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Linkage of Non-Fungible (NFT) Tokens to Measures of Uncertainty: Does Fear Bode Well for NFT Holders?

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ABSTRACT: The study investigates the relationship between the returns of Non-Fungible Tokens (NFT) and its categories; and fear indices during times of crisis. The fear indices considered are Global Fear Index (GFI), Global Economic Policy Uncertainty Index (GEPU), Twitter based Economic Uncertainty Index (TEU), Global Consumer Confidence Index (CCI), Infectious Diseases Equity Market Volatility Index (IDEMV) and Crypto Volatility Index (CVI). Employing Granger Causality Test, Autoregressive Distributed Lag technique and ARDL Bounds test on data for the period starting 1st February 2020 and ending 28th February 2022, it is found that short run association exists between TEU, CVI and NFT returns. Further, GFI leads NFT Art returns while TEU leads NFT Metaverse returns by lag 5 and lag 2 respectively. No association between fear metrics and NFT Collectible, NFT Game and NFT utility is observed. No long run association in found between NFT returns and fear indices except TEU which influences NFT returns. It is concluded that NFT, NFT Art and NFT Metaverse returns have positive association to at least one fear index during times of turmoil, especially for the short run.

KEYWORDS: NFT, NFT categories, fear metrics, crisis period, returns, causality, short run association, long run association

I. BACKGROUND

The cyclical nature of diseases and the occurrence of health crisis has been studied by medical researchers since decades. On 8 May, 2020, Norwegian Minister of Health and Care Services, M. Bent Hoie, made a public assertion to their national newspaper, VG, stating that the world would be hit by a pandemic every 10 years (Amundsen, 2020). Although there was no substantial research backing his claim at the time, the statement cannot be disregarded completely. World Health Organisation (WHO) Online Archive for Epidemics lists 20 events, the most prominent of them being SARS (2003), Ebola Virus (2016), Zika Virus (2019) and Novel Coronavirus (2019-present) (WHO, Archived outbreaks). Nassim Taleb, Professor of Risk Management at NYU, Stern and author of “The Black Swan”, in an interview with Bloomberg stated that Pandemics are not Black Swan events (timesnownews, 2021).They are in fact White Swan events. His rationale was that the impact of these unfortunate medical occurrences can be measured accurately and forecasted clearly versus a Black swan event which occurs suddenly, is highly unlikely to occur again and comes with severe impact. He also stated that with pandemics and health crisis, it is not a question of “if” but “when”. There is complete certainty that the event will repeat itself again in the future (timesnownews, 2021).

Such events impact financial markets by increasing volatility and negatively impacting investor returns. Within the first four months of Covid-19, the BSE Sensex dropped from 42273 points to 29894 points. The P/E ratio of the Sensex fell to an all-time low of 17.81. The US S&P 500 took a hit of 20% in just six trading days post February 19th, 2020. The volatility was an effect of an increase in general market fear due to Covid-19 pandemic. Investors were terrified of the impact of the virus on health and livelihood of people. Increasing infections and mortality rates pose great danger to the lives of people as does the increased rates of spreading of infection. The Covid-19 pandemic is an excellent example of how a widespread crisis gives rise to fear sentiments due to uncertainty and how that general market fear can lead to market volatility and can further erode investors wealth. There has been much speculation and research about how financial markets and different asset classes respond to such information with negative connotation, how the volatility spikes can be managed to mitigate losses and protect asset value during times of crisis. It is seen that whenever investors witness uncertain times, the factors causing which are uncontrollable and not completely understood, fear rises leading people to look for safe heaven investments. Fear actually impacts investor decisions. Investors panic as traditional asset classes become volatile and start giving lower or negative returns. It leads investors to look out for different investment avenues which provide positive returns, where their investment will not lose its value overnight or in a matter of days and will remain protected against all market uncertainty. When it further becomes clear that events such as Covid-19 are cyclical, that it is only a matter of time before another event of similar magnitude strikes and that the uncertainty and crisis period is not a onetime event, it becomes even more necessary to look for investment avenues that can provide sufficient hedging benefits to a portfolio and insulation to an investor's rate of returns. Traditional investment avenues such as Gold (Baur & Lucey, 2010), Crude Oil (Liu, Naeem, Rehman, Farid, & Shazad, 2020), Foreign Exchange (Grisse & Nitschka, 2015) and Cryptocurrency (Urquhart & Zhang, 2019) have been considered safe options during turbulent times. Although, no clear definition exists of a Safe-Haven investment, it is generally considered that an asset which has no correlation to other assets or moves in the opposite direction to other assets will provide the benefit of hedging losses and act as a safe-haven investment (Bouri, Shahzad, Roubaud, Kristoufek, & Lucey, 2020). A safe heaven investment can also provide higher returns than other asset classes during times of turmoil. However, during Covid-19, Gold, Crude Oil and Cryptocurrency did not exhibit the characteristics of a safe haven investment, at least in the short run (Disli, Nagayev, Salim, Rizkiah, & Aysan, 2021). In fact, Bitcoin, the most traded cryptocurrency does not even qualify to be a safe haven investment avenue (L.A.Smales, 2019). Even Forex rates of EUR-USD, the most liquid currency pair failed to provide diversification benefits (Ji, Zhang, & Zhao, 2020). Therefore, these exists a striking need to re-evaluate the investment options and find avenues that can protect investor returns during uncertain times. In fact, safe-haven investments can change over periods of time and gain or lose their safe haven characteristics (Hasan, Hassan, Rashid, & Alhenawi, 2021).

One such notable category of investments emerged during early 2021 called Non-Fungible Tokens. Popularly known as NFTs, these tokens represent a unique underlying digital asset and give ownership rights to the holder. It gained traction very fast as every token is non- replicable which means everyone can open and view it on the internet but ownership remains with one person- the true NFT holder. NFTs are protected by the blockchain on which they are registered and can be traded by using the cryptocurrency Ethereum. Initially, NFTs were being made by artists and musicians who created tokens out of digital art, cartoons, audio files and snippets. Today, NFTs have expanded their ambit. There are NFTs available for art, music, game characters, sports items such as swords, rockets, shoes etc., selfies, movie posters and fashion items such as an exclusive couture dress. The valuation of NFTs have skyrocketed to billions of dollars as they provide a sense of rarity and exclusivity to the holder. For example, an art piece curated by Beeple was auctioned for 69 billion dollars while the original tweet by twitter CEO was sold by an NFT trade of 2.9 million. Even a cat meme, known as the Nyan Cat meme was auctioned off by its creator Chris for 0.6 million dollars. While there has been an ongoing debate about the valuation metrics of NFTs which serve no real utility to the holder and generally can be attributed to the nature of a Collectible item, some NFTs do provide actual utility and functionality to the holder. These include NFTs of domain names, web pages, internet protocols and decentralised finance systems. One of the most popular NFTs is Metaverse which allows users to own, hold and trade in virtual land in virtual cities and ecosystems. Accordingly, (Nadini, et al., 2021) categorises NFTs into collectible, metaverse, game, art, utility and others. Collectibles are items owned for its uniqueness while serving minimum utilitarian purpose. Metaverse is virtual land owned by the user in many spaces such as social media, e-commerce websites or virtual gaming ecosystems. Games and Sports items accrue high levels of utility on a subjective basis and only within their arena or universe in which they can be used. Lastly, Art represents digital art which is converted into a smart contract using NFT tokens. While investment in any asset depends on the investor's perception of value, the drivers of NFT value are multiple such as the size of the community, ownership history, age of the NFT, rarity and uniqueness quotient, third party ratings etc.

The emergence of NFTs and their sharp rise in value during the same time as Covid-19 might have been a co-incidence at best. However, the property of NFTs to stand strong during times of turmoil cannot be ruled out, especially due to its steep accruing values over time. NFTs are nascent market with pricing inefficiency but rapid growth in value (a.Dowling, 2022).NFTs have shown steady rise in prices since their inception. NFT sales rose from approximately USD 95 million in 2020 to USD 2.5 billion in first two quarters of 2021(Howcroft, 2021). Owing to their prominent and rapid development, they have been identified as a distinct, separate and new evolving asset class with low spill over between the categories (Dowling, 2022).They also show no connectedness to traditional asset classes such as equity, foreign exchange, crude oil, Gold, Bonds and Ethereum due to which they can act as diversifiers during times of turmoil (Aharon & Demir, 2021). Apart from that, there are additional benefits of trading in NFT such as royalty payments to the creator and the ability to trade in fractions.

II. THEORETICAL MODEL FOR ESTIMATION OF FEAR

Knowing the benefits of NFT and its potential to emerge as a new asset class, it is important to analyse the impact of fear on NFT returns during crisis periods. Negligible impact of fear metrics on NFT can lead to the opening up of a new safe heaven investment avenue during future times of dynamicity. As stated earlier, fear is an important factor to assess financial markets as such pandemic related fear can affect investor's decisions, instrument performance and returns significantly ((a)Salisu, Akanni, &

Ibrahim, 2020). To estimate the impact of fear of Covid 19 on equity markets, a model has been developed by (Salisu & Akanni, 2020) known as the Global Fear Index. The Global Fear Index is an Index built to capture market fear due to Covid. It represents the increased fear in people after the Covid-19 pandemic stroke in 2020, thereby mirroring human emotions arising out of the crisis situation witnessed by them. As such, the Global Fear Index has been developed to be a composite index. It consists of two main components or subparts- namely the Reported Cases Index and the Reported Death Index. Both components are given equal weights in the Index. The first subpart RCI or Reported Cases Index is calculated by dividing the total number of cases reported globally at a particular date by the sum of total number of reported cases on that date and total number of reported cases at the beginning of the period which is 14 days preceding to the date under consideration. The researchers have introduced 14 days as standard timeframe for every cross section since the WHO recommended incubation period for Covid-19 is 14 days. The resultant value is multiplied by 100 to arrive at the RCI value. The second subpart RDI or Reported Death Index is also calculated in a similar manner to the RCI. The total number of Covid-19 deaths reported globally on a particular date is divided by the sum of the total number of Covid-19 deaths on that date and the total number of covid 19 deaths 14 days preceding that date. The indices show the people's fear arising out of reported cases or reported deaths. In other words, RCI and RDI indices indicate by how much the expectation of people regarding number of cases or deaths in the incubation period deviated from the current day numbers. Once the components have been arrived at, the composite GFI is calculated by assigning each index equal weightage and adding them up. The GFI so constructed returns an index value between 0 to 100, 100 being the highest or extreme fear and 0 being the lowest or no fear. The aggregated Global Fear Index can ideally be used in several areas of economic, strategic and financial policy research. The model has been tested on OECD as well as BRICS nations data of stock market returns to validate the accuracy of the model. After its introduction, the GFI has been used in multiple papers to draw a parallel between Covid Fear and Stock market returns in various countries. ((a)Salisu, Akanni, & Ibrahim, 2020), (Sadiq, Hsu, Zhang, & Chien, 2021).

The GFI Model is as follows:

1. GFI = 0.5(RCI+RDI)
2. RCI= Sum of Total number of reported covid cases at time n / {Sum of (Total number of reported covid cases at time n + Total number of reported covid cases 14 days preceding time n) X 100
3. RDI = Sum of Total number of reported covid deaths at time n / {Sum of (Total number of reported covid deaths at time n + Total number of reported covid deaths 14 days preceding time n) X 100 *(Salisu & Akanni, 2020)*

Although the Model is a good indicator of investor fear during Covid, however it includes only two aspects related to the number of cases and number of deaths. Human fear can originate from a number of variables during uncertain times. Containment measures such as lockdowns severely impact livelihoods and earnings of households which in turn impacts savings, investments and liquidity in the markets. The global economic situation worsens as inflation rises, proportion of government spending towards healthcare increases and financial institutions witness withdrawals as people struggle to make ends meet. Further, conversations on social media regarding the impending economic uncertainty and deaths heighten investor anxiousness and negatively impact markets. While case statistics is one of the indicators of fear or volatile environment, a rise in the economic uncertainty, negative social media sentiments, decreasing consumer confidence and spike in financial market volatility indices can lead to heightened sense of a rapidly changing, unprecedented and uncertain environment which can lead to an increase in investor fear and a changed in the perceived notion of value from investments. What felt safe before may not feel safe anymore in light of fear metrics. Thus, it is important to weigh in all aspects of uncertainty and their impacts on financial returns to make informed choices. Such choices are related to the diversification of portfolio and choosing of certain assets for investment, one of which remains NFT as NFT absorb the shock and remain stable during dynamic conditions. It's patterns remain disassociated even with Ethereum, indicating a separate asset class capable of providing diversification benefits during uncertain times (Aharon & Demir, 2021).In furtherance of the research, this paper studies the impact of fear and uncertainty during dynamic times on the returns generated by NFT. The fear metrics used for the purpose are Global Fear Index, Economic Policy Uncertainty Index, Twitter Based Uncertainty Index, Global Consumer Confidence Index, Infectious Diseases Equity Market Volatility index and Crypto Volatility Index.

The Global Economic Policy Uncertainty Index exhibits the economic policy uncertainty in 21 countries which together constitute 71% of global GDP and 80% of exchange rates approximately. It is developed by following a weighted average method of the individual Economic policy index of each country and thereafter normalising the index using regression methods ((a)Baker, Bloom, & Davis, 2016). The Twitter Based Uncertainty Index indicates the overall social media sentiment of users regarding economic uncertainty. It is derived from the daily tweets mined from 2011 onwards containing the words related to economy such as economical, economics, economies, economists etc. as well as words related to uncertainty such as uncertain, uncertainly etc. The Index was developed by Steve Davis, Nicholas Bloom, Scott R. Baker and Thomas Renault from University of

Chicago, Stanford University, North-western University and University of Paris respectively ((a) Baker, Bloom, Davis, & Renault, 2021). The Global Consumer Confidence Index is an economic indicator developed by the Conference Board. It accounts for the responses of over thirty thousand consumers every quarter to a survey conducted by the board. The survey spans across Asia, America, Africa, Europe and the Middle East, making it a global indicator of consumer confidence (The Conference Board, 2022). The Infectious Diseases Equity Market Volatility Tracker (Index) is a text-based Index which tracks Equity Market Volatility during health crisis periods. The tracker notably tracks four types of text sets which include Economic text, Stock Market based text with major emphasis on indices developed by S&P, Volatility and disease identification such as SARS, Covid etc. The resulting index is scaled and rescaled and ultimately matched to VIX values to arrive at the final index. The methodology to formulate the index is given by (Baker, et al., 2020). The Crypto Volatility Index, popularly known as CIV is an Index that tracks volatility in cryptocurrency prices. It is similar to VIX except that it is decentralised in nature. The CIV index is formulated to allow investors to hedge against losses and impairment of investments in the cryptocurrency market (CVI, 2021). All the considered indices indicate fear arising out of different factors such as cases and deaths, economic policies, social media, equity market volatility, cryptocurrency market volatility and consumer confidence.

III. PURPOSE OF STUDY

The paper studies the interconnectedness of NFT returns to measures of uncertainty. The underlying rationale of this study is that close and positive association between NFT returns and fear measures would indicate that NFTs provide higher returns when market fear rises. As such, it would be wise for investors to adopt NFT as a hedging tool in dynamic times if the relationship proves to be true. It will also enable them to choose a suitable and appropriate NFT category to invest in amongst those available. Such an analysis will enable investors to brace against value loss or loss of investment returns during times of future crisis.

IV. RESEARCH- DESIGN

A. *Objectives of study*

- To ascertain whether the chosen fear metrics impact NFT returns or not.
- To analyse the impact of fear metrics on NFT and its categories in the short run.
- To understand the effect of fear metrics on NFT and its categories in the long-run.
- To suggest on the suitability of NFT and its categories as a hedging tool during uncertain times.

B. *Variables of study*

There are six independent variables considered for this study. They are Global Fear Index (GFI), Global Economic Policy Uncertainty Index (GEPU), Twitter based Economic Uncertainty Index (TEU), Global
Consumer Confidence Index (CCI), Infectious Diseases Equity Market Volatility Index (IDEMV) and Crypto Volatility Index (CVI). The dependent variable is NFT returns. Further, for category wise analysis, the dependent variables considered in place of NFT returns are returns of NFT Art, NFT Collectible, NFT Game, NFT Metaverse and NFT Utility.

C. *Time period and Scope of study*

The period for which historical data of all variables has been collected is from 1st February 2020 to 28th February 2022 i.e. a period of two years. The scope of the study is Global in nature. All indices selected for the study are Global indices and not country specific indices. However, the scope of independent variables is limited to the study of the impact of four macroeconomic indices (GFI, GEPU, TEU, CCI) and two financial indices (IDEMV, CVI). The scope of dependent variables is limited to five NFT categories and overall NFT returns. Other independent variables, macroeconomic factors, fear metrices and NFT projects evade the scope of this study.

D. *Sources of Data collection*

Table 1: Data Collection sources

SL NO.	*VARIABLE NAME*	*DATA SOURCE*	*DATA FREQUENCY*
1	*GFI*	*WHO Covid-19 Global Data*	*Daily*
2	*GEPU*	*Policyuncertainity.com*	*Monthly*
3	*TEU*	*Policyuncertainity.com*	*Daily*
4	*CCI*	*Statista.com*	*Quarterly*

5	*IDEMV*	*Policyuncertainity.com*	*Daily*
6	*CVI*	*www.investing.com*	*Daily*
7	*NFT*	*Nonfungible.com*	*Daily*
8	*NFT Collectible*	*Nonfungible.com*	*Daily*
9	*NFT Art*	*Nonfungible.com*	*Daily*
10	*NFT Game*	*Nonfungible.com*	*Daily*
11	*NFT Metaverse*	*Nonfungible.com*	*Daily*
12	*NFT Utility*	*Nonfungible.com*	*Daily*

**All data has been converted to Daily time frequency for analysis.*

V. RESEARCH METHODOLOGY AND HYPOTHESIS

A. Research Tools

The statistical software used for data analysis is E-Views 12 Student Version. All collected data is cleaned and further converted to daily data. A total of 759 observations were obtained.

The statistical tests employed are as follows.

Table 2: Tools for analysis

SL NO.	PURPOSE	TEST
1	Stationarity of Time series	Augmented Dickey Fuller Unit Root Test
2	Causality between independent and dependent variables	Pair-wise Granger Causality Test
3	Short Run relationship between independent and dependent variable	Autoregressive distributed lag model-ARDL
4	Long Run Relationship between independent and dependent variable	ARDL Bounds Test
5	Residual Diagnostics- Serial correlation	Breusch-Godfrey Serial Correlation LM Test
6	Residual Diagnostics- Heteroskedasticity	Breusch-Pagan-Godfrey Heteroskedasticity Test
7	Stability Diagnostics – Specification appropriateness	Ramsey RESET Test
8	Stability Diagnostics- Model structural stability	CUSUM Test

B. Hypothesis

Hypothesis 1

H0: There is a Unit Root in the series. (Series is non-Stationary)

H1: There is no Unit Root in the series (Series is Stationary)

Hypothesis 2

H0: GFI /GEPU/ TEU/ IDEMV/CVI does not Granger Cause NFT (NFT Art, NFT Collectible, NFT game, NFT Utility, NFT Metaverse)

H1: GFI /GEPU/ TEU/ IDEMV/CVI does Granger Cause NFT (NFT Art, NFT Collectible, NFT game, NFT Utility, NFT Metaverse)

Hypothesis 3

H0: There is no relationship between Fear indices and NFT returns in the short run.

H1(a): There exists a positive relationship between fear indices GFI /GEPU/ TEU/ IDEMV/CVI and NFT returns NFT (NFT Art, NFT Collectible, NFT game, NFT Utility, NFT Metaverse) in the short run.

H1(b): There exists a negative relationship between fear indices GFI /GEPU/ TEU/ IDEMV/CVI and NFT returns NFT (NFT Art, NFT Collectible, NFT game, NFT Utility, NFT Metaverse) in the short run.

Hypothesis 4

H0: There is no relationship between Fear indices and NFT returns in the long run.

H1 (a): There exists a positive relationship between fear indices GFI /GEPU/ TEU/ IDEMV/CVI and NFT returns NFT (NFT Art, NFT Collectible, NFT game, NFT Utility, NFT Metaverse) in the long run.

H1 (b): There exists a negative relationship between fear indices GFI /GEPU/ TEU/ IDEMV/CVI and NFT returns NFT (NFT Art, NFT Collectible, NFT game, NFT Utility, NFT Metaverse) in the long run.

Hypothesis 5

H0: Residual has no serial correlation.

H1: Residual has serial correlation

Hypothesis 6

H0: Residual is homoscedastic.

H1: Residual is heteroskedastic.

Hypothesis 7

H0: t=0/ Model is well specified and does not have omitted variables.

H1: t≠0/ Model is not well specified and has omitted variables.

Hypothesis 8

H0: Model of interest is stable.

H1: Model of interest is not stable.

VI. ANALYSIS AND INTERPRETATION

A. Augmented Dickey Fuller Unit Root Test

The unit root test is used to identify stationarity in the time series. If absolute value of Dickey Fuller t-statistic is higher than critical values, then we reject the null hypothesis. If absolute value of Dickey Fuller t-statistic is not higher than critical values, then we fail to reject the null. Further, if prob value is < 0.05 at 5% significance level, we reject the null hypothesis.

Table 3: Summary of ADF Test statistic

Augmented Dickey-Fuller test statistic							
Variables	*At level*		*at 1st Difference*		*at 2nd Difference*		*Test critical values*
	t-statistic	*p-value*	*t-statistic*	*p-value*	*t-statistic*	*p-value*	*5% level*
GFI	-2.731556	0.0692	-6.141663	0.0000	-2.242933	0.3416	-2.865235
GEPU	-1.967558	0.3014	-4.198454	0.0007	-1.534730	0.2518	-2.865163
TEU	-2.083367	0.2516	-9.537278	0.0000	-1.986973	0.1532	-2.865193
CCI	-1.604607	0.4797	-2.067600	0.2581	-1.368590	0.1256	-2.865178
IDEMV	-3.272054	0.0166	-8.216335	0.0000	-2.398972	0.4987	-2.865219
CVI	-3.721839	0.0040	-8.646981	0.0000	-1.466987	0.3476	-2.865173
NFT	-16.99886	0.0000	-10.63487	0.0000	-2.715681	0.3271	-2.865240
NFT Collectible	-23.53861	0.0000	-10.51883	0.0000	-2.823718	0.2245	-2.865143
NFT Art	-24.83725	0.0000	-13.04812	0.0000	-2.349873	0.1547	-2.865143
NFT Game	-14.11346	0.0000	-11.89656	0.0000	-1.289765	0.4598	-2.865148
NFT Metaverse	-4.967803	0.0000	-11.31926	0.0000	-2.707654	0.2765	-2.865230
NFT Utility	-29.09965	0.0000	-13.14604	0.0000	-1.765998	0.5431	-2.865138

Table 3 shows that the ADF test has been applied using Akaike Info Criterion with Max lag length as 19 to all variables under study. Lag length can be taken up to 20 lags for daily data. The absolute value of Dickey-Fuller t statistic at level is lower than critical values at 5% significance level for GFI, GEPU, TEU and CCI. The corresponding p-values for GFU, GEPU, TEU and CCI at level are greater than 0.05. Therefore, we fail to reject the null hypothesis. GFI, GEPU, TEU and CCI have a unit root. They are non-stationary series at level. IDEMV, CVI, NFT and all NFT categories have an absolute value of t-statistic greater than absolute critical values at 5% level. The corresponding p-values are lower than 0.05. This indicates that IDEMV, CVI, NFT and NFT categories are stationary at level. Consequently, we reject null hypothesis for the above-mentioned variables. When converted to first difference, all variables exhibit an absolute value of t-statistic greater than absolute critical value at 5% level except CCI. The corresponding p-values of all variables at first difference are less than 0.05 except CCI. This indicates that all variables are stationary at First difference and integrated to first order I(1) except CCI. CCI has unit root at first difference. When converted to second difference, all variables exhibit an absolute value of t-statistic lower than absolute critical value at 5% level. The corresponding p-values of all variables at second difference are higher than 0.05. This indicates that all variables are non-stationary at Second difference and exhibit unit root.Overall, Augmented Dickey Fuller Unit root test indicates that all series under study, both dependent and independent, are either integrated to order I(0) or integrated to first order I(1) but none are integrated to second order I(2) with the exception of the independent variable CCI which is not integrated to I(0), I(1) or I(2). Therefore, CCI has been dropped from the study going further as it fails to satisfy the condition of stationarity of time series data at level or first order. Once stationarity has been determined, we can proceed to check causality between the independent and dependent variables.

B. Granger Causality Test

Granger Causality test indicates causality or cause effect relationships between the variables under study. It is used to indicate whether we can predict the values of one series using the lagged values of the other series. If the relationship holds true, it shows a cause-and-effect relationship between the two series. Granger Causality assumes Stationarity. Since all series of independent variables (GFI, GEPU, TEU, IDEMV, CVI) except CCI and dependent variables (NFT, NFT Art, NFT Collectible, NFT Game, NFT Metaverse, NFT Utility) are stationary at I(1), we can proceed with Granger Causality Test. The null hypothesis is rejected if prob value < 0.05.

Granger Causality for dependent variable NFT

Table 4 shows that in all cases, the prob value is higher than 0.05 except TEU and CVI as independent variables. Thus, we fail to reject the null hypothesis of no causation for all other independent variables. This means that GFI, GEPU and IDEMV does not granger cause NFT since the p-values are higher than 0.05. However, the p-values of TEU and CVI are lower than 0.05. Thus, we reject the null hypothesis and conclude that TEU and CVI does Granger cause NFT returns but the opposite is not true. It is a unidirectional relationship.

Table 4: E-views Results of Granger Causality between Fear metrics and NFT

Pairwise Granger Causality Tests
Date: 04/16/22 Time: 14:24
Sample: 2/01/2020 2/28/2022
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
D(GFI) does not Granger Cause D(NFT)	756	0.39873	0.6713
D(NFT) does not Granger Cause D(GFI)		0.08722	0.9165
D(GEPU) does not Granger Cause D(NFT)	751	0.47385	0.6228
D(NFT) does not Granger Cause D(GEPU)		1.19811	0.3023
D(TEU) does not Granger Cause D(NFT)	756	3.66662	0.0260
D(NFT) does not Granger Cause D(TEU)		0.50295	0.6050
D(IDEMV) does not Granger Cause D(NFT)	756	1.75644	0.1734
D(NFT) does not Granger Cause D(IDEMV)		1.82174	0.1625
D(CVI) does not Granger Cause D(NFT)	756	5.14114	0.0061
D(NFT) does not Granger Cause D(CVI)		0.22183	0.8011

Granger Causality for dependent variable NFT Art

Table 5: E-views Results of Granger Causality between Fear metrics and NFT Art

Pairwise Granger Causality Tests
Date: 04/16/22 Time: 14:39
Sample: 2/01/2020 2/28/2022
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
D(GFI) does not Granger Cause D(NFT_ART)	756	2.80134	0.0314
D(NFT_ART) does not Granger Cause D(GFI)		2.29575	0.1014
D(GEPU) does not Granger Cause D(NFT_ART)	751	0.04428	0.9567
D(NFT_ART) does not Granger Cause D(GEPU)		0.04624	0.9548
D(TEU) does not Granger Cause D(NFT_ART)	756	0.54341	0.5810
D(NFT_ART) does not Granger Cause D(TEU)		0.38212	0.6825
D(IDEMV) does not Granger Cause D(NFT_ART)	756	0.26649	0.7661
D(NFT_ART) does not Granger Cause D(IDEMV)		0.80488	0.4475
D(CVI) does not Granger Cause D(NFT_ART)	756	2.14606	0.1177
D(NFT_ART) does not Granger Cause D(CVI)		0.01584	0.9843

As seen in Table 5, the prob value is higher than 0.05 for independent variables GEPU, TEU, IDEMV, CVI while it is lower than 0.05 for independent variable GFI. Thus, we fail to reject the null hypothesis of no causation. It is concluded that GEPU, TEU, IDEMV, CVI does not granger cause NFT Art since the p-values are higher than 0.05. However, the p-values of GFI is lower than 0.05. Thus, we reject the null hypothesis and conclude that GFI does Granger cause NFT Art returns. However, NFT Art does not Granger cause GFI as prob value is greater than 0.05. So, there is a unidirectional relationship between GFI and NFT Art returns.

Granger Causality for dependent variable NFT Collectible

As shown in Table 6, in all cases, the prob value is higher than 0.05. Thus, we fail to reject the null hypothesis of no causation for all independent variables. It is concluded that GFI, GEPU, TEU, IDEMV, CVI does not granger cause NFT Collectible since the p-values are higher than 0.05. Similarly, NFT Collectible returns do not granger cause GFI, GEPU, TEU, IDEMV and CVI since the p-values are higher than 0.05.

Table 6: E-views Results of Granger Causality between Fear metrics and NFT Collectible

Pairwise Granger Causality Tests
Date: 04/16/22 Time: 14:46
Sample: 2/01/2020 2/28/2022
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
D(GFI) does not Granger Cause D(NFT_COLLECTIBLE)	756	0.02218	0.9781
D(NFT_COLLECTIBLE) does not Granger Cause D(GFI)		0.16058	0.8517
D(GEPU) does not Granger Cause D(NFT_COLLECTIBLE)	751	0.79556	0.4517
D(NFT_COLLECTIBLE) does not Granger Cause D(GEPU)		0.28964	0.7486
D(TEU) does not Granger Cause D(NFT_COLLECTIBLE)	756	1.90706	0.1492
D(NFT_COLLECTIBLE) does not Granger Cause D(TEU)		1.57858	0.2070
D(IDEMV) does not Granger Cause D(NFT_COLLECTIBLE)	756	1.62736	0.1971
D(NFT_COLLECTIBLE) does not Granger Cause D(IDEMV)		2.40000	0.0914
D(CVI) does not Granger Cause D(NFT_COLLECTIBLE)	756	1.98482	0.1381
D(NFT_COLLECTIBLE) does not Granger Cause D(CVI)		1.59067	0.2045

Granger Causality for dependent variable NFT Game

As shown in Table 7, in all cases, the prob value is higher than 0.05. Thus, we fail to reject the null hypothesis of no causation. It is concluded that the independent variables GFI, GEPU, TEU, IDEMV and CVI does not granger cause NFT Game returns since the p-values are higher than 0.05. Similarly, NFT Game returns do not show causality to any of the independent variables.

Table 7: E-views Results of Granger Causality between Fear metrics and NFT Game

Pairwise Granger Causality Tests
Date: 04/16/22 Time: 14:51
Sample: 2/01/2020 2/28/2022
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
D(GFI) does not Granger Cause D(NFT_GAME)	756	0.07000	0.9324
D(NFT_GAME) does not Granger Cause D(GFI)		0.04755	0.9536
D(GEPU) does not Granger Cause D(NFT_GAME)	751	0.07147	0.9310
D(NFT_GAME) does not Granger Cause D(GEPU)		0.17855	0.8365
D(TEU) does not Granger Cause D(NFT_GAME)	756	0.31444	0.7303
D(NFT_GAME) does not Granger Cause D(TEU)		0.12883	0.8791
D(IDEMV) does not Granger Cause D(NFT_GAME)	756	0.96486	0.3815
D(NFT_GAME) does not Granger Cause D(IDEMV)		0.35580	0.7007
D(CVI) does not Granger Cause D(NFT_GAME)	756	1.04984	0.3505
D(NFT_GAME) does not Granger Cause D(CVI)		0.17009	0.8436

Granger Causality for dependent variable NFT Metaverse

Table 8: E-views Results of Granger Causality between Fear metrics and NFT Metaverse

Pairwise Granger Causality Tests
Date: 04/16/22 Time: 14:56
Sample: 2/01/2020 2/28/2022
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
D(GFI) does not Granger Cause D(NFT_METAVERSE)	756	0.07053	0.9319
D(NFT_METAVERSE) does not Granger Cause D(GFI)		0.25858	0.7722
D(GEPU) does not Granger Cause D(NFT_METAVERSE)	751	0.06679	0.9354
D(NFT_METAVERSE) does not Granger Cause D(GEPU)		1.14064	0.3202
D(TEU) does not Granger Cause D(NFT_METAVERSE)	756	4.11873	0.0166
D(NFT_METAVERSE) does not Granger Cause D(TEU)		1.70902	0.1817
D(IDEMV) does not Granger Cause D(NFT_METAVERSE)	756	0.54460	0.5803
D(NFT_METAVERSE) does not Granger Cause D(IDEMV)		0.90987	0.4030
D(CVI) does not Granger Cause D(NFT_METAVERSE)	756	2.95361	0.0528
D(NFT_METAVERSE) does not Granger Cause D(CVI)		0.91231	0.4020

As shown in Table 8 , in all cases, the prob value is higher than 0.05 except TEU as independent variable. Thus, we fail to reject the null hypothesis of no causation. It is concluded that GFI, GEPU, IDEMV and CVI does not granger cause NFT Metaverse, nor does NFT Metaverse returns Granger cause GFI, GEPU, IDEMV or CVI, since the p-values are higher than 0.05. However, the p-values of TEU is lower than 0.05. Thus, we reject the null hypothesis and conclude that TEU does Granger cause NFT Metaverse returns. However, NFT Metaverse does not Granger cause TEU (p>0.05). Thus it is a unidirectional relationship between TEU and NFT Metaverse returns.

Granger Causality for dependent variable NFT Utility

Table 9: E-views Results of Granger Causality between Fear metrics and NFT Utility

Pairwise Granger Causality Tests
Date: 04/16/22 Time: 14:59
Sample: 2/01/2020 2/28/2022
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
D(GFI) does not Granger Cause D(NFT_UTILITY)	756	0.24415	0.7834
D(NFT_UTILITY) does not Granger Cause D(GFI)		0.41677	0.6593
D(GEPU) does not Granger Cause D(NFT_UTILITY)	751	0.70697	0.4935
D(NFT_UTILITY) does not Granger Cause D(GEPU)		0.05780	0.9438
D(TEU) does not Granger Cause D(NFT_UTILITY)	756	0.55029	0.5770
D(NFT_UTILITY) does not Granger Cause D(TEU)		0.99678	0.3696
D(IDEMV) does not Granger Cause D(NFT_UTILITY)	756	0.53401	0.5865
D(NFT_UTILITY) does not Granger Cause D(IDEMV)		0.48468	0.6161
D(CVI) does not Granger Cause D(NFT_UTILITY)	756	1.22921	0.2931
D(NFT_UTILITY) does not Granger Cause D(CVI)		2.21284	0.1101

As observed in in Table 9, in all cases, the prob value is higher than 0.05. Thus, we fail to reject the null hypothesis of no causation. GFI, GEPU, TEU, IDEMV, CVI does not granger cause NFT Utility since the p-values are higher than 0.05. Neither does NFT Utility returns succeed in predicting GFI, GEPU, TEU, IDEMV and CVI. There is no causal relationship between the variables.Overall, change in TEU and CVI causes a change in NFT returns unidirectionally. Change in GFI causes change in NFT Art returns unidirectionally. Change in TEU causes change in NFT Metaverse Returns unidirectionally. However, fear indices do not cause an effect in the returns of NFT Collectible, NFT Game and NFT Utility returns.

C. Time series modelling for NFT

The ARDL model estimates both short and long run co-integrating relationship between the variables. The ARDL model combines endogenous as well as exogenous variables and is therefore suitable for studies with both dependent and independent variable classifications. The ARDL Model can be carried out if data series are stationary purely at I(0) or purely at I(1), or a mixture of I(0) and I(1). However, the data series must not be stationary at I(2). Based on Unit Root test, the variables are a mixture of I(0) and I(1) and are integrated at level and first difference but not integrated to second order.

Short run estimation for NFT– ARDL MODEL

Table 10: Table depicting ARDL model for NFT

Dependent Variable: NFT1
Method: ARDL
Date: 04/20/22 Time: 18:14
Sample (adjusted): 2/10/2020 2/28/2022
Included observations: 750 after adjustments
Maximum dependent lags: 8 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (8 lags, automatic): TEU1 CVI1
Fixed regressors: C
Number of models evaluated: 648
Selected Model: ARDL(8, 1, 2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
NFT1(-1)	-1.148669	0.036077	-31.83962	0.0000
NFT1(-2)	-1.134933	0.054059	-20.99439	0.0000
NFT1(-3)	-0.995783	0.065563	-15.18811	0.0000
NFT1(-4)	-0.916681	0.070376	-13.02545	0.0000
NFT1(-5)	-0.705225	0.070310	-10.03021	0.0000
NFT1(-6)	-0.494322	0.065437	-7.554159	0.0000
NFT1(-7)	-0.293296	0.053914	-5.440054	0.0000
NFT1(-8)	-0.140560	0.035929	-3.912144	0.0001
TEU1	0.049495	0.000439	-1.130390	0.2587
TEU1(-1)	0.231076	0.000439	-2.454621	0.0143
CVI1	0.001077	0.003892	0.276624	0.7821
CVI1(-1)	0.002333	0.003882	0.600941	0.5481
CVI1(-2)	0.113779	0.003884	-3.548107	0.0004
C	-0.002173	0.017350	-0.125220	0.9004

R-squared	0.784769	Mean dependent var	-0.000933
Adjusted R-squared	0.773611	S.D. dependent var	0.739843
S.E. of regression	0.475109	Akaike info criterion	1.367944
Sum squared resid	166.1360	Schwarz criterion	1.454185
Log likelihood	-498.9789	Hannan-Quinn criter.	1.401174
F-statistic	83.09585	Durbin-Watson stat	1.997893
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

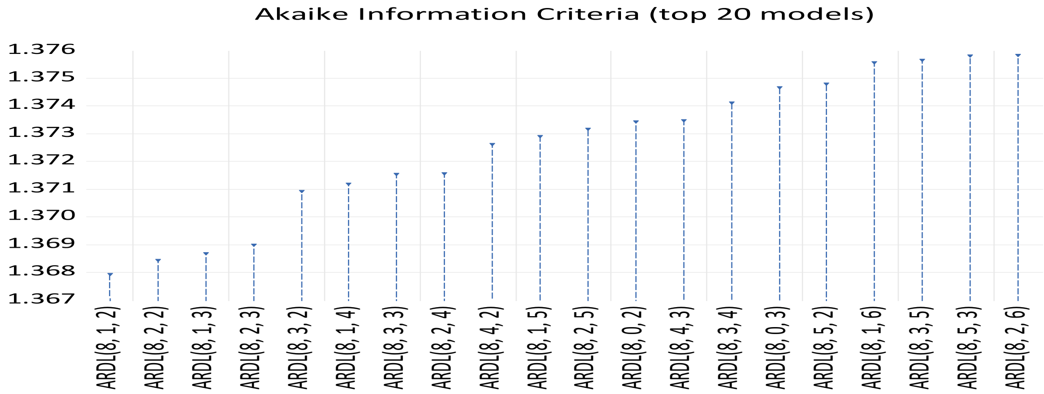

Figure 1: Figure showing best choice for ARDL NFT Model

As observed from Table 10 and Figure 1, The ARDL model stands ARDL (8,1,2) and is the best choice as it is exhibited as the shortest line on the graph. This model has been developed using NFT as dependent variable and TEU and CVI as independent variable. Lag length selection is automatic based on Akaike Info criterion. Intercept is devoid of trend. The model states that NFT returns today is a function of past 8-day NFT returns, TEU values of today and yesterday and CVI value of 2 days prior. For NFT itself, the lagged returns have a negative influence on the current period returns. NFT lag 1 up to lag 8 can influence itself. The same can be verified using prob values of lagged variables. Prob value of NFT returns of all 8 days is less than 0.05 which indicates that lagged 8 days returns is statistically significant is ascertaining NFT returns today. Similarly, Lagged TEU value of 1 day is statistically significant in determining NFT return of today since TEU (-1) prob value is less than 0.05. However, TEU at level is not statistically significant in determining NFT returns at level. CVI (-2) prob value is less than 0.05. Thus 2 days lagged value of CVI is statistically significant to predict NFT returns today. However, CVI at level and CVI lag 1 cannot influence NFT returns of today.The model shows that if TEU (-1) increases by 1%, NFT returns increases by 0.23% in the short-run. Similarly, If CVI (-2) increases by 1%, NFT returns increases by 0.11% in the short-run. There is a positive impact of both independent variables on NFT returns. It also shows that an increase in fear metrics beings about a less than proportional increase in NFT returns. The Adjusted R squared value of 77.36% indicate that the model is a best fit since 77.36% of change in NFT returns can be explained by change in TEU and CVI. The prob (F-Statistic) value of 0.00 is less than 0.05. Thus, the model is statistically significant at 5% level. Durbin Watson value is 1.99, which proves that the model is free from serial correlation (Durbin Watson between 1.5 to 2.5).

Long run estimation for NFT – ARDL BOUNDS TEST

Table 11: Bounds test result for relationship between NFT, TEU and CVI.

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TEU	-0.000230	0.000105	-2.188543	0.0289
CVI	-0.001518	0.000962	-1.578391	0.1149
C	-0.000318	0.002540	-0.125225	0.9004

EC = NFT - (-0.0002*TEU -0.0015*CVI - 0.0003)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	87.50338	10%	2.63	3.35
k	2	5%	3.1	3.87
		2.5%	3.55	4.38
		1%	4.13	5
Actual Sample Size	750		Finite Sample: n=80	
		10%	2.713	3.453
		5%	3.235	4.053
		1%	4.358	5.393

In reference to Table 11, there exists a long-term relationship between the variables if the F-statistic is greater than upper bound at 5% level. There exists no long-term relationship if the F-statistic is lower than lower bound at 5% level. In this case, the F-statistic (87.50) is greater than upper bound at 5% level (3.87). Therefore, a long run relationship exists between at least one of the independent variables under study (TEU and CVI) and NFT returns. The prob value of TEU is less than 0.05 (0.02<0.05) while the prob value of CVI is greater than 0.05 (0.11>0.05). This indicates that TEU is statistically significant variable and has long run relationship to NFT returns. It also implies that the series are related and can be combined in a linear fashion. Even if there are shocks in the short run, which may affect the movement in the individual series, they would converge with time in the long run.

However, CVI does not have a statistically significant relationship to NFT returns in the long run. Further, 1% increase in TEU leads to 0.000230% decrease in NFT returns in the long run. It also implies that the speed of adjustment towards long run equilibrium is 0.02% or system corrects its previous period disequilibrium at a speed of 0.02% within one period of time. This means that during times of turmoil, NFT markets get corrected at a very slow rate in the long run. Thus, disequilibrium is maintained in the markets for a long time, providing opportunities for higher returns.

Residual diagnostics for Modelling

Breusch-Godfrey Serial Correlation LM Test

Table 12: Godfrey Serial Correlation LM test E-views output for NFT Model Residual

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

F-statistic	1.890993	Prob. F(2,734)	0.1517
Obs*R-squared	3.844618	Prob. Chi-Square(2)	0.1463

In reference to Table 12, LM Test proves that the residual obtained from the ARDL model is free from serial correlations if the prob value is higher than 0.05. The observed R squared is 3.844 and the prob value 0.1463. Thus, the ARDL Model is free from serial correlation.

Breusch-Pagan-Godfrey Heteroskedasticity Test

Table 13: Heteroskedasticity test E-views output for NFT Model Residual

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.983230	Prob. F(13,736)	0.4660
Obs*R-squared	12.80278	Prob. Chi-Square(13)	0.4632
Scaled explained SS	87.70525	Prob. Chi-Square(13)	0.0000

In reference to Table 13, The Breusch-Pagan-Godfrey Test proves that the residuals are free from heteroskedasticity if the prob value is higher than 0.05. The observed R squared is 12.802 and prob value is 0.4632. Thus, we fail to reject the null hypothesis of homoskedasticity. The residuals are free from heteroskedasticity.

Stability diagnostics for Modelling

Ramsey RESET Test

Table 14: Ramsey RESET Test Results for NFT Model

Ramsey RESET Test
Equation: UNTITLED
Omitted Variables: Squares of fitted values
Specification: NFT1 NFT1(-1) NFT1(-2) NFT1(-3) NFT1(-4) NFT1(-5) NFT1(-6) NFT1(-7) NFT1(-8) TEU1 TEU1(-1) CVI1 CVI1(-1) CVI1(-2) C

	Value	df	Probability
t-statistic	0.836363	735	0.4032
F-statistic	0.699504	(1, 735)	0.4032
Likelihood ratio	0.713440	1	0.3983

In reference to Table 14, The Ramsey RESET test was used to check the appropriate functional form. The probability value of 0.4032 is greater than 0.05. Thus, the null hypothesis cannot be rejected. It suggests that the model is well specified.

CUSUM Test

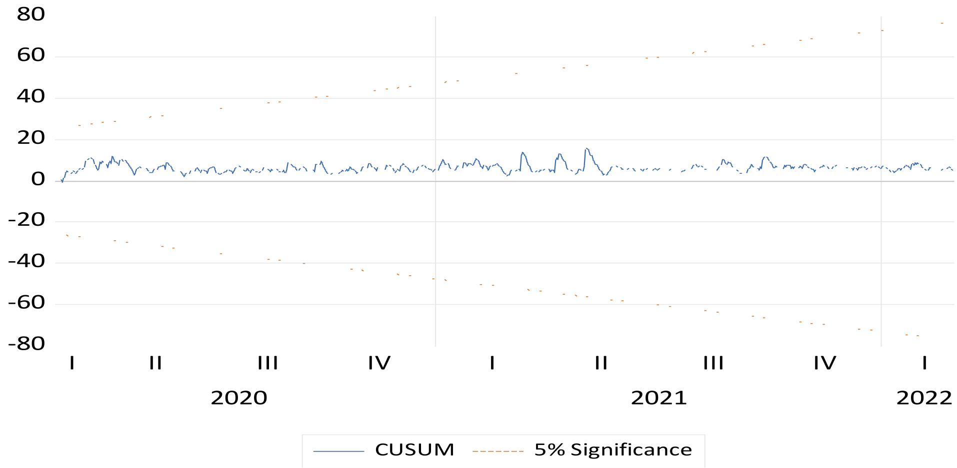

Figure 2: Graph showing CUSUM Test Results for NFT ARDL Model.

As observed in Figure 2, The plot of CUSUM remained between the 5% critical bounds which prove the stability of parameters. The model is structurally stable.

D. Time series modelling for NFT Art

Short run estimation for NFT Art– ARDL MODEL

Table 15: Table depicting ARDL model for NFT Art

Dependent Variable: NFT_ART1
Method: ARDL
Date: 04/20/22 Time: 19:57
Sample (adjusted): 2/10/2020 2/28/2022
Included observations: 750 after adjustments
Maximum dependent lags: 8 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (8 lags, automatic): GFI1
Fixed regressors: C
Number of models evaluated: 72
Selected Model: ARDL(8, 5)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
NFT_ART1(-1)	-1.241196	0.036523	-33.98421	0.0000
NFT_ART1(-2)	-1.226298	0.056392	-21.74587	0.0000
NFT_ART1(-3)	-1.100096	0.068274	-16.11287	0.0000
NFT_ART1(-4)	-0.935427	0.073452	-12.73524	0.0000
NFT_ART1(-5)	-0.767091	0.073314	-10.46310	0.0000
NFT_ART1(-6)	-0.599952	0.067816	-8.846736	0.0000
NFT_ART1(-7)	-0.363582	0.055903	-6.503830	0.0000
NFT_ART1(-8)	-0.102231	0.036115	-2.830673	0.0048
GFI1	-0.001131	0.102882	-0.010997	0.9912
GFI1(-1)	0.265537	0.107983	2.459055	0.0142
GFI1(-2)	0.099318	0.110497	-0.898841	0.0699
GFI1(-3)	0.266134	0.110325	2.412261	0.0161
GFI1(-4)	0.104899	0.108017	-0.971141	0.0317
GFI1(-5)	0.305492	0.102870	-2.969708	0.0031
C	-0.002776	0.026869	-0.103306	0.9177

R-squared	0.635187	Mean dependent var	-0.000427
Adjusted R-squared	0.628238	S.D. dependent var	1.186450
S.E. of regression	0.723405	Akaike info criterion	2.210103
Sum squared resid	384.6367	Schwarz criterion	2.302505
Log likelihood	-813.7887	Hannan-Quinn criter.	2.245707
F-statistic	91.40942	Durbin-Watson stat	2.036779
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

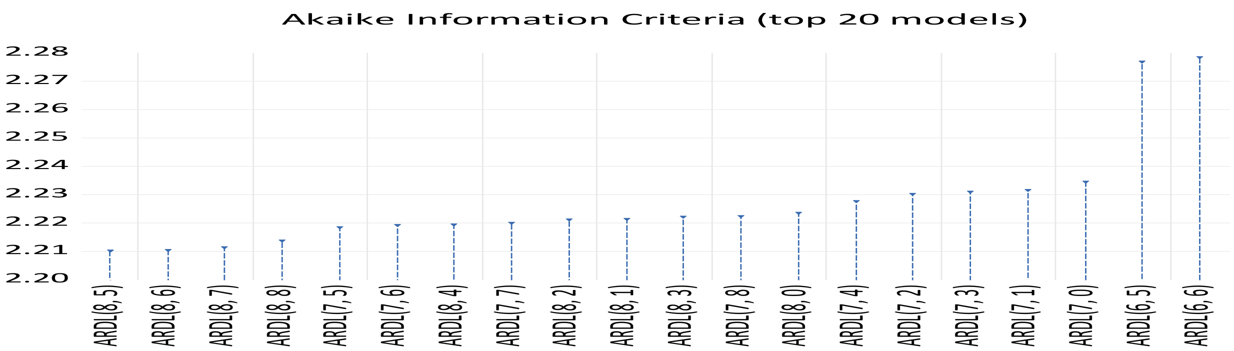

Figure 3: Figure showing best choice for ARDL NFT Art Model

As observed from Table 15 and Figure 3, the ARDL model stands ARDL (8,5) and is the best choice as it is exhibited as the shortest line on the graph. This model has been developed using NFT Art as dependent variable and GFI as independent variable. Lag length selection is automatic based on Akaike Info criterion. Intercept is devoid of trend. The model states that NFT Art returns today is a function of past 8-day NFT Art returns, GFI values of past 5 days except GFI at level and GFI lag 2. For NFT Art itself, the lagged returns have a negative influence on the current period returns. NFT Art lag 1 up to lag 8 can influence itself. The same can be verified using prob values of lagged variables. Prob value of NFT returns of all 8 days is less than 0.05 which indicates that lagged 8 days returns is statistically significant is ascertaining NFT Art returns today. Similarly, Lagged GFI value of 1,3,4 and 5 days is statistically significant in determining NFT Art return of today since GFI (-1), GFI (-3), GFI (-4) and GFI (-5) prob value is less than 0.05. However, GFI at level and GFI (-2 is not statistically significant in determining NFT Art returns at level. The model shows that if GFI (-1), GFI (-3), GFI (-4) and GFI (-5), increases by 1%, NFT Art returns increases by 0.26%, 0.26%, 0.10% and 0.30% respectively in the short-run. There is a positive impact of the independent variable, on NFT Art returns. It also shows that an increase in fear metrics beings about a less than proportional increase in NFT returns. The Adjusted R squared value of 62.82% indicate that the model is a best fit since 62.82% of change in NFT returns can be explained by change in GFI. The prob (F-Statistic) value of 0.00 is less than 0.05. Thus, the model is statistically significant at 5% level. Durbin Watson value is 2.03, which proves that the model is free from serial correlation (Durbin Watson between 1.5 to 2.5).

Long run estimation for NFT Art – ARDL BOUNDS TEST

Table 16: Bounds test result for relationship between NFT Art and GFI

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GFI1	0.002839	0.011039	0.257190	0.7971
C	-0.000378	0.003662	-0.103313	0.9177

EC = NFT_ART1 - (0.0028*GFI1 - 0.0004)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	119.5350	10%	3.02	3.51
k	1	5%	3.62	4.16
		2.5%	4.18	4.79
		1%	4.94	5.58
Actual Sample Size	750		Finite Sample: n=80	
		10%	3.113	3.61
		5%	3.74	4.303
		1%	5.157	5.917

In reference to table 16, there exists a long-term relationship between the variables if the F-statistic is greater than upper bound at 5% level. There exists no long-term relationship if the F-statistic is lower than lower bound at 5% level. In this case, the F-statistic (119.5350) is greater than upper bound at 5% level (4.16). Therefore, we can further investigate the significance of the independent variable in estimating NFT Art returns for a long time period. The prob value of GFI is higher than 0.05 (0.79>0.05) This indicates that GFI is not statistically significant and has no long run relationship to NFT Art returns. It also implies that the series cannot be combined in a linear fashion in the long run.

Residual diagnostics

Breusch-Godfrey Serial Correlation LM Test

Table 17: Godfrey Serial Correlation LM test E-views output for NFT Art Model Residual

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

F-statistic	6.900362	Prob. F(2,733)	0.0510
Obs*R-squared	13.85985	Prob. Chi-Square(2)	0.0609

As shown in table 17, LM Test proves that the residual obtained from the ARDL model is free from serial correlations if the prob value is higher than 0.05. The observed R squared is 13.85 and the prob value 0.0609. Thus, the ARDL Model is free from serial correlation.

Breusch-Pagan-Godfrey Heteroskedasticity Test

Table 18: Heteroskedasticity test E-views output for NFT Art Model Residual

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	1.505224	Prob. F(14,735)	0.1030
Obs*R-squared	20.90386	Prob. Chi-Square(14)	0.1041
Scaled explained SS	102.5512	Prob. Chi-Square(14)	0.0000

As shown in table 18, The Breusch-Pagan-Godfrey Test proves that the residuals are free from heteroskedasticity if the prob value is higher than 0.05. The observed R squared is 20.903 and prob value is 0.1041. Thus, we fail to reject the null hypothesis of homoskedasticity. The residuals are free from heteroskedasticity.

Stability diagnostics

Ramsey RESET Test

Table 19: Ramsey RESET Test Results for NFT Art Model

Ramsey RESET Test
Equation: UNTITLED
Omitted Variables: Squares of fitted values
Specification: NFT_ART1 NFT_ART1(-1) NFT_ART1(-2) NFT_ART1(-3) NFT_ART1(-4) NFT_ART1(-5) NFT_ART1(-6) NFT_ART1(-7) NFT_ART1(-8) GFI1 GFI1(-1) GFI1(-2) GFI1(-3) GFI1(-4) GFI1(-5) C

	Value	df	Probability
t-statistic	2.810365	734	0.5051
F-statistic	7.898154	(1, 734)	0.5051
Likelihood ratio	8.027209	1	0.3046

As shown in table 19, The probability value of 0.5051 is greater than 0.05. Thus, the null hypothesis cannot be rejected. It suggests that the model is well specified.

CUSUM Test

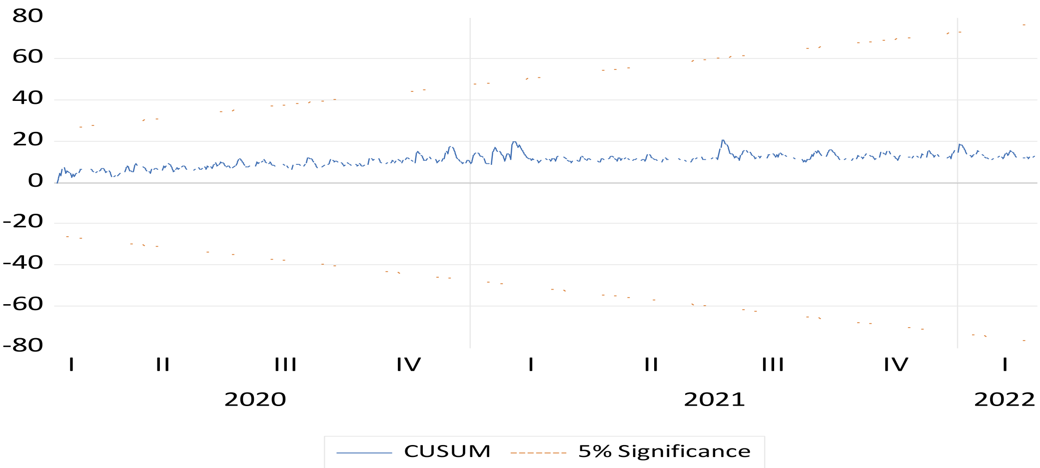

Figure 4: Graph showing CUSUM Test Results for NFT Art ARDL Model

Figure 4 shows that the plot of CUSUM remained between the 5% critical bounds which prove the stability of parameters. The model is structurally stable.

E. Time series modelling for NFT Metaverse

Short run estimation for NFT Metaverse– ARDL MODEL

Table 19: Table depicting ARDL model for NFT Metaverse

Dependent Variable: NFT_METAVERSE
Method: ARDL
Date: 04/16/22 Time: 16:53
Sample (adjusted): 2/10/2020 2/28/2022
Included observations: 750 after adjustments
Maximum dependent lags: 8 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (8 lags, automatic): TEU
Fixed regressors: C
Number of models evaluated: 72
Selected Model: ARDL(8, 2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
NFT_METAVERSE(-1)	-1.138409	0.036230	-31.42207	0.0000
NFT_METAVERSE(-2)	-1.139238	0.054076	-21.06750	0.0000
NFT_METAVERSE(-3)	-1.059772	0.065004	-16.30326	0.0000
NFT_METAVERSE(-4)	-0.946353	0.070485	-13.42624	0.0000
NFT_METAVERSE(-5)	-0.764984	0.070419	-10.86336	0.0000
NFT_METAVERSE(-6)	-0.587727	0.064840	-9.064256	0.0000
NFT_METAVERSE(-7)	-0.321634	0.053927	-5.964205	0.0000
NFT_METAVERSE(-8)	-0.155598	0.036227	-4.295069	0.0000
TEU	-0.001600	0.001209	-1.323773	0.1860
TEU(-1)	0.000233	0.001272	0.183361	0.8546
TEU(-2)	0.102339	0.001211	1.932078	0.0437
C	-0.003311	0.046838	-0.070685	0.9437

R-squared	0.683120	Mean dependent var	-0.002075
Adjusted R-squared	0.676906	S.D. dependent var	1.971964
S.E. of regression	1.282676	Akaike info criterion	3.351645
Sum squared resid	1214.200	Schwarz criterion	3.425566
Log likelihood	-1244.867	Hannan-Quinn criter.	3.380128
F-statistic	93.84506	Durbin-Watson stat	2.022748
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

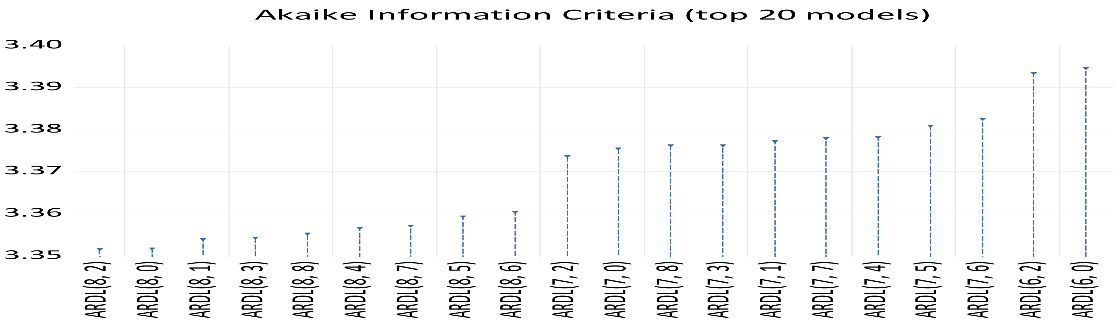

Figure 5: Figure showing best choice for ARDL NFT Metaverse Model

As seen from table 19 and figure 5, The ARDL model stands ARDL (8,2) and is the best choice as it is exhibited as the shortest line on the graph. This model has been developed using NFT Metaverse as dependent variable and TEU as independent variable. Lag length selection is automatic based on Akaike Info criterion. Intercept is devoid of trend. The model states that NFT Metaverse returns today is a function of past 8-day NFT Metaverse returns and TEU values of 2 days prior. For NFT Metaverse itself, the lagged returns have a negative influence on the current period returns. NFT Metaverse lag 1 up to lag 8 can influence itself. The same can be verified using prob values of lagged variables. Prob value of NFT Metaverse returns of all 8 days is less than 0.05 which indicates that lagged 8 days returns is statistically significant is ascertaining NFT Metaverse returns today. Similarly, Lagged TEU value of 2 days is statistically significant in determining NFT Metaverse return of today since TEU (-2) prob value is less than 0.05. However, TEU at level and lag 1 is not statistically significant in determining NFT Metaverse returns at level. The model shows that if TEU (-2) increases by 1%, NFT Metaverse returns increases by 0.10% in the short-run. There is a positive impact of the independent variables on NFT Metaverse returns. It also shows that an increase in fear metrics beings about a less than proportional increase in NFT Metaverse returns. The Adjusted R squared value of 67.69 % indicate that the model is a best fit since 67.69% of change in NFT Metaverse returns can be explained by change in TEU. The prob (F-Statistic) value of 0.00 is less than 0.05. Thus, the model is statistically significant at 5% level. Durbin Watson value is 2.02, which proves that the model is free from serial correlation (Durbin Watson between 1.5 to 2.5).

Long run estimation for NFT Metaverse– ARDL BOUNDS TEST

Table 20: Bounds test result for relationship between NFT Metaverse and TEU

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TEU	0.000137	0.000385	0.355501	0.7223
C	-0.000465	0.006584	-0.070685	0.9437

EC = NFT_METAVERSE - (0.0001*TEU - 0.0005)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	121.5936	10%	3.02	3.51
k	1	5%	3.62	4.16
		2.5%	4.18	4.79
		1%	4.94	5.58
Actual Sample Size	750		Finite Sample: n=80	
		10%	3.113	3.61
		5%	3.74	4.303
		1%	5.157	5.917

In reference to Table 20, There exists a long-term relationship between the variables if the F-statistic is greater than upper bound at 5% level. There exists no long-term relationship if the F-statistic is lower than lower bound at 5% level. In this case, the F-statistic (121.5936) is greater than upper bound at 5% level (4.16). Therefore, we can further investigate the significance of the independent variable in estimating NFT Metaverse returns for a long time period. The prob value of TEU is higher than 0.05 (0.72>0.05) This indicates that TEU is not statistically significant and has no long run relationship to NFT Metaverse returns. It also implies that the series cannot be combined in a linear fashion in the long run.

Residual diagnostics

Breusch-Godfrey Serial Correlation LM Test

Table 21: Godfrey Serial Correlation LM test E-views output for NFT Metaverse Model Residual

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

F-statistic	38.17163	Prob. F(2,746)	0.3467
Obs*R-squared	69.99853	Prob. Chi-Square(2)	0.2765

Table 21 shows that the LM Test proves that the residual obtained from the ARDL model is free from serial correlations if the prob value is higher than 0.05. The observed R squared is 69.99 and the prob value 0.2765. Thus, the ARDL Model is free from serial correlation.

Breusch-Pagan-Godfrey Heteroskedasticity Test

Table 22: Heteroskedasticity test E-views output for NFT Metaverse Model Residual

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.959293	Prob. F(5,748)	0.4420
Obs*R-squared	4.804134	Prob. Chi-Square(5)	0.4402
Scaled explained SS	56.49723	Prob. Chi-Square(5)	0.0000

In reference to table 22, The Breusch-Pagan-Godfrey Test proves that the residuals are free from heteroskedasticity if the prob value is higher than 0.05. The observed R squared is 4.804 and prob value is 0.4402. Thus, we fail to reject the null hypothesis of homoskedasticity. The residuals are free from heteroskedasticity.

Stability diagnostics

Ramsey RESET Test

Table 23: Ramsey RESET Test Results for NFT Metaverse Model

Ramsey RESET Test
Equation: UNTITLED
Omitted Variables: Squares of fitted values
Specification: NFT_METAVERSE1 NFT_METAVERSE1(-1) NFT_METAVERSE1(-2) NFT_METAVERSE1(-3) NFT_METAVERSE1(-4) TEU1 C

	Value	df	Probability
t-statistic	4.469423	747	0.4078
F-statistic	19.97574	(1, 747)	0.3567
Likelihood ratio	19.89805	1	0.0156

In reference to table 23, The Ramsey RESET test was used to check the appropriate functional form. The probability value of 0.4078 is greater than 0.05. Thus, the null hypothesis cannot be rejected. It suggests that the model is well specified.

CUSUM Test

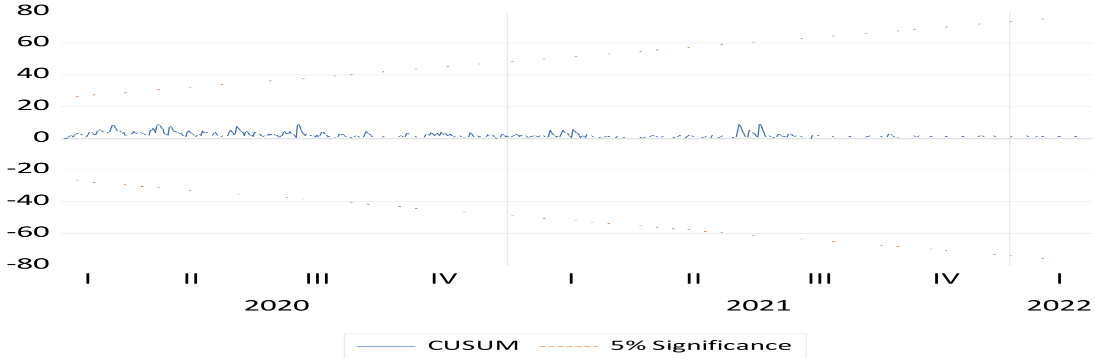

Figure 6: Graph showing CUSUM Test Results for NFT Metaverse ARDL Model

As depicted in figure 6, The plot of CUSUM remained between the 5% critical bounds which prove the stability of parameters. The model is structurally stable.

VII. FINDINGS

- GFI, GEPU, TEU and CCI have a unit root. They are non-stationary series at level. IDEMV, CVI, NFT and NFT categories are stationary at level. When converted to First difference, all variables are stationary and integrated to first order I (1) except CCI. All variables including CCI are not stationary at second difference. Thus, the series under study have a mixed order of integration.
- Out of all independent variables studied, only TEU and CVI Granger cause NFT returns. Further, causality is established between GFI and NFT Art returns as well as TEU and NFT Metaverse Returns. The above stated causal relationships are unidirectional.
- Fear metrics do not exhibit causal relationship to NFT Collectible, NFT Game and NFT Utility.
- In the short run, NFT returns can be predicted by ARDL (8,1,2). NFT returns today is a function of past 8-day NFT returns (NFT lag 1 to 8), TEU values of today (TEU at level) and CVI value of 2 days prior (CVI lag 2).
- If TEU (-1) increases by 1%, NFT returns increases by 0.23% in the short-run. Similarly, If CVI (-2) increases by 1%, NFT returns increases by 0.11%. There is a positive impact of both independent variables on NFT returns. It also shows that an increase in fear metrics beings about a less than proportional increase in NFT returns.
- In the short run, NFT Art returns can be predicted by ARDL (8,5). NFT Art returns today is a function of past 8-day NFT Art returns, GFI values of past 5 days except GFI at level and GFI lag 2.
- If GFI (-1), GFI (-3), GFI (-4) and GFI (-5), increases by 1%, NFT Art returns increases by 0.26%, 0.26%, 0.10% and 0.30% respectively in the short-run. There is a positive impact of the independent variable, on NFT Art returns. It also shows that an increase in fear metrics beings about a less than proportional increase in NFT returns.
- In the short run, NFT Metaverse returns can be predicted by ARDL (8,2). NFT Metaverse returns today is a function of past 8-day NFT Metaverse returns and TEU values of 2 days prior.

- If TEU (-2) increases by 1%, NFT Metaverse returns increases by 0.10% in the short-run. There is a positive but less than proportional impact of the independent variable on NFT Metaverse returns.
- In the long run, TEU has a statistically significant relationship to NFT returns while CVI does not. Further, GFI and TEU do not have long term cointegrating relationship to NFT Art returns and NFT Metaverse returns respectively.

VIII. RECOMMENDATION

Out of all the variables studied, only Twitter Based Policy Uncertainty Index and Cryptocurrency Volatility Index show causality to NFT returns overall. Social media sentiments regarding potential economic turmoil drives NFT returns. So does Cryptocurrency Volatility, which is understandable since NFTs are primarily traded in Cryptocurrency. However, NFT returns have no connection to other fear metrices such as Economic Policy Uncertainty, Consumer Confidence or Infectious Diseases Equity Market Volatility. Further, in the long run, only social media sentiments continue to impact NFT returns. A potential investor should follow social media sentiments and Cryptocurrency volatility (in the short run) to analyse weather to invest in NFT or not. The study shows that when fear metrics indicate rise in fear represented by social media chatter and rise in cryptocurrency volatility, NFT returns also increase in the short run. However, the change is less than proportional. Investors should use NFTs only as a mean to hedging risks and potential loss on portfolio investments but they should not expect supernormal profits from NFT investment in times of crisis.Within NFT’s, so as far as hedging during crisis period is concerned, an investor should avoid analysing NFT Collectible, NFT Game and NFT Utility purely from a fear perspective since these categories show no causality to any fear metric either in the short or the long run period. Factors influencing the returns of these categories needs to be studied separately. Some of the factors could be number of active wallets, number of secondary trades, volume of trades and the potential of wash trading activities in the NFT market. Another explanation could be their emergence as a distinct asset class or inefficiencies in their markets due to being in an early stage. It could also be that Collectibles have perceptive value in the minds of buyers whereas Game and Utility have utilitarian value, both of which might be more than the value of NFT art or metaverse in the minds of buyers who are sceptical to invest in digital art or digital land when the real thing is readily available and profitable. Thus, the higher value of Collectible, Game and Utility Tokens means they do not move during times of fear or fear does not affect them at all.However, Investors can choose to invest in NFT art or NFT metaverse for the short run. While investing in NFT art, one should estimate returns basis of the global fear index. While investing in NFT Metaverse, one should check social media chatter on policy uncertainty. The higher the fear, the higher the returns from both Categories. However, such an investment can only assure positive returns but they do not assure supernormal profits. An investor can effectively hedge his portfolio using NFT.

- It is advisable to invest in NFT during times of crisis for a short time period. While investing in the short run, an investor should carefully analyse social media chatter for negative sentiments regarding economic policy uncertainty. He should also follow trends in cryptocurrency volatility. As these two fear metrics increase, NFT returns also increase, thereby creating opportunity for the investor to reap profits on his investment.
- Within the NFTs, investors can choose to invest in NFT art or NFT metaverse for the short run. While investing in NFT art, one should estimate returns basis of the global fear index. While investing in NFT Metaverse, one should check social media chatter on policy uncertainty. The higher the fear, the higher the returns from both Categories.
- For an investor interested to invest long term, NFT is not a suitable avenue. This is because there is no causality between Fear metrics and NFT returns in the long run for the categories explicitly studied (NFT Art and NFT Metaverse). This means that in case a crisis period extends beyond a year, an investor should carefully analyse his position based on factors other than fear indices.
- The overall analysis of NFT shows that social media chatter does in fact, have a long run impact on NFT returns. However, for the categories studied, this relationship did not hold true. The relationship needs to be examined by the investor for other NFT categories such as De-Fi. This opens up possible investment avenues for the investor worth considering.
- So as far as hedging during crisis period is concerned, an investor should avoid analysing NFT Collectible, NFT Game and NFT Utility purely from a fear perspective since these categories show no causality to any fear metric either in the short or the long run period.
- A 1% change in fear is shown to have 0.10% to 0.30% change in NFT returns. This shows that although a rise in fear leads to a rise in profits from NFT, such profits are less than proportional to fear which means a large increase in fear brings about a small increase in returns. So, when all other investment avenues generate losses during crisis, investing in NFT will assure the investor of positive returns to set-off that loss. Thus, an NFT can be a good hedging technique. However, it is difficult

for NFT to provide supernormal returns during crisis periods, unless the same can be generated by increasing the unit volume of trades entered into thereby having a cumulative impact on returns.

- To the effect that relationship between Fear indices and NFT returns has been established, it is seen that lagged values of both the dependent and independent variables impact today's NFT returns. Thus, past values impact future values and take time from 1-day upto 5 days to be included and reflected in NFT returns. This indicates that NFT markets are inefficient and have the potential to be exploited to make profits during times of turmoil but the same needs to be exploited within a week at the maximum.

IX. CONCLUSIONS

The study had the objective to determine whether Fear metrics impact NFT and NFT category returns during times of crisis in the short as well as long run period. Analysing data for the period between 1st February 2020 to 28th February 2022, it is concluded that there is lack of causality between fear metrics and NFT returns for the categories of NFT Collectible, Game and Utility. Unidirectional Causality is observed between TEU, CVI and NFT returns; GFI and NFT Art Returns; as well as TEU and NFT Metaverse Returns. Further, a short run association is observed between the aforesaid causal pairs. Thus, it is concluded that NFTs can generate positive returns in the short run. ARDL model for NFT short run estimation is (8,1,2,), NFT Art is ARDL (8,5) and NFT Metaverse is NFT (8,2). It indicates that lagged values of independent variables feature in NFT returns of the current period. Thus, the NFT markets are inefficient and there exists the possibility to reap higher returns using cumulative impact of volume. In the long run, fear indices do not lead NFT returns except TEU.

The study would enable investors to make informed decisions regarding investing in NFTs during turbulent times, so as to maximise returns and mitigate losses. Investors can also hedge their portfolios by including certain NFT categories in their traditional portfolios. Overall, NFT, NFT Art and NFT Metaverse have positive relationship to at least one fear metrics in the short run. So as long as the investor is aware of the fear metric impacting the particular NFT, he can make positive returns on NFT in the short run during crisis period.

The study can be extended to explore the factors other than fear metrics which impact NFTs during turbulent times. An in-depth study can also be done on the NFT category Defi and its relationship to fear indices.

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