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Hydrogen in financial markets: A hybrid asset at the crossroads of technology and clean energy

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Abstract

Hydrogen is increasingly presented as a key solution for decarbonization in the context of the energy transition. This paper investigates how financial markets perceive hydrogen-related companies and whether these assets display distinct financial behaviors compared to other clean energy sectors—namely solar, wind, and renewable energy producers. Using daily data and a multi-faceted econometric approach, accounting for non-linearities, long-run dynamics, and time-varying correlations, we analyze both returns and dynamic correlations of hydrogen stocks relative to other energy segments. Our results show that hydrogen indices behave more like speculative technological assets than mature renewable energy sources. Their returns are more sensitive to financial stress indicators (e.g., the VIX) and to the performance of technology stocks. Dynamic correlations with other energy sectors are shaped by macroeconomic conditions: oil prices act as a synchronizing factor, while gold increases returns but reduces correlations. In contrast, geopolitical and financial uncertainty tends to increase comovements, reflecting flight-to-safety behavior. These findings highlight hydrogen's hybrid identity in financial markets—volatile, innovation-driven, and not yet integrated into the traditional renewable asset class, raising implications for both investors and policymakers regarding the financial interconnectedness and strategic support of the hydrogen sector within the broader clean energy transition.

Keywords: Hydrogen, Renewable energy, Asset pricing, Stock returns, Cross-market correlations

JEL Classification: G12, Q42, Q48

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1 Introduction

The decarbonization of energy systems and industrial sectors known as hard-to-abate, such as the chemical, cement, and steel industries, has become a central pillar in the fight against climate change (IEA 2024a). In line with the objectives set by the Paris Agreement, it is essential to drastically reduce greenhouse gas emissions on a global scale. While the latest Intergovernmental Panel on Climate Change (IPCC) report emphasizes that achieving carbon neutrality by 2050 requires a massive scale-up of low-carbon technologies, current deployment rates remain insufficient (IPCC 2023). Whether produced from renewable energy sources via electrolysers or from natural gas coupled with carbon capture, utilization and storage (CCUS) technologies, hydrogen emerges as a promising technological solution both for the decarbonization of numerous industrial sectors and energy storage (Griffiths et al. 2021; Pivetta et al. 2024; UNFCC 2024; Ameli et al. 2025).

However, the hydrogen sector remains at an early and rapidly evolving stage of development. In October 2025, 65 countries had adopted a national strategy for the development of hydrogen, compared to only four in 2019 (IEA 2025a). This policy momentum has been accompanied by an increasing number of projects, particularly those focused on low-carbon hydrogen production. According to the International Energy Agency (IEA), the number of production projects that reached a final investment decision (FID) have doubled between 2023 and 2024 (IEA 2024b). Moreover, in 2025, investment levels would need to nearly double to finance projects that have already reached FID. It is therefore crucial to scale up both public and private investment to support the development of the hydrogen sector (Sharma et al. 2023; IRENA 2024; IEA 2025b). This strong growth must be put into perspective, as numerous constraints continue to hinder the large-scale development of the hydrogen sector. The high costs associated with hydrogen production (particularly through water electrolysis) as well as the deployment of the necessary infrastructure, especially for transport and storage, represent major barriers to its large-scale deployment (Rolo et al. 2024). Beyond technical and economic barriers, the hydrogen sector also faces regulatory and financial constraints that directly influence investment dynamics. In the United States, support introduced under the Inflation Reduction Act (particularly the 45V tax credit) initially offered long-term visibility. But this framework was destabilized by policy changes under Donald Trump's second term, notably through the One Big Beautiful Bill Act (OBBBA), which reopened uncertainty over eligibility timelines and, consequently, over realized and planned investments.[2]

Finally, to finance these capital-intensive projects, companies must secure reliable funding and offtake agreements to guarantee future demand (Ason 2025). Initially, this often involves raising venture capital (VC), which allows investment in high-growth, technology-intensive companies that require substantial capital. Such investments typically target young companies that cannot access debt financing and repre-

[2] The 45V tax credit provided up to \$3/kg of clean hydrogen and applied to projects whose construction began before 31 December 2032. While early proposals under the OBBBA aimed to end eligibility for projects starting after 31 December 2025, the final legislation extended the deadline to 31 December 2027 and preserved credit transferability, partially restoring investment flexibility (Quitzow and Zabanova 2025).

sent nearly 10% of all energy-related VC investments (IEA 2025a; Black and Gilson 1998). This pattern is particularly evident among companies relying almost exclusively on low-carbon hydrogen, which currently face fragile financial positions, remain relatively young, and struggle to secure sufficient funding (IEA 2024b; IEA 2025a). At a later stage, as these companies grow, they seek to attract additional capital while providing returns to their early investors. Initial public offerings (IPOs) constitute one of the main exit channels for venture capital funds. In 2021, the hydrogen sector experienced a period of strong investor interest, characterized by a surge in investments and a wave of IPOs (IRENA 2024; IEA 2025a). These IPOs strengthen the credibility of companies with clients, banks, and investors, as they are required to publish financial and operational information regularly. They also open opportunities for further financing through debt or additional equity issuance, while accounting for potential dilution effects. Moreover, when VCs retain their investments for several years after the IPO, companies generally exhibit better long-term performance compared to those that go public without VC support (Basnet et al. 2025).

When these companies become publicly listed, their stock prices reflect market perception and investor expectations, which can directly influence their ability to raise additional funds and implement new projects. Since the peak in 2021, the hydrogen sector has experienced a sustained decline in company valuations (see Figure 3.1), a trend fueled by the gap between initial technological optimism and the reality of uncertain demand and regulatory delays. In this context, market quality and stability become critical challenges (UNFCC 2024). As highlighted by the World Bank (World Bank 2024), the scaling of hydrogen infrastructure is confronted by a multi-level risk environment that directly influences capital allocation. These factors include macroeconomic factors (e.g., inflation), political risks (e.g., geopolitical conflicts), regulatory risks (e.g., compliance), as well as risks related to demand volatility, technological uncertainties, and potential supply chain disruptions.

The main objective of this paper is to analyze how financial markets perceive and value hydrogen-related companies compared with other segments of the clean energy industry which directly affects their ability to raise capital and finance large-scale projects. More specifically, we investigate whether hydrogen exhibits distinctive financial dynamics, both in terms of returns and intersectoral correlations, that set it apart from more mature renewable energy sources such as solar and wind power. Understanding these dynamic relationships helps to reveal how shocks, whether economic, regulatory, or technological, can propagate across sectors or remain isolated, providing crucial insights into the systemic risks and diversification potential within the broader energy market. This will allow us to assess the integration of hydrogen with other energy sectors by analyzing the evolution of its correlations with them across different economic and market contexts. Variations in correlation directly influence the effectiveness of diversification strategies and the ability to reduce risk exposure in portfolios heavily invested in the hydrogen sector or the renewable energy sector as a whole. By combining several complementary econometric approaches, including quantile regressions, ARDL-ECM models, and DCC-GARCH specifications, we aim to identify the key economic, financial, and technological factors driving the behavior of hydrogen stocks. Our empirical results indicate that hydrogen-related stocks exhibit financial dynamics that differ markedly from those of more mature renewable energy sectors. In particular, hydrogen assets behave more like speculative, technology-oriented investments than like traditional renewable energy assets. Their returns are significantly more sensitive to financial stress indicators, such as the VIX, and to the performance of technology stocks. Moreover, dynamic correlations between hydrogen and other clean energy sectors vary substantially across macroeconomic conditions: oil prices tend to act as a synchronizing factor, while gold increases returns but reduces intersectoral correlations. By contrast, periods of heightened geopolitical and financial uncertainty are associated with stronger comovements across energy assets, reflecting flight-to-safety behavior. Overall, these findings highlight the hybrid financial identity of hydrogen in capital markets, characterized by high volatility, innovation-driven dynamics, and an incomplete integration into the broader renewable energy asset class.

The contributions of this paper are threefold. First, it provides the first comprehensive empirical assessment of the stock market dynamics of hydrogen-focused firms, a sector that remains largely overlooked in the financial literature on clean energy. Second, it explicitly compares hydrogen with established renewable subsectors, thereby shedding light on its hybrid position at the intersection of technology and energy markets. Third, it offers new insights into how macroeconomic, geopolitical, and financial uncertainty affects the comovements among clean energy assets, with direct implications for portfolio diversification and policy support to the hydrogen industry.

The article is organized as follows. Section 2 presents the literature review, followed by the data description in Section 3. Section 4 develops the methodology, while Section 5 presents and discusses the empirical results. Section 6 is dedicated to robustness checks. Finally, we conclude in Section 7.

2 Literature review

The analysis of stock market returns and cross-asset correlations has long been a central topic in financial and economic research, because understanding the factors that determine firms' valuations provides valuable insights into market dynamics, investor confidence, and, by extension, the ability of companies to raise capital. This is particularly critical for hydrogen companies. However, despite its growing importance, research on this emerging energy sector remains scarce. In contrast, other renewable energy segments have been extensively studied, highlighting a clear gap in the literature.

2.1 Determinants of clean energy stock returns

A substantial body of literature has analyzed stock returns and price volatility in renewable energy markets. The WilderHill Clean Energy Index (ECO Index), widely used in empirical studies, reflects the stock market performance of U.S. companies engaged in the development of clean energy solutions. Ahmed and Sleem (2023) identify four key determinants affecting both the short- and long-run returns of this index: gold prices, oil prices, public attention to clean energy, and the performance of the clean technology market. These determinants can be further grouped into three broad effects: energy market dynamics, global uncertainty, and technological asset performance.

Regarding the impact of energy markets on clean energy stock returns, the effect of oil prices has been the most extensively studied. Evidence shows that oil prices exert a nonlinear and asymmetric influence on alternative energy stocks, as represented by the ECO index (Henriques and Sadorsky 2008; Kumar et al. 2012; Reboredo and Ugolini 2018; Kyritsis and Serletis 2019). These studies suggest that oil prices negatively affect the index before the financial crisis but became strongly positive afterward. When oil prices rise, investment decisions tend to shift toward clean energy solutions (Broadstock et al. 2012; Managi and Okimoto 2013; Tsai 2015). Furthermore, the impact of oil prices varies depending on the market state, bullish markets favor investments in riskier sectors, such as renewable energies, which are perceived as a sector of the future (Kocaarslan and Soytas 2019; Dawar et al. 2021; Hashmi et al. 2022; Sardar and Sharma 2022; Mohammed and Mellit 2023; Cao and Xie 2023). Beyond oil prices, other energy prices have also been examined. Reboredo and Ugolini (2018), using multivariate dependence methods, show that the impact varies significantly across regions. In Europe, electricity prices appear to have the greatest impact on the stock price fluctuations of renewable energy companies, whereas in the United States, oil prices explain most of the variations. Coal and natural gas prices have a relatively smaller effect.

Secondly, the impact of global uncertainty has been widely studied, as the past decade has been marked by numerous significant events that have generated substantial uncertainty. These include political events such as elections, global geopolitical tensions like the war in Ukraine, as well as the COVID-19 pandemic. Such shocks have not only increased economic and financial uncertainty but have also broadly affected energy and financial markets. In this context, several studies show that geopolitical events tend to increase fossil fuel prices, particularly oil, and, through a substitution effect, indirectly influence clean energy stock prices (Song et al. 2019; Yang, Wei, et al. 2021). Similarly, global shocks such as the COVID-19 pandemic have generally exerted a negative impact on financial markets, including green assets, although to a lesser extent than on fossil fuel–related assets. Finally, political events such as elections may also affect green stock returns, for instance, the U.S. elections have been associated with negative cumulative abnormal returns for green stocks (Cosma et al. 2025).

Finally, most studies focus on the Arca Tech 100 Index (PSE), listed on the New York Stock Exchange (NYSE), as a proxy for technology stock prices. Several works emphasize a positive and significant influence of technology stock prices on clean energy stock returns. Henriques and Sadorsky (2008), among others, find that this effect can even surpass that of oil prices, suggesting that investors tend to perceive clean energy companies as technology firms with high disruptive potential. This finding is consistent with the fact that clean energy companies rely on advanced technologies to produce energy, highlighting their close operational link with the broader technology sector (Sadorsky 2012; Kumar et al. 2012;

Kocaarslan and Soytas 2019).

While these factors are well-documented for general clean energy indices, their specific impact on hydrogen stocks, which combine high capital intensity with deep technological dependency, remains to be explored.

2.2 Sectoral interdependencies and comovements

While the analysis of individual stock returns provides insights into the drivers of the hydrogen and clean energy sectors, it offers an incomplete picture for institutional investors and policymakers. From a portfolio management perspective, the attractiveness of an asset depends not only on its intrinsic performance but also on its comovement with other asset classes. More fundamentally, these correlations reflect the degree of financial interdependence of hydrogen within the broader clean energy sector (Karanasos and Yfanti 2021). In this context, a substantial body of the literature has focused on modeling asset return correlations in order to characterize the risk of transmission across different asset classes. To this end, most studies rely on multivariate Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) frameworks. Following the inintial work of Bollerslev (1990) on the Constant Conditional Correlation (CCC) GARCH model, the litertuare has evolved toward time-varying correlations, notably the Dynamic Conditional Correlation (DCC) model (Engle and Kelly 2012), the Asymmetric Dynamic Conditional Correlations (ADCC) model (Cappiello et al. 2006) and the Dynamic Equicorrelation (DECO) GARCH (Engle and Kelly 2012).

Using such methodologies, authors enable investors to identify assets that offer diversification benefits and those that are likely to exhibit heightened comovement during periods of market stress, thereby limiting their effectiveness as hedging instruments. In the context of clean energy and related sectors, this literature helps to determine whether renewable energy assets exhibit significant interconnectedness with other asset classes, such as technology or fossil energy. To begin with, Pham (2019) decomposes the stock prices of alternative energy companies by subsector using indices from the NASDAQ OMX Green Economy Index Family, which includes biofuels, solar, wind, fuel cells, among others. This approach allows the author to demonstrate that the impact of oil prices on stock returns varies across energy subsectors. Using dynamic DCC-GARCH model, a strong positive correlation is found for biofuels and energy management stocks, suggesting that these assets provide limited hedging benefits against oil price fluctuations. In contrast, wind, geothermal and fuel cell stocks appear to be less exposed due to their weaker correlation with oil prices. As a result, investors and policymakers should account for this sectoral heterogeneity when making decisions, ensuring alignment with the specific characteristics of each subsector (Reboredo, Rivera-Castro, et al. 2017; Pham 2019; Yahya et al. 2020). Moreover, several studies show that correlations between asset classes tend to increase during periods of crisis, such as episodes of economic or financial uncertainty, and decrease during more stable periods. This pattern reflects flight-to-safety mechanisms in times of stress and stronger investor confidence during periods of economic stability. To identify these dynamics, authors typically rely on multivariate GARCH frameworks to estimate time-varying correlations and subsequently regress exogenous variables on the extracted dynamic conditional correlations in order to examine the determinants of variations in these correlations (Karanasos and Yfanti 2021; Antonakakis et al. 2013; Yang, Zhou, et al. 2012).

In summary, the existing literature provides a robust framework for understanding the financial drivers of mature renewable energies, such as solar and wind, but leaves a significant gap regarding recent and promising energy sectors such as hydrogen. Existing studies have predominantly focused on the technological, industrial, or policy dimensions of hydrogen development, leaving its financial characteristics, particularly stock market behavior and intersectoral correlations, underexplored. This gap is even more pronounced when analyzing the influence of exogenous variables on correlations between assets, an area that remains largely unexplored within the clean energy finance literature. By explicitly focusing on hydrogen-related firms and comparing them with other clean energy sectors, this paper seeks to fill this gap and contribute to a clearer understanding of hydrogen's financial identity within the broader clean energy transition.

3 Data

We consider daily data covering the period from September 16, 2021, to June 30, 2025. We use indices from Global X Thematic Growth Exchange-Traded Funds (ETFs), specifically those under the "Infrastructure and Environment" category. First, the Global X CleanTech ETF (CTEC) includes companies developing technologies aimed at reducing environmental impacts, such as energy production, storage, or pollution mitigation products. We also use the Global X Renewable Energy Producers ETF (RNRG), which invests exclusively in companies that produce energy from renewable sources, excluding hydrogen-related activities. In addition, we use more specific indices targeting particular energy subsectors, such as the Global X Solar ETF (RAYS), which focuses on companies involved in solar energy development, and the Global X Wind Energy ETF (WNDY), which targets firms active in the wind power sector. Most importantly for this study, we consider the Global X Hydrogen ETF (HYDR), which invests in firms operating in the hydrogen sector. This includes diverse activities related to fuel cells, electrolyzer development, and other hydrogen-related technologies, covering both energy producers and technology developers involved in the hydrogen sector. The geographical distribution of the five indices is broadly similar, with companies predominantly located in the United States, China, South Korea, and Taiwan. These countries account for almost 70% of the total weight in the Clean Technologies Index (CTEC), 94.7% in the Solar Index, 59.6% in the Hydrogen Index, and 44.9% in the Wind Index. For the Renewable Energy Producers index, we observe a fairly different distribution, with 41% of the total weight concentrated in the United States, Brazil, and New Zealand. Denmark and Canada are also heavily represented in the Wind Index, together accounting for 41.2% of its composition and 12% of the Renewable Energy Producers index. Similarly, Great Britain and Germany represent a significant share of the Hydrogen Index, contributing 26.5% to its overall diversification (Global X Management

Company LLC n.d.). For all these variables, we aim to identify the factors that influence returns.[3] All sources of the original data series used in this study are listed in Appendix A.

To analyze the factors influencing these returns, we consider various elements based on variables commonly used in the literature. First, we examine whether prices of different energy sources affect these returns. To assess the impact of oil prices, we initially use West Texas Intermediate (WTI) crude oil price quotes sourced from the FRED database. Furthermore, we consider natural gas prices (NGAS) using Henry Hub spot prices obtained from the FRED website and electricity prices based on the baseload rates of Pennsylvania-New Jersey-Maryland Interconnection (PJM), reflecting average wholesale electricity prices per megawatt-hour, obtained from Refinitiv Eikon Datastream. We use data from the United States due to the strong representation of U.S. companies in the various stock indices. The electricity price series has been seasonally adjusted prior to the analysis.

Given the significant fluctuations observed in recent years, we incorporate uncertainty variables, notably geopolitical uncertainty measured by the Geopolitical Risk index (GPR) developed by Caldara and Iacoviello (Caldara and Iacoviello 2022). Furthermore, we capture financial market uncertainty using the VIX index (VIX), based on the S&P 500 and widely recognized as a measure of investor 'fear'. VIX data were obtained from the Chicago Board Options Exchange (CBOE) via the FRED database. Moreover, as noted in the literature, we also include gold prices and technology stock prices (Ahmed and Sleem 2023). The gold prices are retrieved from DBnomics and correspond to the LBMA Gold Prices, in U.S. Dollars (PM fixing), representing the afternoon spot price of gold on the London Bullion Market Association. For technology stocks, we use the Arca Tech 100 Index (PSE), also sourced from Yahoo Finance, which is listed on the New York Stock Exchange (NYSE) and tracks the performance of leading technology companies.

Table 1 presents the main descriptive statistics of the returns analyzed. We denote by DlHYDR, DlRAYS, DlWNDY, DlRNRG and DlCTEC the returns of the hydrogen index, solar index, wind index, renewable energy producers index and clean technologies index, respectively. Based on the Jarque-Bera test, the five indices exhibit non-normal distribution characteristics with a p-value well below 0.05. This is evidenced by either positive excess kurtosis, implying a leptokurtic distribution, which is steeper than the normal distribution, or by skewness values differing from zero. These findings support the use of methods robust to deviation from normality, such as unconditional quantile regressions, which allow for a better understanding of asymmetries in return distributions (Koenker and Bassett 1978; Firpo et al. 2009).

The price and return series are shown in Figures 3.1 and 3.2, respectively. In the first figure, shaded areas have been added to highlight certain episodes of apparent comovements among the various clean energy indices. Beyond a general downward trend observed across all indices during the studied period,

[3]Returns are defined as the first difference of the logarithm of the price series

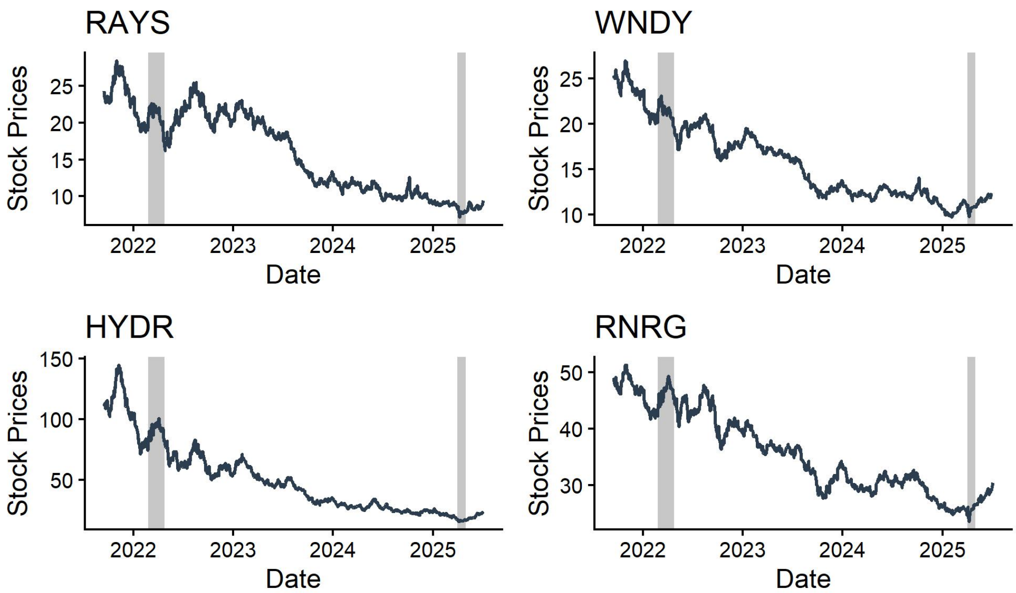
Table 1: Descriptive statistics of clean energy market returns

Variable	Min	Mean	Max	SD	Skew	Kurtosis	Jarque-Bera
DlHYDR	-0.10	-0.00	0.11	0.03	0.29	0.98	0.00
DlRAYS	-0.11	-0.00	0.10	0.02	0.07	1.22	0.00
DlWNDY	-0.08	-0.00	0.07	0.02	-0.00	2.19	0.00
DlRNRG	-0.07	-0.00	0.06	0.01	-0.06	1.68	0.00
DlCTEC	-0.09	-0.00	0.10	0.02	0.26	0.88	0.00

Note: This table reports key descriptive statistics for the logarithmic returns of the hydrogen index (DlHYDR), the solar index (DlRAYS), the wind index (DlWNDY), the renewable energy producers index (DlRNRG), and the clean technologies index (DlCTEC). The statistics presented include the minimum (Min), mean (Mean), maximum (Max), standard deviation (SD), skewness (Skew), excess kurtosis (Kurtosis), and the p-value of the Jarque-Bera test for normality (Jarque-Bera).

several marked fluctuations appear to occur simultaneously. These movements may be linked to major macroeconomic or geopolitical events. For instance, the first shaded area, beginning on February 24, 2022, marking the start of the Ukraine war, is accompanied by particularly pronounced stock market fluctuations, suggesting a significant market reaction to this major geopolitical event. Similarly, the last shaded area, corresponding to the announced implementation of reciprocal tariffs by the Trump administration in April 2025, coincides with a slight generalized decline in prices, followed by an increase across all four indices.

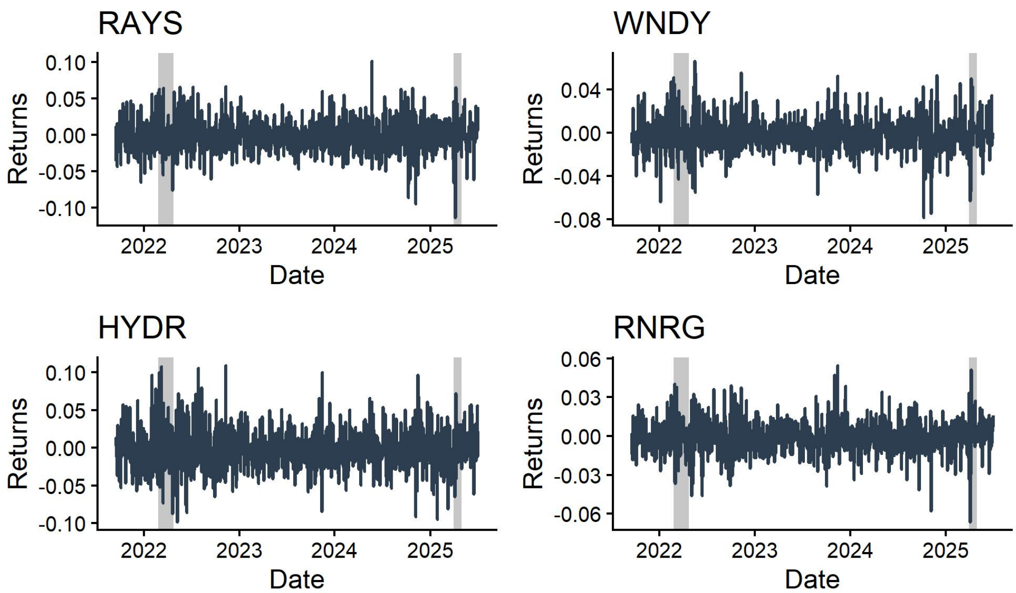
Figure 3.1: Evolution of Stock Prices in Clean Energy Markets



Note: The figure displays the evolution of stock prices for the different indices analyzed: the Hydrogen Index (HYDR), Clean Technologies Index (CTEC), Solar Index (RAYS), Renewable Energy Index (RNRG), and Wind Index (WNDY). The first shaded area begins on February 24, 2022, marking the onset of the war in Ukraine, while the second one starts in April 2025, corresponding to the implementation of U.S. tariffs.

In Figure 3.2, which displays the stock returns, we observe the presence of similar volatility clusters across all series. A period of lower volatility notably appears in the first half of 2023, suggesting a common slowdown in fluctuations across the indices considered. Conversely, periods of higher volatility are observed in the shaded areas, particularly around the first one, which also corresponds to the onset of the war in Ukraine. These similarities observed in the dynamics of stock prices and returns justify the use of DCC-GARCH (Dynamic Conditional Correlation GARCH) models, which allow these common movements to be modeled. Indeed, these models capture the dynamic conditional correlations between multiple series while accounting for the heteroskedasticity inherent in each of them. The presence of common volatility clusters suggests the existence of synchronized or interdependent movements among the different indices, thereby requiring a multivariate framework designed to model both the individual volatility of each series (through univariate GARCH models) and their comovements over time (via the dynamic correlation matrix). The DCC-GARCH model thus proves particularly well-suited for analyzing the temporal structure of interdependencies among the returns of these clean energy subsectors (Engle 2002).

Figure 3.2: Evolution of Returns in Clean Energy Markets



Note: The figure presents the evolution of logarithmic returns for the indices analyzed: the Hydrogen Index (HYDR), Clean Technologies Index (CTEC), Solar Index (RAYS), Renewable Energy Index (RNRG), and Wind Index (WNDY). The first shaded area begins on February 24, 2022, marking the onset of the war in Ukraine, while the second one starts in April 2025, corresponding to the implementation of U.S. tariffs.

4 Methodology

Following approaches commonly used in the literature, including Karanasos and Yfanti (2021), we conduct two main analyses. First, we examine the effect of selected variables on asset returns, following the methodology presented in Section 4.1. This step allows us to identify the factors that directly influence the performance of clean energy companies in public markets and to determine whether certain sectors are more or less sensitive to crises, commodity prices, or global events. Second, we examine the correlations between assets and the factors influencing them, as described in Section 4.2, providing insights into the interconnectedness of clean energy sectors, potential contagion risks, and diversification opportunities for investors.

4.1 Analysis of stock returns

Before proceeding with the estimations, we performed unit root tests to assess the stationarity of the time series. The results are presented in Table 7 in Appendix B and indicate that the return series of the five indices are stationary, which is consistent with the properties typically observed in financial time series. Among the explanatory variables, electricity prices and the geopolitical risk index are found to be stationary, while crude oil prices, natural gas prices, gold prices, stock prices of technology companies, and the VIX index, are integrated of order one (I(1)). In order to gain a clearer understanding of the mechanisms underlying the conditional correlations, we begin by analyzing the direct effects of the explanatory variables on the returns of the five sectoral indices. This preliminary step is essential for capturing the dynamics of stock returns and identifying the main economic, financial, and energy-related drivers. To that end, we estimate a standard OLS regression, ensuring that all non stationary variables have been transformed accordingly to satisfy the stationarity assumption. We estimate $r_t^i = \alpha + \sum_{j=1}^{7} \beta_j X_{j,t} + \varepsilon_t$, where r_t^i is the return of sector i (Hydrogen, Solar, Wind, Clean Technologies, and Renewable Energy Producers indices) at time t, and $X_{j,t}$ denotes the stationarized explanatory variables, WTI crude oil, natural gas, geopolitical risk, electricity prices, VIX, technology stocks, and gold prices. β_j are the associated coefficients, and ε_t is the error term. Given the presence of heteroskedasticity and autocorrelation in the estimation residuals, a Newey-West correction was applied to obtain robust results. Subsequently, and due to the asymmetries identified earlier, the unconditional quantile regression version can be written as follows: $Q_{r_t^i}(\tau \mid \mathbf{X}_t) = \alpha(\tau) + \sum_{j=1}^{7} \beta_j(\tau) X_{j,t}$, where $Q_{r_t^i}(\tau \mid \mathbf{X}_t)$ denotes the quantile of order τ of the sectoral return r_t^i, given the explanatory variables $\mathbf{X}_t$. The coefficients $\alpha(\tau)$ and $\beta_j(\tau)$ are quantile-dependent parameters, estimated for each quantile level τ of interest. Here as well, a Newey-West correction has been applied (Firpo et al. 2009).

4.2 Analyses of correlations

4.2.1 Dynamic Conditional Correlations

We also focus on the potential comovements among clean energy indices, which we model using an approach widely applied in the literature, the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model (Engle 2002). This framework allows us to capture time-varying correlations, thereby accounting for periods with differing levels of financial stress. To estimate the DCC-GARCH model, we follow a two-step procedure. First, we specify the individual volatility dynamics of each return series using Exponential GARCH (EGARCH) processes with a Student-t distribution (Nelson 1991). In a second step, we model the dynamic correlation structure between the series. Traditional GARCH models (Bollerslev 1986) as extensions of ARCH models (Engle 1982) allow for the modeling of conditional volatility based on past information, but they assume that shocks have symmetric effects on volatility, regardless of whether they are positive or negative. In contrast, the EGARCH model offers several advantages over the standard GARCH, particularly its ability to capture the asymmetric effects of shocks. Negative shocks may induce a larger increase in volatility than positive shocks of the same magnitude, a phenomenon commonly referred to as the "leverage effect". Let a return series be such that the residuals are expressed as $\varepsilon_t = r_t - \mu$ where r_t denotes the observed return and μ is the mean return (intercept). The variance equation with the EGARCH(1,1) model is then specified as follows:

$$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \alpha \left(\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - E\left[\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| \right] \right) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{1}$$

where σ_t^2 is the conditional variance of the series at time t, ε_t is the residual from the associated mean equation, ω is a constant term, β represents the persistence of volatility, α captures the magnitude effect of past standardized shocks adjusted by their expected absolute value, and γ measures the asymmetry of these effects. Specifically, if $\gamma < 0$, negative shocks increase volatility more than positive shocks of the same magnitude. In this framework, the choice of the error distribution, such as the standard normal (norm), Student's t (std), or skewed Student's t distribution (sstd), is crucial to accurately capture the characteristics of the residuals, including fat tails and asymmetry. To determine the most appropriate distribution for each series, we first tested the normality of the standardized residuals using the Jarque-Bera test. We then examined the skewness and compared the information criteria values. The results are presented in Appendix C. Based on these findings, the Student-t distribution was selected for the final estimation. After describing the univariate conditional variance dynamics, we also include a vector autoregressive (VAR) mean equation for our five stock indices, with a lag order of one selected optimally using the Akaike Information Criterion (AIC). This leads to a mean equation of the form $Y_t = \alpha_0 + AY_{t-1} + \varepsilon_t$. In this equation, Y_t is a 5×1 vector of returns including the five indices under study. The vector α_0, of dimension 5×1, gathers the intercept terms specific to each equation in the system. The matrix A, of size 5×5, contains the coefficients capturing the dynamic effects of the lagged values of the indices on each other. Finally, ε_t is the 5×1 vector of error terms. Specifying a mean equation of this type allows us to account for potential autocorrelations among the series, thereby mitigating possible contagion biases between the indices.

Following the estimation of univariate EGARCH models (one for each series), and in line with the procedure proposed by Engle (2002), we construct the matrix D_t, a 5×5 diagonal matrix containing the conditional standard deviations of each of the five univariate series at time t. Given the relationship between correlation and covariance matrices, the conditional variance-covariance matrix of the residuals, denoted H_t, can be written as $H_t = D_t R_t D_t$ where R_t is the dynamic conditional correlation matrix.

The dynamics of R_t are driven by a matrix Q_t, defined as follows:

$$Q_t = (1 - a - b)\bar{Q} + a v_{t-1} v_{t-1}^{\top} + b Q_{t-1} \tag{2}$$

where $\bar{Q}$ denotes the empirical covariance matrix of the standardized residuals $v_t = D_t^{-1}\varepsilon_t$, a and b are two parameters to be estimated, such that $a+b<1$ to ensure the stationarity of the process, and Q_t is a symmetric, non-standardized variance-covariance matrix. Finally, the conditional correlation matrix R_t is obtained by normalizing Q_t as follows, $R_t = \mathrm{diag}(Q_t)^{-1/2} Q_t \,\mathrm{diag}(Q_t)^{-1/2}$ where $\mathrm{diag}(Q_t)^{-1/2}$ produces a diagonal matrix containing the inverse of the standard deviations, thereby converting the covariance matrix into a correlation matrix.

In our analysis, the dynamic conditional correlation series extracted from this DCC-GARCH model will be used as dependent variables in subsequent regressions to assess the extent to which conditional correlations between hydrogen and various renewable energy sectors respond to changes in economic, financial, and energy-related factors.[4] We denote by $DCC_{ij,t}$ the conditional correlation between the hydrogen-related index ($i = \text{HYDR}$) and each of the other indices ($j = \text{Solar}, \text{Wind}, \text{RNRG}$) representing solar energy, wind energy, and renewable energy producers, respectively.

4.2.2 Analyses of factors influencing dynamic correlations

To begin with, we examine the stationarity of the conditional correlation series. We find that they are non-stationary and I(1) (see Appendix B, Table 8 for the results). Given the heterogeneity in the orders of integration among the explanatory variables as shown in section 4.1, some being I(0) and others I(1), it is essential to adopt an estimation method capable of accommodating this mix. In this context, the Autoregressive Distributed Lag (ARDL) model represents a particularly suitable framework (Shin and Pesaran 1995; Karanasos and Yfanti 2021). The ARDL approach allows for the simultaneous inclusion of both I(0) and I(1) variables, providing flexibility in modeling short- and long-run dynamics.

We first begin by estimating the baseline ARDL model, which can be described as follows:

$$DCC_{ij,t} = \alpha + \sum_{i=1}^{p} \phi_i DCC_{ij,t-i} + \sum_{k=1}^{K} \sum_{j=0}^{q_k} \beta_{kj} X_{k,t-j} + \varepsilon_t \tag{3}$$

where $DCC_{ij,t}$ denotes, in turn, the dependent variables under study, namely the three dynamic conditional correlation series ($DCC_{HYDR-RAYS,t}$, $DCC_{HYDR-WNDY,t}$ and $DCC_{HYDR-RNRG,t}$). $X_{k,t-j}$ represents the K explanatory variables, WTI, NGAS, GPR, PJM, VIX, PSE, and GOLD. The parameters p and q_k correspond to the optimal lag orders selected based on information criteria, for the dependent variable and for each of the K explanatory variables. The aim of this modeling approach is

[4] Following the literature and due to the bounded nature of correlations, we applied a Fisher transformation to unbound the correlations and ensure correct estimation. We have: $DCC_{ij,t} = \ln(\frac{1+\rho_{DCC_{ij,t}}}{1-\rho_{DCC_{ij,t}}})$ where $\rho_{DCC_{ij,t}}$ represents the estimated correlations between i and j from the initial DCC-GARCH estimations.

to identify both the lagged and contemporaneous impacts of each explanatory variable on the conditional correlations. The estimation is performed using Newey–West robust standard errors to account for potential heteroskedasticity and autocorrelation in the residuals.

Furthermore, the ARDL method offers the major advantage of allowing joint modeling of both short-term and long-term dynamics between the variables studied. Indeed, in its original formulation, the ARDL model captures the lagged effects of explanatory variables on the dependent variable, providing an overall view of their influence. However, it is the reformulation of the model as an error correction model (ARDL-ECM) that explicitly distinguishes these two time horizons. The error correction term (ECM) represents the long-term adjustment, it measures the speed at which the dependent variable returns to its equilibrium following a shock and should therefore be negative and statistically significant to indicate this return to the equilibrium value. Meanwhile, the coefficients associated with the differenced variables represent the short-term effects, that is, the immediate or transitory responses to changes in the explanatory variables. We can extend the ARDL model to its ECM form only when Pesaran's bounds test confirms the presence of cointegration (Pesaran et al. 2001). These tests determine the presence of a long-term equilibrium relationship among the variables, even when they are integrated of different orders, I(0) or I(1), as long as none of the variables is integrated of order two (I(2)). Validation of the bounds tests means that the null hypothesis of no cointegration can be rejected, justifying the estimation of an ECM. In the absence of confirmed cointegration, using an ECM would be statistically inappropriate, as there would be no stable long-term equilibrium relationship to correct. Writting the ARDL-ECM form of Equation (3), we get:

$$\begin{aligned}\Delta DCC_{ij,t} = \alpha + \sum_{i=1}^{p-1} \phi_i^* \Delta DCC_{ij,t-i} + \sum_{k=1}^{K} \sum_{j=0}^{q_k-1} \beta_{kj}^* \Delta X_{k,t-j} \\ + \lambda \left(DCC_{ij,t-1} - \sum_{k=1}^{K} \psi_k X_{k,t-1} \right) + \varepsilon_t\end{aligned} \tag{4}$$

In this formulation, $\Delta DCC_{ij,t}$ represents the short-term change of the dependent variable, while the first difference terms of the explanatory variables capture their short-term effects. The coefficient λ is the adjustment speed parameter that measures how quickly the dependent variable returns to its long-term equilibrium after a shock. This coefficient must be negative and statistically significant to confirm the existence of an error correction mechanism. This model simultaneously captures short-term dynamics, through the first differences of the variables in Equation (4), and long-term adjustment, via the error correction term. To obtain the long-term coefficients ψ_k, the permanent effect of each variable k can be derived from the basic ARDL estimation performed according to Equation (3). In the long run, the values are constant, which allows us to write :

$$\psi_k = \frac{\sum_{j=0}^{q_k} \beta_{k,j}}{1 - \sum_{i=1}^{p} \phi_i} \tag{5}$$

ψ_k then represents the persistent effect of the explanatory variable k on our dependent variable, in the case where a cointegration relationship has been demonstrated by the Pesaran test, and when the coefficient associated with the error correction term λ is significantly negative, indicating a long-term equilibrium adjustment effect.

5 Empirical results and discussions

To better interpret the results, we first examine the risk-return profile of the individual companies within the hydrogen index. By extracting the market-derived Beta coefficients from Yahoo Finance for 19 major companies in the *HYDR* index, we can establish a microeconomic baseline for the sensitivities observed in our subsequent regressions. This firm-level analysis reveals a predominantly high-beta profile, with a mean coefficient of approximately 1.5. This indicates that hydrogen stocks act as systemic risk amplifiers, exhibiting volatility significantly higher than the broad market. Notably, only three companies in the sample possess a Beta below 1. These exceptions are highly diversified firms where hydrogen constitutes only a marginal portion of their operations, collectively representing only 7% of the total index weight. This concentration of high-beta stocks suggests that investors demand a substantial risk premium, a required rate of return significantly higher than the market average, to compensate for the sector's inherent exposure to systematic shocks. However, the sector's ability to generate such returns is severely constrained by its current financial health. Out of the 15 companies for which Earnings Per Share data was available, 11 report negative earnings, indicating a widespread lack of profitability. Among the remaining four, two show marginal profitability (below 0.5), while others owe their positive results to significant diversification into more mature sectors. Although we recognize the inherent limitations of the CAPM, such as its reliance on market efficiency and the time-varying nature of Beta coefficients, it remains, nevertheless, an interesting diagnostic tool. It explains why the hydrogen sector is particularly vulnerable to shifts in investor sentiment and financial stress. These fundamental characteristics provide the necessary context for the empirical results presented in the following sections, where we quantify how this risk-sensitive architecture reacts to global energy and financial shocks. Building on these microeconomic insights, we now evaluate the average impact of global factors on sectoral returns.

5.1 Determinants of Stock Returns: Evidence from OLS and Quantile Regressions

Table 2 presents the results of the OLS estimations for the five indices under study (*HYDR*, *RAYS*, *WNDY*, *CTEC*, and *RNRG*). Regarding fossil fuel prices, such as natural gas and oil, we find that natural gas has a significant effect on the renewable energy producers index (RNRG) at the 5% significance level, likely due to its global and diversified composition, which makes it sensitive to broader energy market fluctuations. In contrast, oil prices exert a significant and positive influence on all indices except the renewable energy producers index. These findings are broadly consistent with the well-documented mechanism in the literature, according to which rising oil prices stimulate increased investment in renewable energy sources (Song et al. 2019). This substitution effect arises as capital reallocates from fossil fuels to clean and renewable sectors, which are perceived as strategic long-term alternatives when oil prices surge. To further investigate whether the impact of fossil energy prices varies across market conditions, we extend the analysis using a quantile regression approach as presented in Section 4. This allows us to examine how the sensitivity of returns to oil prices may differ between bearish, normal, and bullish market states. Oil prices exhibit some degree of heterogeneity across quantiles, as illustrated in Figure 5.1a.[5] While no pronounced asymmetry is observed in most cases, a few exceptions emerge in specific parts of the return distribution. The difference between OLS and quantile regression results arises from the fact that OLS capture the average effect of oil prices on returns, whereas financial return distributions are typically skewed and exhibit heterogeneous responses across market conditions. In the quantile regression framework, the estimated coefficients are mostly not statistically significant; however, zero is often found near the boundary of confidence intervals, suggesting that oil prices may still exert a non-negligible influence on average returns.

To further the analysis, the continuation of Table 2 shows that financial factors such as the VIX, appear to exert a negative influence on the stock returns of the renewable energy producers index. For the remaining four indices, no statistically significant relationship is detected at the mean level. In this context, as an uncertainty factor, it is relevant to examine whether the effect varies across market conditions. As shown in Figure 5.1b, we observe a heterogeneous impact across quantiles. For the hydrogen index, the influence of the VIX is increasingly negative in bearish market conditions, becoming statistically insignificant above the fourth decile. This behavior is broadly consistent with the patterns observed for other indices, such as the Clean Technology Index, the Solar Index, and the Renewable Energy Producers Index. While the first two indices do not exhibit significant effects on average (OLS estimates), they show sensitivity to the VIX in the lower tails of the return distribution. This increased vulnerability in downturns can be attributed to the more speculative nature of these sectors, particularly the hydrogen sector, which exhibits the strongest and most significant effect across the lower quantiles. This is consistent with the high average Beta coefficient identified earlier, as high-beta assets, hydrogen stocks naturally act as risk amplifiers during market contractions. As an emerging industry, hydrogen related assets are likely perceived by investors as more volatile and risky, making their valuations more sensitive to periods of financial stress (low quantiles). These findings are in line with the existing literature, which shows that the VIX typically exerts a negative and statistically significant influence on broad and diversified market indices. However, when the analysis is restricted to specific clean energy subsectors, such as wind, the effect of the VIX often becomes negligible or statistically insignificant (Ahmad et al. 2018; Gordo et al. 2024). To go further in the analysis, the VIX is itself influenced by major geopolitical and macroeconomic events, such as trade policy announcements or global crises, which reflect increases in investor fear during such periods and directly affect stock returns, particularly

[5] Given the generally weak or non-significant effects of natural gas prices, quantile-based results for this variable are not presented, as no meaningful differences emerge across market states; however, the results are available upon request.

in relatively recent and riskier sectors (Smales 2021).

Moreover, and in line with existing literature, the index representing technology stock prices exhibits a significant positive effect on the returns of all renewable energy indices. This suggests that investors perceive technology companies and clean energy firms as similarly innovative and forward-looking, so that increased interest in one sector often translates into increased investment in the other, reflecting the strong demand for technological innovation in the development of clean energy (Kocaarslan and Soytas 2019). Figure 5.1c shows that this effect is particularly pronounced in bullish markets (high quantiles), where investors are more inclined to allocate capital to sectors perceived as riskier but offering higher growth potential. Hydrogen, in particular, exhibits the largest coefficient, reflecting the sector's exceptionally dynamic technological development and high innovation intensity. This suggests that its returns are more closely aligned with the broader technology market than with more established sectors. As a recent sector, characterized by intensive research aimed at improving technological efficiency, reducing costs, and developing large-scale technologies, hydrogen is generally regarded as a technological domain, rather than as a mature energy sector. These patterns indicate that investor behavior in emerging clean energy sectors is strongly shaped by expectations of innovation and technological progress, rather than by traditional fundamentals alone.

Table 2: Estimated OLS regressions for stock returns

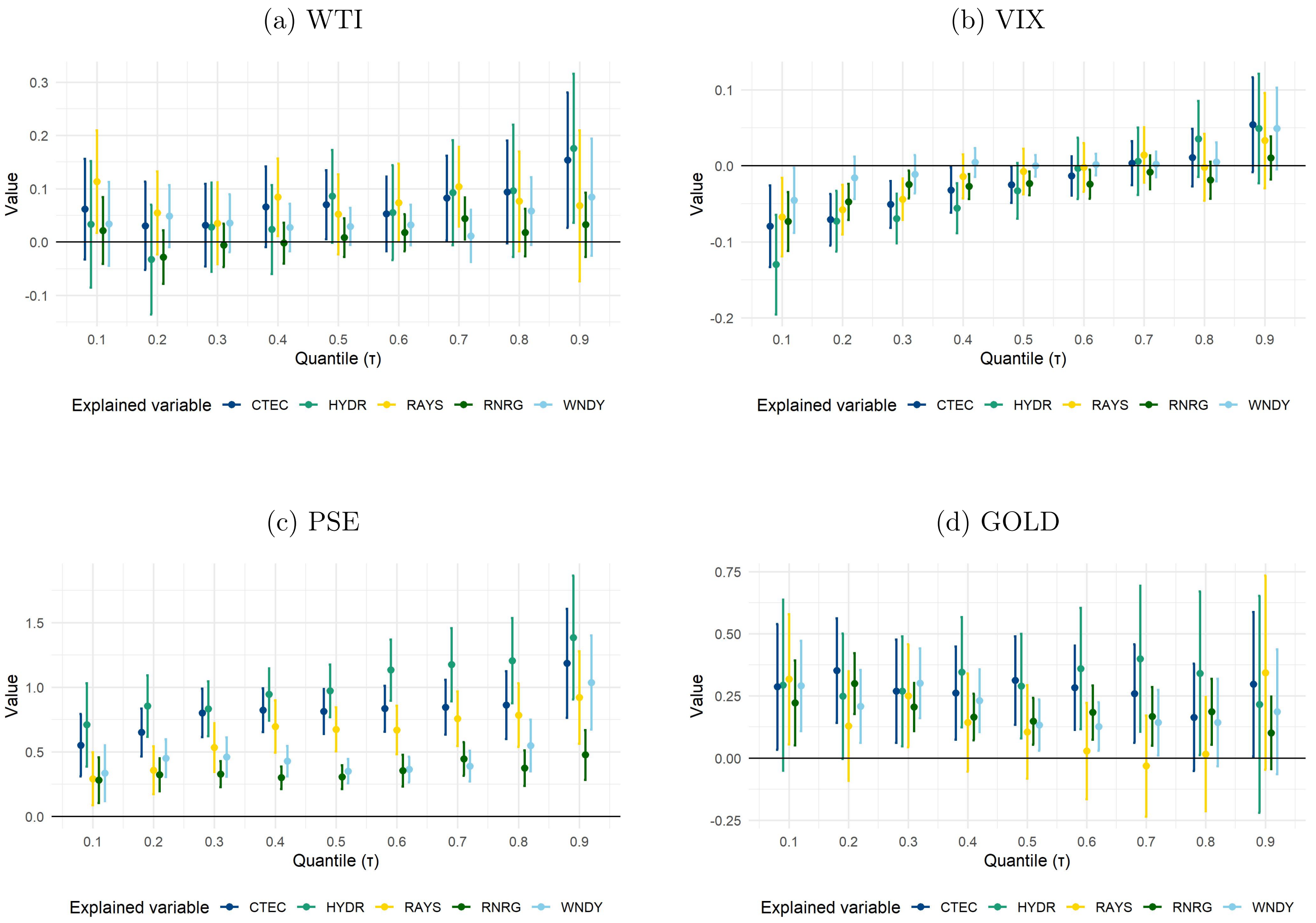
	DlHYDR	DlRAYS	DlWNDY	DlRNRG	DlCTEC
(Intercept)	0.0007	-0.0154	-0.0188***	-0.0085	-0.0077
DlWTI	0.0701**	0.0885***	0.055**	0.0216	0.0892***
DlNGAS	0.0055	0.0085*	0.0049	0.0068**	0.0058
lGPR	-0.0009	0.0014	0.003**	0.0009	0.0001
lPJM	0.0004	0.0019	0.0007	0.0009	0.0015
DlVIX	-0.0232	-0.0067	0.0031	-0.0244***	-0.0138
DlPSE	1.0689***	0.6597***	0.5386***	0.4151***	0.8951***
DlGOLD	0.3577***	0.1562**	0.2169***	0.1878***	0.283***

*p<0.1; **p<0.05; ***p<0.01

Note: This table presents the coefficients and their statistical significance from OLS regressions, with standard errors corrected for heteroskedasticity and autocorrelation. Dependent variables are the returns of Hydrogen (DlHYDR), Solar (DlRAYS), Wind (DlWNDY), Renewable Energy Producers (DlRNRG) and Clean Technologies (DlCTEC) indices. Explanatory variables include oil prices (DlWTI), natural gas prices (DlNGAS), Geopolitical Risk (lGPR), electricity prices (lPJM), VIX (DlVIX), technology stocks (DlPSE), and gold prices (DlGOLD). All series were pre-processed to ensure stationarity.

To conclude the analysis of stock returns, we observe that gold prices are also positively linked to the returns of all five indices. This relationship can be interpreted through the mechanisms driving investor behavior in periods of economic or energy uncertainty. Rising fossil fuel prices or broader market stress may increase the perceived risk of conventional investments, prompting a reallocation of capital towards assets that either represent strategic alternatives (renewable energy stocks) or store value under uncertainty (gold). Such dynamics create a parallel movement between gold and clean energy assets, reflecting a broader pattern of investor response to a perceived risky environment (Bibi et al. 2022; Erdoğan et al. 2022). When the analysis is extended across quantiles (see Figure 5.1d), the positive association between gold and sectoral stock indices persists across the distribution. Finally, gold serves as both a risk signal and a safe-haven asset, while investors may simultaneously favor renewable energy stocks, which are perceived as high-growth sectors supported by technological innovation and public policies. In such cases, capital can be reallocated toward renewable energy either as a strategic alternative to more expensive fossil fuels or due to their strong long-term growth potential.

Figure 5.1: Estimated quantile regression results for stock returns



Note: These figures show the evolution of the coefficients and their associated confidence intervals from the quantile regressions for each dependent variable (Hydrogen in light green, Clean Technologies in dark blue, Rebewable Energy Producers in dark green, Solar in yellow, and Wind in light blue). The evolution of four explanatory variables is presented, oil prices (WTI), financial stress indicator (VIX), technology stock prices (PSE), and gold prices (GOLD).

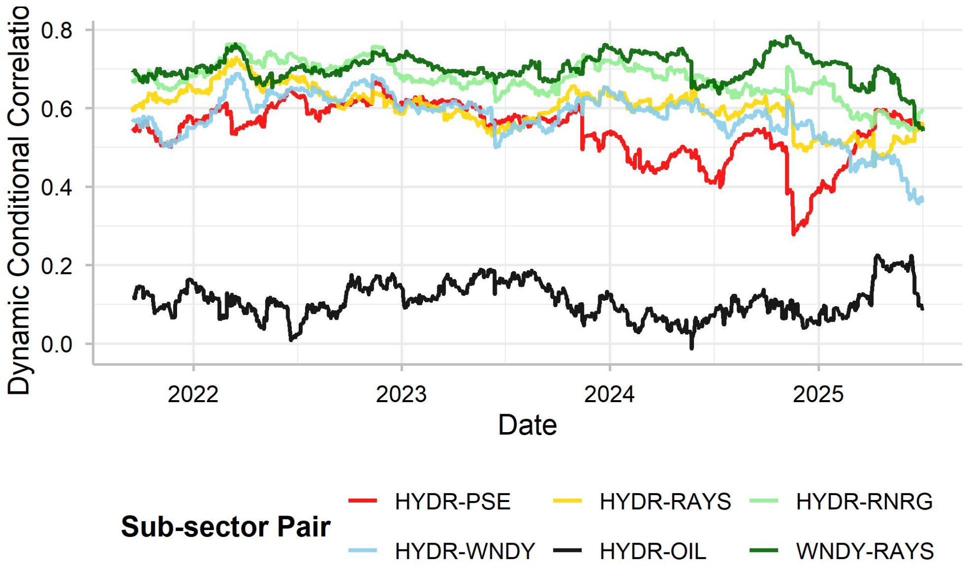
To summarize, the emerging hydrogen sector is particularly sensitive to financial and market uncertainties, such as the VIX during bearish periods and gold prices. Hydrogen firms are generally younger, highly innovative, and capital-intensive, which makes them more vulnerable to negative market events than more established renewable energy sectors. Our previous findings on firm-level Betas and negative EPS explain this vulnerability, with high capital costs and a lack of internal profitability, these firms are highly dependent on favorable market conditions. This vulnerability can limit their ability to raise funds and potentially delay project development. These characteristics highlight the crucial role of public policies and regulatory support. Policymakers could implement targeted subsidies for green hydrogen projects, establish stable regulatory frameworks to encourage private investment, and fund R&D programs to accelerate technological maturation. To secure long-term investment, financial stabilization mechanisms are essential. Public guarantees and dedicated support funds are vital to decouple project financing from short-term market volatility and strengthen investor confidence. One example is the European Hydrogen Bank (EHB), operating under the EU Innovation Fund. The EHB leverages competitive bidding processes, notably through 'Auctions-as-a-Service', to allocate Carbon Contracts for Difference (CCfDs) (European Commission 2020). This mechanism guarantees long-term revenue and thus provide strong evidence of stability, which can help companies raise funds. It also appears important to develop market instruments tailored to periods of stress, such as futures contracts or specialized hedging instruments, which can reduce specific risks and further reassure investors. Ultimately, when a company demonstrates solid financial health and gains investor confidence, with stock prices that react only moderately to crises, it can facilitate fundraising, either through new equity issuance (where higher stock prices allow companies to issue fewer shares for the same amount, mitigating dilution) or through bank loans, as lenders are then more willing to provide financing.

5.2 Drivers of Sectoral Interdependencies: Evidence from DCC-GARCH and ARDL-ECM Models

After estimating the impact of our explanatory variables on stock returns, it is relevant to analyze their influence on the dynamic correlations computed via the DCC-GARCH model between our indices. This step goes beyond assessing individual asset sensitivities and provides insights into how shocks propagate across sectors. In particular, it allows us to examine whether periods of market stress, technological optimism, or commodity price volatility simultaneously alter the strength of comovement among clean energy sectors. Such an understanding is crucial for investors seeking to manage portfolio risk through diversification and for policymakers monitoring systemic stability, especially in emerging segments like the hydrogen market, where sectoral interdependencies are still evolving. By studying dynamic correlations, we can identify whether the interconnections between sectors are driven primarily by shared exposure to macroeconomic factors, technology cycles, or investor sentiment, and we can assess the extent to which the hydrogen sector is integrated with other renewable energy subsectors. For instance, a rise in oil prices may simultaneously increase renewable energy returns and strengthen correlations between renewable sectors if capital reallocates across alternative energy investments, whereas shocks affecting only a single subsector may leave cross-sector correlations largely unchanged.

We begin by presenting in Figure 5.2 the dynamic conditional correlations between the hydrogen sector and several indices, including the main clean energy indices (HYDR-WNDY, HYDR-RAYS and HYDR-RNRG), technology companies (HYDR-PSE), and oil prices (HYDR-WTI). We also include the dynamic conditional correlation between the Solar and Wind (WNDY-RAYS) indices in order to gain insight into the correlation between two more mature segments of the renewable energy sector. This figure reveals marked differences in correlation dynamics. To begin with, we observe an overall stronger correlation between the solar and wind indices (around 0.75) compared to the dynamic correlations between hydrogen and the two energy subsectors, which are both around 0.6. This lower level of correlation supports the idea that hydrogen remains an emerging segment whose dynamics are not yet comparable to those observed in more mature energy subsectors. Hydrogen is likely to be more dependent on sector-specific (and notably speculative) factors than on the overall dynamics of the renewable energy market itself. Furthermore, as highlighted in the literature, renewable energy sectors tend to exhibit stronger correlations with the stock market performance of technology companies than with oil prices, with the correlation between hydrogen and PSE fluctuating around 0.5, compared to less than 0.2 between hydrogen and oil (Kocaarslan and Soytas 2019; Pham 2019; Janda et al. 2022). This pattern reflects investors' perception of technological and renewable energy firms as similarly innovative and future-oriented, leading to comovements driven by expectations of technological progress and the energy transition rather than by traditional energy cost factors. In contrast, the low correlation observed with oil prices suggests a potential for diversification, as oil-linked assets could theoretically serve as a hedge against fluctuations in the hydrogen sector. However, coupling with a fossil-based asset runs counter to sustainability objectives and raises coherence concerns for portfolios oriented toward the energy transition. The correlation between hydrogen and the other clean energy subsectors is comparable to that observed between hydrogen and technology companies, although this correlation tends to weaken toward the end of 2024. This sharp decline in correlation coincides with Donald Trump's election in early November 2024, falling below 0.3 on November 18, before returning to previous levels only in February 2025. This event has likely increased political uncertainty, with investors anticipating potential changes in energy and environmental policies that could affect subsidies, regulatory frameworks, and support programs for emerging sectors. Given hydrogen's speculative and technology-driven nature, investors may have temporarily reallocated capital toward more mature or less policy-sensitive sectors. This defensive reallocation can partly explain the marked but short-lived decoupling observed during this period. Once policy expectations stabilized in early 2025, correlations returned to previous levels, highlighting the transient nature of political shocks on structural interdependence within the renewable energy market. This analysis highlights the importance of precisely identifying periods and events during which the correlation between hydrogen and other green sectors may decrease, enabling hedging strategies aligned with environmental objectives.

Figure 5.2: Dynamic conditional correlations (DCC) between hydrogen and clean energy sectors



Note: This figure presents the evolution of the dynamic conditional correlations (DCC) estimated between the Hydrogen Index and five other variables, Renewable Energy Producers (light green), Oil (black), Technology stocks (red), Solar (yellow), and Wind (light blue), as well as the dynamic conditional correlation between Solar and Wind (dark green).

The results of the ARDL model, based on Equation (3), for the dynamic conditional correlations are presented in Appendix D. The findings highlight a pronounced persistence effect in the dynamic conditional correlations, with past values significantly influencing current values. This dynamic reflects a persistence in the comovement behavior between the subsectors. This persistence is inherent to the structure of DCC-GARCH models, where the dynamic conditional correlation is explicitly specified as a function of past conditional correlations, among other components (Bauwens et al. 2003). In the continuation of our analysis, we tested the cointegration relationship using the Pesaran bounds test (Pesaran et al. 2001), with the results presented in Table 3. These results confirm the presence of cointegration among all considered series, which justifies the subsequent use of the ARDL-ECM model, as specified in Equation (4). This model has the advantage of simultaneously estimating both short-term and long-term coefficients. The results of this regression are displayed in Table 4. The validity of the error correction model is confirmed by the consistent presence of a negative and statistically significant error correction term across all cases considered.

Table 3: Bounds test for cointegration

Variable	**t-test**		**F-test**	
	Stat	**p-value**	**Stat**	**p-value**
HYDR-RAYS	-5.0856	0.0131	3.7856	0.0282
HYDR-WNDY	-3.8822	0.1825	4.5798	0.0046
HYDR-RNRG	-4.7844	0.0292	4.2614	0.0101

Note: This table presents the results of the Pesaran bounds cointegration test. The variables HYDR-RAYS, HYDR-WNDY and HYDR-RNRG correspond to the dynamic conditional correlations between the hydrogen sector and other clean energy indices, namely the Solar, Wind and Renewable Energy Producers indices, respectively. The t-test examines whether the lagged level of the dependent variable is significantly different from zero, while the F-test evaluates the joint significance of all lagged levels. The decision on cointegration is based on comparison with the 5% critical bounds.
Critical bounds at the 5% level: t-test lower bound = -2.8691, upper bound = -4.5649; F-test lower bound = 2.3335, upper bound = 3.4973.

We observe in Table 4 that rising oil prices tend to strengthen the conditional correlations between the hydrogen sector and each of the three other clean energy subsectors. As previously mentioned, increases in oil prices generally stimulate investments in alternative energies, boosting the returns of these sectors. However, this coordinated flow of investments into the entire clean energy sector induces a common movement across subsectors, thereby amplifying comovements and increasing conditional correlations. To further illustrate this effect, we report scatter plots of oil prices against the dynamic conditional correlations (DCC) with a LOESS fit, a locally weighted smoothing technique that captures the general trend of the relationship without imposing a specific functional form. The results, presented in Appendix E, show that correlations are significantly higher when oil prices are elevated, The LOESS curves, even in this simple bivariate framework that does not control for other factors, display a continuously increasing pattern for the pairs involving hydrogen and the other clean energy sectors, reinforcing the robustness of this positive relationship. In contrast, for pairs between two established energy indices, such as solar and wind, the curves appear largely flat, showing no significant differences across the range of oil prices. These findings indicate that periods of high oil prices are associated with higher coefficients in dynamic conditional correlations between hydrogen-related returns and those of other renewable energy indices. In financial terms, such a pattern suggests a temporary rise in systemic risk, as diversification among energy indices loses effectiveness under stronger correlations, particularly during sharp increases in oil price. This effect is observed in both the short- and long-term, as shown in Table 4, with a more pronounced long-term response in the correlation between hydrogen and wind (HYDR-WNDY) compared to other pairs. Ultimately, the interconnection between hydrogen and other renewable energy sources strengthens during periods of high oil prices, exhibiting more coordinated responses to future shocks.

Regarding natural gas, we observe that increases in its price tend to reduce the conditional correlations between the hydrogen sector and the other clean energy subsectors. Unlike oil, natural gas remains structurally integrated into low-carbon energy production chains. It plays a central role in current hydrogen production, primarily through methane steam reforming, and in the advancement of carbon capture and storage (CCS) technologies. Consequently, a rise in natural gas prices can generate a partial decoupling among clean energy markets, as higher input costs may differentially affect subsectors. This is reflected in the decline of dynamic correlations, particularly with the wind segment. This effect, observed consistently in both the short- and long-run, is corroborated by the results presented in Table 4.

Furthermore, when examining uncertainty variables such as geopolitical risk (measured by the GPR index) and implied equity market volatility (measured by the VIX), we observe that the conditional correlations between the hydrogen and solar sectors (HYDR–RAYS) tend to intensify during periods of instability. This pattern is also evident for the correlation between the hydrogen and the broader renewable energy sector (HYDR–RNRG), particularly over the long term (Table 4). In contrast, HYDR–WNDY is affected only by the VIX and not by the GPR, and this effect is observed over the long term. Whether geopolitical or financial in nature, uncertainty thus appears to strengthen sectoral comovements. This phenomenon, well documented in finance, reflects the tendency of assets to move more synchronously during episodes of systemic stress. Faced with a shared risk perception, structural differences between subsectors become secondary, leading to homogeneous investor behaviors, such as collective disengagement through flight-to-safety movements (Lehnert 2022). This synchronization is exacerbated by the high-beta nature of the hydrogen sector, as speculative assets with high systematic risk, they are the first to be liquidated during periods of stress, a behavior that aligns them mechanically with other risk-sensitive clean energy indices. Consequently, exogenous shocks tend to affect all segments of the energy sector simultaneously, temporarily reducing diversification opportunities through increased correlations among clean energy indices. These effects can be linked to international and political events, such as the U.S. presidential elections in November 2024 and the initial implementation of tariffs in April 2025, which heighten environmental and policy uncertainty and may undermine investor confidence (Kaczmarek et al. 2025). Donald Trump's stance on climate change, particularly regarding the Inflation Reduction Act (IRA), is likely to have had a substantial impact on the renewable energy sector. Firms engaged in environmental practices or renewable energy activities performed significantly worse than "brown" firms, reflecting expectations of policies potentially unfavorable to clean energy industries (Cosma et al. 2025). Such developments can ultimately cause negative market reactions, including flight-to-safety behavior. Excessive volatility may, in turn, make it more difficult for firms to raise capital and, consequently, to develop clean energy projects (Ding et al. 2025; Botta and Sakariyahu 2025). For instance, in October 2025, the Trump administration cancelled USD 1.2 billion in subsidies previously allocated to the Alliance for Renewable Clean Hydrogen Energy Systems (ARCHES) hydrogen hub, a program initially approved under the Biden administration to promote hydrogen as a fuel, with total funding of nearly USD 7 billion. While other similar projects have so far remained unaffected by cancellation decisions, this action underscores the high sensitivity of energy subsectors to political decisions and regulatory disruptions. Such policy shifts can rapidly alter market expectations, influence investor behavior, and create uncertainty that hampers the development of strategic energy industries. These findings highlight the critical importance of stable regulatory frameworks and targeted support measures to secure the growth and resilience of emerging clean energy sectors.

Table 4: ARDL–ECM Regression Results for DCC Series

Var	HYDR-RAYS	HYDR-WNDY	HYDR-RNRG
Short run - (Intercept)	-0.0380	0.0274	0.0346
Short run - lWTI	0.0120**	0.0082**	0.0058
Short run - lNGAS	-0.0026*	-0.0052***	-0.0027**
Short run - lGPR	-0.0009	-0.0009	-0.0004
Short run - lPJM	0.0015	0.0015	0.0011
Short run - lVIX	-0.0023	0.0072***	-0.0147**
Short run - lPSE	-0.0210	0.0229	-0.0518
Short run - lGOLD	-0.0245***	-0.0133***	-0.0215***
Error correction term - (ECM)	-0.0471***	-0.0261***	-0.0385***
Long run - (Intercept)	-0.8063	1.0474	0.8981
Long run - lWTI	0.2552***	0.3151**	0.1498
Long run - lNGAS	-0.0554**	-0.1983***	-0.0701*
Long run - lGPR	0.0823***	0.0531	0.0908**
Long run - lPJM	0.0323	0.0559	0.0273
Long run - lVIX	0.1424**	0.2763**	0.1590**
Long run - lPSE	0.4032***	0.1249	0.3020**
Long run - lGOLD	-0.5192***	-0.5091***	-0.5588***

*p<0.1; **p<0.05; ***p<0.01

Note: This table presents the coefficients and their statistical significance from ARDL-ECM regressions in both the long and short run. The dependent variables are the dynamic conditional correlations (DCC) for HYDR-RAYS, HYDR-WNDY, and WNDY-RAYS. The explanatory variables are oil prices (lWTI), natural gas prices (lNGAS), Geopolitical Risk (lGPR), electricity prices (lPJM), VIX (lVIX), technology stocks (lPSE), and gold prices (lGOLD).

In contrast, we observe that rising gold prices, a traditional safe-haven asset, tend to reduce the dynamic conditional correlations between the hydrogen sector and other clean energy subsectors, both in the short- and long-term (Table 4). This result suggests that, in the face of negative exogenous shocks, investors tend to favor gold as a defensive asset, reallocating their investments in a way that does not affect all sectors equally. Some segments are more affected than others by this reallocation. As such, gold appears to play an indirect stabilizing role by temporarily enhancing the diversification potential within clean energy-related assets. Finally, we observe that technology stock prices have a significant and positive long-term effect on the correlation between hydrogen and solar (HYDR-RAYS), as well as between hydrogen and renewable energy producers (HYDR-RNRG). This suggests that when technology stock returns rise, the comovement with these subsectors tends to intensify over time. However, no significant relationship is found between technology prices and the correlation between hydrogen and wind (HYDR-WNDY). While a strong and positive impact was previously identified across all return series in Table 2, this influence does not appear to uniformly strengthen the correlations between hydrogen and other clean energy segments, suggesting heterogeneous transmission channels between technology and renewable energy assets.

Finally, energy subsectors are not uniformly affected by economic, energy, or geopolitical shocks. Some shocks, such as increased uncertainty (rising oil prices or the VIX), tend to homogenize variations by increasing dynamic conditional correlations, while others, such as gold price fluctuations, impact subsectors heterogeneously. In these cases, the hydrogen sector does not synchronize with other renewable energies, highlighting the importance of understanding its vulnerabilities. We also observe that this sector is more closely linked to technology stock prices and reacts more strongly to changes in the VIX and gold prices, particularly in the lower quantiles of the distribution. Finally, its returns appear largely unaffected by the traditional energy sphere. These findings have important implications for supporting hydrogen companies, notably emphasizing the need to reduce dependence on sources of uncertainty which lowers investor confidence and is essential for raising funds in this sector. In the current context, without targeted support, renewable energy assets, and particularly those in the hydrogen sector, would be the last to be selected by institutional investors. Highly exposed to external sources of uncertainty and constrained by still-maturing technologies and high production costs, these assets appear extremely risky. In this setting, support mechanisms are essential to ensure the development and sustainability of these strategic yet fragile sectors.

6 Robustness analysis

This section presents robustness analyses aimed at assessing the stability and validity of the results reported in the previous section. By employing alternative model specifications, estimation methods, and datasets, we examine whether the key findings remain consistent under different assumptions.

6.1 Methods

We first extend the quantile regression analysis by considering additional quantiles at 0.05 and 0.25, in addition to the standard 0.1 increments. In all cases, the results remain consistent.[6] Second, we tested the validity of the ARDL model by employing an alternative approach based on local projections (Jordà 2023). This method offers the advantage of estimating dynamic responses directly at each forecast horizon without imposing a specific parametric lag structure, making it less sensitive to potential misspecifications in the number of lags or functional form of the ARDL. By comparing the responses obtained from local projections with those derived from the ARDL model, we can verify that the observed short- and long-term effects are robust to the choice of dynamic specification. In this sense, we estimate the following model for each horizon h:

$$DCC_{ij,t+h} - DCC_{ij,t-1} = \alpha_h + \beta_h \cdot \text{Shock}_t + \Gamma_h X_t + \varepsilon_{t+h} \tag{6}$$

[6]Results are available upon request.

where $DCC_{ij,t}$ represents, in turn, the dependent variables under study, namely the three dynamic conditional correlation series ($DCC_{HYDR-RAYS,t}$, $DCC_{HYDR-WNDY,t}$ and $DCC_{HYDR-RNRG,t}$). Shock_t corresponds to one of the explanatory variables previously considered, namely oil prices (WTI), natural gas prices, the geopolitical risk index (GPR), volatility index (VIX), gold prices (GOLD), the stock prices of technology companies (PSE), or electricity prices (PJM). For each specification, the remaining variables are included in X_t as exogenous controls to isolate the specific impact of the considered shock, with Γ_h denoting their associated coefficients. Confidence intervals at the 95% level are computed and the regressions are estimated using a Newey-West correction to account for autocorrelation and heteroskedasticity in the residuals (Jordà and Taylor 2024). Here, α_h is a horizon-specific intercept, β_h measures the impulse response of y to the shock at horizon h, and ε_{t+h} is the error term.

The impulse responses obtained through local projections are generally consistent with the ARDL results (in Appendix D). As shown in Appendix F, a positive shock to oil prices increases two of the three dynamic conditional correlation series (HYDR-RAYS and HYDR-WNDY) both of which exhibit statistically significant coefficients at the 5% level. Similarly, natural gas prices have a negative and strongly significant effect on HYDR-WNDY, while no significant impact is observed on the other two series, consistent with the low significance observed in these two cases in the previous ARDL-ECM model (Table 4). This pattern is also evident when considering the impact of the GPR index, which has a positive effect only on the correlations between hydrogen and the solar index and between hydrogen and the renewable energy producers index, but not with the wind index, as indicated in the ARDL-ECM model. Finally, gold prices exhibit a strong negative effect across all dynamic conditional correlation series.

Overall, the local projection estimates confirm the empirical robustness of the initial ARDL-ECM results. The dynamic relationships identified in the baseline model do not appear to depend on the particular ARDL specification but instead reflect a structural link between energy and financial shocks.

To go further, we also re-estimate all estimations on four distinct subsamples. First, we split the full sample into two equally sized halves, each containing 474 observations. We then focus on a subsample starting from the date of the Russian invasion of Ukraine in 2022, as energy markets were strongly affected by this event. Finally, we conduct the analysis on the entire period up to Donald Trump's inauguration in January 2025, in order to mitigate the influence of extreme events on financial markets. We find that our main results remain consistent across all subperiods, with hydrogen consistently exhibiting the highest sensitivity to uncertainty and to the returns of technology firms. However, a notable difference, though consistent with our previous interpretation, concerns the effect of oil prices on the returns of renewable energy indices, particularly hydrogen. We observe that in the first half of the data, oil prices have a strongly positive effect on the returns of certain energy indices, especially hydrogen. This reflects the fact that this period (surrounding the invasion of Ukraine) was characterized by a sharp increase in oil prices and a significant rise in geopolitical uncertainty. This led to strong substitution effects toward alternative energies, which in turn drove a substantial increase in returns, particularly in the hydrogen sector, where investor interest remained relatively high at that time.[7]

6.2 Alternative data sources and market regions

6.2.1 Oil volatility

After having focused on the impact of oil prices themselves, we now turn to their volatility in order to capture potential uncertainty effects on clean energy markets. Oil price volatility may convey different information than price levels, as it reflects investors' perceptions of risk and instability in energy markets. To account for this dimension, we use the OVX index (CBOE Crude Oil ETF Volatility Index) from the FRED database as a proxy for oil market uncertainty. The literature on this topic is particularly extensive. Dutta (2017), for instance, shows that the volatility of renewable energy stock prices is strongly correlated with oil price volatility. An increase in oil price volatility reflects greater market uncertainty, reinforcing the need for supportive policies for environmentally friendly companies, particularly through fiscal measures aimed at promoting the decoupling of renewable and fossil energies. Zhang and Chen (2026) also identify periods of volatility spillovers from oil markets to renewable energy markets, especially during times of crisis. In our study, we estimated the impact of oil price volatility, as measured by the OVX index, on both returns and dynamic conditional correlations. To this end, we included the OVX variable and excluded oil price and VIX variables to avoid potential multicollinearity that could bias coefficient estimates. Our results indicate that oil volatility has a strongly negative and significant effect on all five of our clean energy variables, as well as a positive and significant effect on two of our three dynamic conditional correlations.[8] These findings suggest a period of heightened uncertainty, as oil price volatility is associated with broader financial instability that spills over into most sectors, particularly the more emerging ones. The results are characterized by both declining returns and increased synchronization among energy subsectors, reflecting a more uniform market response to oil-related shocks. This pattern is consistent with the typical effects of uncertainty discussed earlier, heightened uncertainty tends to synchronize price movements, as investors become driven more by speculative behavior than by underlying fundamentals.

6.2.2 Regional disparities

As presented in Section 3, the financial data previously used are composed of global companies, with the distribution of these companies varying across series. For instance, U.S. firms constitute more than 50% of the Hydrogen index's weight, whereas they represent only about 11% of the RNRG index. These differences raise the question of whether the use of U.S. (energy-related) data might influence our results. To address this, we considered two alternative scenarios using different datasets, European and Asian. For the European dataset, we used Brent crude prices to represent oil prices, obtained from the

[7]Results for these subperiods estimations are available upon request.
[8]Results are available upon request.

EIA, and natural gas prices from the Dutch Title Transfer Facility (TTF), available via Yahoo Finance (TTF=F). Finally, we included electricity prices for Germany from the ENTSO-E Transparency Platform, expressed in euros per MWh. For the Asian market, we again used Brent prices for oil, the spot electricity prices (System Marginal Price, SMP) provided by the Korea Power Exchange (KPX), the official electricity market operator in South Korea, and liquefied natural gas (LNG) prices based on the Japan/Korea Marker (JKM) index published by Platts and retrieved from Refinitiv Eikon Datastream, expressed in U.S. dollars per million BTU. The data sources are summarized in the table in Appendix A.

We first examined whether the returns of the five energy sectors considered were sensitive to these variations in data sources. Whether using the average effect estimated through OLS or quantile regression, we obtained very similar results regardless of whether the underlying energy data were American, European, or Asian.[9] To go further, we then investigated whether the effect of our dynamic conditional correlations varied across these markets, applying the same methodology as before, namely, an ARDL-ECM model. The results are presented in Table 5.

Table 5: Regional robustness analysis: long-term ARDL–ECM coefficients

Variable	**HYDR-RAYS**	**HYDR-WNDY**	**HYDR-RNRG**
Panel A: European market			
Short run - lBRENT	0.0097**	0.0055	0.0048
Short run - lTTF	-0.0009	-0.0032**	-0.0015
Short run - lELEC	-0.0003	0.0008	0.0001
Long run - lBRENT	0.2403***	0.2643*	0.1342
Long run - lTTF	-0.0215	-0.1507**	-0.0437
Long run - lELEC	-0.0073	0.0365	0.0027
Panel B: Asian market			
Short run - lBRENT	0.0088*	0.0069	0.0065
Short run - lLNG	-0.0004	-0.0034***	-0.0175**
Short run - lSMP	-0.0012	0.0013	0.0008
Long run - lBRENT	0.2182**	0.2731**	0.1653
Long run - lLNG	-0.0111	-0.1351***	-0.0486*
Long run - lSMP	-0.0293	0.0506	0.0193
Panel C : US market			
Short run - lWTI	0.0128***	0.0083**	0.0060
Short run - lNGAS	-0.0026*	-0.0051***	-0.0028**
Short run - lPJM	0.0014	0.0015	0.0012
Long run - lWTI	0.2868***	0.3192**	0.1552
Long run - lNGAS	-0.0586**	-0.1968***	-0.0737*
Long run - lPJM	0.0320	0.0574	0.0302

*p<0.1; **p<0.05; ***p<0.01

Note: This table presents the coefficients and their statistical significance from ARDL–ECM regressions in both the short- and long-run. The dependent variables are the dynamic conditional correlations (DCC) for HYDR-RAYS, HYDR-WNDY, and WNDY-RAYS. The explanatory variables include oil prices (lWTI and lBRENT), natural gas prices (lNGAS, lLNG, and lTTF), Geopolitical Risk (lGPR), electricity prices (lPJM, lSMP, and lELEC), the VIX index (lVIX), technology stock returns (lPSE), and gold prices (lGOLD).

We observe that, regardless of the combination of series used, electricity prices have no significant

[9]Results are available upon request.

effect on our dynamic conditional correlations. In contrast, for natural gas and oil, there is a marked decline in the significance of the coefficients, although their signs remain unchanged. Natural gas prices appear to primarily affect the HYDR–WNDY pair (significant at the 5% level in the long run), which was also the pair most responsive to U.S. gas prices in the baseline analysis. Similarly, for oil, Brent prices show a weaker effect across all series, particularly on HYDR–RAYS, the pair previously most sensitive to WTI prices. These results suggest that the impact of energy markets on dynamic correlations depends on the regional reference, with U.S. markets exerting a stronger influence than European ones. This observation can be explained by the composition of the indices, the HYDR index, representative of the hydrogen sector, is composed of more than 50% U.S. firms, while a significant share of companies from this country are also present in the RNRG, RAYS, and WNDY indices. Consequently, the observed dynamics appear to be largely driven by U.S. markets. Hence, it seems relevant to deepen this analysis by examining the potential heterogeneity among the firms included in our benchmark index, the hydrogen sector. Given the pronounced heterogeneity that can exist across regions and companies, it would be highly relevant to conduct individual analyses at the firm level, for example using panel regressions, once the number of hydrogen-related companies increases. Such an approach would allow for a more precise assessment of region-specific effects and the inclusion of firm-specific variables.

7 Conclusion

This study aimed to analyze how financial markets perceive the hydrogen sector in comparison with other clean energy segments. Given the sector's relatively recent emergence and the fragility of its firms (IEA 2025a), this analysis helps identify the conditions most conducive to its development, as well as those that could hinder its growth. Such insights are essential for designing effective support policies aligned with the sector's ambitions and the broader objectives of the energy transition. To this end, we first employed quantile regressions to assess how the returns of different indices (hydrogen, wind, solar, clean technologies, and renewable energy producers) are influenced by various economic, energy, and geopolitical factors under different market conditions. In a second step, we used a DCC-GARCH model to capture the dynamics of conditional correlations between the hydrogen index and several indices representing different renewable energy subsectors, including wind, solar, and broader renewable energy markets. To investigate the macroeconomic drivers of these relationships, we then estimated ARDL-ECM models, which allowed us to distinguish between the short- and long-term effects of variables such as oil prices on these correlations. In this context, an increase in correlation between two segments indicates a more synchronized return behavior, thereby reducing diversification opportunities within a clean energy portfolio.

Our results reveal the hybrid and still unstable nature of hydrogen in financial markets. Hydrogen appears to be more influenced by technological factors and uncertainty factor than other indices. Our estimations further support this idea: during periods of heightened uncertainty, whether financial or geopolitical, the long-term correlations between hydrogen and other renewable energy subsectors tend to strengthen. In contrast, rising natural gas prices appear to weaken the correlation with the wind sector, although the effect is not statistically significant for the other subsectors. These results highlight differentiated interactions between hydrogen and other clean energy subsectors, underscoring the importance of not viewing the renewable energy sector as a homogeneous block. Finally, hydrogen's returns are more sensitive to fluctuations in technology indices than other clean energy segments, reinforcing the idea that the sector is perceived as a speculative innovation asset rather than an established component of renewable energies. Moreover, we also show that the returns of energy indices react strongly to periods of financial stress. Quantile regressions reveal that during bearish markets, an increase in the VIX leads to a significant decline in returns, with the hydrogen sector being the most strongly affected. This dynamic is accompanied by a sustained rise in the correlation between hydrogen and other sectors, reflecting flight-to-safety behavior. In these tense periods, investors' reallocations appear to be driven less by the characteristics of energy technologies and more by financial protection imperatives. At the same time, gold acts as a factor that increases returns while reducing correlations, suggesting that it does not contribute to the synchronization of price movements. Finally, oil appears to drive significant comovements among the analyzed energy subsectors. During periods of economic uncertainty, the simultaneous rise in oil and gold prices encourages a shift of investments toward alternative energies, boosting their returns. Oil synchronizes long-term correlations between hydrogen and other sectors, whereas gold reduces these links, thereby enhancing diversification opportunities. This duality highlights the complexity of interactions between commodities and energy transition assets.

Our findings have significant implications for the strategic positioning of hydrogen companies and their ability to raise funds. The fact that this sector is perceived more as a technological asset than as an established component of renewable energy highlights the need to implement stable and tailored support mechanisms. Despite its technological potential, the hydrogen sector currently has limited access to capital markets. Unlike more established renewable energy segments, hydrogen companies often struggle to raise substantial funds through public equity or bond issuances, reflecting the market's perception of the sector as speculative and not yet fully integrated into traditional investment frameworks. This limited financial liquidity reinforces the importance of targeted public support instruments. It is essential to develop instruments such as public subsidies, tax credits, or financial guarantees to strengthen the resilience of the sector and support its development. Initiatives in this direction already exist. In the United States, the Inflation Reduction Act (IRA), signed into law by Joe Biden in 2022, introduced several support measures for the green industry, including hydrogen-specific tax credits such as the Clean Hydrogen Production Tax Credit and the Credit for Carbon Oxide Sequestration (IRS 2022a; IRS 2022b). However, their deployment was subsequently hindered by the Trump administration, creating regulatory uncertainty that weighed on investors' confidence. In Europe, notable progress has also been made. In February 2023, the European Commission adopted two delegated acts aimed at establishing a clear framework for the production of renewable hydrogen, thereby enhancing visibility for economic actors (European Commission 2023a; European Commission 2023b). Moreover, programs such as the Innovation Fund and the LIFE Programme offer concrete sources of financing for projects related to hydrogen and the energy transition. Overall, these mechanisms help to mitigate the impact of macroeconomic and financial shocks on a still emerging sector. By ensuring a certain degree of regulatory stability, they strengthen investor and bank confidence and reduce the sensitivity of hydrogen companies to market uncertainties. This is crucial to enable these companies to raise sufficient funds to develop projects worldwide and support the broader development of hydrogen technologies.

Finally, given the still emerging nature of the hydrogen market, a promising avenue for future research would be to replicate this analysis at the firm level, using a panel of individual companies rather than aggregated indices. This would allow for a more nuanced assessment of how firm-specific characteristics—such as their activities, geographic location, or technological focus—affect financial integration and market perceptions as the sector matures.

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A Data Sources

Table 6: Sources of the Data Series Used

Main Analysis Data	
Data Series	**Sources**
Global X Hydrogen ETF (HYDR)	Refinitiv Eikon Datastream
Global X Solar ETF (RAYS)	Yahoo Finance
Global X Wind Energy ETF (WNDY)	Yahoo Finance
Global X CleanTech ETF (CTEC)	Yahoo Finance
Global X Renewable Energy Producers (RNRG)	Yahoo Finance
West Texas Intermediate (WTI)	U.S. Energy Information Administration n.d.(a) (FRED)
Henry Hub Natural Gas Spot Price (NGAS)	U.S. Energy Information Administration n.d.(b) (FRED)
Electricity PJM Interconnection (PA-NJ-MD)	Refinitiv Eikon Datastream
Geopolitical Risk (GPR)	Caldara and Iacoviello 2022
CBOE Volatility Index (VIX)	Chicago Board Options Exchange n.d. (FRED)
LBMA Gold Prices	DBnomics - London Bullion Market Association
NYSE Arca Tech 100 Index (ˆPSE)	Yahoo Finance
Robustness Analysis Data	
Data Series	**Sources**
CBOE Crude Oil ETF Volatility Index (OVX)	U.S. Energy Information Administration (FRED)
Europe Brent Spot Price	Thomson Reuters via U.S. Energy Information Administration
Dutch Title Transfer Facility (TTF=F)	Yahoo Finance
Germany Spot Electricity Price	ENTSO-E Transparency Platform
Korea System Marginal Price (SMP)	Korea Power Exchange (KPX)
Japan/Korea LNG Marker (JKM)	Platts via Refinitiv Eikon Datastream

B Unit root test results

Table 7: Augmented Dickey-Fuller (ADF) Test Results

Series	**Model Chosen**	**ADF Coefficient**	**Critical Value**
lHYDR	None	-1.873	-1.95
lRAYS	None	-1.438	-1.95
lWNDY	None	-1.686	-1.95
lRNRG	None	-1.216	-1.95
lCTEC	None	-1.324	-1.95
lWTI	None	-0.170	-1.95
lNGAS	None	-1.207	-1.95
lPJM	Intercept	-9.838	-2.86
lVIX	None	-0.445	-1.95
lGOLD	None	2.646	-1.95
lPSE	None	0.742	-1.95
lGPR	Intercept	-10.320	-2.86
Δ lHYDR	None	-21.527	-1.95
Δ lRAYS	None	-22.880	-1.95
Δ lWNDY	None	-23.659	-1.95
Δ lRNRG	None	-22.077	-1.95
Δ lCTEC	None	-21.327	-1.95
Δ lWTI	None	-22.316	-1.95
Δ lNGAS	None	-28.168	-1.95
Δ lVIX	None	-22.215	-1.95
Δ lGOLD	None	-21.675	-1.95
Δ lPSE	None	-22.025	-1.95

Note: This table reports the results of the Augmented Dickey-Fuller (ADF) unit root tests applied to the time series used in the study. The *Series* column indicates the variable considered, where l denotes the natural logarithm and Δ the first difference of the series. The *Model Chosen* column specifies the deterministic component included in the test: None indicates no constant or trend, and Intercept indicates a constant term only. The *ADF Coefficient* column presents the computed test statistic, while the *Critical Value* column reports the 5% significance threshold. A test statistic smaller than the critical value indicates rejection of the null hypothesis of a unit root, implying stationarity. The results show that all level series are non-stationary, except for $lPJM$ and $lGPR$, which are stationary with a constant. All first-differenced series (Δ) are stationary.

Table 8: Augmented Dickey-Fuller (ADF) Test Results

Series	**Model Chosen**	**ADF Coefficient**	**Critical Value**
HYDR-RAYS	None	-0.411	-1.95
HYDR-WNDY	None	-0.835	-1.95
HYDR-RNRG	None	-0.542	-1.95
Δ HYDR-RAYS	None	-24.130	-1.95
Δ HYDR-WNDY	None	-23.082	-1.95
Δ HYDR-RNRG	None	-22.590	-1.95

Note: This table reports the results of the Augmented Dickey-Fuller (ADF) unit root tests applied to the dynamic conditional correlation (DCC) series between the hydrogen index and other clean energy indices. The Series column indicates the variable considered, where Δ indicate the first difference of the series. The Model Chosen column specifies the deterministic component included in the test: None indicates no constant or trend. The ADF Coefficient column presents the computed test statistic, while the Critical Value column reports the 5% significance threshold. A test statistic smaller than the critical value indicates rejection of the null hypothesis of a unit root, implying stationarity. Results indicate that all DCC series are non-stationary in levels but become stationary after first differencing (Δ).

C Distribution DCC GARCH

Table 9: Model selection results for EGARCH specifications

Series	Skewness	Jarque-Bera	AIC_{STD}	BIC_{STD}	AIC_{SSTD}	BIC_{SSTD}
DlHYDR	0.2893	0.00	-4.2995	-4.2687	-4.3036	-4.2677
DlRAYS	0.0668	0.00	-4.6680	-4.6373	-4.6702	-4.6343
DlRNRG	-0.0605	0.00	-5.8338	-5.8030	-5.8317	-5.7958
DlWIND	-0.0029	0.00	-5.4715	-5.4407	-5.4696	-5.4337

Note: Series indicates the return series analyzed. Skewness shows the asymmetry of the distribution. Jarque-Bera reports the test statistic for normality. AIC_{STD} and BIC_{STD} are the Akaike and Bayesian Information Criteria for the Student-t distribution. AIC_{SSTD} and BIC_{SSTD} are the corresponding criteria for the skewed Student-t distribution.

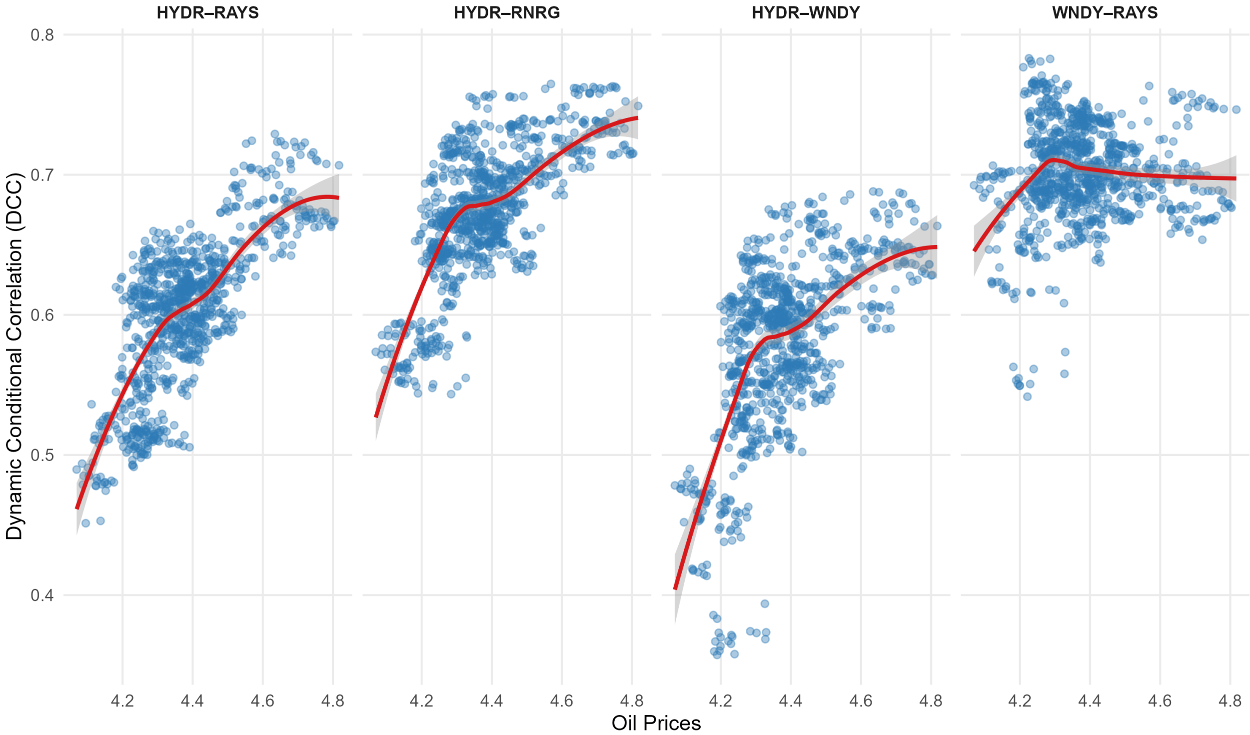
D ARDL - DCC Regressions

Table 10: ARDL Regression Results on DCC series

	Dependent variable:		
	Returns		
	HYDR-RAYS	HYDR-WNDY	HYDR-RNRG
$Correlation_{t-1}$	0.900***	0.974***	0.961***
	(0.040)	(0.006)	(0.008)
$Correlation_{t-2}$	0.052		
	(0.041)		
$lWTI$	0.012***	0.008**	0.006
	(0.005)	(0.004)	(0.005)
$lNGAS$	−0.003**	−0.005***	−0.003*
	(0.001)	(0.001)	(0.001)
$lGPR$	−0.001	−0.001	−0.0004
	(0.002)	(0.001)	(0.001)
$lGPR_{t-1}$	0.002*	0.002*	0.001
	(0.001)	(0.001)	(0.001)
$lGPR_{t-2}$	0.001		0.002
	(0.002)		(0.002)
$lGPR_{t-3}$	0.001		
	(0.001)		
$lPJM$	0.002	0.001	0.001
	(0.001)	(0.001)	(0.001)
$lVIX$	−0.002	0.007***	−0.015**
	(0.006)	(0.002)	(0.006)
$lVIX_{t-1}$	0.020**		0.021***
	(0.010)		(0.006)
$lVIX_{t-2}$	−0.027***		
	(0.010)		
$lVIX_{t-3}$	0.016**		
	(0.007)		
$lPSE$	−0.021	0.023	−0.052
	(0.036)	(0.026)	(0.036)
$lPSE_{t-1}$	0.147**	0.054	0.140***
	(0.060)	(0.055)	(0.053)
$lPSE_{t-2}$	−0.107**	−0.073	−0.077*
	(0.047)	(0.046)	(0.041)
$lGOLD$	−0.024***	−0.013***	−0.022***
	(0.006)	(0.004)	(0.004)
Intercept	−0.038	0.027	0.035
	(0.034)	(0.043)	(0.042)
Note:			*p<0.1; **p<0.05; ***p<0.01

E Distribution

Figure E.1: Scatter plot of DCC across clean energy subsectors against oil prices with LOESS fit



Note: This figure displays scatter plots of the dynamic conditional correlations (DCC) as a function of oil prices. Four series are shown, HYDR-RAYS, HYDR-WNDY, HYDR-RNRG, and RAYS-WNDY. The red line represents the LOESS fit.

F Local Projections

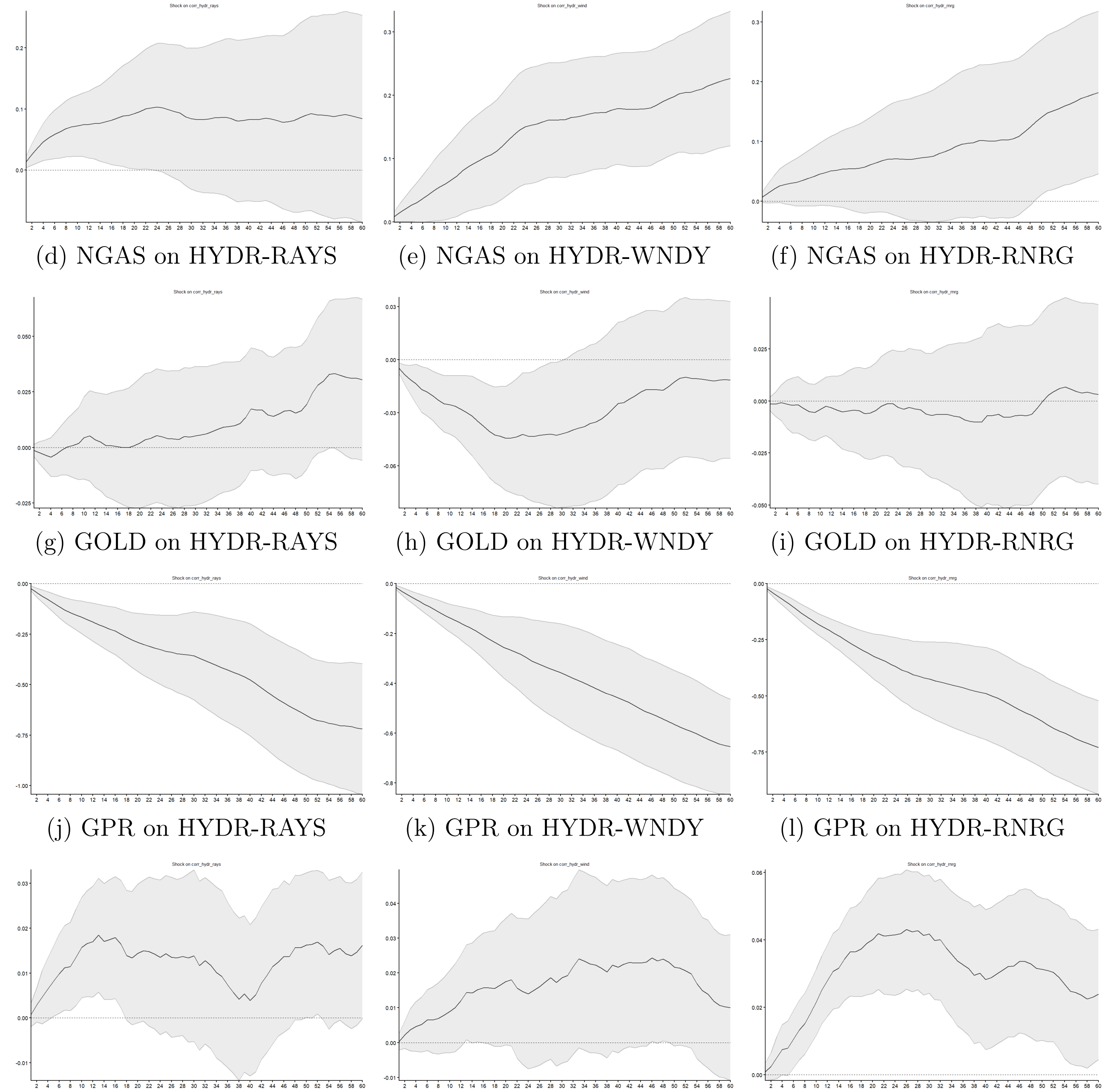
Figure F.1: Local projections

(a) WTI on HYDR-RAYS (b) WTI on HYDR-WNDY (c) WTI on HYDR-RNRG

(d) NGAS on HYDR-RAYS (e) NGAS on HYDR-WNDY (f) NGAS on HYDR-RNRG

(g) GOLD on HYDR-RAYS (h) GOLD on HYDR-WNDY (i) GOLD on HYDR-RNRG

(j) GPR on HYDR-RAYS (k) GPR on HYDR-WNDY (l) GPR on HYDR-RNRG



Note: The figure displays the impulse responses from local projection estimations showing the dynamic effects of oil prices (WTI), natural gas prices (NGAS), gold prices (GOLD), and geopolitical risk (GPR) on the dynamic conditional correlations (DCC) between hydrogen and other clean energy subsectors, solar (HYDR-RAYS), wind (HYDR-WNDY), and renewable energy producers (HYDR-RNRG). The x-axis represents the forecast horizon (up to 60 trading days), while the y-axis shows the cumulative response of each DCC following a one-unit shock to the corresponding explanatory variable. Estimates and confidence intervals are computed using Newey–West robust standard errors.