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Technological Innovations and Volatility Dynamics: Exploring the Interplay Between Clean Cryptocurrencies, Natural Gas, and Clean Energy

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Abstract—**The study utilizes to analyze the conditional correlations and volatility persistence of S&P Global Clean Energy Index, Natural Gas, and clean cryptocurrencies (Cardano and Solana). It employs a DCC GARCH model (Dynamic Conditional Correlation model) this examines the existing time-varying correlations among various assets. Results demonstrate that Clean Energy Index stabilizes rapidly, but clean cryptocurrencies and natural gas display significant and persistent volatility. Solana has significant connections with Natural Gas and Clean Energy, illustrating interrelated market dynamics. The research provides valuable insight for decision-makers, financiers, and investors into how digital, clean, and dirty energy assets interact.**

Keywords— Clean Cryptocurrencies, Clean Energy Index, Natural Gas, DCC GARCH, Dynamic Conditional Correlation, Volatility Persistence, Energy Transition.

I. INTRODUCTION

The worldwide energy market has been greatly affected by the conflict between Russia and Ukraine, which has increased volatility and changed the relationship between the established and new energy sectors. The conflict has brought energy security to the forefront of political and economic agendas in Europe, since the continent is highly dependent on Russian gas and oil.[1] The need of transitioning to renewable energy sources has been brought to light by this situation. This will help alleviate environmental concerns and lessen the geopolitical threats associated with our reliance on fossil fuels.[2]The conflict has also shed light on the complicated web of interconnections between new clean energy markets, more established dirty energy sectors, and newly developed financial products like cryptocurrency-based energy-related products.[3]

Several considerations are made in this study to go into these unexpected relationships: The S&P Global Clean Energy Index tracks the success of major clean energy companies; in contrast, natural gas is a dirty energy source that is both necessary and detrimental to the environment; the geopolitical tensions surrounding this conflict have a significant impact on this source [4]. We incorporate clean cryptocurrencies like as Cardano and Solana to assess the connection between these established and developing markets and digital assets linked to sustainable technology.[5]

These developments have challenged the notion that clean energy markets operate independently from, rather than in conjunction with, traditional energy markets, particularly in geopolitical instability. [6] [7] The conflict between Russia and Ukraine has shown a possible correlation between these markets, implying that even environmentally friendly energy sectors are vulnerable to shocks caused by conventional energy supplies, such as natural gas. [8] Investors and lawmakers must take the lead in comprehending the interplay between the markets because of the importance of these markets' interdependence during crises.[9]

Cardano and Solana are two examples of clean cryptocurrencies that have emerged recently, adding another level of complexity to the international energy sector. [10] This new investment opportunity is based on digital assets that are connected to blockchain technology that are energy efficient. Simultaneously, they have raised the level of uncertainty and volatility in the market.[11] The role played by these cryptocurrencies in the energy market, especially during geopolitical conflicts such as the Russia-Ukraine War, is hardly explored.[12]Since the S&P Global Clean Energy Index is already struggling, investors should be aware of how these two cryptocurrencies impact the interaction between clean energy and dirty energy sectors, including the natural gas market, which is experiencing more and more dynamic opportunities.[13]

In this empirical study, the impact of the conflict between Russia and Ukraine on clean energy markets (S&P Global Clean Energy Index), dirty energy markets (natural gas), and clean cryptocurrencies (Cardano and Solana) is to be identified.[14] This research, therefore, looks to investigate the dynamic connectedness between these markets before, during, and after the onset of conflict to find out how geopolitical tensions influence these interrelated energy sectors.[15] This analysis is essential as the war has caused considerable disruptions to global energy supply chains, which led to price shocks and increasing market uncertainty. [16]

The findings from this study will introduce new perspectives to investors, policymakers, and market participants who must assume risks and capture opportunities under events of geopolitical instability.[17] The findings from this study will introduce new perspectives to investors, policymakers, and market participants who must assume risks and capture opportunities under events of geopolitical instability. [18]Stakeholders will need to know how the clean energy markets interact with natural gas and other dirty energy sources and clean energy-related cryptocurrencies when making decisions about portfolio diversification, risk management, and policy creation. [19] As the energy world continues to change because of the conflict between Russia and Ukraine, this should improve stakeholders' understanding of the energy market's complex interdependencies and guide their navigation of the challenges and opportunities ahead.[20]
The structure of this paper is outlined as follows: Section 2 presents a tabular assessment of the literature, while Section 3 outlines the data, methodology, and tools employed. Section 4 presents the outcomes derived from the utilized models. Section 5 presents the conclusion and its associated consequences..

II. LITERATURE REVIEW

Clean cryptocurrency, clean energy, and dirty energy have recently gained popularity, substance, and importance. much research has recently been done on these topics. Economic factors, markets, asset classes, and macroeconomic variables have all been the subject of much research over the years, with policy implications that assist various stakeholders in managing risk and diversifying their investment portfolios**.**
Table 1 summarizes the literature on the dynamic relationships between clean energy, dirty energy, and clean cryptocurrency. much research has investigated the links between various asset groups, yielding valuable insights but leaving significant gaps.
For instance, [21] employed wavelet coherence to show the complex, inconsistent linkages between energy cryptocurrency and energy markets. While insightful, this approach provides a static perspective, ignoring the time-varying dynamics required to comprehend dynamic market situations. Similarly, [22] investigated risk spillovers between Islamic stock markets and renewable energy using VAR-ADCC models, although their emphasis needed to be bigger, limiting the study's overall usefulness. Studies such as [23] and [24] investigated volatility spillovers using advanced models such as GJR-GARCH and DCC-GARCH. However, they should have included the significance of geopolitical events in driving these dynamics. Furthermore, research on clean and dirty energy ([25], [26]) frequently uses static models that fail to reflect how linkages evolve, particularly during market disruptions.
Few studies have included clean cryptocurrencies such as Cardano and Solana, with the most of research focusing on Bitcoin or Ethereum ([21], [27], [28]). This creates a significant vacuum in understanding the function of digital assets in energy markets. Furthermore, while some research ([27], [28]) emphasizes diversification potential, it overlooks short-term volatility dynamics and the impact of geopolitical tensions, such as the Russia-Ukraine war.
The review of existing literature identifies three significant gaps, which this study seeks to address. First, there needs to be more focus on clean cryptocurrencies, leaving a significant gap in understanding the function of digital assets in the broader energy markets. Secondly, most previous research still needs to incorporate geopolitical circumstances, reducing the significance of their findings during times of global conflict. Finally, an excessive reliance on static approaches fails to capture the dynamic, time-varying relationship required to comprehend the increasing interconnections of current asset classes.
This study employs the DCC-GARCH model, a robust framework for analyzing dynamic conditional correlations and volatility persistence, to address these shortcomings. Using data from February 2022 to July 2024, marked by the Russia-Ukraine war, this study contextualizes its analysis within a real-world geopolitical crisis, offering more significant insights into how such tensions impact market behaviours. This study enhances understanding of asset relationships by integrating short-term and long-term perspectives, thereby addressing methodological limitations in the current literature.

III. DATA AND ECONOMETRIC MODELS

A. Data Description

The dynamic connections between Clean Energy, Dirty Energy, and Clean Cryptocurrency are examined in this paper. Table 2 provides a thorough explanation of the variables. The analysis considers the daily prices of the Clean Energy Index, Cardona, Solano, and Natural Gas. The daily data from 22 February 2022 to 10 July 2024 is collected. These asset classes are chosen as Natural Gas is one of those variables affected the most by the Russia-Ukraine War. Solana and Cardona, called Clean Cryptocurrency, this asset class can be a diversifying tool for the dirty cryptocurrency, Bitcoin. The third index is the Clean Energy index; only the most persuasive index, the S&P 500 Clean Energy index, is selected. The selected time period was preferred over the others as it thoroughly analyses the effect of the war on the chosen assets. Significant fluctuations in asset classes can be seen during this period. Daily data of all the asset classes is taken as the weekly or the monthly data could have overstated or underestimated the effect of volatility in the market. Time-frequency connectivity and volatility spillover effects have been examined using the DCC GARCH model.

B. Methodology

This section delineates the quantitative approaches employed in the study. The DCC GARCH model is utilized to analyze the conditional correlations and volatility spillovers among the indices. The specifications of the employed model are shown below:

1) "Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity Model" (DCC-GARCH Model)

Understanding relationships among risk, volatility, and investment portfolio returns is crucial for identifying optimal financial strategies, specifically, investors are protected against risk. Consequently, when studying the univariate volatility models, it must become more attractive, but additional information is required to evaluate time-varying asset correlations. To fill the gap ascertained in univariate volatility model, multivariate GARCH models were developed, which are essential for thorough financial analysis [23]. The model (CCC GARCH Model) used in the paper was first developed by Bollerslev in year 1990 and further revised by Engle in 2002, DCC GARCH model [24]. The model is considered to be significant as it calculates the dynamic conditional correlation coefficients between two variables. The procedure to estimate the values is divided into two stages [25], [26]. First, univariate GARCH models are used to forecast each element's variability. The second phase involves using the data obtained in the previous stage to determine the conditional correlation parameters of DCC [29]. Figure 1 is a framework diagram for each proposed algorithm to indicate how these employed models work to receive the experimental results.

Eagle's DCC model has the following structure:

$$H_t = D_t R_t D_t$$

Where D_t = diag. ($h_{1\,1t}^{1/2}$, ……, $h_{N\,Nt}^{1/2}$), each h_{iit} is a separate univariate GARCH model, and

$$R_t = \text{diag.}\ (q_{11\,t}^{1/2}, \ldots, q_{N\,Nt}^{1/2})\ Qt\ \text{diag.}\ (q_{N\,Nt}^{1/2})$$

The matrix $Q_t = (q_{ijt})$ is the N×N positive symmetric matrix has been updated as follows:

$$Q_t = (1 - \alpha - \beta)\ \bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1}$$

Where, $u_t = \varepsilon_{it}\ /\ \sqrt{h_{it}}$

TABLE 2: OVERVIEW OF THE INDICES

Variables	Cardano	Solana	Natural Gas	Clean Energy
Indices	ADA	SOL	DJCING	SPGTCLEE
Source	ADA is a green cryptocurrency, Cardano's proof of stake (PoS) consensus system, which uses less energy, reducing its environmental impact.	SOL is a green cryptocurrency due to Solana's energy-efficient Proof of History (PoH) and Proof of Stake (PoS) mechanisms.	The NYMEX natural gas contracts serve as the basis for futures contracts used by the Dow Jones Commodity Index Natural Gas to measure the natural gas market.	This index, which is a component of the Dow Jones and S&P 500 indexes, evaluates the performance of global clean energy firms.

Data Source: investing.com

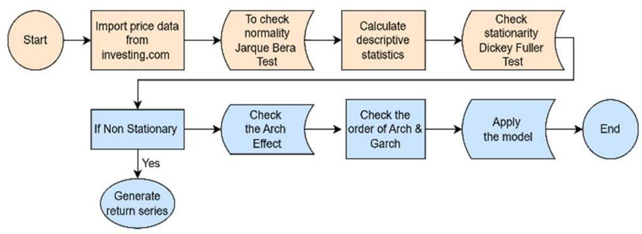

Fig 1. Research Framework

IV. EMPIRICAL RESULTS AND DISCUSSIONS

Table 3 is a tabular representation of the descriptive statistics of the variables chosen for analysis. The assets are listed alongside their corresponding tickers. The minimum value of all the variables with a significant maximum value has been discussed in the table; SOL has the lowest minimum return, while clean energy SPGTCLEE has the highest minimum return. Comparing the minimum and the maximum return, SOL indicates the highest volatility, whereas SPGTCLEE indicates the lowest volatility. The table compares the mean returns of variables, which reflects the average return over the period. SOL has a slightly positive mean return, which indicates a small average growth over the period.

In contrast, DJCING has the lowest mean return with a slight average decline. The standard deviation measures the dispersion and volatility of returns from the mean; a larger number indicates more variability. The least volatile with the lowest standard deviation is SPGTCLEE, whereas SOL has the most significant standard deviation. Furthermore, skewness is considered to measure the asymmetry in the distribution of the returns. SOL shows strongly negative skewness, reflecting a more extreme negative return, whereas ADA and SPGTCLEE have positive skewness, indicating more extreme positive returns. Kurtosis is a measure of the "tailedness" of the distribution. SOL has the highest kurtosis, showing frequent extreme returns, while DJCING has the lowest kurtosis. This indicates that the distribution is closer to the normal distribution with a few extreme values. According to the Jarque Bera Test findings, which look for normality, none of the variables have a normal distribution. The ADF Test indicates that all variables are stationary. Figure 2 is a time series plot of the constituent market showing the fluctuations. Figure 3 graphically shows the log return of the constituent markets.

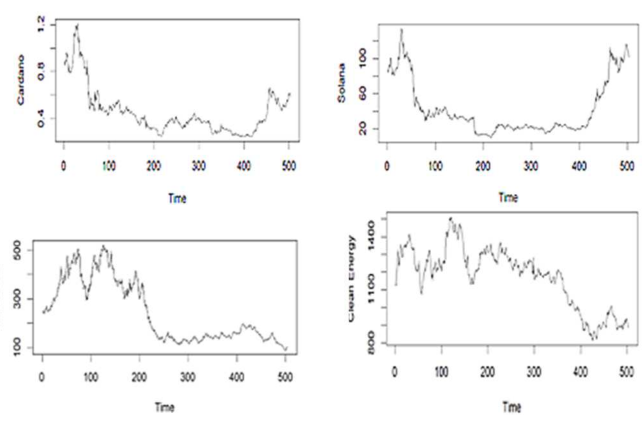

Fig. 2. Time series plot of closing prices of constituent markets

TABLE 1: REVIEW OF LITERATURE				
Authors	Assets Classes	Data Period	Methods	Findings
[21]	Energy Cryptocurrencies, Clean Energy and Dirty Energy	2 January 2018 to 25 January 2023	Bivariate wavelet coherence and Partial Wavelet Coherence	The paper highlights the heterogeneous relationships of energy cryptocurrencies with energy assets significantly influenced by uncertainty.
[22]	Islamic Stock Markets and Renewable Energy	1 January 2015 to 29 December 2022	VAR-ADCC models and conditional value at risk (CoVaR) techniques	Risk spillover between renewable energy and Islamic stock markets is asymmetric, with Canadian markets showing the most sensitivity.
[30]	Dirty Energy and Clean Energy	18 May 2011 to 12 August 2020	Glosten-Jagannathan-Runkle (GJR) model, DY and BK	Volatility spillover between clean and dirty energy markets is asymmetric, with bad news having a more significant impact than good news.
[31]	Green Bonds, Renewable Energy and Cryptocurrency	1 October 2015 to 24 February 2022	DCC,DY, and BK models	Long-term volatility spillover from green bonds to renewable energy and cryptocurrencies provide short-term diversification advantages.
[32]	Clean energy stocks and Dirty energies	7 March 2006 to 16 June 2021	Wavelet coherence analysis	Clean energy markets have shown a weak correlation from dirty energy markets, especially during COVID-19, which led to enhanced diversification opportunities.
[33]	Dirty Energy Stock Indexes and Clean Energy Stock Indexes	3 May 2018 to 2 May 2023	Descriptive statistics, Unit root tests, Residue stability tests, and a Granger VAR causality model	The indices for dirty and clean energy are interrelated, but they do not show any hedging or safe-haven properties, particularly in times of economic instability.
[27]	Dirty Energy Stock Indexes and Clean Energy Stock Indexes	16 May 2018 to 15 May 2023	Gregory and Hansen's cointegration methodology and Forbes and Rigobon's t-test for heteroscedasticity of two samples	Clean energy stocks show potential as safe havens for "dirty" cryptocurrencies, but relationships vary depending on the specific assets and market conditions.
[28]	Green Equity Index, Traditional Assets, and Non-Traditional Assets	25 October 2016 to 20 April 2021	Network and Wavelet analyses	Bitcoin is primarily isolated from green equity indices and other assets, making it a robust diversification tool for investors, particularly those seeking to offset the environmental impact of Bitcoin investments.
[34]	Green Financial Assets and Cryptocurrency Uncertainty/Attention Indices.	3 January 2014 to 31 December 2021	Bivariate wavelet coherence approach	Cryptocurrency uncertainty/attention indices have a predominantly negative relationship with green financial asset returns over time.
[35]	Case study of DONG Energy, a Danish company that successfully transitioned to become Ørsted, a green energy company.	2010 to 2021	Case Study	While challenging, oil and gas companies can transition to clean energy by leveraging internal strengths and responding to external pressures.

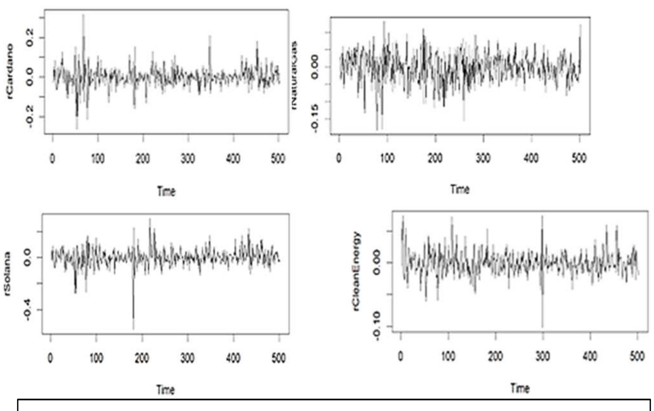

Fig. 3. Graphical depiction of log returns of markets

A. *Results of the DCC GARCH Model*

This study applied the model developed by [36]. It investigates the dynamic relationship between clean energy, dirty energy, and clean cryptocurrency.

TABLE 3: DESCRIPTIVE STATISTICS OF THE CHOSEN VARIABLE				
Indices	ADA	SOL	DJCING	SPGTCLEE
Variables	Cardona	Solana	Natural Gas	Clean Energy
Min	-0.26263	-0.55085	-0.18267	-0.10177
Max	0.3176	0.30098	0.13349	0.07441
Mean	-0.00083	0.00033	-0.00177	-0.00048
Std Dev	0.05008	0.06912	0.04479	0.0182
Skewness	0.22189	-0.91395	-0.32599	0.17921
Kurtosis	6.32441	9.64895	0.81198	3.60895
Jarque Bera Test	0	0	0	0
Adf test (p-value)	0.01**	0.01**	0.01**	0.01**

It has been chosen due to its advantages. For instance, the model investigates dynamic investor behaviour regarding current events and news by identifying potential variations in the asset's conditional correlations.

Table 4 exhibits the model’s outcomes. The spillover effects between various asset class pairs are shown in the table. The terms “mu” is the general mean and “omega” is the constants. ARCH is represented by “alpha1” and the GARCH by “beta1”. Alpha determines whether or not there is short-term variance based on preceding disturbances. In contrast, “beta” evaluates the persistence of volatility and it ascertains the variations on long-term conditional correlation of the market.[26] [37] The “alpha1” and “beta1” readings to show volatility persistence should positive and significant at a level of 5%. Both the parameters “alpha 1” and “beta 1” in both series should be less than 1, are used to check for volatility and determine whether or not time decay happened during this time period.

Cardano to Solana's total of “alpha” is 0.869986 and “beta” is 0.632210. This shows that in contrast to “rCardano”, “rSolana” has a low volatility persistence. Additionally, there is no short-term information spillover, as indicated by the positive but insignificant coefficient of “dcca1” of 0.087472. On the other hand, the long-term significant and positive coefficient of “dccb1” is 0.000000, indicating information spillover. From “rCardano” to “rNaturalGas,” the total of “alpha” is 0.869986 and total of “beta” is 0.947138. “rCardano” has less volatility persistence when compared “rNaturalGas”.

The positive but insignificant coefficient of “dcca1”, which is 0.086794, indicates that short-term information spillover is not evident. The coefficient of “dccb1” is 0.000000, which is significant and positive, signifying long-term information spillover. Alpha and beta total 0.869986 and 0.467624 in “rCardano” and “rCleanEnergy”, respectively. It demonstrates that, unlike “rCardano”, “rCleanEnergy” has minimal volatility persistence. Additionally, there is no short-term information spillover, as evidenced by the positive and minimal coefficient of “dcca1”, which is 0.018515. Nevertheless, the coefficient of “dccb1” is 0.000000, indicating a significant and favorable long-term information spillover. The total of “alpha” is 0.632210 and total of “beta” is 0.947138, for “rSolana” and “rNaturalGas”. It indicates that “rSolana” has lower volatility persistence than “rNaturalGas”.

The coefficients for “dcca1” and dcca2, indicating long-term information spillover, are 0.999881 and 0.000000, respectively. This reflects no information spillover in the short term. The values of alpha and beta for “rSolana” and “rCleanEnergy” are 0.467624 and 0.632210, respectively. The findings indicate that “rCleanEnergy” shows reduced volatility persistence in comparison to “rSolana”. In the context of information spillover, the coefficient of “dcca1” is positive; however, it is insignificant.

The coefficient of “dccb1” is positive and statistically significant, suggesting that information spillover manifests in the long term rather than the short term. The values of alpha and beta for “rNaturalGas” and “rCleanEnergy” are 0.947138 and 0.467624, respectively. It demonstrates “rCleanEnergy”’s sustained low volatility in comparison to “rNaturalGas”. Furthermore, there is no short-term information spillover, since the “dcca1” coefficient is positive yet insignificant. In contrast, the “dccb1” coefficient is significant, indicating information spillover over the long term.

V. Conclusion and Future Implications

The dynamic relationships and volatility persistence between clean cryptocurrencies, Cardano and Solana, the S&P Global Clean Energy Index, and a dirty energy source, natural gas, are examined in this paper. The research reveals a few important observations regarding the relationship between these assets. In contrast to the clean energy index, which has a reduced volatility persistence and a different response to shocks, clean cryptocurrency and dirty energy show that shocks to their returns have a lasting effect on the market. To investigate the dynamic conditional correlations between the assets, DCC GARCH is utilized; the study reveals that the long-term correlation among the assets is significant, whereas the short-term correlation shows varied results for different pairs of assets. Some pairs have shown considerable short-term correlation. It was observed that clean cryptocurrencies, particularly Solana, have shown intense volatility and have significant correlations with both Clean Energy and Natural Gas. Future research should examine how ESG measurements affect the volatility and correlations between clean cryptocurrencies, energy indices, and conventional energy sources, given the increasing significance of sustainability-backed ESG (Environmental, Social, and Governance) considerations. Moreover, future studies might improve the modelling and prediction of volatility and correlations among various assets by integrating AI and machine learning approaches. Longitudinal studies that monitor the development of these markets over time would yield important insights into how global economic trends, regulatory changes, and technological breakthroughs affect the relationships between clean energy, cryptocurrencies, and traditional energy assets.

TABLE 4 – RESULTS OF DCC GARCH Model

	Estimate	Std. Error	t value	Pr(>|t|)
DCC from Cardano to Solana				
[“rCardano”].”mu”	-0.00006	0.00201	-0.03349	0.97328
[“rCardano”]."omega”	0.00012	0.00011	1.08368	0.27850
[“rCardano”].”alpha1”	0.08103	0.03886	2.08497	0.03707
[“rCardano”].”beta1”	0.86998	0.07296	11.92422	0.00000
[“rSolana”].”mu”	0.00118	0.00246	0.47906	0.63189
[“rSolana”].”omega”	0.00066	0.00026	2.46470	0.01371
[“rSolana”].”alpha1”	0.24605	0.10415	2.36229	0.01816
[“rSolana”].”beta1”	0.63221	0.10397	6.08035	0.00000
[Joint]”dcca1”	0.04881	0.02856	1.70888	0.08747
[Joint]”dccb1”	0.79051	0.07944	9.95106	0.00000
DCC from Cardano to Natural Gas				
[“rCardano”].”mu”	-0.00006	0.00200	-0.03372	0.97309
[“rCardano”].”omega”	0.00012	0.00010	1.11559	0.26459
[“rCardano”].”alpha1”	0.08103	0.03852	2.10313	0.03545
[“rCardano”].”beta1”	0.86998	0.07182	12.11194	0.00000

[“rNaturalGas”].”mu”	-0.00116	0.00192	-0.60626	0.54433
[“rNaturalGas”].”omega”	0.00002	0.00001	1.26130	0.20720
[“rNaturalGas”].”alpha1”	0.04283	0.01329	3.22178	0.00127
[“rNaturalGas”].”beta1”	0.94713	0.01466	64.56824	0.00000
[Joint]”dcca1”	0.01171	0.00683	1.71255	0.08679
[Joint]”dccb1”	0.98262	0.00553	177.50669	0.00000
DCC from Cardano to Clean Energy				
[“rCardano”].”mu”	-0.00006	0.00200	-0.03377	0.97305
[“rCardano”].”omega”	0.00012	0.00011	1.09471	0.27364
[“rCardano”].”alpha1”	0.081032	0.03868	2.09484	0.03618
[“rCardano”].”beta1”	0.86998	0.07314	11.89367	0.00000
[“rCleanEnergy”].”mu”	-0.00041	0.00077	-0.53748	0.59093
[“rCleanEnergy”].”omega”	0.00010	0.00009	1.15711	0.24722
[“rCleanEnergy”].”alpha1”	0.20304	0.10894	1.86370	0.06236
[“rCleanEnergy”].”beta1”	0.46762	0.35798	1.30627	0.19145
[Joint]”dcca1”	0.06089	0.02585	2.35514	0.01851
[Joint]”dccb1”	0.81492	0.08313	9.80275	0.00000
DCC from Solana to Natural Gas				
[“rSolana”].”mu”	0.00118	0.00248	0.47401	0.63549
[“rSolana”].”omega”	0.00066	0.00026	2.47254	0.01341
[“rSolana”].”alpha1”	0.24605	0.10418	2.36176	0.01818
[“rSolana”].”beta1”	0.63221	0.10395	6.08156	0.00000
[“rNaturalGas”].”mu”	-0.00116	0.00191	-0.60675	0.54401
[“rNaturalGas”].”omega”	0.00002	0.00001	1.26320	0.20651
[“rNaturalGas”].”alpha1”	0.04283	0.01327	3.22619	0.00125
[“rNaturalGas”].”beta1”	0.94713	0.01467	64.55345	0.00000
[Joint]”dcca1”	0.00000	0.00002	0.00014	0.99988
Joint]”dccb1”	0.92724	0.16441	5.63976	0.00000
DCC from Solana to Clean Energy				
[“rSolana”].”mu”	0.00118	0.00247	0.47715	0.63325
[“rSolana”].”omega”	0.00066	0.00026	2.46347	0.01376
[“rSolana”].”alpha1”	0.24605	0.10435	2.35787	0.01838
[“rSolana”].”beta1”	0.63221	0.10451	6.04924	0.00000
[“rCleanEnergy”].”mu”	-0.00041	0.00077	-0.53796	0.59060
[“rCleanEnergy”].”omega”	0.00010	0.00009	1.16698	0.24321
[“rCleanEnergy”].”alpha1”	0.20304	0.10789	1.88192	0.05984
[“rCleanEnergy”].”beta1”	0.46762	0.35503	1.31710	0.18780
[Joint]”dcca1”	0.08260	0.02963	2.78722	0.00531
[Joint]”dccb1”	0.67703	0.15263	4.43576	0.00000
DCC from Natural Gas to Clean Energy				
[“rNaturalGas”].”mu”	-0.00116	0.00191	-0.60675	0.54401
[“rNaturalGas”].”omega”	0.00002	0.00001	1.26321	0.20651
[“rNaturalGas”].”alpha1”	0.04283	0.01327	3.22624	0.00125

[“rNaturalGas”].”beta1”	0.94713	0.01467	64.55375	0.00000
[“rCleanEnergy”].”mu”	-0.00041	0.00077	-0.54048	0.58886
[“rCleanEnergy”].”omega”	0.00010	0.00009	1.16929	0.24228
[“rCleanEnergy”].”alpha1”	0.20304	0.10780	1.88347	0.05963
[“rCleanEnergy”].”beta1”	0.46762	0.35441	1.31942	0.18702
[Joint]”dcca1”	0.00000	0.00001	0.00042	0.99966
[Joint]”dccb1”	0.90214	0.10412	8.66383	0.0000
DCC from Clean Energy to Natural Gas				
[“rCleanEnergy”].”mu”	-0.00041	0.00077	-0.54048	0.58886
[“rCleanEnergy”].”omega”	0.00010	0.00009	1.16923	0.24231
[“rCleanEnergy”].”alpha1”	0.20304	0.10780	1.88341	0.05964
[“rCleanEnergy”].”beta1”	0.46762	0.35444	1.31933	0.18705
[“rNaturalGas”].”mu”	-0.00116	0.00191	-0.60675	0.54401
[“rNaturalGas”].”omega”	0.00002	0.00001	1.26320	0.20651
[“rNaturalGas”].”alpha1”	0.04283	0.01327	3.22630	0.00125
[“rNaturalGas”].”beta1”	0.94713	0.01467	64.55488	0.00000
[Joint]”dcca1”	0.00000	0.00002	0.00018	0.99985
[Joint]”dccb1”	0.90214	0.10402	8.67270	0.00000
DCC from Solana to Cardano				
[“rSolana”].”mu”	0.00118	0.00246	0.47906	0.63189
[“rSolana”].”omega”	0.00066	0.00026	2.46470	0.01371
[“rSolana”].”alpha1”	0.24605	0.10415	2.36230	0.01816
[“rSolana”].”beta1”	0.63221	0.10397	6.08036	0.00000
[rCardona].”mu”	-0.00006	0.00201	-0.03349	0.97328
[rCardona].”omega”	0.00012	0.00011	1.08372	0.27848
[rCardona].”alpha1”	0.08103	0.03886	2.08498	0.03707
[rCardona].”beta1”	0.86998	0.07295	11.92467	0.00000
[Joint]”dcca1”	0.04881	0.02856	1.70879	0.08748
[Joint]”dccb1”	0.79051	0.07941	9.95390	0.00000
DCC from Natural Gas to Cardano				
[“rNaturalGas”].”mu”	-0.00116	0.00192	-0.60626	0.54433
[“rNaturalGas”].”omega”	0.00002	0.00001	1.26130	0.20720
[“rNaturalGas”].”alpha1”	0.04283	0.01329	3.22178	0.00127
[“rNaturalGas”].”beta1”	0.94713	0.01466	64.56824	0.00000
[“rCardano”].”mu”	-0.00006	0.00200	-0.03372	0.97309
[“rCardano”].”omega”	0.00012	0.00010	1.11559	0.26459
[“rCardano”].”alpha1”	0.08103	0.03852	2.10312	0.03545
[“rCardano”].”beta1”	0.86998	0.07182	12.11194	0.00000
[Joint]”dcca1”	0.01171	0.00683	1.71255	0.08679
[Joint]”dccb1”	0.98262	0.00553	177.5037	0.00000
DCC from Clean Energy to Cardano				
[“rCleanEnergy”].”mu”	-0.00041	0.00077	-0.53748	0.59093
[“rCleanEnergy”].”omega”	0.00010	0.00009	1.15712	0.24722

[“rCleanEnergy”].”alpha1”	0.203045	0.10894	1.86371	0.06236
[“rCleanEnergy”].”beta1”	0.46762	0.35797	1.30629	0.19145
[“rCardano”].”mu”	-0.00006	0.00200	-0.03377	0.97305
[“rCardano”].”omega”	0.00012	0.00011	1.09469	0.27365
[“rCardano”].”alpha1”	0.08103	0.03868	2.09484	0.03618
[“rCardano”].”beta1”	0.86998	0.07314	11.89359	0.00000
[Joint]”dcca1”	0.06089	0.02585	2.35569	0.01848
[Joint]”dccb1”	0.81492	0.08320	9.79460	0.00000
DCC from Natural Gas to Solana				
[“rNaturalGas”].”mu”	-0.00116	0.00191	-0.60675	0.54401
[“rNaturalGas”].”omega”	0.00002	0.00001	1.26320	0.20651
[“rNaturalGas”].”alpha1”	0.04283	0.01327	3.22626	0.00125
[“rNaturalGas”].”beta1”	0.94713	0.01467	64.55380	0.00000
[“rSolana”].”mu”	0.00118	0.00248	0.47401	0.63548
[“rSolana”].”omega”	0.00066	0.00026	2.47254	0.01341
[“rSolana”].”alpha1”	0.24605	0.10418	2.361760	0.01818
[“rSolana”].”beta1”	0.63221	0.10395	6.08143	0.00000
[Joint]”dcca1”	0.00000	0.00000	0.00177	0.99858
[Joint]”dccb1”	0.92724	0.16451	5.63626	0.00000
DCC from Clean Energy to Solana				
[“rCleanEnergy”].”mu”	-0.00041	0.00077	-0.53796	0.59060
[“rCleanEnergy”].”omega”	0.00010	0.00009	1.16699	0.24321
[“rCleanEnergy”].”alpha1”	0.20304	0.10789	1.88193	0.05984
[“rCleanEnergy”].”beta1”	0.46762	0.35503	1.31711	0.18780
[“rSolana”].”mu”	0.00118	0.00247	0.47716	0.63324
[“rSolana”].”omega”	0.00066	0.00026	2.46331	0.01376
[“rSolana”].”alpha1”	0.24605	0.10435	2.357890	0.01837
[“rSolana”].”beta1”	0.63221	0.10451	6.049030	0.00000
[Joint]”dcca1”	0.08260	0.02962	2.788110	0.00530
[Joint]”dccb1”	0.67703	0.15294	4.426730	0.000010

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