Analyzing the Impact of Macroeconomic Factors on Renewable and Non-Renewable Energy Markets post COVID-19

Authors: *Soumya Basu*[a,*], *Hideyuki Okumura*[b]

Abstract:

Renewable-Energy and Non-Renewable-Energy markets have different phenomena for interactions with macroeconomic factors. Moreover, the dual shocks of COVID-19 (demand shock) and Ukraine-Russia crisis (oil shock) have severely impacted the stability of energy markets, and pose a threat for hampering the targets of a 'net-zero' society. Existing literature does not provide an empirical analysis as to how renewable markets can be stabilized in the aftermath of these two economic shocks that have been prevalent for over three years. This study provides an analysis of the interactions of renewable and non-renewable energy markets of India, China, Japan, European Union and United States of America with macroeconomic markets of oil and gold during the dual shocks of COVID-19 and the Russian aggression on Ukraine, using a time-frequency coherence measure of Wavelet Coherence. The key findings of this study are: (1) developing countries are impacted more than developing countries towards the stability of renewable markets during demand shock, (2) an oil shock should be followed by a ramping up of electric vehicle production, which can encourage investors to hedge towards renewable markets, (3) photovoltaic producing and exporting nations can quickly recover the volatility in renewable markets during any economic shock, and (4) despite a ban on oil trade, economic sanctions hamper the stability of renewable markets. These results can be used by researcher and policy-makers to plan a pathway towards energy transition as the world is coming out of the dual shocks.

Keywords: *COVID-19; Ukraine-Russia; sanctions, stability; hedging; renewable energy markets*

Competing Interest

The authors declare no financial or non-financial interests that are directly or indirectly related to the work.

Funding

This work was supported by JST SPRING, Grant Number JPMJSP2110, given to Soumya Basu.

[a] *Graduate School of Energy Science, Kyoto University, PhD Student, Japan; ORCID: 0000-0002-9075-2016*
[b] *Graduate School of Energy Science, Kyoto University, Associate Professor, Japan; ORCID:*
[*] Corresponding author. *Email address: soumyabasu@rocketmail.com, Phone: +818095286313 (Basu S.), Address: Yoshidahonmachi, Sakyo-ku, Kyoto 606-8501 Japan*

Table i: List of Abbreviations

GENERAL NOMENCLATURE	
RE	Renewable Energy
NRE	Non-Renewable Energy
GDP	Gross Domestic Product
TROP	Trade Openness
VAR	Vector Auto-Regression
ARDL	Auto-Regressive Distributed Lag
GARCH	Generalized AutoRegressive Conditional Heteroskedasticity
STFT	Short-time Fourier Transform
CWT	Continuous Wavelet Transform
WTC	Wavelet Coherence
IEA	International Energy Agency
BSE	Bombay Stock Exchange
BRICS	Brazil, Russia, India, China, South Africa
USA	United States of America
EU	European Union
FTSE	Financial Times Stock Exchange
TOPIX	Tokyo Stock Price Index
ERIX	European Renewable Energy Total Return Index
SXEP	STOXX Europe 600 Oil & Gas
SSEC	Shanghai Stock Exchange Composite
MODELLING VARIABLES	
SP	Stock Price
CoI	Cone of Influence
GP	Gold Price
OP	Oil Price
BRENT	Broom, Rannoch, Etive, Ness and Tarbert
XAU	Troy Ounce of Aurum

1. Introduction

Renewable Energy (RE) development is a key strategy towards achieving energy transition for a net-zero society by 2050. Simultaneously, Non-Renewable Energy (NRE) as fossil fuels have existed since the industrial revolution, and is an integral part of national economic structures [1]. To successfully overcome the burden of climate change due to emission from fossil fuels, it is essential to couple RE to national economic structures. The emergence of an economy is from money supply, which is dependent on the interactions of companies in markets, and eventually interactions of two or more markets [2]. RE markets are generally more unstable than NRE markets where NRE equities perform much better than RE equities [3]. Thus, to integrate RE into the economic structure, it is imperative to uncover the interactions of RE markets with macroeconomic markets, where the investment capital is the highest, and extract the economics that can stabilize national RE markets over a long-term. It has to be noted that a forced and immediate decoupling of NRE markets from macroeconomic markets is unwarranted, since it will lead to instability in the economic structures [4]. These NRE-macroeconomic markets' interactions also have to be simultaneously considered, treating the RE-NRE-macroeconomic market as a nexus, with a motivation to stabilize RE-macroeconomic interactions over long periods.

The first aspect of the analysis carried out in this paper is to empirically quantify market interactions at domestic and international levels. Existing research on impact of macroeconomic factors on RE development deal with highly aggregated data such as Gross Domestic Product (GDP), Trade Openness (TROP), and analyzes the causal direction towards energy and emissions [5-8]. Such low frequency data is incapable of detecting stochastic interactions that account for short-term and long-term market stability. Existing research has focused on time-series analysis tools such as Vector Auto Regression (VAR) and Auto Regressive Distributed Lags (ARDL) [9, 10], which are not sufficient for dealing with high frequency data with inherent Gaussian noise. Thus, in this paper we focus on a branch of literature that deals with high frequency data analysis by converting such data into the time-frequency domain [11]. A frequency domain is capable of removing the noise from time series data, but loses all aspects of time, whereas a time-frequency domain enables us to visualize the frequency component in time slices. This study utilizes a Continuous Wavelet Transform (CWT) to convert time series data to time-frequency data and Wavelet Coherence (WTC) to analyze the interactions between two CWT data series. The advantage of CWT over Short Time Fourier Transform (STFT) is the advantage of resolution in both the time and frequency domains [12].

The second aspect of this paper is selection of study regions and macroeconomic factors for analysis of their impact on domestic RE and NRE markets. In a previous study by the author, that analyzed the impact of several macroeconomic market factors on RE and NRE market stability in India from 2012 to 2022, it was found out that gold and oil markets were key for stabilizing the Indian RE market in the aftermath of the COVID-19 economic shock [13]. This study provides an extension of the previous empirical analysis by focusing on the impact of gold and oil market fluctuations on the RE and NRE market stabilities of the top five global emitters. Namely, United States of America (USA), the European Union (EU), Japan, China and India are the geographical boundaries for this paper. The EU is composed of different countries but due to the interconnected pipelines and visa-free travel across borders, along with the mostly unified currency of 'euro', for the brevity of a macroeconomic analysis [14], the EU is considered as a region with several commonalities on its own. Together, accounting for 47% of the world population [15], 57% of the global GDP [16], 65% of global primary energy-use [17] and 60% of global carbon emission [18], this study can be assumed to be a global analysis of the differences in time-frequency feedback between national energy markets (RE and NRE) with the international oil and gold markets.

Finally, the third aspect of this research focuses specifically on economic shocks. The International Energy Agency (IEA) reported a 6% drop in global energy consumption in 2020, for the first time in over seven decades [19], with the onset of COVID-19 in March, 2020. Essentially, COVID-19 is a shock in demand of energy with transportation and service industry electricity being hampered the most due to global lockdowns [20]. Global markets have also been rendered unstable due to the sudden fluctuation in demand across sectors. [20]. While the COVID-19 was prevalent, Russian aggression against Ukraine in early 2022, affected global oil supply. USA, and several other countries, imposed sanctions against the import of Russian oil, with Russia being a major global oil supplier [21]. This has led to high volatility in the international oil market throughout 2022, leading to market investments being chaotic [21]. Thus, this can be considered as an oil shock. It is imperative to study the differences in impacts of the dual shocks on the development of RE, and which country has fared better in terms of policies for stabilizing the fragile energy market. The temporal boundary of this study is selected to be January 1, 2020 to March 31, 2023, which covers both the shocks, and the eventual resumption of social activities post-COVID-19.

The paper aims to tie in the aforementioned three aspects. The focus is to analyze how the dual shocks impacted the feedback of national RE and NRE markets with international oil and gold markets in the top five global economies (and carbon emitters), within the time-frequency domain. Gold being the most stable invest option for investors globally [33, 34], and oil being the most geopolitically polarizing and most traded entity [32], it is essential to see how renewable development is linked to these macroeconomic markets during different economic shocks from a global context. To the best of our knowledge, such an analysis of the differential impacts from oil and gold markets to RE and NRE markets during economic shocks has not been performed in existing literature, specifically in the time-frequency domain.

The remainder of this paper is as follows: section 2 introduces some related literature for time-frequency analysis on energy markets. In section 3, the data and section 4, the methods are introduced, while section 5 shows the results of our analysis and section 6 offers discussion on policy implications. We conclude the study in the final section.

2. Literature Review

Time-frequency domain analyses to quantify the interaction of a macroeconomic market with energy markets is a fairly modern branch of energy economics. Specifically, with regards to economic shocks, the literature is quite sparse and is detailed in *Table 1* below, along with the main conclusions from each study.

Table 1: Details of the Literature for time-frequency analysis on the interactions between energy and non-energy markets impacted by economic shocks

Ref.	Method	Region	Main Conclusion

[22]	WTC and Granger Causality	Global	Economic Activity strongly comoves with NRE but not RE market indices during COVID-19.
[23]	Non-Linear ARDL	United Kingdom (UK)	COVID-19 led to an increase in RE, which decreased CO_2 emissions. Negative variation in COVID cases decreased CO_2 emissions
[24]	Quantile Regression	USA	RE consumption was more affected than NRE consumption during COVID-19 lockdown.
[25]	Quantile VAR	Global	Clean energy transmits shocks to other markets in short- and long-terms during COVID-19, while crude oil transmits shocks during Ukraine-Russia crisis.
[26]	Dynamic Regression	Asia-Pacific	COVID-19 cases led to volatility in stock markets and spilled over to the RE sector.
[27]	DCC-GARCH	Global	Green bonds do not help reduce volatility in financial markets in economic shocks. Effects from green bond market to stock market done.
[28]	ARDL	China	RE and confirmed COVID-19 cases reduce CO_2 emissions while NRE increases it.
[29]	Dynamic Regression	European Union (EU)	Alternative gas cannot reach Europe because of decreased investment in LNG due to spread of COVID-19 and sharp transition to RE.
[30]	WTC	Saudi Arabia	COVID-19 increased relationship between oil as a main NRE source and Saudi stock market
[31]	Non-linear Regression	Global Firms	COVID-19 caused RE stock market to perform better than NRE stock market.
[32]	WTC	USA	During COVID-19 Agro and Oil markets spillover is more than before. Agriculture commodity markets comove with each other.
[33]	WTC	USA	Oil, GDP, stock market, electricity indices decrease with increase in COVID index, Oil market low co-movement with stock and gold
[34]	Multiple WTC	Japan, BRICS, USA, Canada	Co-movement intense during COVID and 2008 crisis for gold, oil and stock indices.
[35]	WTC	Global	Six RE technology markets are connected during COVID-19, but lose hedging efficiency with rare-earth markets.
[36]	CWT	China	Non-energy commodity markets affect energy commodity in short-run during COVID-19 by reducing hedging

Note: All the abbreviations are provided at the beginning of the paper in Table i.

As detailed in the literature above, there are very few studies that have analyzed the differential impact of COVID-19 on RE and NRE markets [22-25], and just one study that has considered how the dual shock impact the RE and NRE markets differently [25]. In fact, this study is the first study to consider the global impact of how macroeconomic markets of oil and gold differentially affect domestic RE and NRE markets when two simultaneous shocks (demand and oil) are prevalent. Thus, our study contributes to the literature by addressing the gap of how to align and hedge RE markets with oil and gold markets differently in different economies.

3. Data and Characteristics

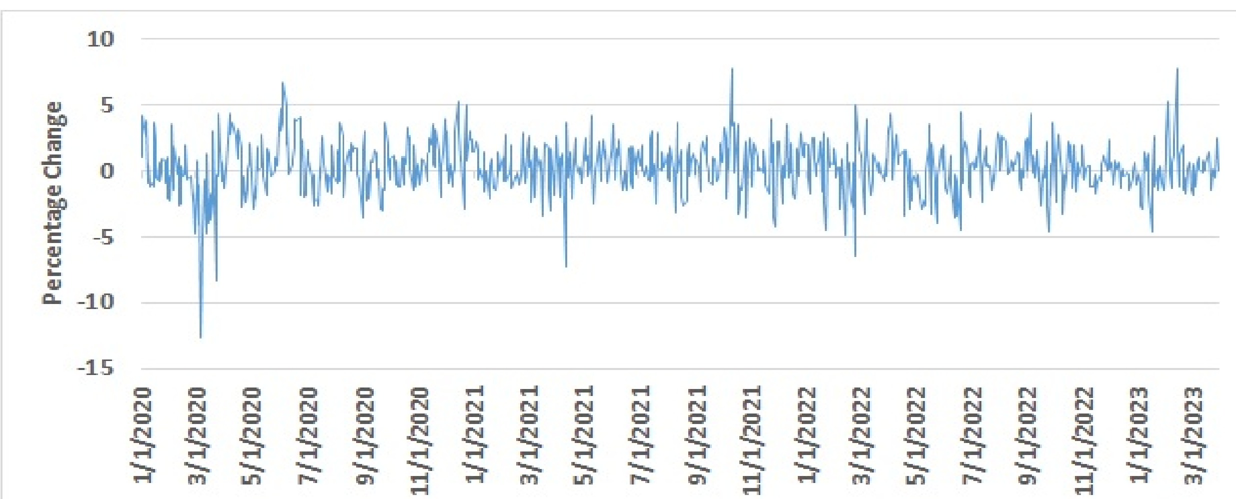
A comparison of the countries' extent of RE integration with macroeconomic markets is evident from the data itself. China and India are the only two countries where the stock markets do not indicate a clean energy index. Surprisingly, the Japanese stock exchange does not have an NRE or Oil and Gas index. For these three factors, the daily closing stock prices of the top market capitalizing listings in the respective stock markets are selected. A weighted average of the percentage change in daily stock prices, as per number of stocks, is used to create the respective indices. The time bounds for the time series is 01 January 2020 to 31 March 2023, which covers the pre-COVID, the COVID-19 onset, the Ukraine-Russia crisis onset, and the COVID-19 lockdown relaxation periods. *Table 2* gives the details of the RE, NRE and macroeconomic indices and their data sources.

Table 2: Market indices construction and sources

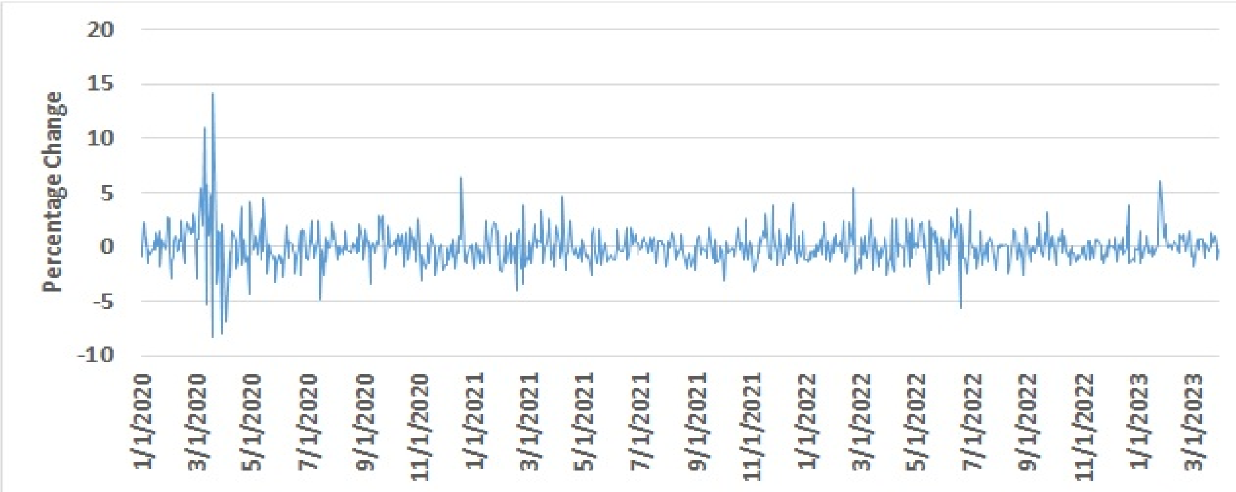
Category	Index Representation	Source
India RE	SUZLON ENERGY LTD.	[37]
	WEBSOL ENERGY SYSTEM LTD.	
	TATA POWER CO. LTD.	
	JSW ENERGY LTD.	
	BOROSIL RENEWABLES LTD.	
	SOLAR INDUSTRIES INDIA LTD.	
	INOX WIND LTD.	
	ADANI GREEN ENERGY LTD.	
India NRE	BSE Oil & Gas Index	[38]
China RE	KGRN Clean Energy Capital	[39]
	Xinyi Energies	[40]
	Shenhua Corporation	[41]
	FTSE Energy Returns China	[42]
	FTSE Energy Production China	[43]
China NRE	FTSE China A 600 Oil & Gas	[44]
Japan RE	Japan Clean Energy Index (weighted from S&P global clean energy index with TOPIX)	[45]
Japan NRE	Tokyo Gas	[46]
	Osaka Gas	
	Japan Petroleum Energy Center	
	TOPIX	
EU RE	European Renew Energy Index	[47]
EU NRE	STOXX EU 600 Oil & Gas	[48]
USA RE	NASDAQ Clean Energy Index	[49]
USA NRE	Dow and Jones Oil & Gas Index	[50]
India Stock	BSE Daily Closing Price	[37]

China Stock	SSEC Daily Closing Price	[51]
Japan Stock	TOPIX Daily Closing Price	[46]
EU Stock	FTSE Daily Closing Price	[52]
USA Stock	NASDAQ Daily Closing Price	[53]
BRENT	Daily Closing Spot Price per Barrel	[54]
GOLD	Daily Closing Spot Price per XAU	[55]

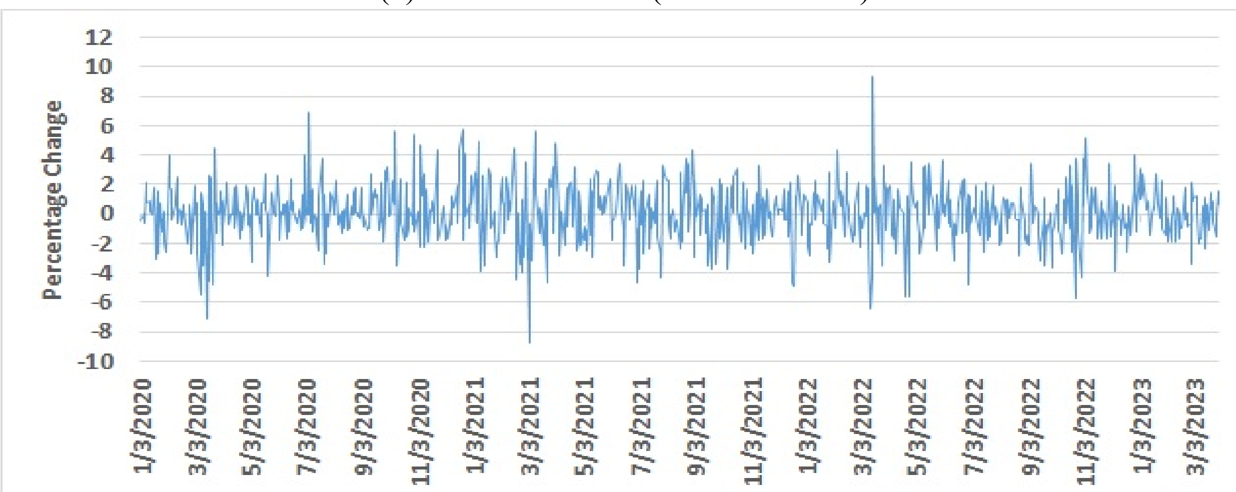
Figure 1 shows the time series daily percentage change data for each indicator from 01 January 2020 to 31 March 2023. *Table 3* shows the descriptive characteristics of each data series. Interesting diasporic market situations are seen in *Figures 1a to 1q*, especially during the phases of the dual shocks. The RE and NRE markets of India, Japan and USA show maximum deviation from equilibrium at the COVID-19 onset, while only the NRE index of EU shows a similar movement. On the other hand, Japan RE, EU RE and both RE-NRE of China shows maximum mean diverging behavior during the Russia-Ukraine crisis onset. This may be because EU and Japan is heavily dependent on imports for the NRE markets, which percolated to the RE market investments. China, because of the export disruption for RE and COVID-19 waning phase, shows the diverging behavior during the Russia-Ukraine crisis. EU, Japanese and Indian stock markets show maximum instability (divergence) during the COVID-19 onset, while NASDAQ index is interestingly divergent at the post COVID-19 phase. Gold shows no discernable erratic behavior apart from a brief COVID-19 onset disturbance, while Oil market obviously shows sharp movements during the COVID-19 and Russia-Ukraine crises onset. The energy markets of USA RE and EU NRE have maximum kurtosis, showing the impact of financial policy to diverge from the equilibrium (*Table 3*). As evidenced from the *Figures 1p and 1q*, Oil market has more kurtosis and standard deviation than Gold market, showing that the Oil equilibrium is more sensitive than the Gold equilibrium during shocks (*Table 3*). The negative skew in almost all energy markets shows the lack of investments during the dual shocks, which makes this research imperative.



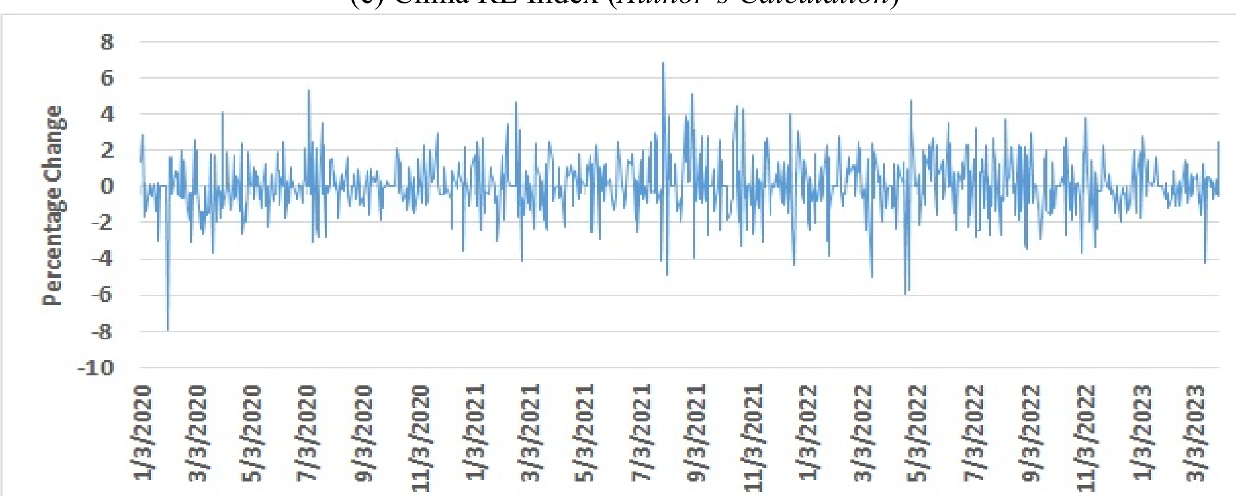
(a) India RE Index (*Author's Calculation*)



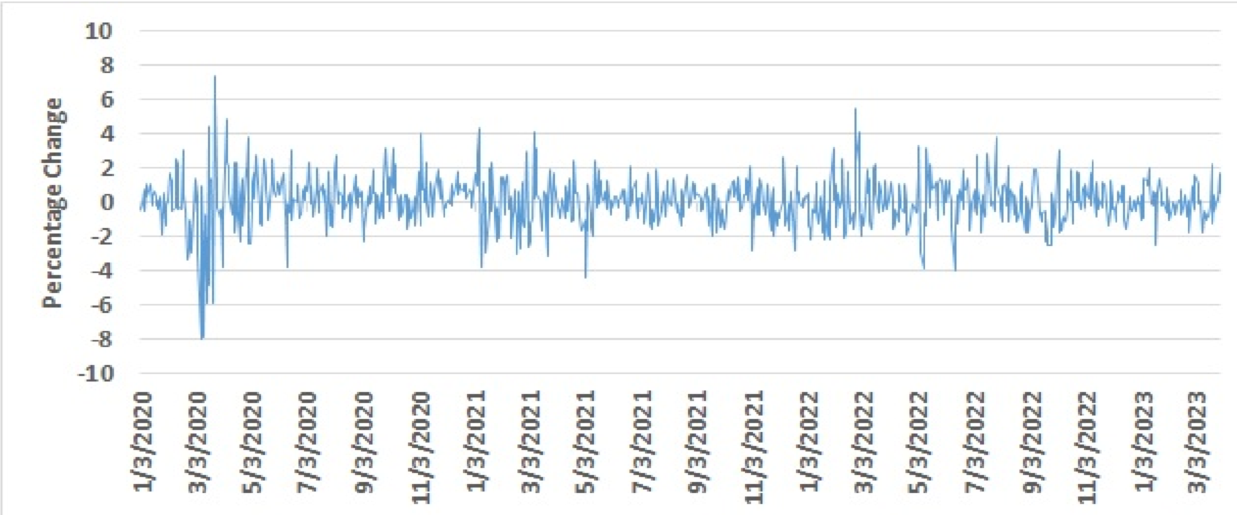
(b) India NRE Index (BSE Oil & Gas)



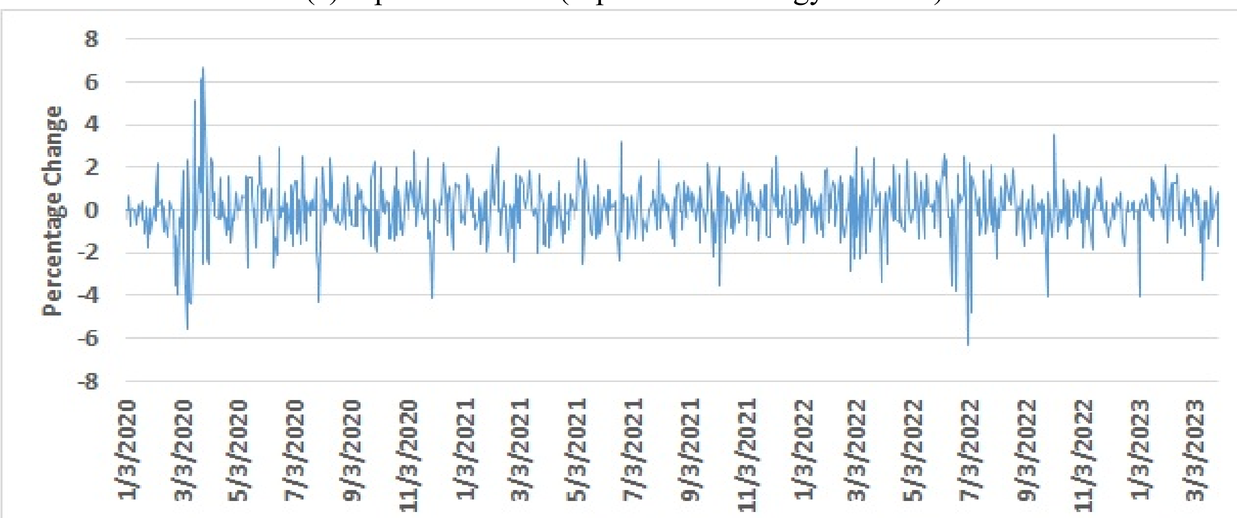
(c) China RE Index (*Author's Calculation*)



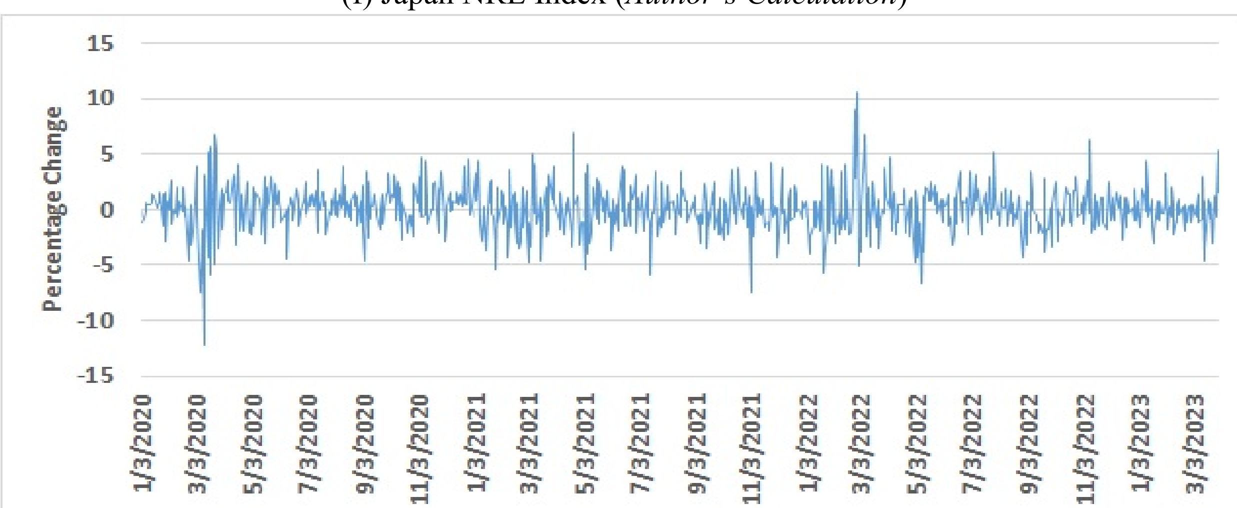
(d) China NRE Index (FTSE China A 600 Oil & Gas)



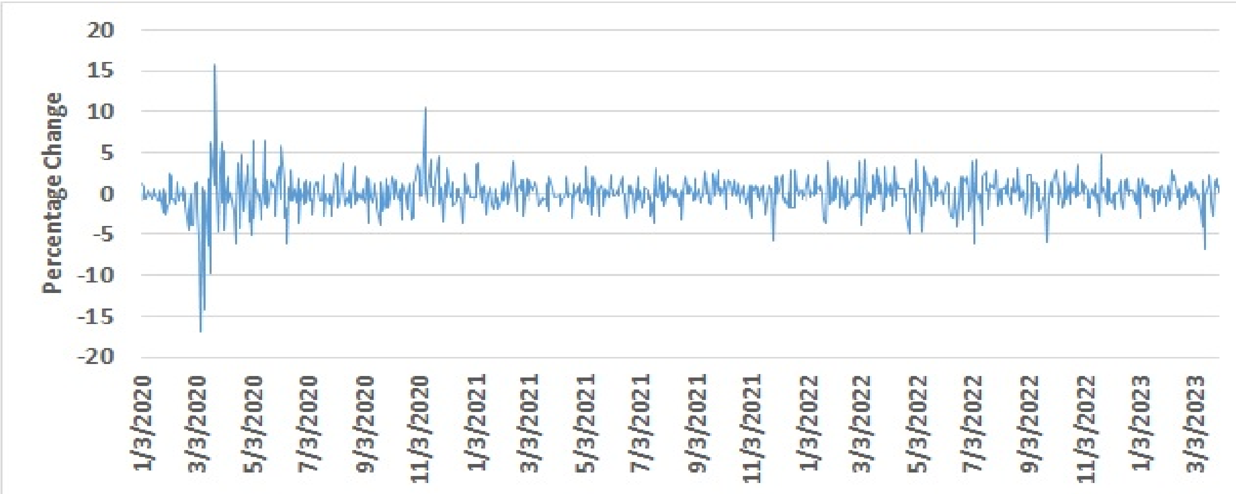
(e) Japan RE Index (Japan Clean Energy – JCEX)



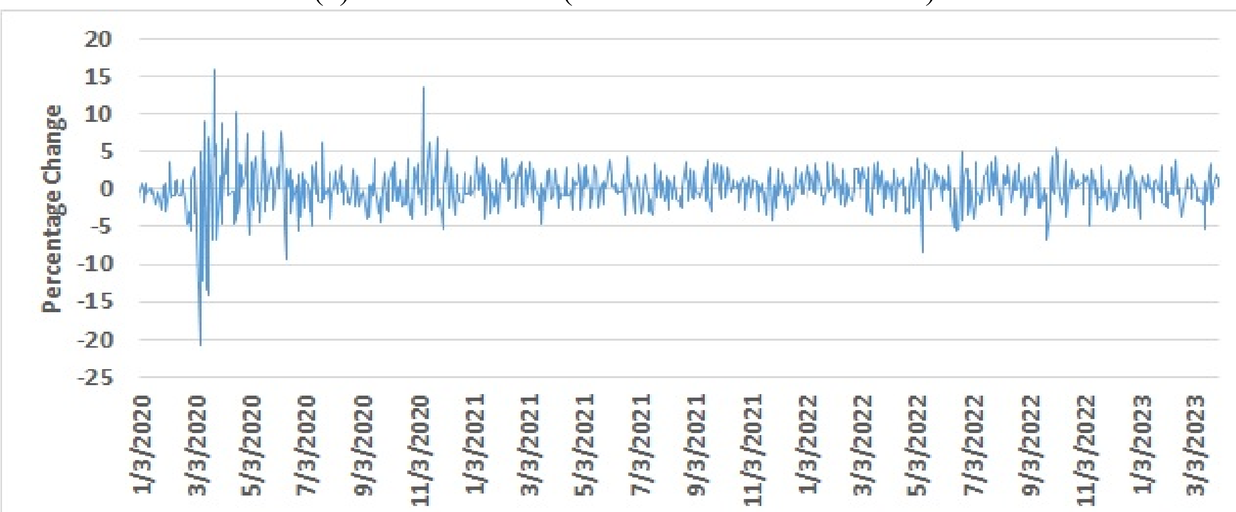
(f) Japan NRE Index (*Author's Calculation*)



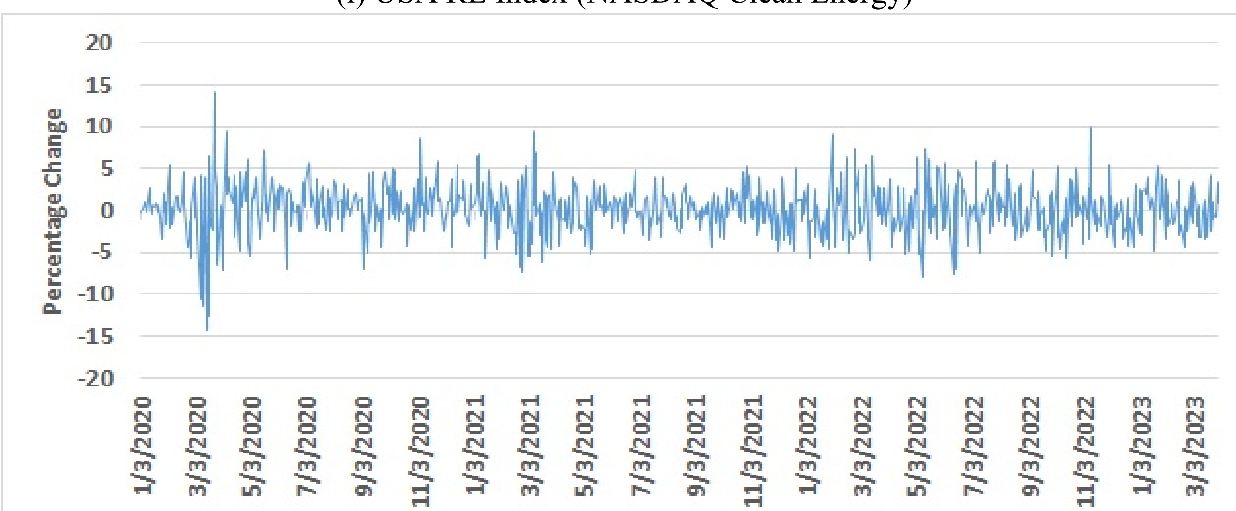
(g) EU RE Index (European Clean Energy – ERIX)



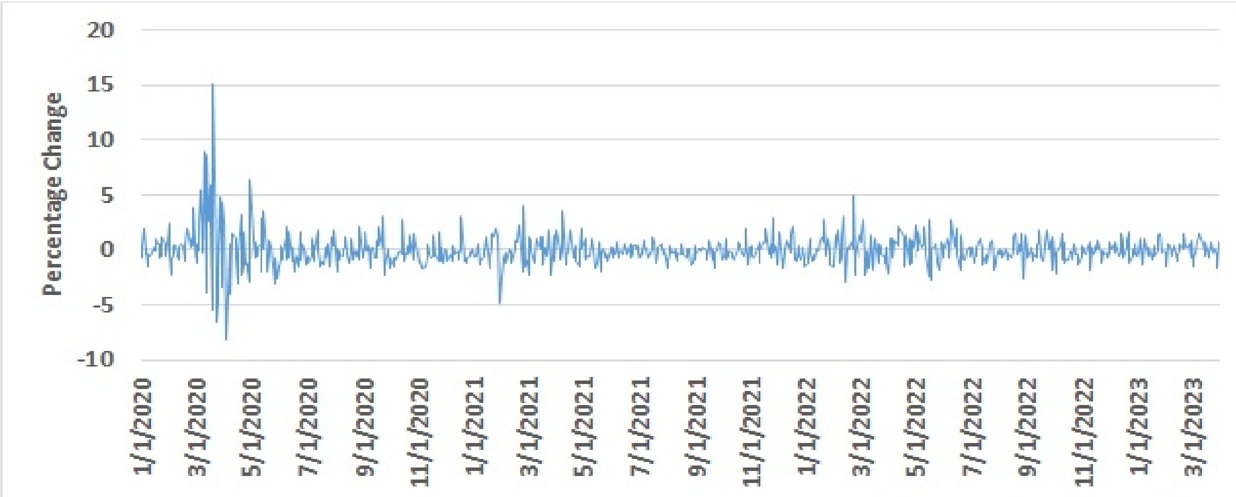
(h) EU NRE Index (STOXX EU 600 Oil & Gas)



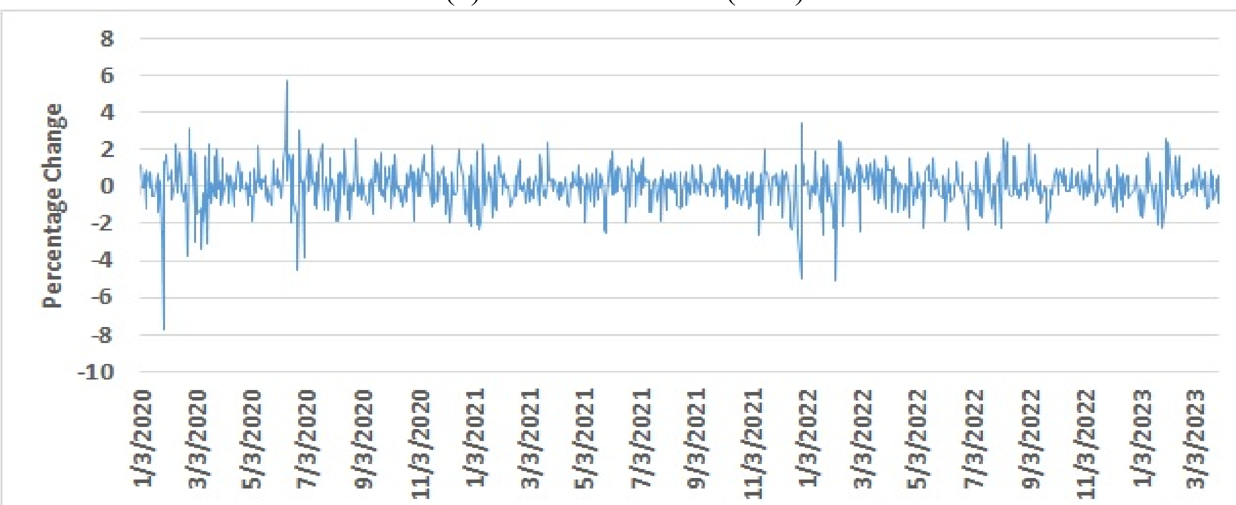
(i) USA RE Index (NASDAQ Clean Energy)



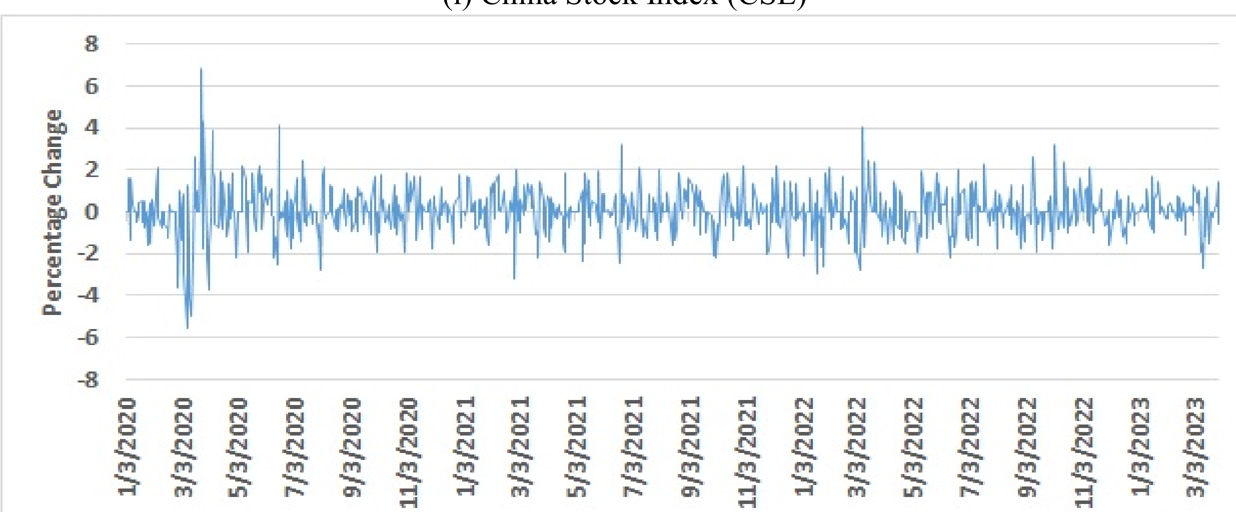
(j) USA NRE Index (Dow Jones Oil & Gas)



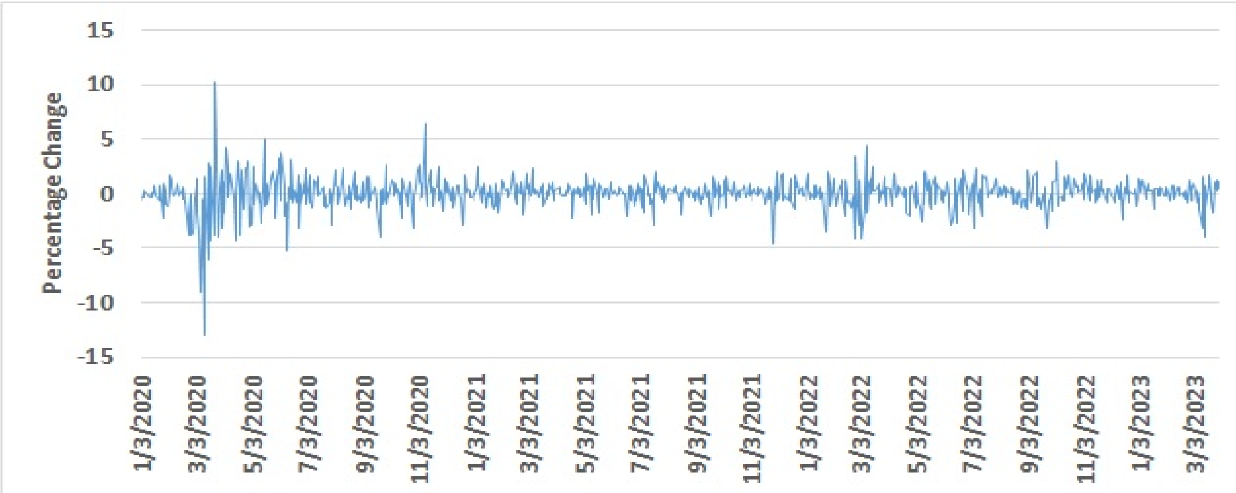
(k) India Stock Index (BSE)



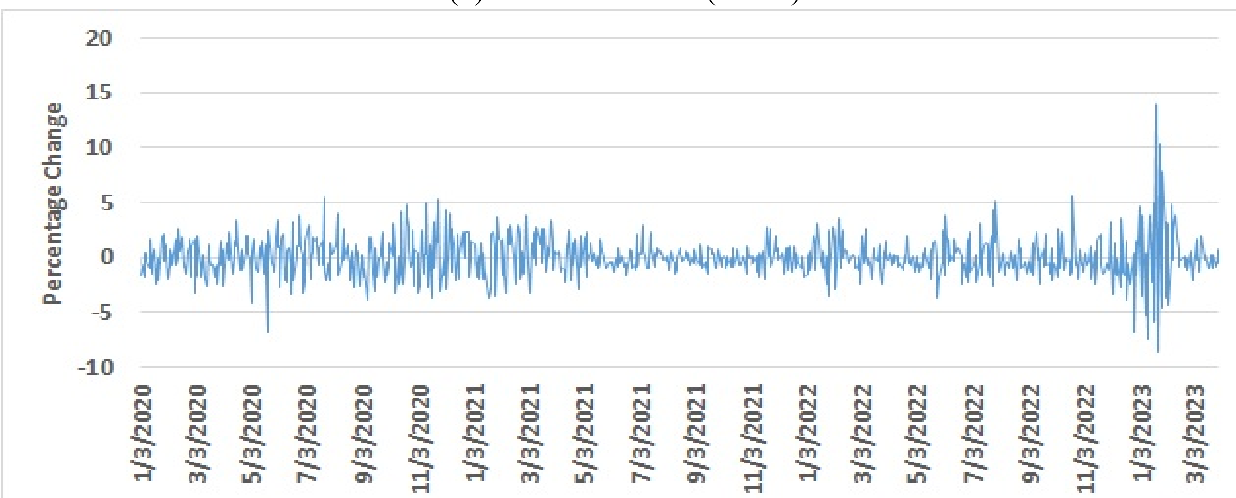
(l) China Stock Index (CSE)



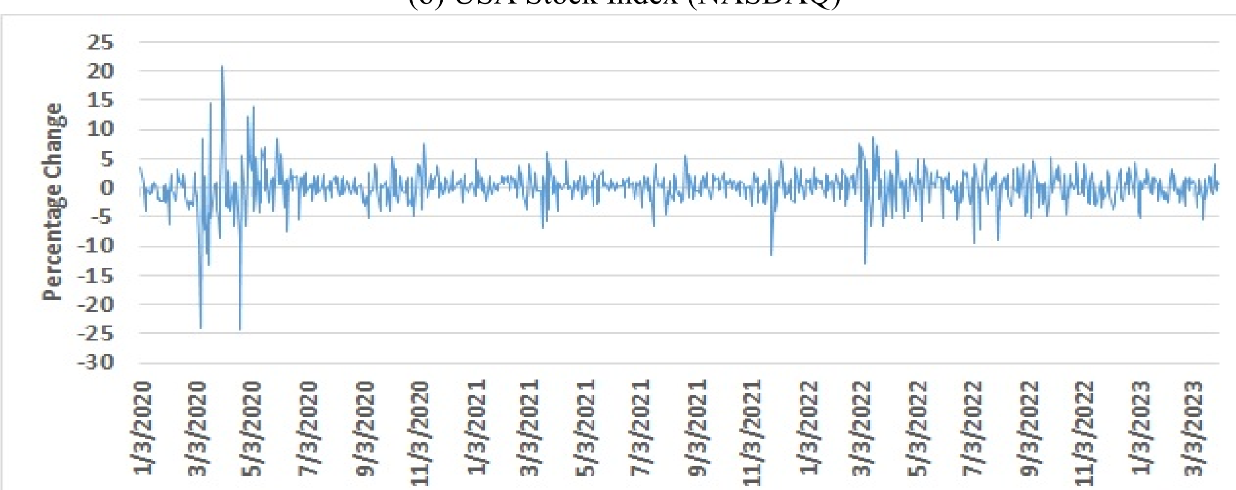
(m) Japan Stock Index (TOPIX)



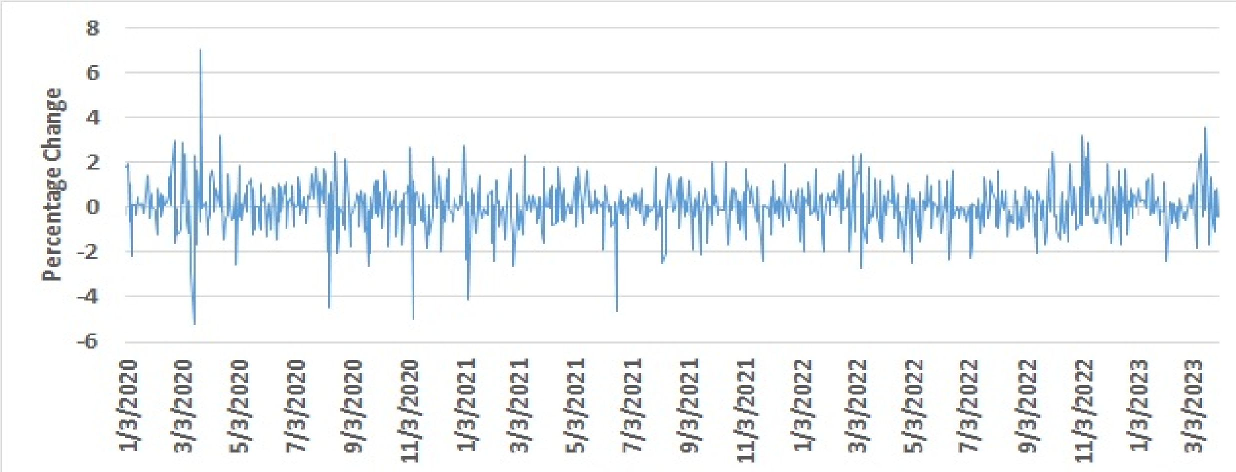
(n) EU Stock Index (FTSE)



(o) USA Stock Index (NASDAQ)



(p) BRENT Daily Closing Spot Price (USD)



(q) Gold Daily Closing Spot Price (XAU in USD)

Figure 1: Time Series Percentage Change data with daily sampling frequency (except for stock market closing days) for country-wise RE, NRE and Stock, and macroeconomic indicators.

Table 3: Descriptive Statistics of Variable for Global Analysis

Variable	Mean	Median	Standard Deviation	Skewness	Kurtosis
India RE	0.2591	0.2774	1.9140	-0.4411	3.5594
India NRE	-0.0077	-0.1231	1.6347	1.1137	11.312
China RE	0.0647	0.0395	1.9055	-0.1074	1.6985
China NRE	0.0267	0	1.5377	-0.0930	2.1176
Japan RE	0.0389	0.0523	1.4180	-0.2553	4.4511
Japan NRE	0.0258	0.0308	1.2413	-0.2584	3.7687
EU RE	0.0659	0.1166	2.0855	-0.0623	2.9598
EU NRE	0.0273	0.0415	2.0795	-0.5212	12.666
USA RE	0.0749	0.0723	2.6835	-0.4995	8.6016
USA NRE	0.1324	0.2933	2.9445	-0.1448	2.0138
India Stock	-0.0331	-0.0856	1.4338	1.9921	21.399
China Stock	0.0165	0.0200	1.0816	-0.6484	5.3109
Japan Stock	0.0169	0	1.0954	0.0738	3.8839
EU Stock	0.0183	0.1100	1.4335	-1.0477	14.165
USA Stock	-0.0193	-0.1294	1.8447	0.7965	6.6381
BRENT	0.0641	0.1984	3.1177	-0.7738	13.135
GOLD	0.0353	0.0315	1.0365	-0.1495	4.8236

4. Methodology

The holiday effect in differing countries makes the time-series mismatch in date stamps. Index and Match function of MS-Excel is used, such that the data in all time-series has same date stamps. Subsequently, each data series is subjected to the Wavelet Transform (WT), according to *Equation 1*:

$$X_m(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} f(t)\psi\left(\frac{t-\tau}{s}\right) dt \qquad (1)$$

where, X_m is the WT of the discrete time-series data f(t). s is a binary dilation and τ is the corresponding binary position of the mother wavelet ψ used in transforming the time-series to wavelets. In this research, the mother wavelet used is a Morlet wavelet which is defined in *Equation 2*. The Morlet wavelet is an orthonormal system which is used to define in a Hilbert basis [56]. $\frac{1}{\sqrt{|s|}}$ is a normalization factor to counter the impact of inflation of the wavelet coefficients in different time scales. In this study, an average number of days for market closure was found to be 7 in a month, where the window size was selected as 24 (31-7=24), where each window essentially represents a month. The phase threshold for this research is considered to be 0.7, where the scalar for phase display is between 0 and 1 for MATLAB R2016a, which is used to conduct the programming in this study.

$$\psi(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-t^2/2} \qquad (2)$$

where, ω_0 is the central frequency of Morlet wavelet, which controls the oscillations number in the selected Gaussian envelope [56]. Thereafter, Wavelet Coherence (WTC) is used to analyze the interactions between the individual market indicators' WTs, given in *Equation 3*. The WTC is a useful tool to analyze the time-varying frequency overlaps, since we get resolution in both the time and frequency domains. The WTC can be used by both investors, who can focus on high frequency components for gauging short-term cycles between two markets for maximizing returns quickly, and policy makers, who can focus on low frequency components to derive policies that can benefit one market over long-period cycles in relation to the other market.

$$C_{XY}(f) = \frac{S|s^{-1}X_m(f)*Y_m^*(f)|}{S|s^{-1}X_m^2(f)|*S|s^{-1}Y_m^2(f)|} \qquad (3)$$

where, $X_m(f)$ represents the WT of either RE or NRE investments and $Y_m(f)$ represents the WT of the macroeconomic factors. $Y_m^*(f)$ is the complex conjugate of $Y_m(f)$. $C_{XY}(f)$ represents the coherence of the two WTs, that gives the information of the time-frequency correlation between two time-series. S is a Gaussian smoothing operator in both axes. The values of WTC vary between 0 and 1, where 0 shows poor time-frequency correlation and 1 represents a complete correlation. The frequency where higher correlations occur can be interpreted as the cycling interval between two time-series indicators.

Finally, the most important aspect of time-frequency relation between two markets' time-series is the evolution of phase dependency over the period of time, given in *Equation 4*. A leading market indicator in phase over another may indicate the direction of investment and fund flow, or even how policy and economic shocks percolate among differing markets. In-phase movements can be interpreted as a constructive inference, where the lead-lag relationship benefit both the markets, whereas in anti-phase relationship represents a destructive interference.

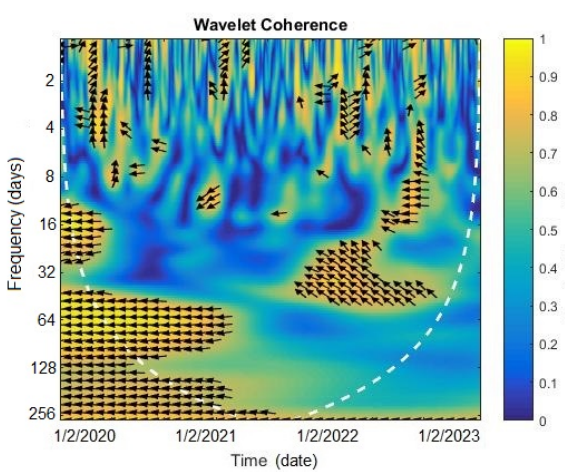
$$\varphi_{XY}(f) = tan^{-1}\frac{Im\{S|s^{-1}X_m(f)*Y_m^*(f)|\}}{Re\{S|s^{-1}X_m(f)*Y_m^*(f)|\}} \qquad (4)$$

where, φ_{XY} represents the phase difference between X (RE or NRE market) and Y (macroeconomic market), and Im and Re show the imaginary and the real parts of the wavelet cross-spectrum for X and Y. When $\varphi_{XY} = \left[0, \frac{\pi}{2}\right]$, X is leading Y with an in-phase relationship; $\varphi_{XY} = [0, -\frac{\pi}{2}]$, Y is leading X with an in-phase relationship; $\varphi_{XY} = [-\pi, -\frac{\pi}{2}]$, X is leading Y with an anti-phase relationship; $\varphi_{XY} = [\pi, \frac{\pi}{2}]$, Y is leading X with an anti-phase relationship.

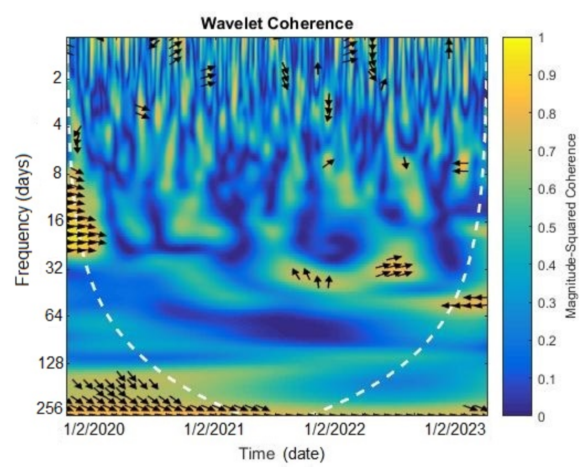
5. Results

5.1 Coherence of RE and Stock markets

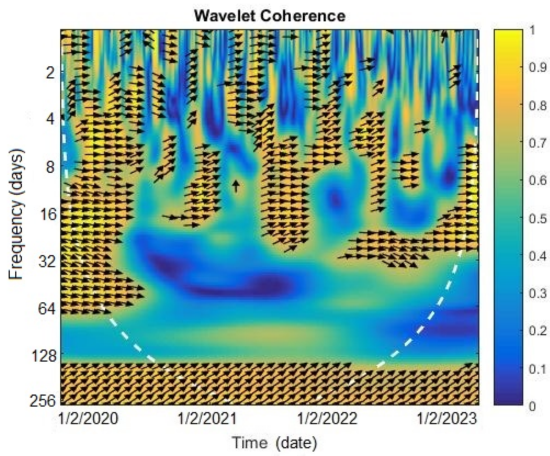
Figure 2 below shows the wavelet coherence between RE and stock indices of the studied nations, with the details for the figure representations given in the caption. It is seen that Japan has characteristic mid- and high- frequency interactions between RE and stock markets, with RE leading, throughout the shocks. It is interesting to see that the RE and stock markets cycle at the 8-16 days band periodically, showing that the COVID-19 (demand) and Ukraine-Russia (oil) shocks have no discernable impact in this investment pattern. However, the 32-64 days band ceases between RE and stock for Japan, at the onset of COVID-19. India and EU started a mid-term 16-64 day cycling of RE-stock, right after the onset of Ukraine-Russia crisis. India specifically having an anti-phase relation of RE leading, shows that the two markets were destructively interfering, as the cycling dissipated within one year, while EU having an in-phase relation with RE leading, shows that hedging is currently continuing between RE and other stock indices. Surprisingly, for China and USA, the RE and stock markets are barely connected, with brief correlation happening for USA in the low frequency domain towards the start of COVID-19. This shows that China and USA being major oil exporters (China exporting refined oil [34]), have continuously decoupled RE and stock markets, having different financial channels to stimulate RE markets than at the stock market-level.



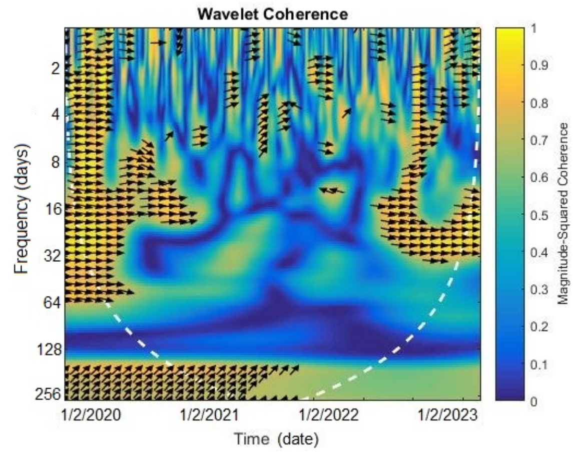
(a) India



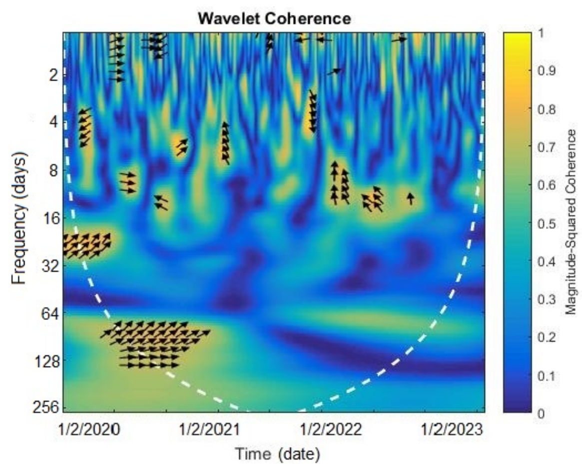
(b) China



(c) Japan



(d) EU



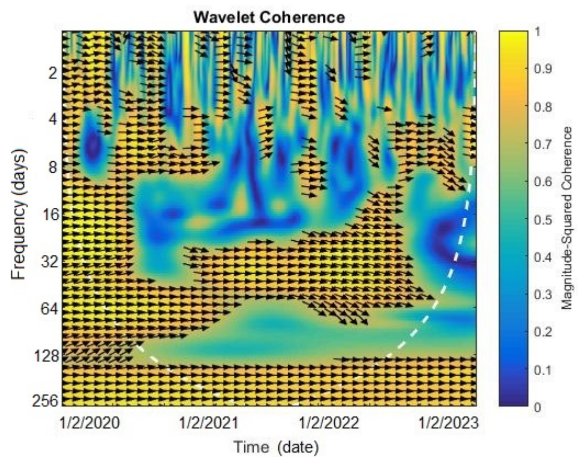
(e) USA

Figure 2: Wavelet Coherence (WTC) between RE indices and Stock Market indices for the respective countries (a) to (e).

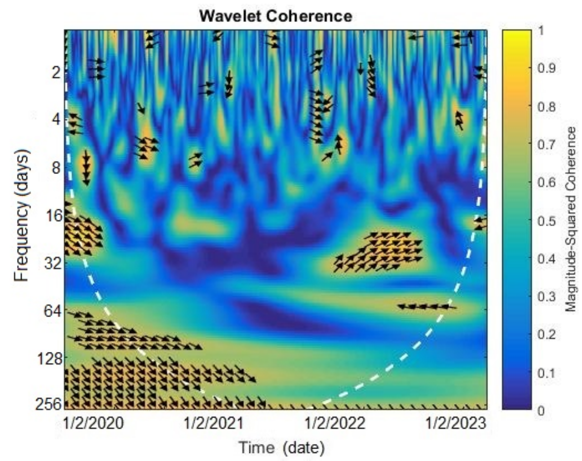
Note: The x-axis shows the time bounds of the study (as mentioned in section 3). The y-axis shows the frequency in periods, comprising high frequency (0 to 8 days), mid frequency (8 to 64 days), and low frequency (64 to 256 days) cycling periods. The coherence values range from 0 to 1, with the color-coding representative of the level of time-frequency correlation. The white dotted line shows the Cone of Influence (CoI), the region within which the correlations are statistically significant. The arrows show the phase difference between X and Y, where the direction of the arrow shows the region of in-phase and anti-phase movements with the lead-lag signals.

5.2 Coherence of NRE and Stock markets

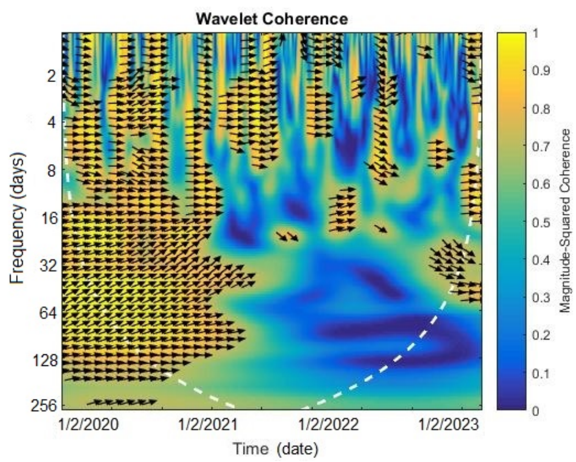
Figure 3 below shows the wavelet coherence between NRE and stock indices of the studied nations, with the details for the figure representations given in the caption. There is an overwhelming correlation between NRE market and stock indices for India and EU, specifically in the short- and long-term. For EU, a break is seen during the onset of the Ukraine-Russia oil crisis in the mid-term cycling (16-64 days), but appears after roughly one year. While Japan shows a similar behavior to India and EU till the onset of the oil shock, the recoupling does not happen in this case, like with the EU. Like RE-Stock cycling, American and Chinese NRE markets are not correlated and do not cycle with the stock index, except for a brief mid-term cycling for China, after the imposition of the sanctions, with NRE leading.



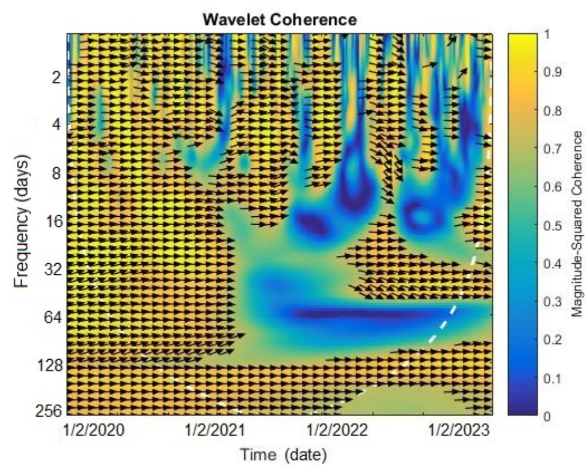
(a) India



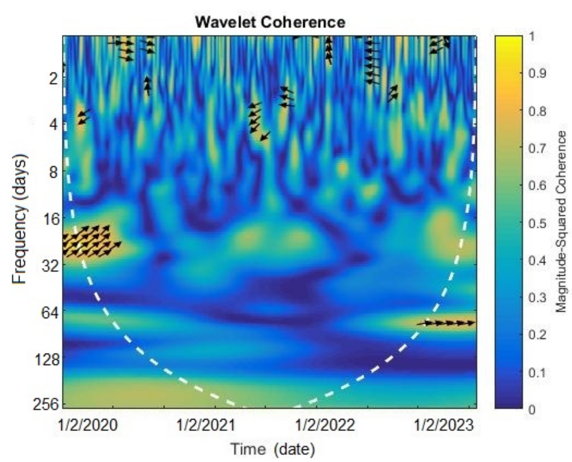
(b) China



(c) Japan



(d) EU



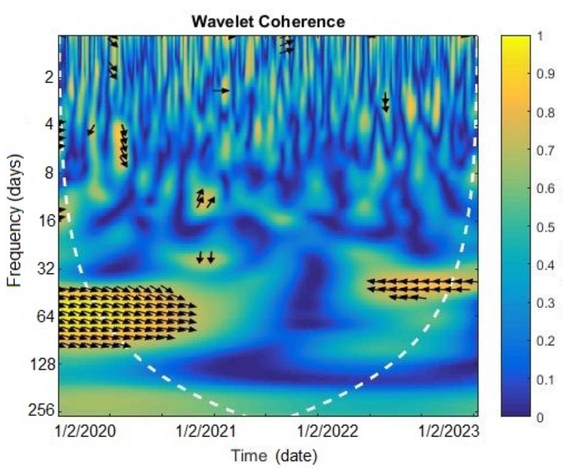
(e) USA

Figure 3: Wavelet Coherence (WTC) between NRE indices and Stock Market indices for the respective countries (a) to (e).

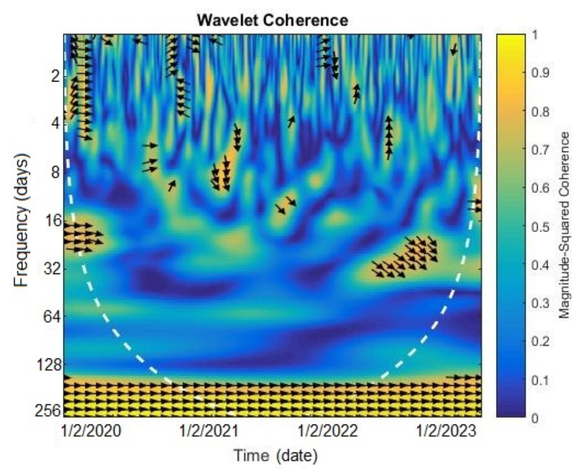
Note: The x-axis shows the time bounds of the study (as mentioned in section 3). The y-axis shows the frequency in periods, comprising high frequency (0 to 8 days), mid frequency (8 to 64 days), and low frequency (64 to 256 days) cycling periods. The coherence values range from 0 to 1, with the color-coding representative of the level of time-frequency correlation. The white dotted line shows the Cone of Influence (CoI), the region within which the correlations are statistically significant. The arrows show the phase difference between X and Y, where the direction of the arrow shows the region of in-phase and anti-phase movements with the lead-lag signals.

5.3 Coherence of RE and Oil market

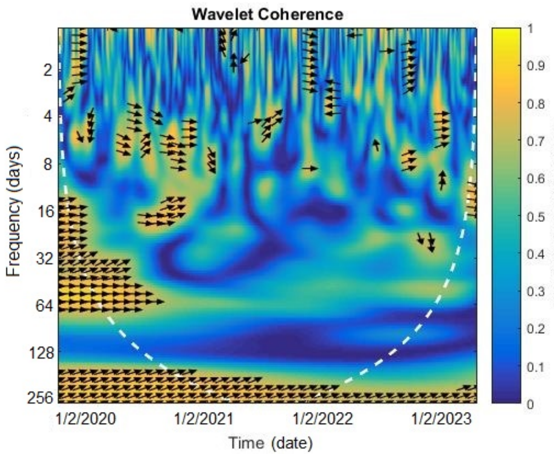
Figure 4 below shows the wavelet coherence between national RE and international oil market indices (BRENT), with the details for the figure representations given in the caption. It is seen that the majority of the countries that had mid-term cycling (16-64 days) between RE and OP, with RE leading, ceased to have the cycling after the onset of COVID-19 crisis. In the case of India and Japan, the extent of the correlation lasted till the effect of the delta variant-induced lockdown in early 2021, showing a viable distribution between the two markets even in reduced demand. However, a constant very low frequency (>256 days) cycling is existent in all the nations except India, throughout the dual shocks. China, Japan and EU compensate the instability in the RE markets after the impact of the dual shocks, by re-linking the two markets, with OP leading over RE, showing that shock-countering measures may change the direction of financial flows in energy markets. India, on the other hand, did not stabilize the RE and OP markets together, due to anti-phase correlation between them in the mid-term period, after the dual shocks. For USA, the RE market is completely and stably coupled to oil markets, such that demand or oil shocks don't affect the high frequency (2-8 days) hedging between the markets or the low frequency cycling. The oil shock brought about a brief delinking between the RE market of USA and OP in the mid-frequency range, which recovered in less than 6 months. This shows the sanctions imposed by USA have significant less impact on their domestic RE market, but impacts other RE markets.



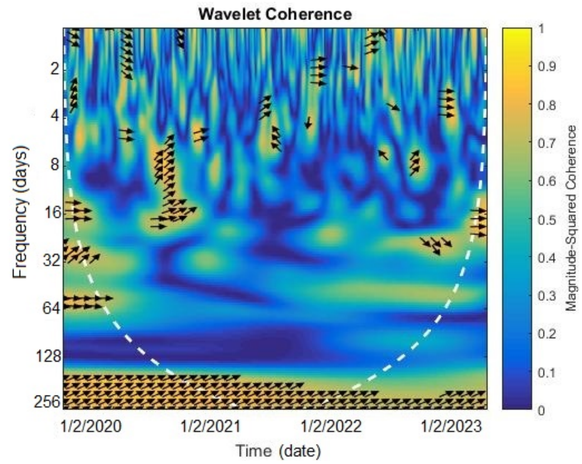
(a) India



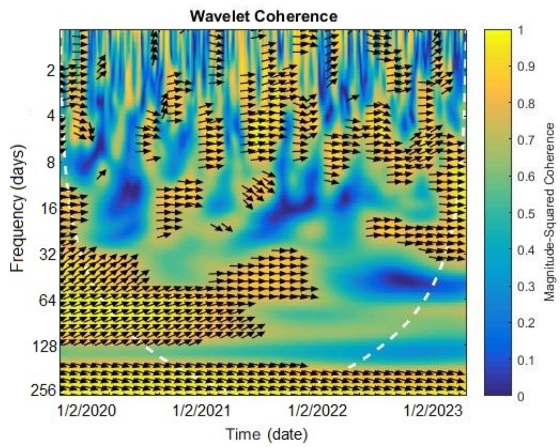
(b) China



(c) Japan



(d) EU



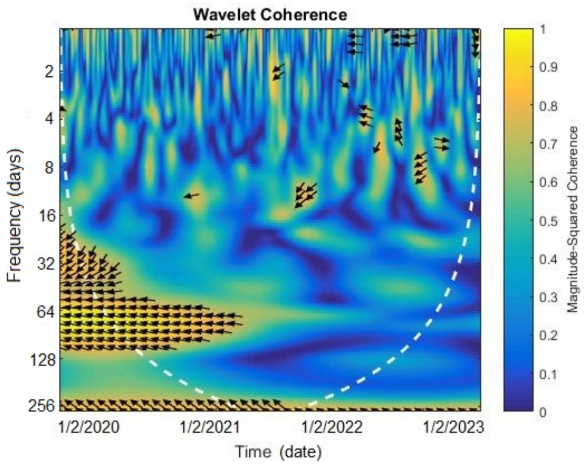
(e) USA

Figure 4: Wavelet Coherence (WTC) between RE indices of the respective countries (a) to (e) with International oil market (BRENT index).

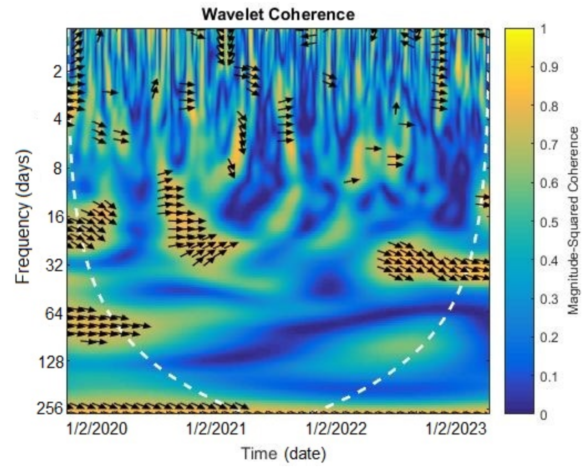
Note: The x-axis shows the time bounds of the study (as mentioned in section 3). The y-axis shows the frequency in periods, comprising high frequency (0 to 8 days), mid frequency (8 to 64 days), and low frequency (64 to 256 days) cycling periods. The coherence values range from 0 to 1, with the color-coding representative of the level of time-frequency correlation. The white dotted line shows the Cone of Influence (CoI), the region within which the correlations are statistically significant. The arrows show the phase difference between X and Y, where the direction of the arrow shows the region of in-phase and anti-phase movements with the lead-lag signals.

5.4 Coherence of NRE and Oil markets

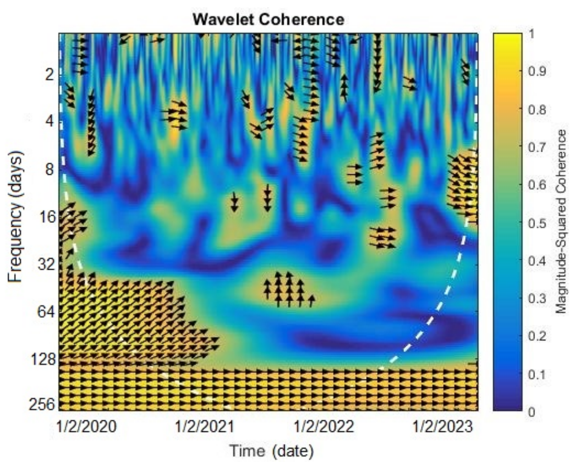
Figure 5 below shows the wavelet coherence between national NRE and international oil market indices (BRENT), with the details for the figure representations given in the caption. It is interesting to note that the NRE index correlation with OP for EU is almost similar to RE-OP for USA, with the exception of the mid-term relinking after the lifting of COVID lockdowns. India is the only country having anti-phase relation between NRE and OP, showing instable financial flows between the two markets, which is why the interactions never recoupled after decoupling during the start of the Ukraine-Russia crisis. Japan and USA show a particular 32-64 day cycling for just six months right after the Ukraine-Russia crisis onset. For Japan, NRE is leading, while for USA, OP is leading. This mid-term cycling is non-existent at this time period for developing countries of India and China, showing a clear divide in financial policies during economic shocks.



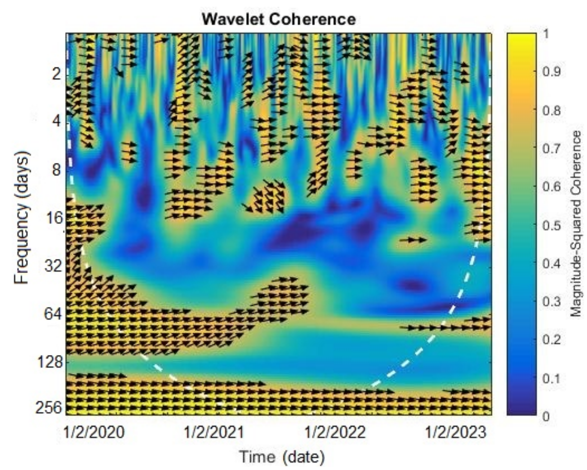
(a) India



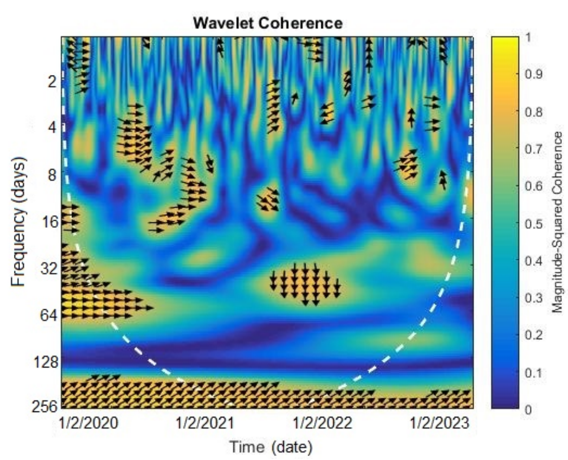
(b) China



(c) Japan



(d) EU



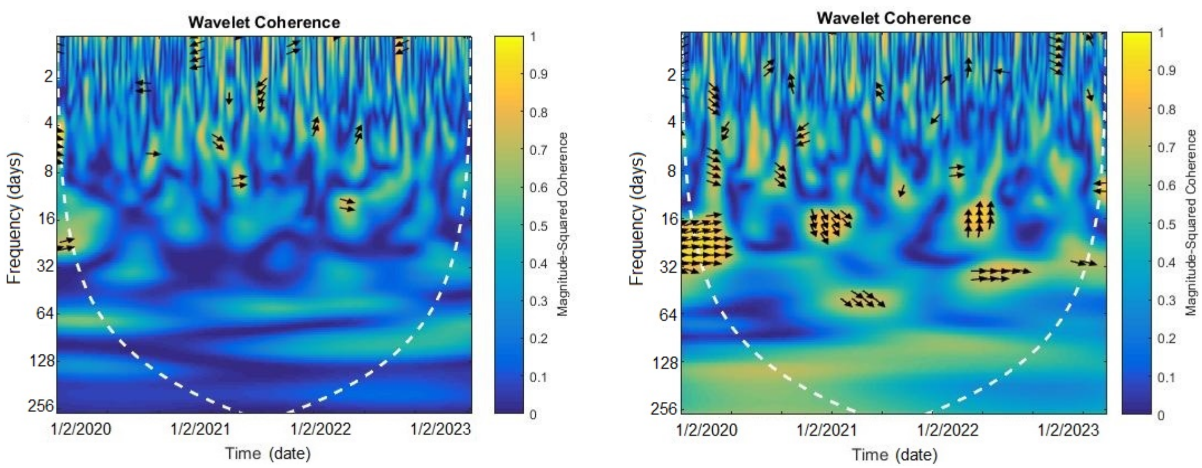
(e) USA

Figure 5: Wavelet Coherence (WTC) between NRE indices of the respective countries (a) to (e) with International oil market (BRENT index).

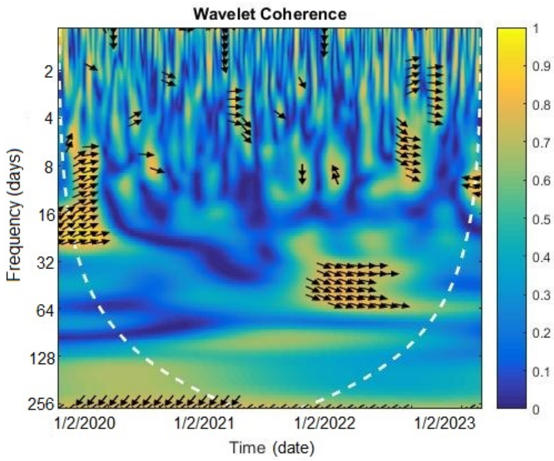
Note: The x-axis shows the time bounds of the study (as mentioned in section 3). The y-axis shows the frequency in periods, comprising high frequency (0 to 8 days), mid frequency (8 to 64 days), and low frequency (64 to 256 days) cycling periods. The coherence values range from 0 to 1, with the color-coding representative of the level of time-frequency correlation. The white dotted line shows the Cone of Influence (CoI), the region within which the correlations are statistically significant. The arrows show the phase difference between X and Y, where the direction of the arrow shows the region of in-phase and anti-phase movements with the lead-lag signals.

5.5 Coherence of RE and Gold markets

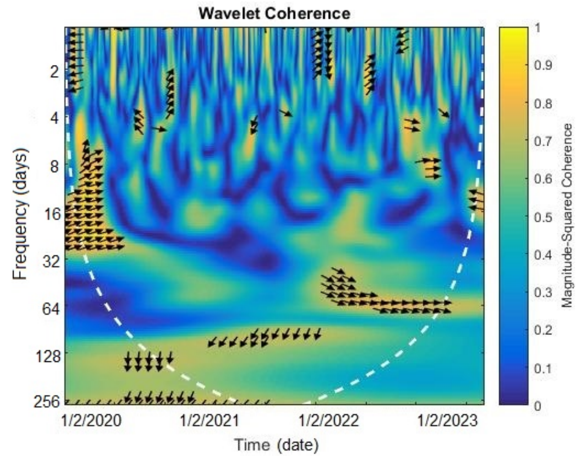
Figure 6 below shows the wavelet coherence between national RE and international gold market indices (XAU), with the details for the figure representations given in the caption. Japan and EU are quite similar in treating the financial flows between RE and gold markets, with both the RE indices losing a stable short- and mid-term cycling with GP that existed pre-COVID. Both the RE indices recoupled to GP, right after the oil shock, but at a lower frequency in the 32-64 day cycling, and GP leading in both cases, which was not the case pre-COVID. China shows a characteristic periodic interaction between RE and GP, which is periodic at the mid-frequencies, which does not follow the shocks in a deterministic pattern. In USA, the periodicity of interaction is not so sharp, but the interaction pathways are quite similar to that of China. Oil-producing nations having like patterns, may indicate RE financial policy planning is steady to stabilize the market over a long-term, rather than a short-term spike. India is shown to have no discernable interaction between RE and GP, which may indicate a very unstable investment cycle for RE in India, since gold has been known to have the most stable market for almost a century [13].



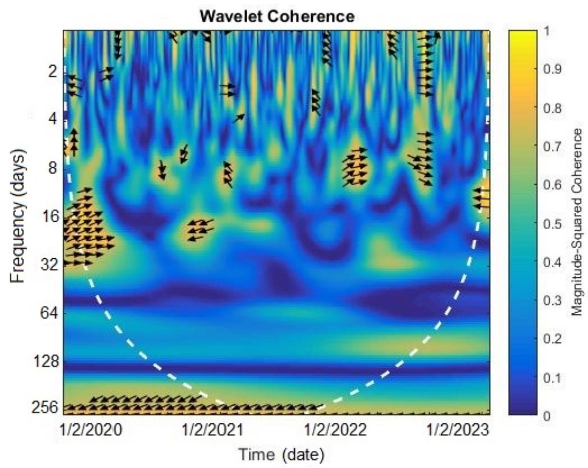
(a) India (b) China



(c) Japan



(d) EU



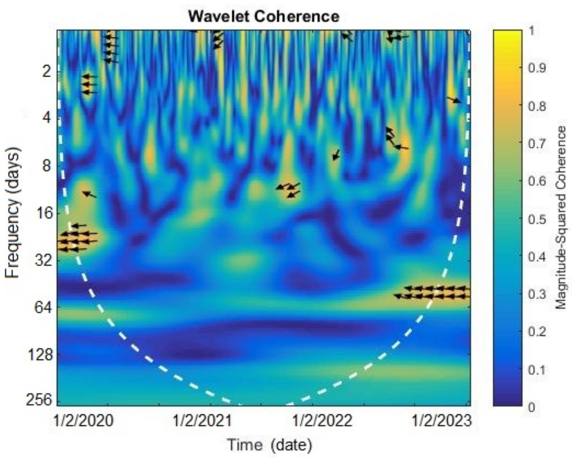
(e) USA

Figure 6: Wavelet Coherence (WTC) between RE indices of the respective countries (a) to (e) with International gold market (BRENT index).

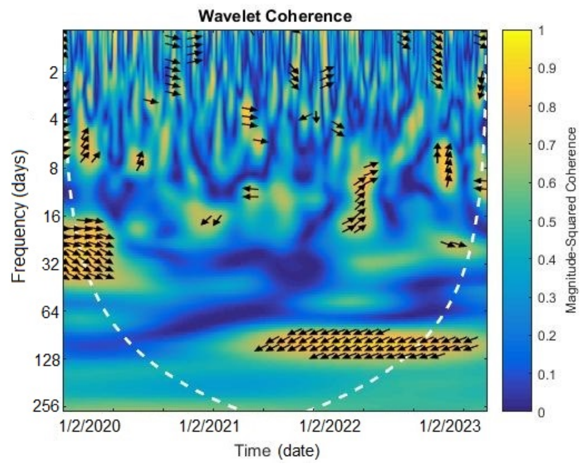
Note: The x-axis shows the time bounds of the study (as mentioned in section 3). The y-axis shows the frequency in periods, comprising high frequency (0 to 8 days), mid frequency (8 to 64 days), and low frequency (64 to 256 days) cycling periods. The coherence values range from 0 to 1, with the color-coding representative of the level of time-frequency correlation. The white dotted line shows the Cone of Influence (CoI), the region within which the correlations are statistically significant. The arrows show the phase difference between X and Y, where the direction of the arrow shows the region of in-phase and anti-phase movements with the lead-lag signals.

5.6 Coherence of NRE and Gold markets

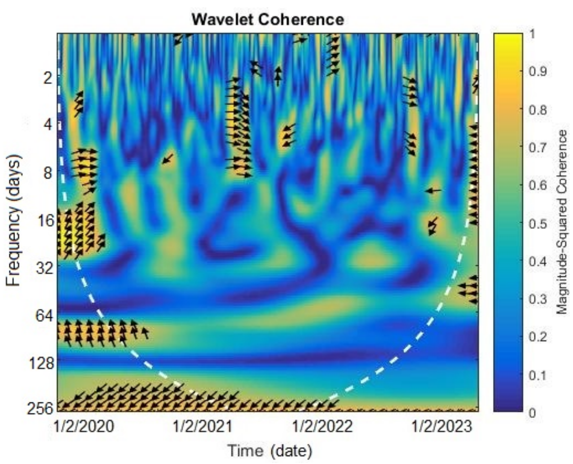
Figure 6 below shows the wavelet coherence between national NRE and international gold market indices (XAU), with the details for the figure representations given in the caption. China, India, Japan, USA and the EU show anti-phase relations with NRE leading in the low frequency (64-256 days) domain, showing a global disruptive investment between domestic NRE markets and international gold market. For USA and China, this offset appears at the onset of the Ukraine-Russia crisis, showing an increasing percolation from the gold markets to the NRE markets. EU surprisingly shows a characteristic behavior with a switch between in-phase and anti-phase relation in the mid-frequency (16-32 days) domain before and after the onset of COVID-19., in both cases NRE leading. EU is the only region to show a mid-frequency interaction during the COVID-19 lockdowns. USA is the only country with an in-phase, mid-frequency interaction at the Ukraine-Russia crisis onset.



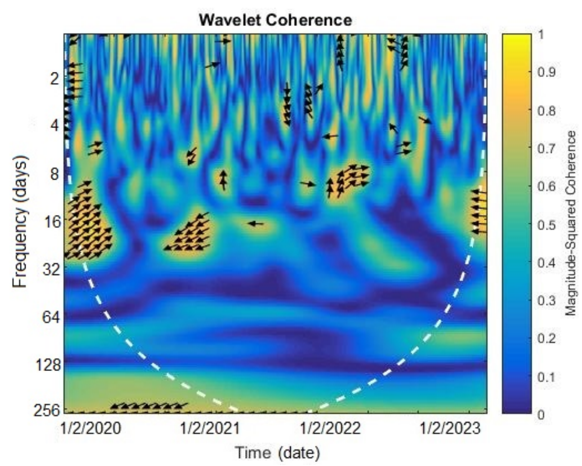
(a) India



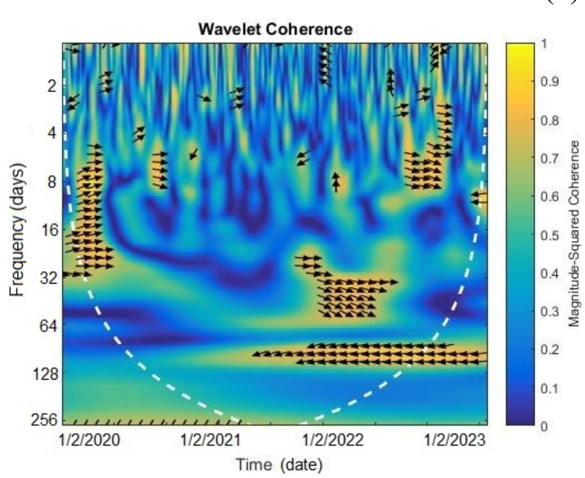
(b) China



(c) Japan



(d) EU



(e) USA

Figure 7: Wavelet Coherence (WTC) between RE indices of the respective countries (a) to (e) with International gold market (BRENT index).

Note: The x-axis shows the time bounds of the study (as mentioned in section 3). The y-axis shows the frequency in periods, comprising high frequency (0 to 8 days), mid frequency (8 to 64 days), and low frequency (64 to 256 days) cycling periods. The coherence values range from 0 to 1, with the color-coding representative of the level of time-frequency correlation. The white dotted line shows the Cone of Influence (CoI), the region within which the correlations are statistically significant. The arrows show the phase difference between X and Y, where the direction of the arrow shows the region of in-phase and anti-phase movements with the lead-lag signals.

6. Policy Discussions

6.1 Comparison of Effects of COVID-19 and Ukraine-Russia Shocks

Significant differences between impact of the dual shocks of COVID-19 (demand shock) and the Ukraine-Russia (oil supply shock) on domestic RE and NRE markets were noted across the studied countries and regions. Most notably, a demand shock significantly disrupts the stability of the domestic RE markets, as mid-term RE indices' cycling with international gold and domestic stock markets gets decoupled. Investors may consider that RE markets cannot have immediate or mid-term returns due to a lack of financial securities in RE markets [22]. On the other hand, an oil shock creates instabilities in all stock markets, which enable mid-term cycling between RE and gold markets for developed nations, and RE and stock markets globally. Developing countries' investors should aim to stabilize RE markets by hedging with the stable gold markets specifically during oil price shocks. Specifically, for the photovoltaics (PV) producing nations like Japan and China, an oil shock drives the value for RE market indices, which can be a key strategy for other developed and developing nations for mitigating RE market instabilities.

Simultaneously, for NRE markets, the NRE indices are decoupled from international oil market during a demand shock, the NRE markets of developed nations recouple their domestic NRE markets during the oil shock. NRE market stability is essential for RE development otherwise natural flow of funds cannot happen from the already heavily-invested NRE markets to the RE markets. Specifically, developed nations should aim for hedging between NRE and RE markets, and developing nations should first establish a proper financial feedback between OP and NRE indices right after the onset of economic shocks. While a demand shock is seen to decouple NRE from the stable international gold market, due to decreased investor faith, an oil shock stabilizes NRE markets with gold in electric vehicle (EV) producing nations like USA and China. This is due to the oil products required in electric vehicle production that are boosted during the insecurity of OP as fuel for internal combustion engine cars.

6.2 Impact of Sanctions

The dual shocks' impact on feedback between stock and RE/NRE energy markets can be clearly delineated by the impact of sanctions imposed during Ukraine-Russia oil shock and a non-sanction COVID-19 demand shock. Specifically, EU NRE market was clearly in feedback with the stock market (*Figure 3d*) till the onset of the oil shock, and the year-after recoupling of NRE and stock markets can be attributed to the impact of sanctions imposed by the USA on Russian oil supply, which indirectly caused the euro to devalue rather sharply. It may be interpreted that the sanctions did not affect Japan, as much as EU, due to import diversification, as the NRE-stock market cycling did not have to reappear to stabilize the NRE market (*Figure 3c*). In fact, the evidence of the impact of sanctions on the oil market is seen even in USA and Japan, specifically in the cycling with NRE and oil markets. Japan lead with NRE, while USA lead with oil itself, to hedge investments between the two markets, which dissipated rather shortly (*Figure 5*). This shows that sanctions can bring about long-term instabilities in NRE markets, which will actually prevent hedging from NRE to RE markets in the long-run.

6.3 Renewable and Non-Renewable Market Mechanisms

China and USA being net exporters of oil and oil products, RE investment strategies in such nations are not related to stock indices (*Figure 2*). Specifically, the NRE index in USA is completely decoupled from NASDAQ index, showing that the hedging of RE market by investors are focused towards the oil and gold markets (*Figure 3c*). A developing nation like India can benefit from this strategy, to exclude the volatility of stock markets by not hedging depreciating stocks with RE stocks, which eventually leads RE markets towards instability during demand shocks. The mechanism of cycling between RE and oil markets for USA is quite similar to NRE and oil markets for the EU. This can be because NRE companies in the EU are now specifically linked to oil and gas business, but also diversify into renewables. China and India both have lots of subsidies towards oil and gas companies, where a mechanism of subsidy for carbon offset or renewable investment can attract investor to seed funding in NRE companies investing in RE technologies. This is evidenced by the fact that RE and stocks aligned in India, similar to the EU, but in anti-phase (*Figure 2*). India should strive to first hedge RE and stock constructively, and slowly shift away from hedging with the stock market, but with the more stable gold market.

A second mechanism that can be seen for developing economies is that RE and OP feedback decouples during the onset of oil shocks (*Figure 4*). However, in developed economies a long-term stable hedging from oil markets to RE markets (RE leading) is seen irrespective of shocks. This strategy is delineated by the long-term stable returns that are achieved from the RE markets, which are in-turn, due to the long-term hedging that is performed. Developing economies should strive to set this equilibrium for RE markets to stabilize irrespective of economic shocks.

Thirdly, the linkage of energy markets with international gold market can shed light on the stability of the energy markets during and after shocks. Pre-COVID, all of the NRE markets were decoupled from gold index, but the oil shock forced all nations to stabilize their NRE markets with gold market cycling. However, the same cannot be said about RE markets, as RE-gold feedback does not exist in developing countries. Investors from developing countries should look towards how immediately after an oil shock, RE and gold were put into long-term feedback of financial flows in the countries that produce EVs. Governments should ramp up the production of EVs in developing countries post-oil shock, to render long-term stability for RE markets.

7. Conclusion

This study conducted an analysis of the interactions of the RE and NRE markets of India, China, Japan, EU and USA with macroeconomic markets of oil and gold during the dual shocks of COVID-19 and the Russian aggression on Ukraine, using a time-frequency coherence measure of Wavelet Coherence (WTC). The following are the main policy findings for the study, to ensure a stable RE market post the impact of the dual shocks for these nations:

1. The COVID-19 crisis, essentially a demand shock, and the Ukraine-Russia crisis, essentially an oil shock, affected developing countries like India and Eastern European nations more than developed countries like USA, Japan and Western Europe.
2. The EU were most impacted by sanctions, with the NRE markets destabilized in the EU. EU should adopt oil-purchasing diversity, post which, RE markets can also be linked to long-term stable movements of the international oil market. Sanctions are not effective for the development of RE, but actually hinders RE progression, despite bans on oil trade.
3. USA's model of decoupling RE and NRE markets from the volatile investments of stock markets during economic shocks, should be a model for developing and developed nations to adopt for a stable growth of RE markets post-economic shock.
4. An oil shock should be the impetus for ramping EV production, which would render short-term growths in RE markets. Investors will be able to link RE and stable gold markets through financial flows with gold leading, enabling a stable RE market out of the oil shock.
5. Specifically in developing economies, investors should hedge international oil and national NRE markets, which would render stability to NRE companies, such that they can be incentivized to invest in RE as well.
6. After an oil shock, developing economy investors should hedge national RE and international gold markets to eventually promote a long-run stable financial flow. This can be achieved when developing nations' Governments subsidize PV production after an oil shock, enabling investors to visualize tangible returns.

This study proved that the dual shocks impacted domestic RE and NRE markets differently across different nations. Stabilization of the RE market is key for a sustained growth of RE technology, otherwise the targets set by nations towards a 'net-zero' society cannot be achieved. This methodological framework can be adopted by policymakers to delineate clear financial policies during economic crises for the 'net-zero' pathway, such that RE markets are strengthened.

This study focused on the two most important macroeconomic factors of oil and gold. However, further research is required into other factors that can be specifically leveraged for individual RE technologies, such as rare earth metals, copper and even for nuclear energy. The time-frequency coherence analysis shows the phase and correlation, but more robust techniques for establishing causality among macroeconomic factors and energy markets are required for delineating how funds should be allocated from the end of investors, and opportunities for hedging.

Author Contributions

Conceptualization, S.B.; methodology, S.B.; software, S.B.; validation, S.B., H.O.; formal analysis, S.B.; investigation, S.B.; resources, S.B.; data curation, S.B.; writing—original draft preparation, S.B.; writing—review and editing, H.O.; visualization, S.B.; supervision, K.N.I. All authors have read and agreed to the published version of the manuscript.

Acknowledgments

The authors are grateful for the financial support from the Japan Science and Technology Agency (JST) of Japan for the doctoral studies of Soumya Basu at Kyoto University. The authors are also grateful to professor emeritus Keiichi N. Ishihara (Kyoto University) for lending support to the conceptualization and policy analysis of the empirical results.

References

1. Wang H., Asif A.M., Arshed N., Mohamed A., Ali S., Haider J.M.A., Khan Y.A.: Fossil Energy Demand and Economic Development in BRICS Countries. *Frontiers in Energy Research* 10 (2022). https://doi.org/10.3389/fenrg.2022.842793.
2. Ralf K.: Market interaction. In: Business Cycles. Contributions to Economics. *Physica*-Verlag HD (2000). https://doi.org/10.1007/978-3-642-51742-6_6.
3. Tang C., Aruga K., Hu Y.: The Dynamic Correlation and Volatility Spillover among Green Bonds, Clean Energy Stock, and Fossil Fuel Market. *Sustainability* 15(8), 6586 (2023). https://doi.org/10.3390/su15086586.
4. Basu S., Ogawa T., Ishihara K.N.: Chapter 10 - The methods and factors of decoupling energy usage and economic growth. Waste-to-Energy Approaches Towards Zero Waste, Elsevier Inc., pp. 269-313 (2022). https://doi.org/10.1016/B978-0-323-85387-3.00002-1.
5. Işik C., Kasımatı E., Ongan S.: Analyzing the causalities between economic growth, financial development, international trade, tourism expenditure and/on the CO2 emissions in Greece. *Energy Sources, Part B: Economics, Planning, and Policy* 12(7), pp. 665-673 (2017). https://doi.org/10.1080/15567249.2016.1263251.
6. Shahbaz M., Zeshan M., Afza T.: Is energy consumption effective to spur economic growth in Pakistan? New evidence from bounds test to level relationships and Granger causality tests. Economic Modelling 29(6), pp. 2310-2319 (2012). https://doi.org/10.1016/j.econmod.2012.06.027.
7. Yuan J.H., Kang J.G., Zhao C.H., Hu Z.G.: Energy consumption and economic growth: Evidence from China at both aggregated and disaggregated levels. Energy Economics 30(6), pp. 3077-3094 (2008). https://doi.org/10.1016/j.eneco.2008.03.007.
8. Nepal R., Paija N., Tyagi B., Harvie C.: Energy security, economic growth and environmental sustainability in India: Does FDI and trade openness play a role? Journal of Environmental Management 281, #111886 (2021). https://doi.org/10.1016/j.jenvman.2020.111886.
9. Ghosh S.: Electricity supply, employment and real GDP in India: evidence from cointegration and Granger-causality tests. Energy Policy 37(8), pp. 2926-2929 (2009). https://doi.org/10.1016/j.enpol.2009.03.022.
10. Abbasi K.R., Shahbaz M., Jiao Z., Tufail M.: How energy consumption, industrial growth, urbanization, and CO2 emissions affect economic growth in Pakistan? A novel dynamic ARDL simulations approach. *Energy* 221, #119793 (2021). https://doi.org/10.1016/j.energy.2021.119793.
11. Turhan-Sayan G., Sayan S.: Use of Time-Frequency Representations in the Analysis of Stock Market Data. In: Kontoghiorghes, E.J., Rustem, B., Siokos, S. (eds) Computational Methods in Decision-Making, Economics and Finance. Applied Optimization, vol 74. Springer, Boston, MA (2002). https://doi.org/10.1007/978-1-4757-3613-7_22.
12. Cui J., Goh M., Li B., Zou H.: Dynamic dependence and risk connectedness among oil and stock markets: New evidence from time-frequency domain perspectives. *Energy* 216, #119302 (2021). https://doi.org/10.1016/j.energy.2020.119302.
13. Basu S., Ishihara K.: Multivariate Time-Frequency Interactions of Renewable and Non-Renewable Energy Markets with Macroeconomic Factors in India. *Energy Systems* (2023). (*In-press*).
14. Eurostat: A macro-economic overview. https://ec.europa.eu/eurostat/cache/digpub/european_economy (Accessed on 15 July 2023).
15. Worldometer: Countries in the world by population (2023). https://www.worldometers.info/world-population/population-by-country/. (Accessed on 15 July 2023).
16. Worldometer: GDP by Country. https://www.worldometers.info/gdp/gdp-by-country/ (Accessed on 15 July 2023).

17. IEA: World Energy Outlook 2020, International Energy Agency, Paris (2020). https://www.iea.org/reports/world-energy-outlook-2020.
18. Worldometer: CO2 Emissions by Country. https://www.worldometers.info/co2-emissions/co2-emissions-by-country/. (Accessed on 15 July 2023).
19. IEA: Global energy demand to plunge this year as a result of the biggest shock since the Second World War. *Press Release* on 30 April 2020.
20. Khan M., Kayani U.N., Khan M., Mughal K.S., Haseeb M.: COVID-19 Pandemic & Financial Market Volatility; Evidence from GARCH Models. *Journal of Risk and Financial Management* 16(1), 50 (2023). https://doi.org/10.3390/jrfm16010050.
21. Gaur A., Settles A., Väätänen J.: Do Economic Sanctions Work? Evidence from the Russia-Ukraine Conflict. *Journal of Management Studies* (2023) (*In-press*). https://doi.org/10.1111/joms.12933.
22. Farid S., Karim S., Naeem M.A., Nepal R., Jamasb T.: Co-movement between dirty and clean energy: A time-frequency perspective. *Energy Economics* 119, #106565 (2023). https://doi.org/10.1016/j.eneco.2023.106565.
23. Adebayo T.S., AbdulKareem H.K.K., Kirikkaleli B.D., Shah M.I., Abbas S.: CO2 behavior amidst the COVID-19 pandemic in the United Kingdom: The role of renewable and non-renewable energy development. *Renewable Energy* 189, 492-501 (2022). https://doi.org/10.1016/j.renene.2022.02.111.
24. Yasmeen R., Hao G., Ullah A., Shah W.U.H., Long Y.: The impact of COVID-19 on the US renewable and non-renewable energy consumption: a sectoral analysis based on quantile on quantile regression approach. *Environmental Science and Pollution Research* 29, 90419–90434 (2022). https://doi.org/10.1007/s11356-022-22054-4.
25. Ha L.T.: An application of QVAR dynamic connectedness between geopolitical risk and renewable energy volatility during the COVID-19 pandemic and Russia-Ukraine conflicts. *Journal of Environmental Management* 342, #118290 (2023). https://doi.org/10.1016/j.jenvman.2023.118290.
26. Yahya F., Shaohua Z., Waqas M., Xiong Z.: COVID-Induced Investor Sentiments and Market Reaction under Extreme Meteorological Conditions: Evidence from Clean Energy Sector of Asia-Pacific, *Problems of Sustainable Development* 16(1), 7-15 (2021).
27. Liu M.: The driving forces of green bond market volatility and the response of the market to the COVID-19 pandemic. *Economic Analysis and Policy* 75, 288-309 (2022). https://doi.org/10.1016/j.eap.2022.05.012.
28. He Y., Zhang Z.: Non-Renewable and Renewable Energies, and COVID-19 Pandemic: Do They Matter for China's Environmental Sustainability? *Energies* 15(19), 7143 (2022). https://doi.org/10.3390/en15197143.
29. Chernova E. Г., Razmanova C. B.: Gas Crisis in the European Commodity Market: Roots and Opportunities to Overcome. *Economy of Regions* 18(4), 1194–1208 (2022). https://doi.org/10.17059/ekon.reg.2022-4-16.
30. Elamer A.A., Elbialy B.A., Alsaab K.A., Khashan M.A.: The Impact of COVID-19 on the Relationship between Non-Renewable Energy and Saudi Stock Market Sectors Using Wavelet Coherence Approach and Neural Networks. *Sustainability* 14(21), 14496 (2022). https://doi.org/10.3390/su142114496.
31. Bilbao-Terol, A. Arenas-Parra, M. Quiroga-García R., Bilbao-Terol C.: Is investing in the renewable energy stock market both financially and ESG efficient? A COVID-19 pandemic analysis. *Review of Managerial Science* (2023). https://doi.org/10.1007/s11846-023-00664-7.
32. Hung N.T.: Oil prices and agricultural commodity markets: Evidence from pre and during COVID-19 outbreak. *Resources Policy* 73, #102236 (2021). https://doi.org/10.1016/j.resourpol.2021.102236.
33. Chien F., Sadiq M., Kamran H.W., Nawaz M.A., Hussain M.S., Raza M.: Co-movement of energy prices and stock market return: environmental wavelet nexus of COVID-19 pandemic from the USA,

Europe, and China. *Environmental Science and Pollution Research* 28, pp. 32359–32373 (2021). https://doi.org/10.1007/s11356-021-12938-2.
34. Mensi W., Rehman M.U., Maitra D., Al-Yahyaee K. H.., Vo X.V.: Oil, natural gas and BRICS stock markets: Evidence of systemic risks and co-movements in the time-frequency domain. *Resources Policy* 72, #102062 (2021). https://doi.org/10.1016/j.resourpol.2021.102062.
35. Hanif W., Mensi W., Gubareva M., Teplova T.: Impacts of COVID-19 on dynamic return and volatility spillovers between rare earth metals and renewable energy stock markets. *Resources Policy* 80, #103196 (2022). https://doi.org/10.1016/j.resourpol.2022.103196.
36. Chen H., Xu C., Peng Y.: Time-frequency connectedness between energy and nonenergy commodity markets during COVID-19: Evidence from China. *Resources Policy* 78, #102874 (2022). https://doi.org/10.1016/j.resourpol.2022.102874.
37. Bombay Stock Exchange Daily Closing Price Historical Data (accessed on 15 July 2023): https://www.bseindia.com/markets/equity/EQReports/StockPrcHistori.html.
38. Bombay Stock Exchange Daily Closing Price for Oil & Gas (accessed on 15 July 2023): https://www.bseindia.com/sensex/code/37.
39. Financial Times: KraneShares MSCI China Clean Technology ETF (accessed on 15 July 2023). https://markets.ft.com/data/etfs/tearsheet/historical?s=KGRN:PCQ:USD.
40. Investing.com: Xinyi Energy Holdings Ltd (accessed on 15 July 2023). https://www.investing.com/equities/xinyi-energy-holdings-historical-data.
41. Investing.com: China Shenhua Energy Co Ltd H (accessed on 15 July 2023). https://www.investing.com/equities/china-shenhua-ss-historical-data.
42. Investing.com: FTSE China Alternative Energy Total Return USD (accessed on 15 July 2023). https://www.investing.com/indices/china-alternative-energy-tr-usd-historical-data.
43. Investing.com: FTSE China Alternative Energy Price USD (accessed on 15 July 2023). https://www.investing.com/indices/china-alternative-energy-price-usd-historical-data.
44. Investing.com: FTSE China A 600 - Oil & Gas (accessed on 15 July 2023). https://www.investing.com/indices/ftse-china-a-600-oil---gas-historical-data.
45. S&P Down Jones Indices: S&P Global Clean Energy Index (accessed on 15 July 2023). https://www.spglobal.com/spdji/en/indices/esg/sp-global-clean-energy-index/#overview
46. Japan Exchange Group: Historical data of Japanese Stock Exchange (accessed on 15 July 2023). https://www.jpx.co.jp/english/markets/paid-info-equities/historical/01.html.
47. Investing.com: European Renewable Energy Total Return (ERIX) (accessed on 15 July 2023). https://www.investing.com/indices/european-renewable-energy-tr-historical-data.
48. Investing.com: STOXX Europe 600 Oil & Gas (SXEP) (accessed on 15 July 2023). https://www.investing.com/indices/stoxx-europe-600-oil---gas-historical-data.
49. Investing.com: NASDAQ Clean Edge Green Energy Historical Data (accessed on 15 July 2023). https://www.investing.com/indices/nasdaq-clean-edge-green-energy-historical-data.
50. Investing.com: Dow Jones Oil & Gas (DJUSEN) (accessed on 15 July 2023). https://www.investing.com/indices/dj-oil---gas-historical-data.
51. Investing.com: Shanghai Composite (SSEC) (accessed on 15 July 2023). https://www.investing.com/indices/shanghai-composite-historical-data.
52. Investing.com: FTSE 100 (accessed on 15 July 2023). https://www.investing.com/indices/uk-100-historical-data.
53. Investing.com: NASDAQ Composition Historical Daily Index (accessed on 15 July 2023). https://www.investing.com/indices/nasdaq-composite-historical-data.

54. Brent Crude Oil Prices: 10 Year Daily Chart (accessed on July 15 2022): https://www.macrotrends.net/2480/brent-crude-oil-prices-10-year-daily-chart.
55. Gold Price: Last 10 Years (accessed on July 15 2022): https://www.macrotrends.net/2627/gold-price-last-ten-years.
56. Wikipedia: Morlet Wavelet https://en.wikipedia.org/wiki/Morlet_wavelet.
57.