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Dynamic correlation between the green hydrogen market and commodities, stock markets, oil, and Bitcoin: A DCC approach

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Abstract

This study analyzes the dynamic correlation between the green hydrogen market and financial assets (iShares MSCI World, Bitcoin, commodities, oil futures) using Engle's (2002) Dynamic Conditional Correlation (DCC) model, with data from August 2021 to February 2024. Findings show strong correlations, peaking at 80%, between green hydrogen and global stock and oil markets, and a 50% correlation with Bitcoin, notably after Russia's invasion of Ukraine. These results inform investors and policymakers on sustainability, ESG compliance, and diversification with green assets.

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1. Introduction

The environment is vital for humanity, in this context the increase in greenhouse gas (GHG) emissions released into the atmosphere poses the risk of climate change. These can cause severe problems for humanity. The Paris agreement is committed to reducing greenhouse gas (GHG) emissions, it was a treaty signed by 194 countries, being a commitment to global sustainability (Allen et al. 2008 and Agreement 2009).

With the growing debate about the importance of reducing carbon emissions, there is a growing search for viable options to replace fossil fuels. As a result, green hydrogen emerges as one of the possible solutions for reducing carbon emissions in the economy (Barreto et al. 2003, Guariero et al. 2022, Bezerra 2021, Clark 2006, Jovan & Dolanc, 2020, IEA 2020). The use of green hydrogen as an energy source can solve several energy problems, as its production originates from renewable energy sources. Furthermore, there are several possibilities for its use, such as: transport, industrial and residential. Green hydrogen can be an important agent in reducing carbon emissions, improving air quality and energy dependence in regions in energy conflict (see, for example, Squadrito et al. 2005).

The “Hydrogen economy” is an expression used to describe the economy based on hydrogen as an energy vector. In addition to being used as a raw material, hydrogen can be used as a fuel, carrier and energy storer, thus making it possible to use in companies in the transport, energy and buildings sectors. Hydrogen has significant benefits such as: not emitting CO₂, thus causing less air pollution. This benefit is seen as a solution to decarbonize industrial processes, but reducing CO₂ emissions is a difficult goal to achieve (Barreto et al. 2003).

Green hydrogen is considered one of the best options for more sustainable industrial production. With increasing discussions about the need to reduce carbon emissions, there is a growing search for viable alternatives to replace fossil fuels. In this context, green hydrogen emerges as a prominent trend, offering a solution to reduce carbon emissions in industry.

According to the (IEA 2019), hydrogen has the potential to solve several energy problems when produced from various sources, such as: renewable energy, nuclear, natural gas and oil. Furthermore, it is possible to use it in various ways, from transportation to residential and industrial supply. This application significantly contributes to reducing emissions in sectors that are difficult to decarbonize, such as: transport long-distance chemical production and steel industries. Furthermore, hydrogen can contribute to improving air quality and energy security.

The spread of green hydrogen, however, depends not only on technological and regulatory advances, but also on its economic sustainability and inclusion in global capital and commodity markets. While existing literature analyzes the role of hydrogen in energy change (Squadrito et al., 2023; Jovan & Dolanc, 2020), little is known about how its market dynamics relate to traditional and alternative assets, such as stocks, oil, commodities, and Bitcoin. Understanding these relationships is critical for investors, policymakers, and energy companies to assess risks, optimize portfolios, and anticipate market crises that may affect the development of the green hydrogen sector.

The use of hydrogen as an energy source, produced from biomass, biofuels or renewable electricity, is considered an efficient and environmentally beneficial option. Especially when combined with fuel cells to generate electricity, hydrogen can be produced in a variety of ways, becoming an integrating element between different technologies (Bezerra 2021). In this context, checking the price dynamics of the green hydrogen market can be important for understanding how the market for this asset works. Thus, the time-varying correlation between the green hydrogen market and other assets was calculated. For this purpose, the model (DCC) Dynamic Conditional Correlation (GARCH) Generalized Autoregressive Conditional Heteroscedasticity was used to verify the conditional demonstration, where DCC means

dynamic conditional expression, ensuring that the modeling uses a model that uses the always positive and defined consolidation matrix.

The DCC-GARCH model has been used in the energy market. (Ali 2024) use this model to investigate the hedge and safe haven property of gold and green investments for conventional stock market. (Antonakakis 2013) analyzed the influence of the oil price on the stock markets of the USA, United Kingdom, Germany, Canada and Norway. The first three countries are importers of oil while the latter two export oil. They collected the monthly series of returns from the main indices in each country: Dow Jones (USA); FTSE 100 (United Kingdom); DAX 30 (Germany); TSX (Canada) and OBX (Norway). They found that changes in oil impacted the correlations between the stock indices of countries, except Canada and Norway.

(Arif 2022) analyzed the diversification of green cryptocurrencies and other assets using a DCC-GARCH model to evaluate dynamic hedging based on correlations. The results show that green cryptocurrencies provide diversification benefits that are at least comparable to, and in some cases superior to, non-green (energy-intensive) cryptocurrencies. Cardano and Tezos are identified as green cryptocurrencies that offer the greatest diversification benefits to investors, followed by EOS, Stellar and IOTA. (Iuga et al. 2024) Using the diagonal BEKK model and the DCC GARCH model, the study analyzes data from February 17, 2020, to September 30, 2024, with the aim of understanding how cryptocurrencies, classified by their environmental impact, affect these indices. The results show that there is a significant transfer of volatility from both clean and dirty cryptocurrencies. Clean cryptocurrencies, such as Cardano, show a stabilizing effect, while dirty cryptocurrencies, such as Bitcoin, demonstrate more pronounced and asymmetric volatility impacts on green finance indices.

(Palazzi et al. 2024) employed DCC-GARCH between August 3, 2020 and June 30, 2022, with 456 observations, to evaluate the relationship between CBIO and future and spot prices of sugar, oil and ethanol. They found a strengthening of the correlation between Chicago-traded ethanol and the CBIO over time.

Regarding studies involving the correlation between the green hydrogen market and other assets, to date, there is only (Ren & Lucey 2022) that analyzes the correlation between hydrogen and oil prices, S&P 500 (American stock exchange) and emissions of carbon between December 2019 to April 2022. By employing a time-varying student t-copula, they captured asset dynamics at various frequencies. To do this, they calculated the value at risk (VaR), conditional value at risk (CoVaR), and Delta CoVaR for various assets to assess their overall risk profile. They found that, in extreme market conditions, such as COVID-19, hydrogen correlates with other assets (oil, American stock exchange and carbon emissions). More applications of DCC-GARCH in safe haven analysis can be seen in studies of (Choudhury et al. 2022, Corbet et al. 2021, Zhang et al. 2021, Bouri et al. 2017, Liu & Li, 2024).

In this paper, a bivariate Dynamic Conditional Correlation (DCC) Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model was used to examine whether the green hydrogen market and the US stock market, oil, commodities and bitcoin have served as a safe haven. Our article contributes to the literature by comparing the green hydrogen market with traditional assets and seeking correlations with bitcoins. Furthermore, this paper extends the previous work of (Lucey et al. 2024) which focuses on having safe harbor within asset classes, by analyzing the connectivity characteristics of the returns of green hydrogen and traditional assets. With this, our study opens a path for investment considerations in risk strategies involving different markets, mainly clean energy.

Therefore, as a research question this study this study investigates the dynamic correlations between the green hydrogen market and key financial and commodity markets, exploring implications for risk diversification and investment strategies. The research contributes by providing the first comprehensive analysis of time-varying correlations between green hydrogen and major asset classes (equities, oil, commodities, and Bitcoin) using a Dynamic

Conditional Correlation (DCC-GARCH) model. Additionally, the study offers valuable insights for policymakers and investors on the financial risks and opportunities arising from green hydrogen's role in the energy transition.

The paper is structured as follows. The data and methodology used for the primary analysis are presented below. Then, Section 3 shows the empirical results of the DCC-GARCH model. The final section articulates the concluding comments.

2. Literature Review

The fight against global climate change has been the subject of significant debates and agreements. One such effort is the Paris Agreement, an international commitment negotiated among 195 countries with the aim of minimizing the consequences of global warming. Adopted during the Conference of the Parties (COP 21) in Paris in 2015, its main objective is to keep the increase in the global average temperature well below 2°C above pre-industrial levels, while striving to limit the rise to 1.5°C.

The agreement represents an alliance developed over time, officially tied to pre-existing environmental accords, and establishes global goals, such as temperature mitigation limits and climate subsidies to support developing countries. It also sets targets to limit greenhouse gas emissions for all nations. Essentially, the agreement serves as a roadmap for reorienting the global economy toward decarbonization. While it was well received, it is widely understood that the real work begins now. Achieving its goals and preventing climate chaos will require pacts far more robust than those announced by countries before COP 21. Moreover, financial literature can play a pivotal role in mitigating greenhouse gas emissions through studies focusing on energy, green bonds, and green cryptocurrencies.

Studies on co-movements in the oil market (Jones & Gautam 1996, Sadorsky 1999, Sawyer 2006, Faff 1999, Cong 2008, Filis 2011, Fang & You 2014, Ghosh & Kanjilal 2016, Cerra 2017) were the first to analyze correlations between the energy market and other assets in financial literature. Changes in oil, the most important commodity in the energy industry, can affect financial markets as well as other commodities. The co-movement in the clean energy market is a significant topic of interest when it comes to correlations between energy markets and other assets. In this regard, (Nasreen et al. 2020) found a co-movement among technology businesses, the clean energy industry, and the oil market. According to the survey, clean energy companies are primarily impacted by changes in the oil market. Analyzing co-movements between the clean energy and conventional energy markets during the Covid-19 pandemic crisis, (Reboredo 2018) also found similar results, noting short-term weak linkages between the clean energy and filthy energy markets. From a different angle, the return transfer mechanisms between the global financial markets and green bond markets have been the subject of numerous research. In particular, a lot of research has looked at the relationships between the market for green bonds and other asset classes (Reboredo 2020, Reboredo et al. 2020, Tang et al. 2023, Yousaf et al. 2024).

Regarding the cryptocurrency market, the energy consumption required for mining is substantial, equaling the energy usage of some countries, such as Argentina. To address the issue of high energy consumption in cryptocurrency mining, green cryptocurrencies have emerged. These cryptocurrencies are mined using renewable energy sources, contributing to the mitigation of greenhouse gas emissions. Among the main green cryptocurrencies are Cardano, Ripple, IOTA, and Stellar. The total market capitalization of green cryptocurrencies amounts to \$250 billion.

Recently, some studies have proposed analyzing the dynamics of green cryptocurrency fluctuations. (Umar et al. 2023) examined the connectivity between five green cryptocurrencies—Cardano, Ripple, IOTA, Stellar, and Nano—and fossil fuels during the COVID-19 pandemic and the Russia-Ukraine conflict in 2022. They identified that Nano acts as a spillover receiver. Another finding was that Cardano and natural gas are the largest spillover transmitters and receivers, respectively. Furthermore, the connectivity dynamics between green cryptocurrencies and fossil fuels tend to intensify during crises. Analyzing green cryptocurrencies such as Ripple (XRP), Stellar (XLM), Cardano (ADA), Nano (XNO), and IOTA (MIOTA), the study revealed some influence of connectivity between green cryptocurrencies and other financial assets during times of turbulence. Additionally, the inefficiency of these cryptocurrencies as hedge assets was examined (Husain et al. 2023). The dynamics of return and volatility spillovers were also analyzed between green cryptocurrencies and G7 countries. While green cryptocurrencies were found to be receivers of volatility spillovers, G7 countries acted as transmitters (Ali et al. 2024). Another significant correlation was observed between green cryptocurrencies and conventional cryptocurrencies (Pham et al. 2022).

There is a scarcity of studies involving the green hydrogen market and its correlations with other markets. To date, the study by (Lucey et al. 2024) is known to have identified the correlation between the green hydrogen market and other assets. For this purpose, they employed a time-varying Student's t-copula model. To analyze the total risk profile, Value at Risk (VaR), Conditional Risk, and Delta CoVaR were calculated. The study identified a positive correlation between hydrogen prices, oil, and carbon emissions. Furthermore, they observed positive co-movements between hydrogen, oil, and carbon emissions, paving the way for future research on the dynamics of hydrogen, especially in relation to other assets such as Bitcoin.

3. Methodology

Data were analyzed between 21-09-21 and 24-02-23. They correspond to Global x Hydrogen (HYDR). The Global end use. Regarding cryptocurrencies, we use Bitcoin, which is the most traded cryptocurrency in the world. For the oil price we use the West Texas Intermediate (WTI) crude oil futures contract (CL = F). For global markets, the URGH ETF, also known as the iShares MSCI World ETF, an exchange-traded fund that tracks the MSCI World index, and for commodities we used the SP GSCI commodities index future (GD=F) was used. To calculate the return on assets, the following log-return was used:

$$R_{Lt} = \ln(P_{t+1}) - \ln(P_t) \quad (1)$$

Here, R_{Lt} is the return, $\ln(P_{t+1})$ is the logarithm and a subsequent price, $\ln(P_t)$ is the logarithm of the price.

This paper proposes an estimator called the dynamic conditional correlation model or DCC. The DCC-GARCH model presented by (Engle 2002) is extensively utilized as a multivariate GARCH model that allows for the modeling of time-varying correlations among multiple variables in a time series. It is a model widely used in finance (Orskaug 2009, Rodriguez-Diaz & Torres 2022, Robiyanto et al. 2021, Lee 2006, Siddiqui 2024, Yang & Liu 2023, Corbet et al. 2020, Abuzayed et al. 2021, Bouri et al. 2017). It holds particular significance in the analysis of financial markets, where the behavior of various assets is intricately interconnected and

interdependent. This model adeptly captures volatility and correlation dynamics, offering valuable insights into the relationships between different assets.

The DCC-GARCH model consists of two main components: the GARCH model and the dynamic conditional correlation model. The GARCH model is utilized to estimate the conditional variance of individual assets, whereas the dynamic conditional correlation model is employed to estimate the time-varying conditional correlation among these assets. By integrating these two components, the DCC-GARCH model provides a comprehensive understanding of volatility and correlation dynamics within financial markets. The GARCH model represents an enhanced iteration of the autoregressive conditional heteroskedasticity (ARCH) model, tailored to capture the volatility patterns in a time series by incorporating its own historical data. In addition to modeling volatility based on past values, the GARCH model introduces an additional element to consider the impact of previous shocks on current volatility. Specifically, the GARCH model posits that the conditional variance of a time series at a given time t can be expressed as a function of its preceding variances and the squared residuals or shocks from past observations:

$$v_t = \omega + \sum (\alpha_i \times \varepsilon_{(t-i)}^2) + \sum (\beta_i \times V_{(t-i)}) \quad (2)$$

In this context, v_t denotes the variance measure at time t , with ω as a constant term. The model parameters α_i and β_i are significant in assessing the influence of the squared residuals or shocks $\varepsilon_{(t-i)}^2$ at earlier time points $t - i$. These elements collectively aid in the estimation of the changing conditional variance and offer valuable perspectives on the volatility dynamics within the time series data.

The dynamic conditional correlation model enhances the traditional correlation model by including changing correlations over time. It suggests that the correlation between two time series at a specific time t depends on the previous correlation and the past shocks of the two series. Thus, a possible representation of the equation would:

$$R_t = \Omega + \sum (\alpha_i \times \varepsilon_{t-i} \times \varepsilon'_{t-i}) + \sum (\beta_i \times R_{(t-i)}) \quad (3)$$

Where Ω is a fixed value, α_i represents the coefficients of the model linked to the shocks ε_{t-i} and ε'_{t-i} at earlier time periods $t-i$, and β_i indicates the coefficients of the model related to the previous correlations $R_{(t-i)}$. This approach captures the changing patterns of correlations over time, offering a deeper understanding of the dynamic connection between the two series.

In this study, the chosen model is the DCC-GARCH (Engle, 2002) given its ability to represent time-varying volatility and correlation dynamics, crucial in financial markets where asset interdependencies change due to macroeconomic events (e.g., energy crises, geopolitical conflicts). Unlike static correlation measures, the DCC-GARCH takes into account heteroscedasticity and clustering effects, making it ideal for examining green hydrogen—an emerging market likely to be affected by external shocks. Our methodology aligns with recent applications in energy finance (Ali et al., 2024; Bouri et al., 2017) and addresses an important limitation of previous work (e.g., Ren & Lucey, 2022, which used copulas but did not focus on hydrogen financial linkages).

4. Results

In Figure 1 below, the heat map of the correlation calculated using the Pearson coefficient can be seen. Here the high correlation between the hydrogen ETF and the URTH (world stock market ETF) and between the commodities ETF (SP GSCI) and the oil ETF (CL=F) can clearly be seen.

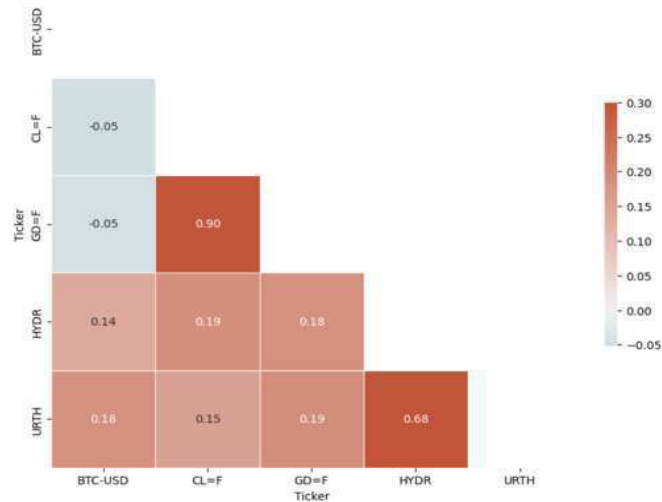
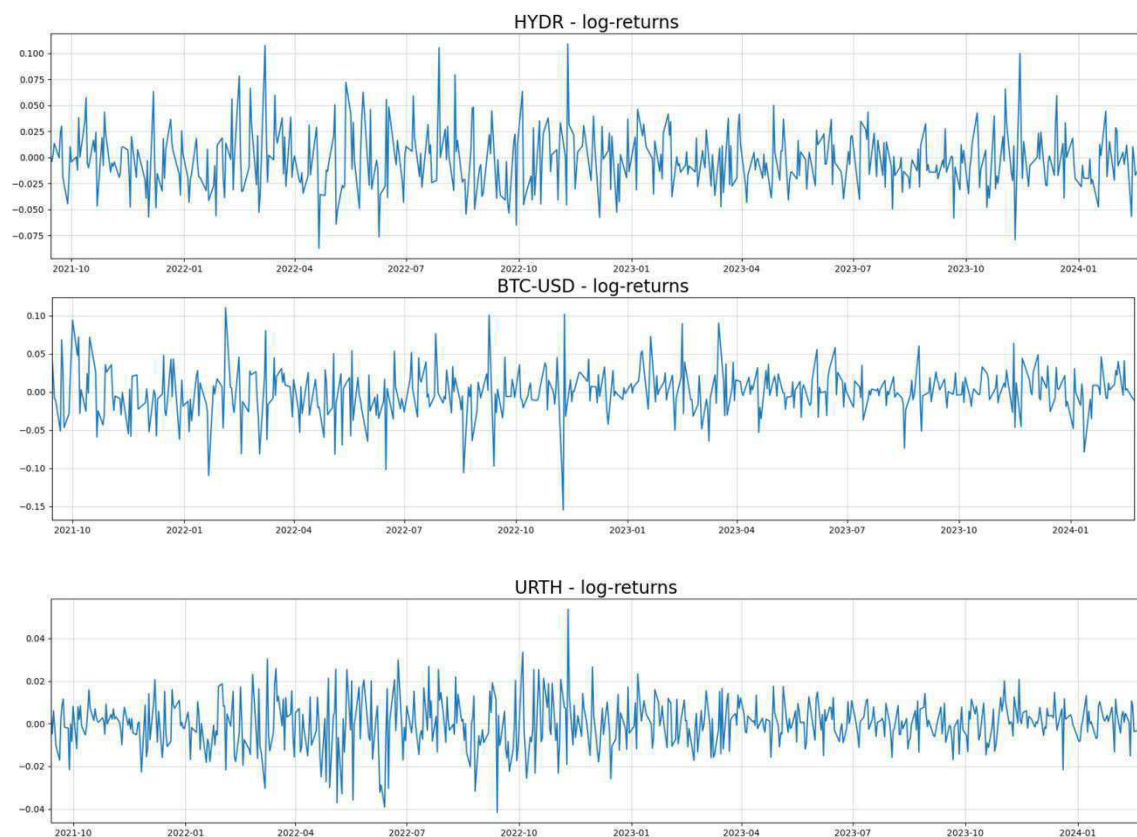


Figure 1: Pearson correlation matrix of cash price log return of Global x Hydrogen ETF, URTH, SP GSCI, and Bitcoin and future contracts of WTI from August 2021 to February 2024.

In Figure 2 below, the returns of the Global x Hydrogen ETF, bitcoin, MSCI World ETF (URTH), Crude oil (CL=F) and commodities (GD=F) are presented.



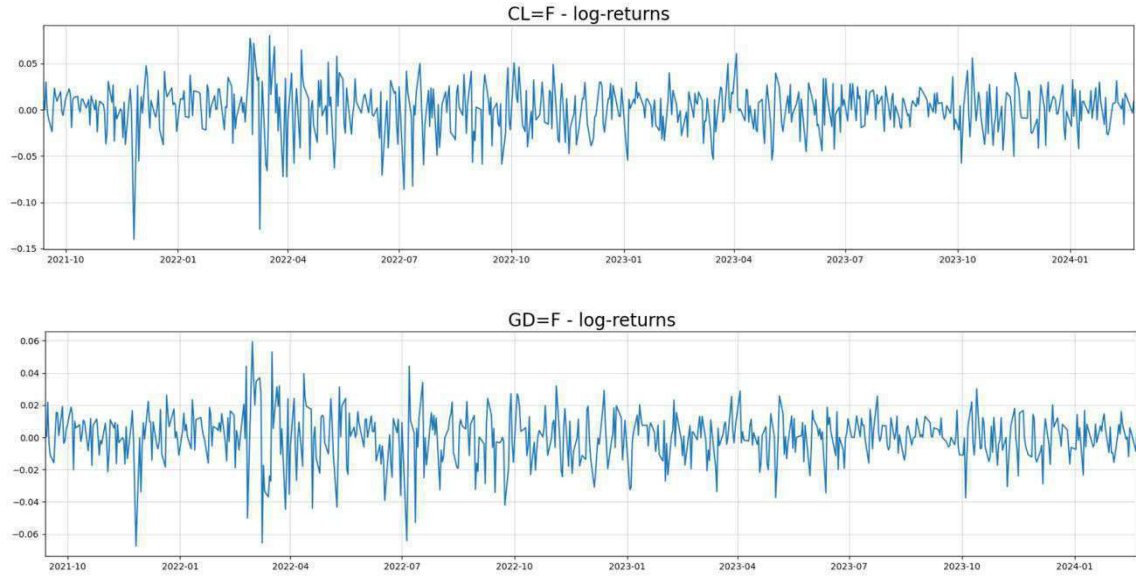


Figure 2: returns of the Global x Hydrogen ETF, bitcoin, MSCI World ETF (URTH), Crude oil (CL=F) and commodities (GD=F).

Table 1 reports the parameter estimates of the DCC-GARCH models. The results indicate that the alpha (α) and beta (β) coefficients are statistically significant for the model, indicating a dynamic (non-constant) conditional correlation between the green hydrogen market and asset prices (oil prices, S&P 500, Bitcoin and commodities). Furthermore, the sum of the GARCH parameters is less than one ($\alpha + \beta < 1$) for the model across all analyzed assets, implying that the conditional correlations are mean reversible. Thus, DCC-GARCH models are justifiably suitable for capturing time-varying conditional correlations between variables.

Table 1. Results of the Bivariate DCC-GARCH Model for the Green Hydrogen and Assets.
Entire Sample Period (August 2021-February 2024)

Parameters	μ (Mean)	ω	α	β	$\alpha + \beta$ Persistence
Assets					
Green Hydrogen	-2.3365e-03 (1.141e-03)	1.6426e-05 (2.524e-06)	0.0443 (2.547e-02)	0.9380 (1.913e-02)	0,9823 Persistence
S&P 500	7.9084e-04 (8.124e-06)	2.8754e-06 (4.252e-12)	0.1000 (3.309e-02)	0.8800 (2.981e-02)	0.9800 Persistence
Crude oil	6.6337e-04 (9.437e-04)	6.5986e-05 (2.133e-05)	0.1091 (2.883e-02)	0.7920 (3.315e-02)	0,9011 Persistence
Commodities	7.9084e-04 (8.124e-06)	2.8754e-06 (4.252e-12)	0.1000 (3.309e-02)	0.8800 (2.981e-02)	0.9800 Persistence
Bitcoin	-6.3746e-05 (1.409e-03)	6.8850e-04 (2.383e-04)	0.1480 (8.032e-02)	0.1471 (0.242)	0,2951 Persistence

In Figure 3, the dynamic correlation between Bitcoin and HYDR increases at the beginning of 2022 and remains high until March 2023, with an abrupt drop and then rising in October 2023 and falling again to reach zero at the beginning of 2024. The dynamic correlation between the MSCI World ETF and the hydrogen ETF was high for most of the period analyzed, reaching above 80% on December 1, with an increase reaching almost 40%, mainly during the year 2023, however, it fell to zero at the end of 2023 and the beginning of 2024. In Figure x, the dynamic correlation between the SP GSCI and the hydrogen ETF reached 40% between the end of 2022 and the beginning of 2023, however, the value drops to close to zero at the beginning of 2024.

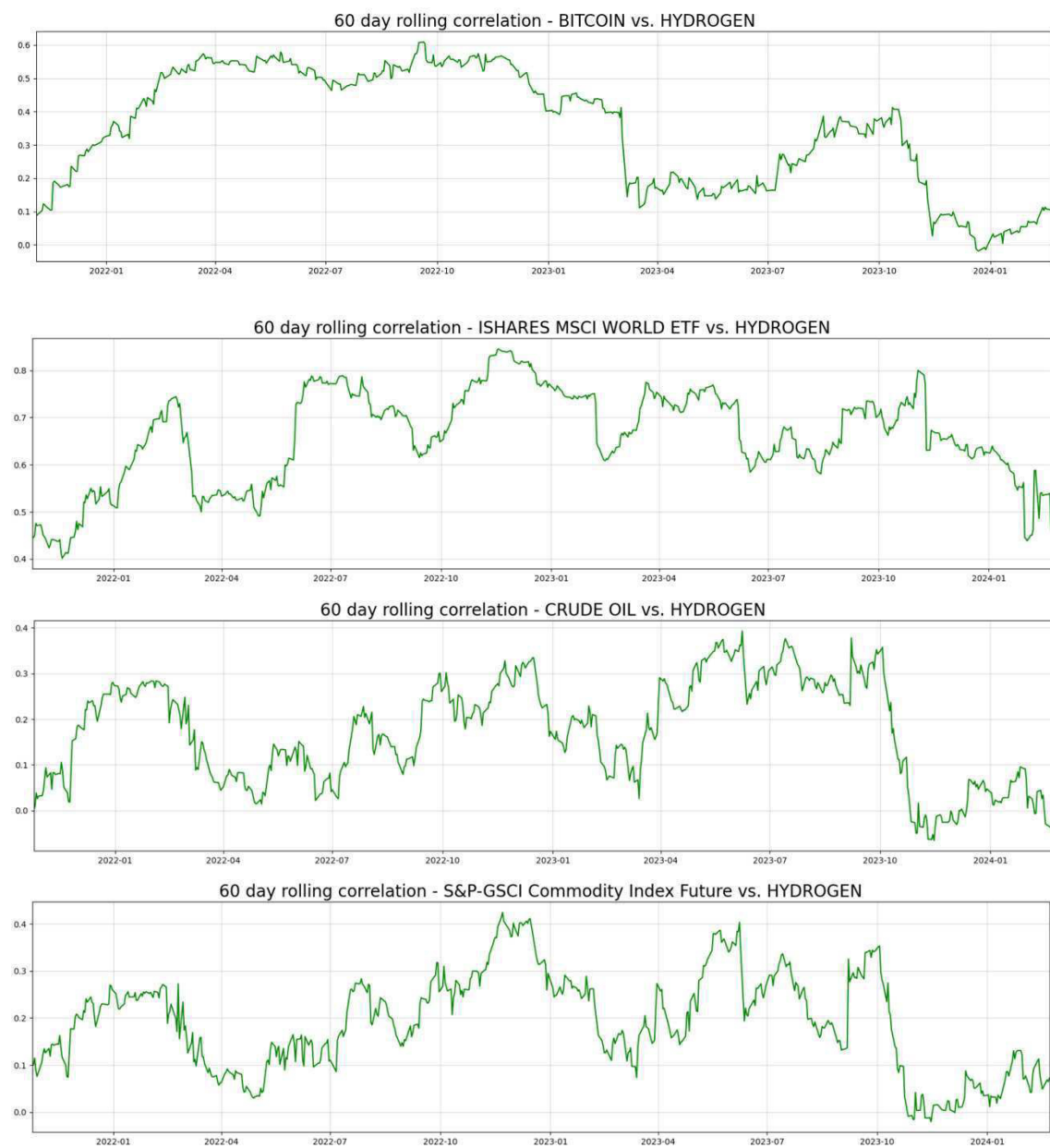


Figure 3: Dynamic correlation between the Global x Hydrogen ETF, bitcoin, MSCI World ETF (URTH), Crude oil (CL=F) and commodities (GD=F) calculated between August 2021 and February 2024.

5. Discussion and Conclusion

The green hydrogen market is one of the most promising today, as in addition to providing clean energy, it is in line with the goals of reducing greenhouse gas emissions. Given this, the aim of this work was to analyze the dynamic correlation between the Global x Hydrogen ETF, which encompasses companies that are in the green hydrogen market and other important financial assets (Bitcoin, SP GSCI commodities, MSCI world ETF and WTI Futures) between August 2021 and February 2024, using DCC-GARCH.

Green hydrogen can contribute to the decarbonization of the economy, becoming vital for achieving the goals set in the Paris Agreement. In this way, green hydrogen presents itself as a renewable energy source that can help reduce carbon emissions in several countries. Therefore, analyzing the green hydrogen market and its movements with other assets can provide insights into future prices and possible market perspectives.

The correlation of the green hydrogen market with other markets, mainly global financial markets, is a risky situation. As global financial markets are subject to volatility and, consequently, downturns, a lower value of companies operating in the green hydrogen sector may discourage investments in the sector. This situation could hamper the economic decarbonization goals established in the Paris Agreement and slow down the fight against global climate change.

In this article the high dynamic correlation was found between the hydrogen ETF and MSCI World, reaching 80%. This shows that the hydrogen market is highly correlated with conventional markets. Another strong correlation was found between the hydrogen ETF and Bitcoin which, during 2022, spent much of the year at around 50%. Regarding the dynamic correlation between the hydrogen ETF and the commodities market, it reached 40% at the end of 2022. Furthermore, the correlation between hydrogen and the oil futures market reached 30% at the end of 2022 and in some moments of 2023. These results show that the hydrogen market is correlated with other financial assets, mainly financial markets (MSCI World) and Bitcoin. In summary, the results point to a positive correlation between the hydrogen ETF and other assets and the results are in line with those found in (Lucey et al. 2024) which showed a positive connectivity between hydrogen and other financial assets.

With regard to Bitcoins, this result is interesting as it shows the correlation between the clean energy market and the largest digital asset and this shows a co-movement between these two markets. This information could be useful for risk analysis in hedge funds and multi-markets and for investors in energy and cryptocurrencies.

For future research, comovements between the green hydrogen market and cryptocurrencies or green hydrogen and selected groups of countries such as the G-7 or BRICS can be explored. Furthermore, econometric models such as copulas or multifractals can be applied to calculate correlation.

Availability of data and material:

The data used in this study is available at: [yahooofinance.com](https://www.yahoo.com/finance).

References

Abuzayed, B., Bouri, E., Al-Fayoumi, N., & Jalkh, N. (2021). Systemic risk spillover across global and country stock markets during the COVID-19 pandemic. *Economic Analysis and Policy*, 71, 180-197.

Agreement, Paris. (2015). Paris agreement. In: Report of the conference of the parties to the United Nations framework convention on climate change (21st session, 2015: Paris). HeinOnline, 2015, p. 2017.

Ali, F., Khurram, M. U., Sensoy, A., & Vo, X. V. (2024). Green cryptocurrencies and portfolio diversification in the era of greener paths. *Renewable and Sustainable Energy Reviews*, 191, 114137.

Ali, S., Naveed, M., Yousaf, I., & Khattak, M. S. (2024). From cryptos to consciousness: Dynamics of return and volatility spillover between green cryptocurrencies and G7 markets. *Finance Research Letters*, 60, 104899.

Allen, M., Dube, O. P., Solecki, W., Aragón-Durand, F., Cramer, W., Humphreys, S., ... & Zickfeld, K. (2018). Global warming of 1.5 C. An IPCC Special Report on the impacts of global warming of 1.5 C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. *Sustainable Development, and Efforts to Eradicate Poverty*.

Antonakakis, N., & Filis, G. (2013). Oil prices and stock market correlation: a time-varying approach. *International Journal of Energy and Statistics*, 1(01), 17-29.

Arif, M., Naeem, M. A., Farid, S., Nepal, R., & Jamasb, T. (2022). Diversifier or more? Hedge and safe haven properties of green bonds during COVID-19. *Energy Policy*, 168, 113102.

Barreto, L., Makihiro, A., & Riahi, K. (2003). The hydrogen economy in the 21st century: a sustainable development scenario. *International Journal of Hydrogen Energy*, 28(3), 267-284.

Bezerra, F. D. (2021). Hidrogênio verde: nasce um gigante no setor de energia.

Bouri, E., Jalkh, N., Molnár, P., & Roubaud, D. (2017). Bitcoin for energy commodities before and after the December 2013 crash: diversifier, hedge or safe haven? *Applied Economics*, 49(50), 5063-5073.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters*, 20, 192-198.

Cerra, V. (2017). How can a strong currency or drop in oil prices raise inflation and the black-market premium? *Economic Modelling*, 67, 1-12.

Choudhury, T., Kinatader, H., & Neupane, B. (2022). Gold, bonds, and epidemics: a safe haven study. *Finance Research Letters*, 48, 102978.

Clark II, W. W., & Rifkin, J. (2006). A green hydrogen economy. *Energy Policy*, 34(17), 2630-2639.

Cong, R., Wei, Y., Jiao, J., & Fan, Y. (2008). Relationships between oil price shocks and stock market: An empirical analysis from China. *Energy Policy*, 36(9), 3544-3553.

- Corbet, S., Hou, Y., Hu, Y., Lucey, B., & Oxley, L. (2021). Aye Corona! The contagion effects of being named Corona during the COVID-19 pandemic. *Finance Research Letters*, 38, 101591.
- Corbet, S., Larkin, C., & Lucey, B. (2020). The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. *Finance Research Letters*, 35, 101554.
- Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3), 339-350.
- Faff, R. W., & Brailsford, T. J. (1999). Oil price risk and the Australian stock market. *Journal of Energy Finance & Development*, 4(1), 69-87.
- Fang, C. R., & You, S. Y. (2014). The impact of oil price shocks on the large emerging countries stock prices: Evidence from China, India and Russia. *International Review of Economics and Finance*, 29, 330-338.
- Filis, G., Degiannakis, S., & Floros, C. (2011). Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. *International Review of Financial Analysis*, 20(3), 152-164.
- Ghosh, S., & Kanjilal, K. (2016). Co-movement of international crude oil price and Indian stock market: Evidences from nonlinear cointegration tests. *Energy Economics*, 53, 111-117.
- Guarieiro, L. L., Anjos, J. P. D., Silva, L. A. D., Santos, A. Á., Calixto, E. E., Pessoa, F. L., ... & Andrade, J. B. D. (2022). Technological perspectives and economic aspects of green hydrogen in the energetic transition: Challenges for chemistry. *Journal of the Brazilian Chemical Society*, 33(8), 844-869.
- Husain, A., Yii, K. J., & Lee, C. C. (2023). Are green cryptocurrencies really green? New evidence from wavelet analysis. *Journal of Cleaner Production*, 417, 137985.
- IEA. (2019). The future of hydrogen: Seizing today's opportunities. Report prepared by the IEA for the G20, Japan.
- Iuga, I. C., Nerişanu, R. A., & Dragolea, L. L. (2024). Volatility and spillover analysis between cryptocurrencies and financial indices: A diagonal BEKK and DCC GARCH model approach in support of SDGs. *Cogent Economics & Finance*, 12(1), 2437002.
- Jones, C., & Gautam, K. (1996). Oil and the stock markets. *Journal of Finance*, 51(2), 463-491.
- Jovan, D. J., & Dolanc, G. (2020). Can green hydrogen production be economically viable under current market conditions. *Energies*, 13(24), 6599.
- Lee, J. (2006). The comovement between output and prices: Evidence from a dynamic conditional correlation GARCH model. *Economics Letters*, 91(1), 110-116.

Liu, X., & Li, B. (2024). Safe-haven or speculation? Research on price and risk dynamics of Bitcoin. *Applied Economics Letters*, 31(4), 281-287.

Lucey, B., Yahya, M., Khoja, L., Uddin, G. S., & Ahmed, A. (2024). Interconnectedness and risk profile of hydrogen against major asset classes. *Renewable and Sustainable Energy Reviews*, 192, 114223.

Nasreen, S., Tiwari, A. K., & Yoon, S. M. (2020). Dynamic connectedness between oil prices and stock returns of clean energy and technology companies. *Journal of Cleaner Production*, 260, 121015.

Orskaug, E. (2009). Multivariate DCC-GARCH model: With various error distributions. *Institutt for matematiske fag*.

Palazzi, R. B., Quintino, D. D., Ferreira, P. J. S., & Bekun, F. V. (2024). Exploring the potential of the carbon credit program for hedging energy prices in Brazil. *Environmental Science and Pollution Research*, 31, 1-11.

Pham, L., Karim, S., Naeem, M. A., & Long, C. (2022). A tale of two tails among carbon prices, green and non-green cryptocurrencies. *International Review of Financial Analysis*, 82, 102139.

Reboredo, J. C. (2018). Green bond and financial markets: Co-movement, diversification and price spillover effects. *Energy Economics*, 74, 38-50.

Reboredo, J. C., & Ugolini, A. (2020). Price connectedness between green bond and financial markets. *Economic Modelling*, 88, 25-38.

Reboredo, J. C., Ugolini, A., & Aiube, F. A. L. (2020). Network connectedness of green bonds and asset classes. *Energy Economics*, 86, 104629.

Ren, B., & Lucey, B. (2022). A clean, green haven?—Examining the relationship between clean energy, clean and dirty cryptocurrencies. *Energy Economics*, 109, 105951.

Robiyanto, R., Nugroho, B. A., Huruta, A. D., Frensidy, B., & Suyanto, S. (2021). Identifying the role of gold on sustainable investment in Indonesia: The DCC-GARCH approach. *Economies*, 9(3), 119.

Rodriguez-Diaz, R. R., & Torres, C. A. R. (2022). Efeito contágio da bolsa brasileira na América do Sul. *Brazilian Journal of Business*, 4(1), 444-458.

Sadorsky, P. (1999). Oil price shocks and stock market activity. *Energy Economics*, 21(5), 449-469.

Sawyer, K. R., & Nandha, M. (2006). How oil moves stock prices. *Working Paper Series*, University of Melbourne.

Siddiqui, A., & Shamim, M. (2024). Modelling stock market volatility using asymmetric GARCH models: Evidence from BRICS stock markets. *Global Business and Economics Review*, 30(1), 107-127.

Squadrito, G., Maggio, G., & Nicita, A. (2023). The green hydrogen revolution. *Renewable Energy*, 216, 119041.

Tang, Y., Chen, X. H., Sarker, P. K., & Baroudi, S. (2023). Asymmetric effects of geopolitical risks and uncertainties on green bond markets. *Technological Forecasting and Social Change*, 189, 122348.

Umar, Z., Choi, S. Y., Teplova, T., & Sokolova, T. (2023). Dynamic spillovers and portfolio implication between green cryptocurrencies and fossil fuels. *PloS one*, 18(8), e0288377.

Yang, S., & Liu, K. (2023). Nvidia and Bitcoin linkage study—Based on DCC-GARCH model. *Financial Engineering and Risk Management*, 6(8), 95-101.

Yousaf, I., Mensi, W., Vo, X. V., & Kang, S. H. (2024). Dynamic spillovers and connectedness between crude oil and green bond markets. *Resources Policy*, 89, 104594.

Zhang, Y., Wang, M., Xiong, X., & Zou, G. (2021). Volatility spillovers between stock, bond, oil, and gold with portfolio implications: Evidence from China. *Finance Research Letters*, 40, 101786.