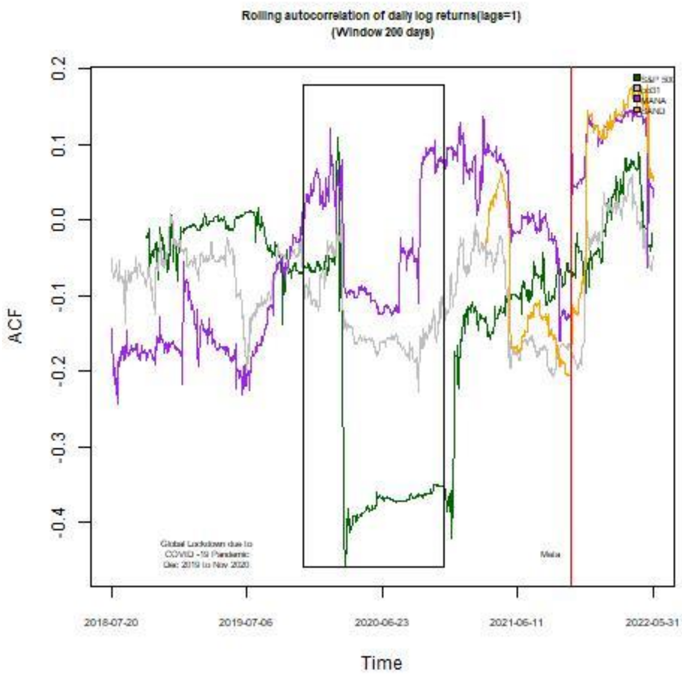

PACF Plot Squared daily returns S.P.500 Index
Partial ACF
-0.1
0.0
0.1
0.2
0.3
0.4
0.5
5
10
15
20
Lag

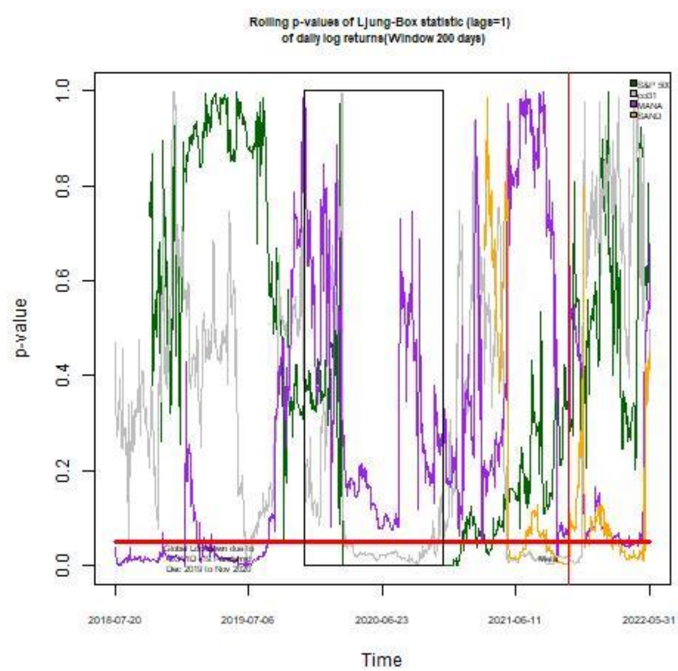

PACF Plot Squared daily returns cci30 Index
Partial ACF
-0.05
0.00
0.05
0.10
5
10
15
20
Lag


PACF Plot Squared daily returns MANA Index
Partial ACF
-0.05
0.05
0.15
0.25
5
10
15
20
Lag

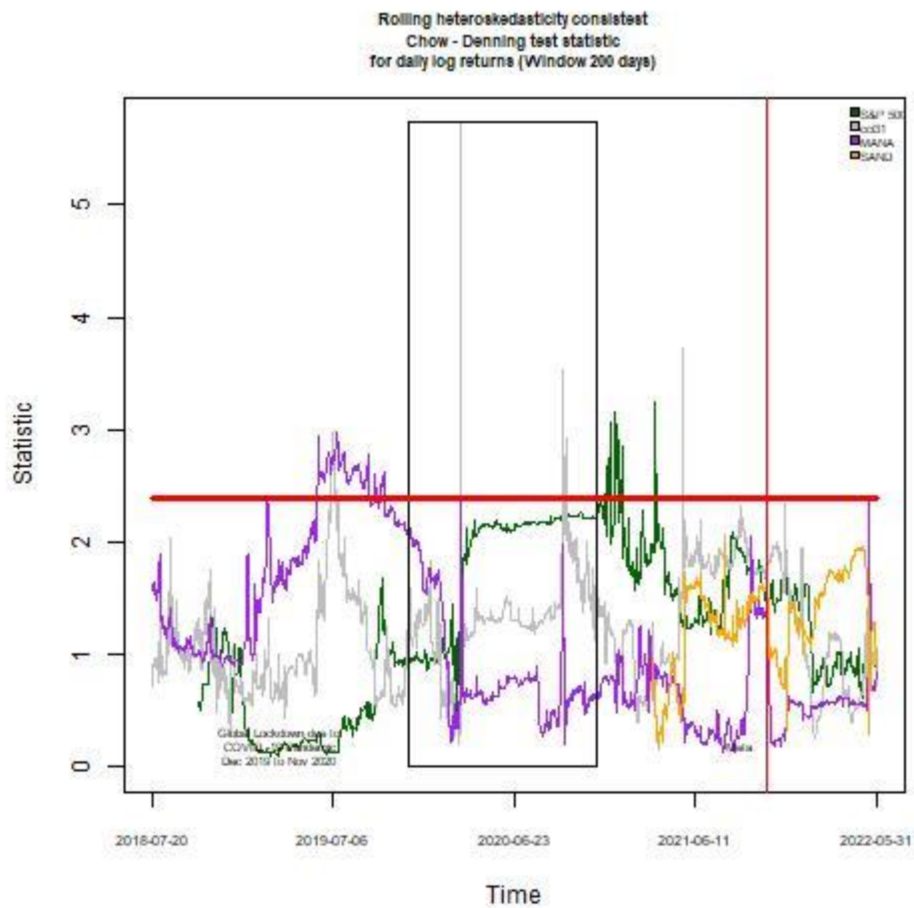

PACF Plot Squared daily returns SAND Index
Partial ACF
-0.05
0.00
0.05
0.10
5
10
15
20
Lag

Annexure 5: Rolling Autocorrelations (lag =1) and Ljung Box tests for daily log returns (Window 200 days)

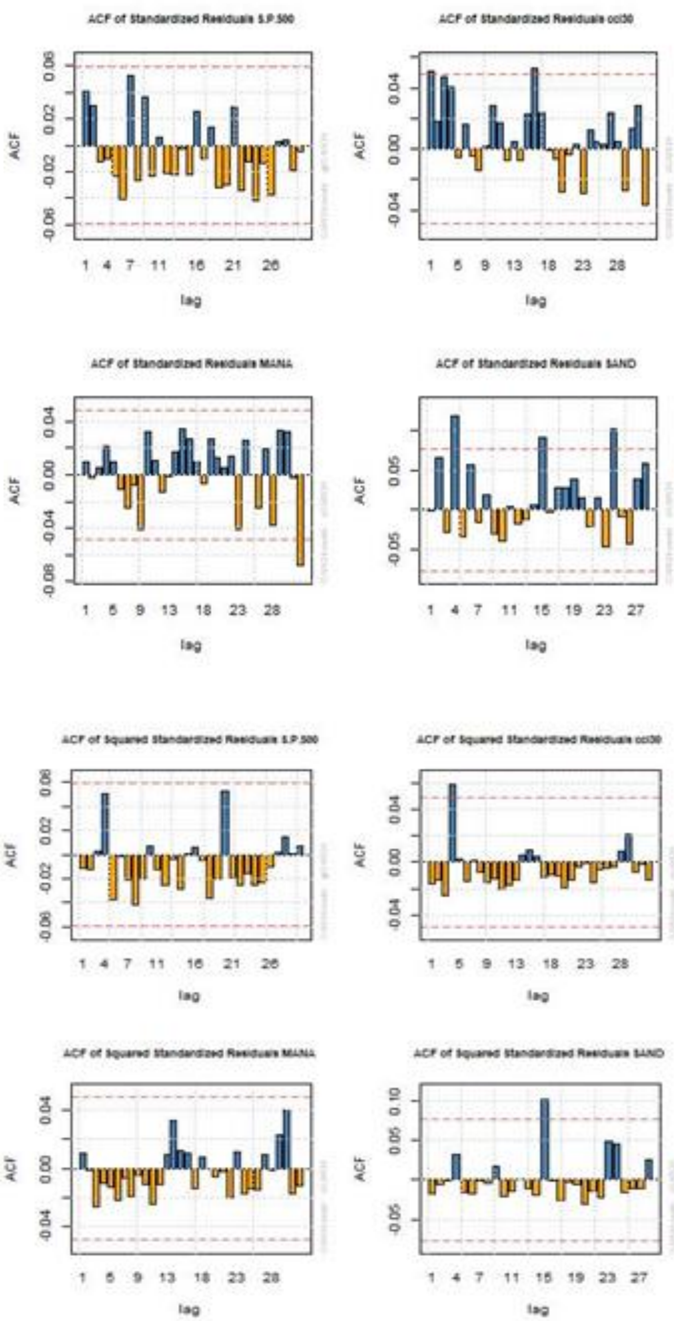




Annexure 6: Rolling Chow - Denning test for daily log returns (Window 200 days)



Annexure 7: ACF plots of standardized and squared standardized residuals



Annexure 8: Q-Q plots of standardized residuals