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Is Hydrogen a diversifier? Insights from Wavelet Quantile Correlation

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Abstract. This study explores the time and distribution-dependent co-movements between the Global X Hydrogen ETF (i.e., HYDR.O) and a range of traditional market assets, including metals (gold, aluminum, and steel), energy commodities (Brent crude oil and natural gas), and equity benchmarks (S&P 500 and Nasdaq 100). Using the Wavelet Quantile Correlation (WQC), we empirically investigate the dynamic dependence structure between HYDR.O and traditional assets in both the time and frequency domains. Our results reveal that HYDR.O exhibits weak or near-zero correlation (i.e., dependence) on fossil fuel-linked markets, especially natural gas and oil, across all quantiles and wavelet scales. This highlights the distinct behavior of clean energy assets, particularly in periods of market stress or extreme returns, such as Russo-Ukrainian War. In contrast, we observe moderate and stable positive correlation with major equity indices such as the S&P 500 and Nasdaq 100, suggesting that HYDR.O partially inherits the growth characteristics of broader stock markets. ETF's correlation with steel is weak, and its relationship with gold is stable but mild, highlighting further diversification from industrial or defensive commodities. These findings highlight the unique diversification role of hydrogen-focused ESG investments.

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1. Introduction

Decarbonization policies and the rapid growth of ESG investing have renewed interest in whether green energy assets move with traditional markets. In this paper, we examine how the Global X Hydrogen ETF (HYDR.O; hereafter HYDR) co-moves with a broad set of benchmarks, including gold, aluminum, steel, Brent crude oil, natural gas, the S&P 500, and the Nasdaq 100. Rather than summarizing the relationship with a single correlation number, we apply the Wavelet Quantile Correlation (WQC) approach of Kumar and Padakandla (2022) to see how dependence shifts with the horizon and with market conditions. This approach allows dependence to be assessed both across investment horizons and across different parts of the return distribution. That distinction is important because cross-asset relationships are rarely constant: they often change with the horizon, may be asymmetric, and tend to become more pronounced in the tails (Kumar and Padakandla, 2022; Jalal and Gopinathan, 2023).

Methodologically, WQC combines quantile-based dependence with a wavelet decomposition of returns. We use the Maximal Overlap Discrete Wavelet Transform (MODWT) in order to split each return series into four horizon periods: 2–4, 4–8, 8–16, and 16–32 trading days. For each period, we estimate quantile regressions at nine quantiles (0.1 through 0.9), which lets us track how dependence behaves under different market conditions, including extreme outcomes. The empirical analysis is based on daily log-returns for HYDR and the benchmark assets. All series are converted to EUR and aligned to a common sample. We group the benchmarks into metals (gold, aluminum, steel), energy commodities (Brent crude oil, natural gas), and U.S. equity indices (S&P 500 and Nasdaq 100). Our dataset covers 15 July 2021 to 30 September 2024, for a total of 735 daily observations.

Across specifications, HYDR shows little to no dependence on oil and natural gas, particularly at the tails and at short horizons. This indicates that HYDR is not tightly tied to carbon-intensive market swings, which is consistent with a diversification role in sustainable portfolios. As an example, HYDR–Brent WQC is near zero at low quantiles and becomes negative at high quantiles, especially at 2–4 and 4–8 trading days, implying that the decoupling is more pronounced when markets move to extremes.

In contrast, HYDR's correlation with broad equity indices such as the S&P 500 and Nasdaq 100 was significantly positive and stable across all quantiles and wavelet scales. This suggests that despite its green positioning, HYDR shares common risk exposures with large-cap growth stocks, aligning with earlier work that connects ESG assets with macroeconomic growth cycles (Demirer et al., 2019). The correlation with gold was found to be weak but persistent across middle quantiles and longer-term scales, implying a partial safe-haven behavior during stable market conditions.

The correlation with steel, represented by SHFE hot rolled coil futures, was heterogenous and volatile across scales and quantiles, reflecting industrial linkages rather than financial co-integration. Meanwhile, natural gas futures, which serve as a bridge fuel and compete with hydrogen in some applications, showed the weakest connection to HYDR. These results align with existing literature highlighting the low synchronicity between clean energy and traditional commodities during transition periods (Li et al., 2015).

A growing literature examines hydrogen related assets and hydrogen ETFs and generally finds meaningful links with equities and other traditional markets. These links are usually studied with average correlations, DCC models, spillover and connectedness frameworks, or broader risk and return comparisons. Tudor (2023) discusses the risk return profile of hydrogen focused ETFs and notes their high volatility and equity like exposure. Pereira (2025) and Pereira et al. (2025) also document time varying correlations that tend to strengthen during periods of geopolitical stress. Even so, the evidence is still limited on how these relationships change across investment horizons and across different parts of the return distribution. This is especially important in the tails, where diversification and hedging matters are mostly in turbulent markets.

We address this gap by using a time frequency and quantile dependent dependence framework that reveals horizon specific and tail specific co movements that standard correlation measures may miss.

This paper makes three specific contributions. First, we provide the first, to our knowledge, wavelet quantile dependence map for the Global X Hydrogen ETF (HYDR) relative to key traditional assets, including oil, natural gas, gold, industrial metals, and major equity market benchmarks. This map jointly characterizes dependence across investment horizons in the time and frequency domain and across market states captured by quantiles and tails. Second, we refine the decoupling narrative by showing which horizons and which parts of the return distribution correspond to hydrogen behaving as a diversifier, and which conditions are associated with stronger equity like exposure. These patterns cannot be inferred from average correlations, DCC estimates, or unconditional spillover summaries. Third, we translate the dependence results into actionable portfolio guidance by identifying regimes in which HYDR is more suitable for diversification, for example relative to fossil fuel linked assets, and regimes in which it is not, such as periods of strong equity co movement. The findings have direct implications for transition themed investing and cross asset allocation.

Hydrogen ETFs come through in our results as assets that are largely aligned with the low-carbon theme and, at the same time, can help with diversification, most noticeably when markets are under pressure. One obvious extension is to run the same analysis on more focused products, for instance sector clean-energy ETFs, and to see whether linkages tighten around policy-driven episodes, such as carbon-pricing changes or major subsidy announcements. A key advantage of WQC is that it lets us track these connections both where risk concentrates, in the tails, and across different holding horizons, which makes it a useful way to think about portfolio choices during the green transition.

These insights are directly relevant for international investors facing transition risk, as they inform cross-asset allocation between green thematic instruments and conventional commodities/equities, particularly under extreme market conditions where diversification is most needed. The paper organizes as follows: Section 2 presents the literature review. Section 3 shows the methodology and data. Section 4 represents empirical results. Section 5 presents the conclusion.

2. Literature Review

The potential of hydrogen as a zero-carbon energy carrier is known. However, its emergence as an asset that worth to invest has risen recently. The expanding hydrogen dataset indicate the high volatility and strong integration with main components of the global financial system. For example, hydrogen is highly related with equities connected to production and infrastructure, since they share similar factors such as sentiment shifts, market stress and policy uncertainty. Moreover, hydrogen seems not always move in line with the rest of the market, which is why may appear useful for diversification. Understanding these abilities helps align sustainable allocation choices with real portfolio results. From investors' perspective, the key is not only whether hydrogen is "green", but whether it can deliver diversification when it matters most (i.e., namely during periods of heightened uncertainty and market stress). What remains less clear is whether these linkages change across investment horizons and across different market states, particularly in downside and upside tail conditions. This motivates the use of a time frequency and quantile dependent approach that can distinguish short horizon dynamics from long horizon dynamics and normal periods from tail regimes.

Existing studies suggest that hydrogen related assets are connected to broader financial markets, especially equities, and that these connections tend to strengthen during stressful periods (Tudor, 2023; Pereira, 2025; Pereira et al., 2025). Most of the evidence, however, relies on average correlations or single horizon analyses, including DCC models and aggregate connectedness measures. This leaves an open question about how hydrogen linkages vary across horizons and across the return distribution, particularly under downside and upside tail conditions. This distinction is crucial because diversification often collapse during extreme conditions, when needed most. We address this gap with WQC econometric methodology, which delivers dependence (i.e., correlation) estimates that are specific to both investment horizons and quantiles. In other words, the existing literature provides valuable evidence on time variation, but it does not extensively investigate how the hydrogen behaves at short versus long horizons and whether it becomes more tightly coupled in the tails where portfolio protection is needed most.

Many studies challenge the hydrogen risk-return trade-off. Tudor (2023) found that hydrogen focused ETFs consistently lagged both conventional equity and broader green energy portfolios, while showing much higher volatility and downside risk. High beta values and negative alphas underline their strong sensitivity to market swings. Hydrogen assets are also closely tied to major markets. Pereira et al. (2025) reported strong correlations of about 0.7 with global equities and 0.4 with Bitcoin. Pereira (2025) showed these linkages can climb to very high levels with oil and global stocks during geopolitical crises like the Russia Ukraine war. Furthermore, Horky et al. (2026) provide evidence indicating the role of hydrogen within financial markets as a key of the energy transition. These results collectively imply that hydrogen themed ETFs can look like equity sensitive assets in stress regimes, which directly raises the question of whether any diversification benefits are stable across horizons and across return states. Taken together, prior evidence supports time variation and stress sensitivity, but it is still less informative about how dependence differs simultaneously across horizons and across the return distribution. This is exactly where a combined horizon and quantile lens becomes necessary.

To move from “who is connected to whom” toward “when and at which horizons the connections matter”, it is useful to consider evidence from spillovers and risk transmission. Volatility spillover research shows hydrogen’s dual role as both a transmitter and receiver of market shocks. Yousfi and Bouzgarrou (2025) observed asymmetric spillovers between oil, clean energy, and green equity, with stronger effects in extreme events. These findings reinforce two points that are directly relevant for our research question. First, dependence can be asymmetric, meaning that downside conditions may produce different co movement patterns than upside conditions. Second, transmission can differ by horizon, because short run shocks and long run adjustment may not coincide. Therefore, an approach that can jointly reflect horizons and tails is more appropriate than relying on average dependence measures.

Related work has long examined cross-market spillovers, hedging effectiveness and uncertainty transmission. Liu and Pan (1997) model mean and volatility spillovers across international equity markets and show that shocks originating in large markets can propagate to other markets, with stronger transmission in turbulent sub-periods. DeMaskey (1997) evaluates portfolio cross-hedging with currency futures and documents that hedge effectiveness depends on the chosen hedge set and can vary materially relative to naive or no-hedge benchmarks. Nikkinen and Sahlstrom (2001) study scheduled U.S. macroeconomic announcements and find that implied volatility rises ahead of releases and falls afterward, with uncertainty effects visible not only domestically but also in foreign markets.

Broader clean energy research offers insights for hydrogen's portfolio role. Dutta et al. (2020) found that high volatility in traditional energy markets reduces clean energy ETF returns, especially during turbulent periods. Tiwari et al. (2025) and Hasan et al. (2024) showed that pairing green bonds with green equities improves diversification and hedging. This approach could also benefit hydrogen assets. Overall, this literature suggests that diversification benefits in green assets are regime dependent and can weaken during stress. This fact makes the horizon and tail specific assessment an important issue. In practical portfolio terms, the relevant test is not whether hydrogen is weakly correlated on average, but whether it remains weakly dependent in the downside tail and whether any decoupling is confined to specific horizons. This perspective links the green asset literature directly to our empirical design.

Beyond financial behaviour, industrial and technological factors also shape hydrogen's investment profile. Fazeli et al. (2025) noted that green hydrogen costs are falling quickly. Under high carbon prices, blue hydrogen projects may become uneconomic sooner than expected. Santamaría et al. (2022) report that hydrogen markets are not equally efficient yet, so pricing isn't always consistent, which can give informed investors an advantage. Lee et al. (2022) describe an AI-based hub for producing and delivering hydrogen that also uses securitization and tokenization, pointing to new ways to finance and run such projects. Tudor (2024) argues that hydrogen should sit alongside other low-carbon options in sustainable portfolios, rather than replacing them, with nuclear energy as one example.

These can broaden diversification within clean energy allocations. Beyond market co-movement, policy and technology transitions can create horizon specific regimes for hydrogen themed investments, because policy announcements and adoption cycles tend to have persistent effects, while market sentiment shocks can be short lived. This reinforces the logic of analyzing hydrogen with a time frequency perspective rather than a single horizon snapshot.

In summary, prior hydrogen ETF studies establish that hydrogen related assets are connected to equities and other markets and that these linkages can intensify during stress. The broader clean energy and spillover literature further suggests that dependence is regime dependent and often asymmetric. What remains unresolved is a joint mapping of dependence across investment horizons and across the return distribution, with particular attention to downside tail conditions where diversification is most valuable. To address this gap, we apply WQC, which provides horizon specific and quantile specific dependence estimates and allows a direct assessment of whether hydrogen behaves as a diversifier under particular horizons and market states rather than on average.

3. Methodology and Data

We use daily data for the HYDR and benchmark assets covering metals, energy commodities, and U.S. equity markets. The benchmark set includes aluminum, gold, steel, Brent crude oil, natural gas, the S&P 500, and the Nasdaq 100. [1] The sample spans from 15 July 2021 to 30 September 2024. We work with daily log returns, convert all series to EUR, and estimate daily log-returns computed as

$$r_t = \ln(P_t) - \ln(P_{t-1}) \tag{1}$$

We focus on these assets because they constitute main components of global financial markets and are employed not only for portfolio diversification, but also for risk management.

Table 1 reports the descriptive statistics for daily returns of HYDR and the selected traditional assets over the sample period, showing

[1] The HYDR data are collected from: https://www.globalxetfs.com/funds/hydr. While the rest data are collected from Thomson Reuters DataStream

Table 1: Descriptive statistics

	HYDR.O	Aluminum	Gold	Oil	Natural Gas	Steel	S&P 500	Nasdaq 100
Mean	-0.0016	0.00012	0.00054	0.00022	0.00363	-0.00065	0.00051	0.00051
Median	-0.0035	0.00003	0.00046	0.0014	0.00197	-0.00058	0.00067	0.0009
Maximum	0.1150	0.0345	0.0315	0.0935	0.5092	0.0818	0.0395	0.0748
Minimum	-0.0953	-0.0628	-0.0278	-0.1315	-0.2994	-0.0801	-0.0400	-0.0506
Std. Dev.	0.0288	0.0114	0.0092	0.0235	0.0843	0.014151	0.0109	0.0147
Skewness	0.4730	-0.5953	-0.0458	-0.5361	0.8196	-0.5917	-0.2740	-0.0084
Kurtosis	4.1953	6.2127	3.7426	6.1296	7.5563	9.0820	4.1565	4.1858
Observations	734	734	734	734	734	734	734	734

relatively low average returns and varying levels of volatility across markets. HYDR exhibits higher return variability than major equity indices but lower than natural gas, while all series display non-normal characteristics, as suggested by their skewness and kurtosis values.

Each return series is decomposed using the Maximal Overlap Discrete Wavelet Transform (MODWT) with the Haar filter and four detail levels j=1,..,4. Because the data are daily, the four bands correspond to progressively longer horizons that we label as 2–4, 4–8, 8–16, and 16–32 trading days, respectively. We interpret variation across bands as horizon-dependent co-movement.

Let $d_j[X]$ and $d_j[Y]$ denote the detail coefficients of assets X and Y at scale j. For a grid of nine quantiles $\tau \in \{0.1, 0.2. \dots, 0.9\}$, we quantify dependence between $d_j[X]$ and $d_j[Y]$ at each $(j.t)$. In our empirical implementation we adopt a robust, practical proxy: we fit two quantile regressions. $d_j[X] \sim d_j[Y]$ and $d_j[Y] \sim d_j[X]$, and summarize dependence by Kendall's τ_k between the fitted values, which preserves the quantile and scale-specific nature of the relationship while remaining stable under heavy tails and outliers. The resulting values produce a WQC matrix (rows = quantiles. columns = scales) that we visualize with 2D heatmaps and 3D surfaces using a blue–white–red palette (blue negative, white near zero, red positive). For cross-pair comparability we use a fixed color range $[-1, 1]$ for sensitivity checks we also report dynamically scaled figures based on $\pm\max|WQC|$. Horizontal variation across scales is interpreted as differences across time horizons, while vertical variation across quantiles captures tail behavior from downside risk to extreme gains.

In practice, for each wavelet scale $j \in \{1,..,4\}$ and each quantile $\tau \in \{0.1, 0.2. \dots, 0.9\}$, we estimate two quantile regressions on the corresponding MODWT detail coefficients, one with HYDR as the dependent variable and one with the benchmark asset as the dependent variable. We then take Kendall's rank correlation between the two fitted-value series and treat it as the dependence estimate for the given (j,τ) combination. Applying the same calculation across all scales and quantiles yields the dependence matrix that we later visualize in the heatmaps and 3D surfaces.

For completeness, we briefly report the formal WQC concept, which defines quantile dependence at a given horizon and quantile level. Our empirical implementation follows a practical proxy that delivers a transparent, replicable horizon-by-quantile dependence map in finite samples. Let Xand Y be return series and $Q_{(\tau.Y)}$ the τ-quantile of Y. Define the centered indicator score

$\phi_\tau(w) = \tau - 1\{w < 0\}$

The quantile covariance is

$$qcov_\tau(Y.X) = E[\phi_\tau(Y - Q_{(\tau.Y)})(X - E[X])].$$

and the corresponding quantile correlation is

$$qcor_\tau(X.Y) = \frac{qcov_\tau(Y.X)}{\sqrt{\mathrm{Var}[\phi_\tau(Y - Q_{(\tau.Y)})]\,\mathrm{Var}[X]}}$$

Applying MODWT to X and Y yields detail coefficients $d_j[X]$ and $d_j[Y]$ at scales $j = 1. \dots .J$. The Wavelet Quantile Correlation (WQC) at (j,τ) is then

$$WQC_\tau(d_j[X].d_j[Y]) = \frac{qcov_\tau(d_j[Y].d_j[X])}{\sqrt{\mathrm{Var}[\phi_\tau(d_j[Y] - Q_{\tau.d_j[Y]})]\,\mathrm{Var}[d_j[X]]}}$$

In addition to this formal definition, our empirical routines report a robust proxy for WQC_τ by computing Kendall's τ_K between the fitted values of the two quantile regressions $d_j[X] \sim d_j[Y]$ and $d_j[Y] \sim d_j[X]$

at each (j, τ), and we visualize all surfaces on a common $[-1, 1]$ color scale for fair comparison across asset pairs.[2]

4. Empirical Results

In this section, we report wavelet–quantile dependence maps between HYDR and each benchmark asset. Results are presented across investment horizons (scales 2–4, 4–16 and 16–32) and across market states (quantiles $\tau = 0.1$–0.9), with particular emphasis on tail regimes ($\tau = 0.1$ and $\tau = 0.9$). The figures therefore summarize how dependence varies simultaneously by horizon and by return conditions, which standard average correlations cannot capture.

Figure 1 presents the results of Hydrogen and Aluminum. From the graph we observe that in the long-term period (16–32), a positive correlation is evident in almost all quantiles. That is, in the long run, the returns of HYDR and Aluminum tend to move together. In the short-term periods (2–4 trading days): at the extreme quantiles ($\tau = 0.1$ and 0.9) there is a slightly faint negative correlation. This indicates that in cases of very strong negative or positive movements, the two markets may react in opposite directions in the short term. In the intermediate range ($\tau \approx 0.5$–0.7): there is a mild positive correlation, which strengthens at longer time horizons. The Hydrogen ETF and Aluminum appear to be synchronized in the long-term horizon, possibly due to common macroeconomic factors. However, short-horizon tail regions show weaker or slightly negative dependence, suggesting that diversification benefits may be more likely to arise in short-run extreme conditions rather than in long-run holding periods. Overall, the evidence points to long-run co-movement, with only limited, state-specific diversification potential in the tails.

Figure 2 represents the analysis of Hydrogen and Gold. Almost all the cells are red, indicating that the correlation is mildly positive across all areas. No significant variation is observed between quantiles

[2] The empirical analysis is conducted in R with the wavelet's packages (MODWT, Haar, periodic boundary), quantreg (quantile regression), ggplot2 and reshape2 (2D heatmaps), and plotly (3D surfaces). The default settings are scales 2–4, 4–8, 8–16, 16–32 and quantiles $\tau = 0.1, \ldots, 0.9$, plotted with a blue–white–red palette under fixed limits $[-1, 1]$ unless otherwise stated.

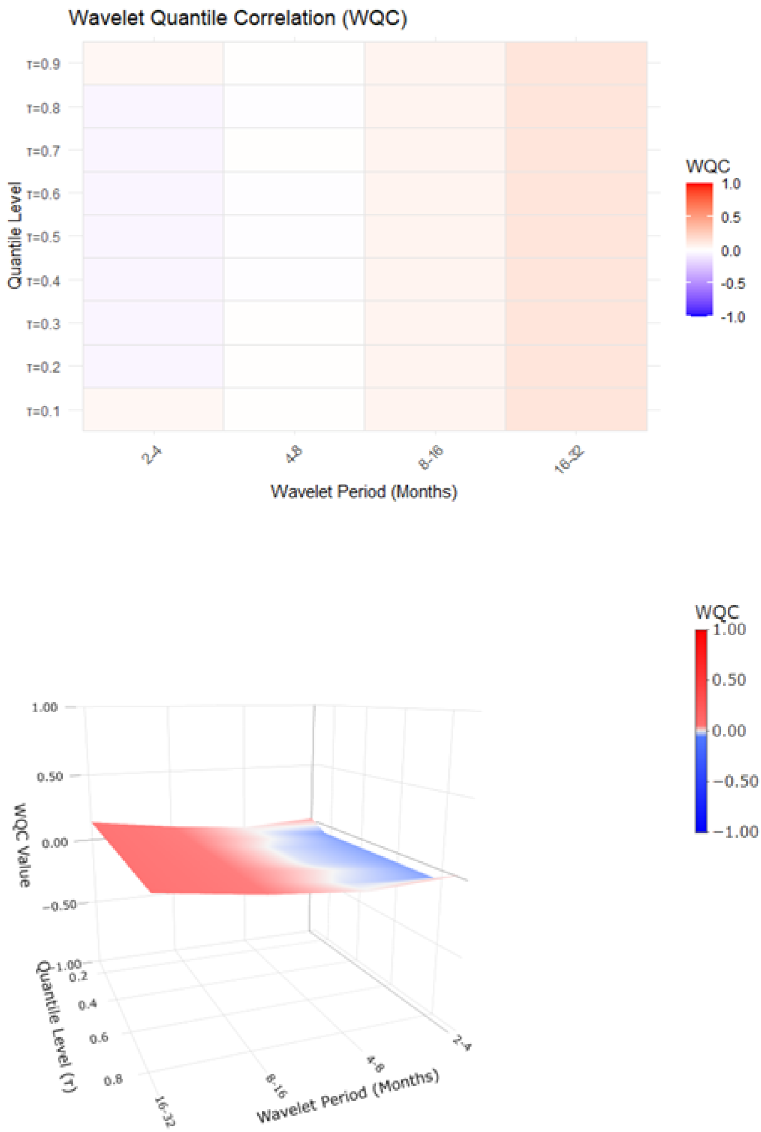


Fig. 1: WQC of Hydrogen and Aluminum

or scales. This means that: the HYDR–Gold correlation is stable and tends to be slightly positive, regardless of time horizon or return scenario. Investing in HYDR and Gold shows that: there is no strong diversification potential. In any type of return (low/high), the two indices move slightly together. We observe that the relationship between the Hydrogen ETF and Gold is weakly positive and stable, regardless of the quantile and frequency. Therefore, gold does not display persistent negative dependence with HYDR in this sample. The pattern is more consistent with mild co-movement, which implies limited hedging capacity, while still leaving room for diversification depending on portfolio weights and the investor's objective.

Figure 3 represents the analysis of Hydrogen and crude oil. We observe a weakly positive correlation between the HYDR ETF and Brent crude oil across all return levels and time horizons. There is no evidence of significant changes or spikes in their relationship during critical situations (e.g., bear or bull markets). The correlation between Global X Hydrogen ETF and Brent crude oil is low and consistently positive, thus we can conclude that the markets are not completely independent, but neither do they move in full synchronization. Overall, the HYDR–oil dependence remains low, with mild positive co-movement rather than pronounced regime shifts. From a portfolio perspective, this is more consistent with limited co-movement than with a clear hedging relationship: oil does not appear to provide systematic protection against HYDR, but it also does not move tightly with HYDR over the full quantile–scale grid.

Figures 4 and 5 present the analysis of Hydrogen with major stock markets. Figure 4 shows the relationship with Nasdaq 100, and Figure 5 with S&P 500. HYDR tends to move in the same direction as the Nasdaq 100 across the different horizons and return states we examine. That pattern suggests it is driven, at least in part, by the same forces that shape growth-oriented equities, so it is unlikely to behave like a reliable hedge. For portfolios that are already tilted toward growth, adding HYDR is therefore more likely to deepen that exposure than to deliver strong diversification, with any benefits appearing only modest.

Similar results are observed for Figure 5. The relationship between Hydrogen and the S&P 500 shows high WQC values across the entire surface, indicating that HYDR returns move in line with the broader U.S. stock market index, regardless of market phase or time horizon. The absence of pronounced negative tail dependence suggests limited hedging capacity against broad equity drawdowns. Overall, adding HYDR to a portfolio already holding the S&P 500 is less likely to

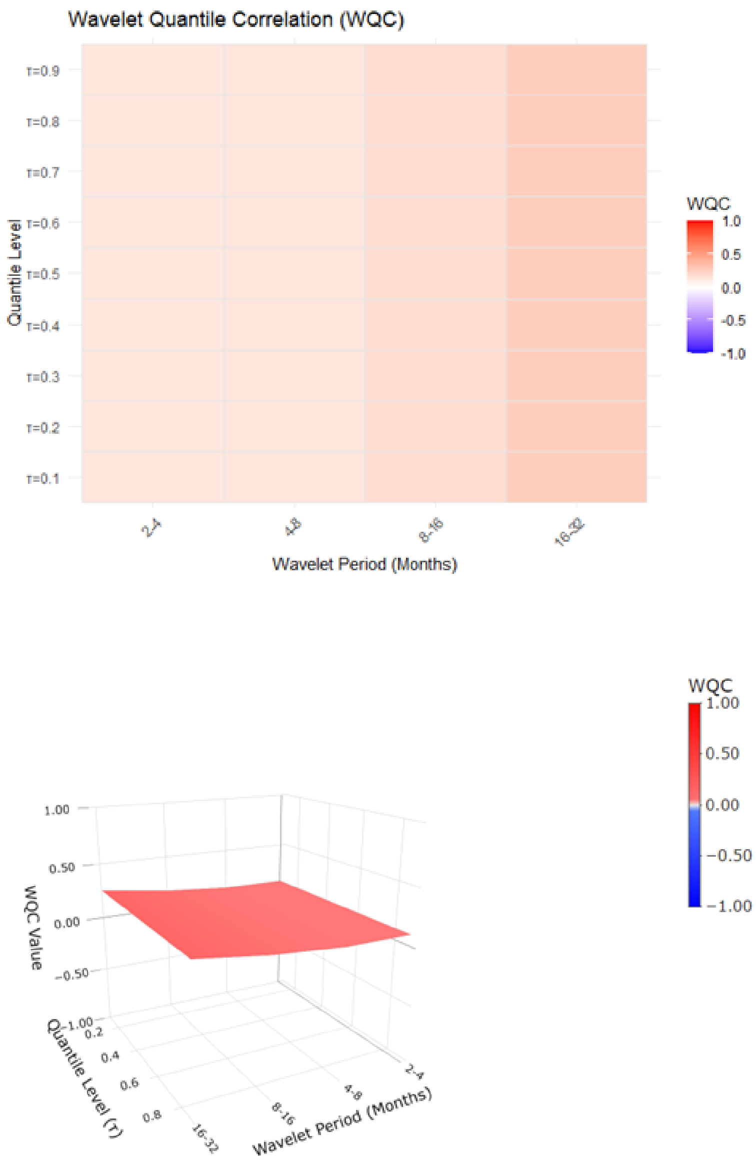
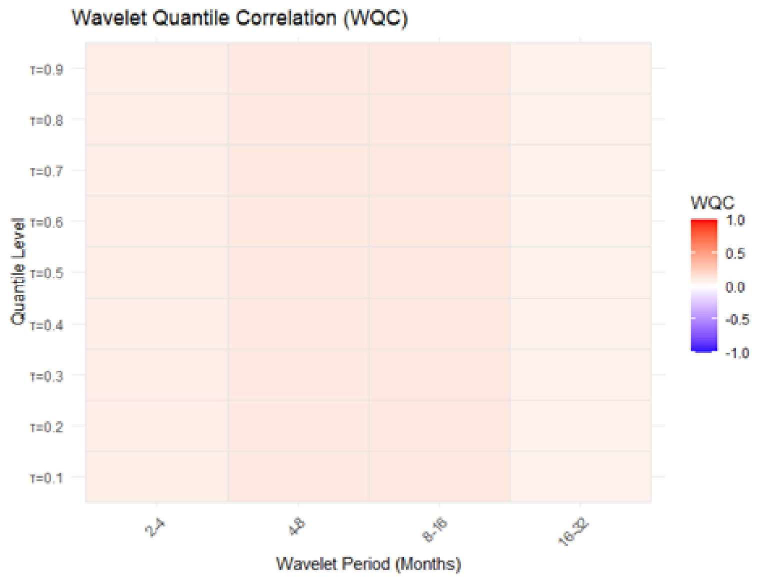


Fig. 2: WQC of Hydrogen and Gold



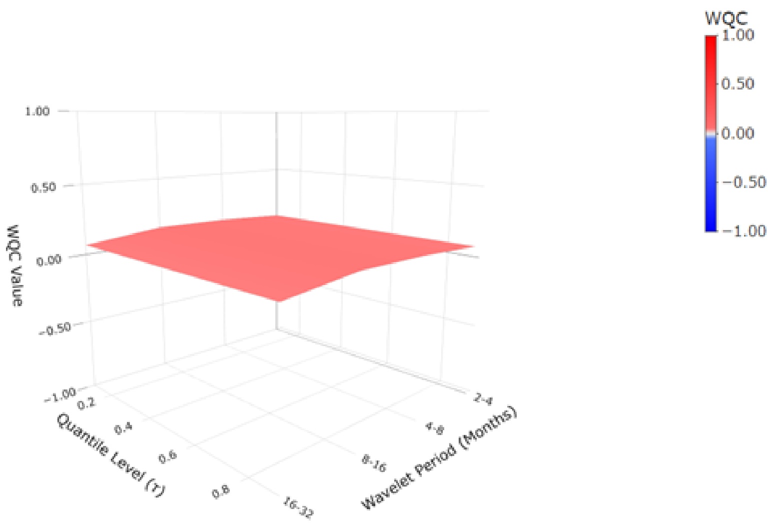


Fig. 3: WQC of Hydrogen and Crude Oil

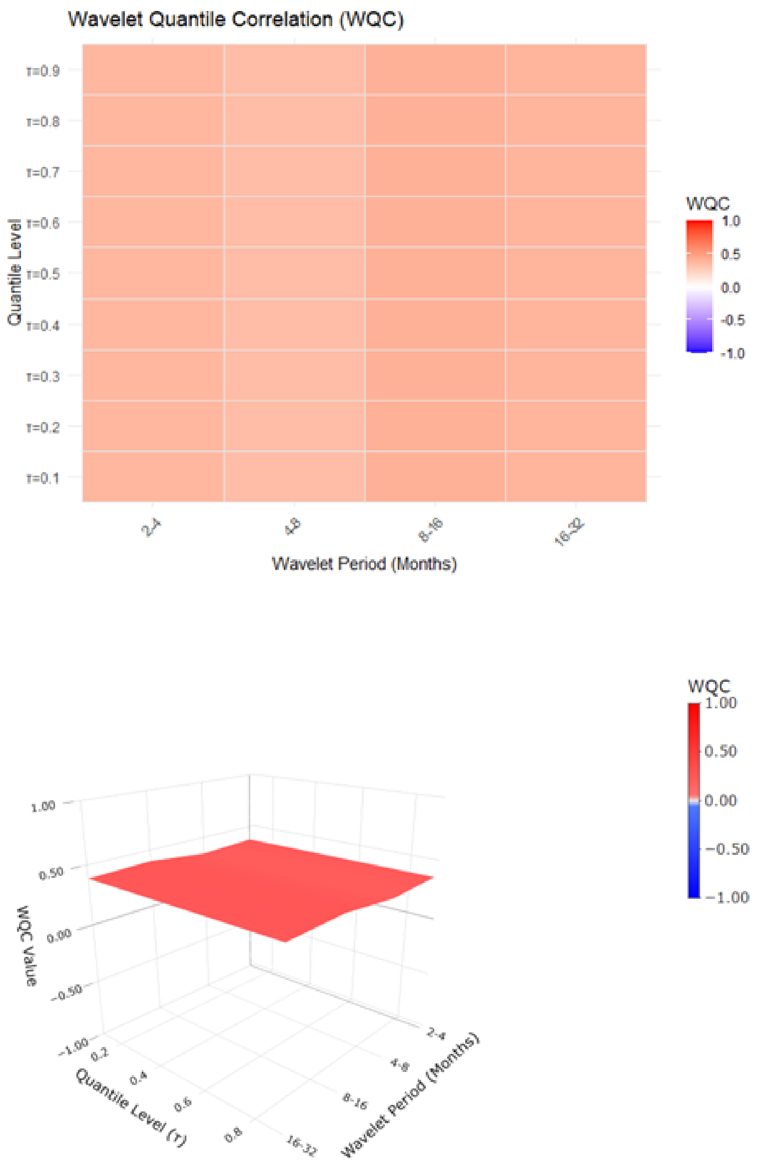


Fig. 4: WQC of Hydrogen and Nasdaq 100

deliver strong diversification benefits and more likely to increase exposure to common equity-market risk. Figure 6 shows the

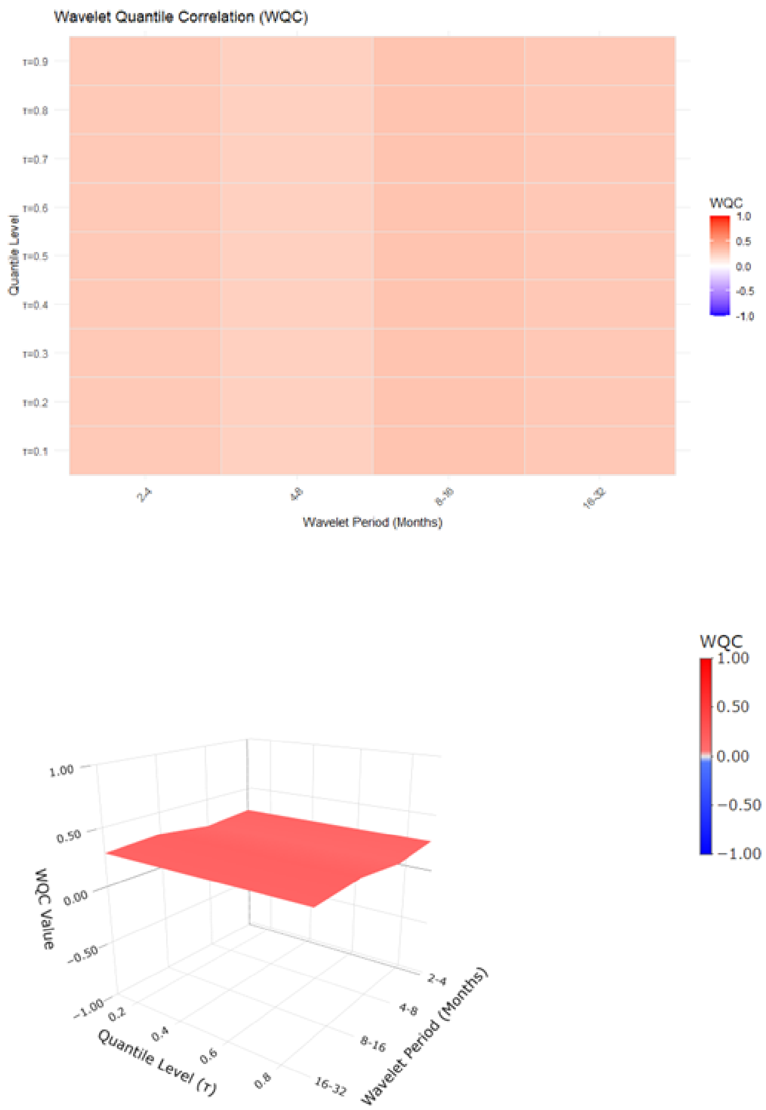


Fig. 5: WQC of Hydrogen and S&P 500

correlations between Hydrogen and Steel. The analysis identifies a low-intensity and generally neutral relationship. The heatmap indicates that the correlation remains close to zero across most areas

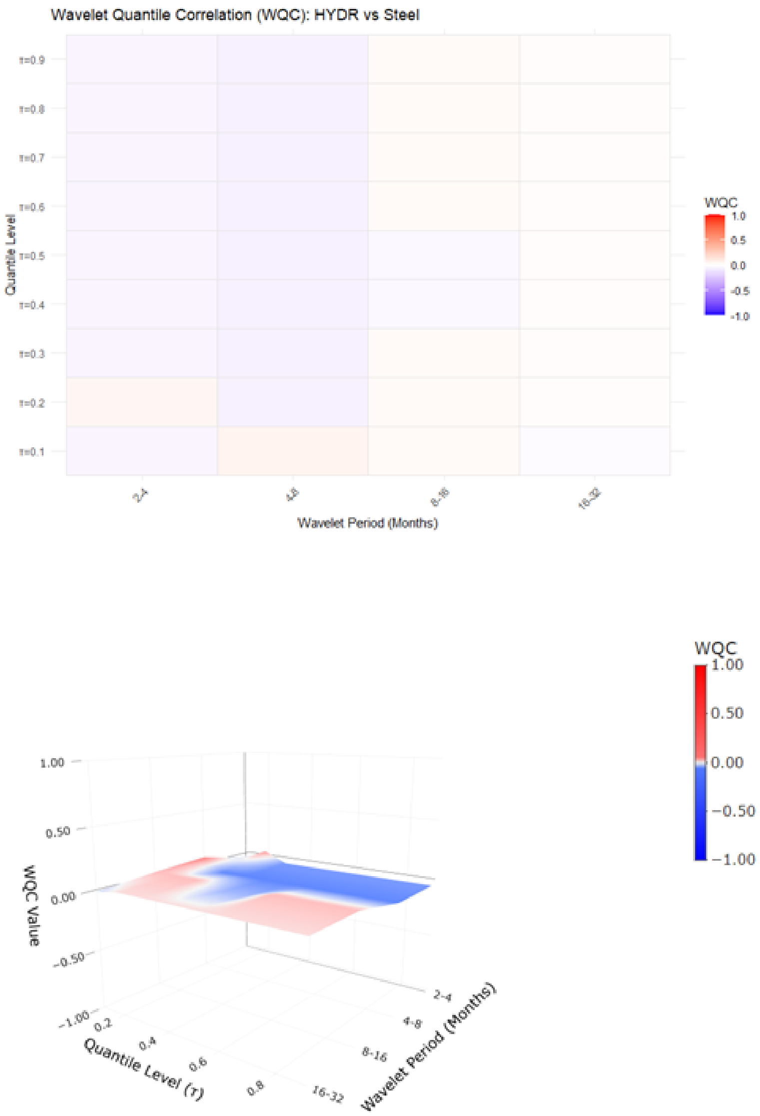


Fig. 6: WQC of Hydrogen and Steel

of the return distribution and across all time horizons, with only a few exceptions of mild positive correlation at the lower quantiles ($\tau = 0.1$–0.2) and at short-term scales (2–4 trading days). In contrast, at

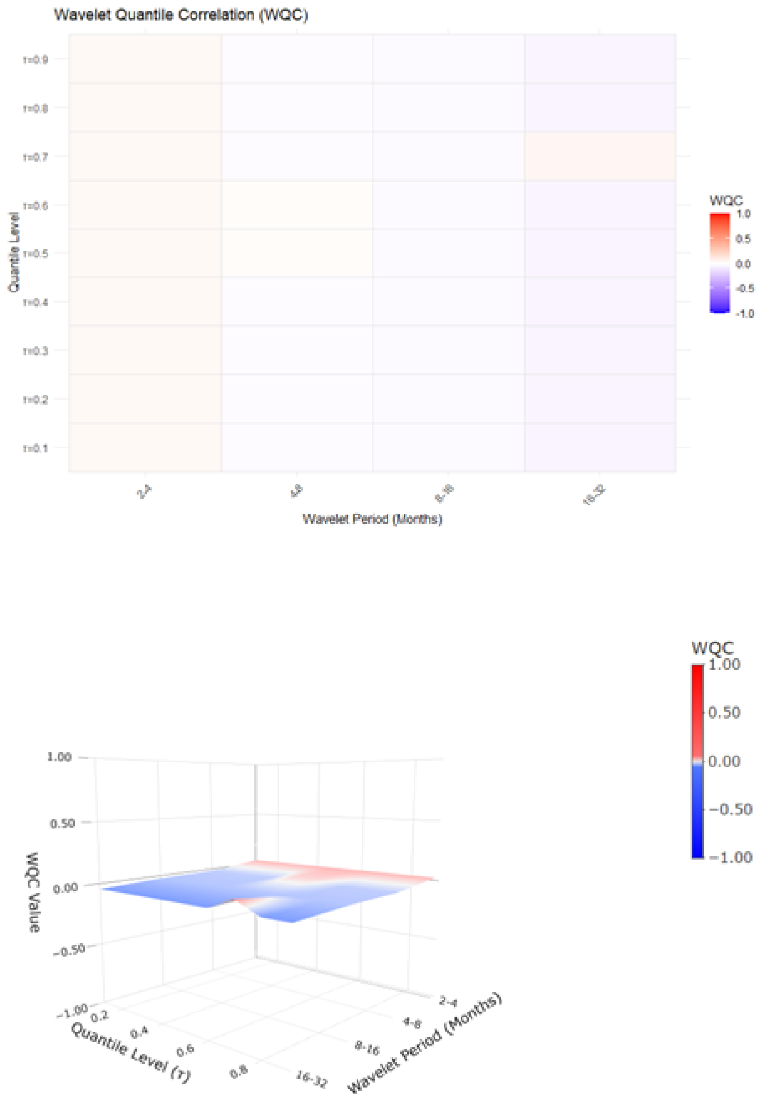


Fig. 7: WQC of Hydrogen and Gas

higher quantiles and longer periods, a mild negative or negligible correlation is observed. Overall, the HYDR–steel relationship appears weak and horizon/state dependent, which is compatible with some diversification potential especially when the two markets respond differently to sector-specific shocks without implying a systematic hedging relationship.

In Figure 7, the Wavelet Quantile Correlation between the Global X Hydrogen ETF and Gas Futures is very weak to non-existent, indicating that there is no significant correlation dynamic at any return level or time horizon. Consequently, natural gas displays low dependence with HYDR in this sample, suggesting diversification potential within an energy portfolio. However, this should be interpreted as weak co-movement rather than "complete diversification" since diversification outcomes also depend on portfolio construction and market conditions.

Our results show that HYDR seems to be a growth-tilted equity theme (than an asset that tracks fossil-fuel markets). The spillover effects also vary a lot during different horizons and the tail regions bring out features that ignored form the average correlation. In contrary, metals seem to follow a different pattern, with dependence that changes more clearly as the horizon lengthens, which is consistent with broader macro and cycle effects. Overall, these findings clarify the "decoupling" theory by indicating when co-movement is genuinely weak and when HYDR stays closely aligned with equities.

5. Conclusion and Practical implications

Wavelet quantile correlation (WQC) analysis uncovers a rich horizon- and state-dependent dependence structure between the Hydrogen ETF (HYDR) and key asset classes that conventional, single-number correlations would miss. Across the full panel of figures (2D heatmaps and 3D surfaces), dependence varies systematically with both frequency (short: 2–4 trading days, medium: 4–16, long: 16–32) and quantiles (from downside tails $\tau \approx 0.1$ to extreme gains $\tau \approx 0.9$), revealing patterns that are economically intuitive and stable across specifications.

Firstly, HYDR exhibits weak and often indistinguishable-from-zero co-movement with fossil fuels (oil and gas) at most horizons and quantiles. The 2D heatmaps are dominated by pale tones and the 3D surfaces hover near the zero plane, with only small pockets of sign changes. This low and unstable linkage suggests that hydrogen equity exposure does not simply proxy for traditional energy beta and can provide partial hedging against fossil-fuel risk, especially outside of crisis spikes.

Secondly, dependence on broad equity markets is materially stronger, for both the S&P 500 and Nasdaq 100. WQC is consistently positive, increases with the investment horizon. and tends to strengthen toward the upper quantiles. The surfaces tilt upward from short to long frequencies and from median to upper-tail states, indicating that in growth phases and equity upswings hydrogen tends to co-move with the market. This pattern is consistent with hydrogen's equity-like risk and its sensitivity to macro growth and financing conditions and it cautions that HYDR may not hedge broad-market drawdowns, particularly when losses are systemic.

Thirdly, gold does not function as a close analogue or hedge for hydrogen. The WQC maps display mild, largely uniform positive co-movement rather than the negative or near-zero association one would expect from a classical safe-haven asset. Hydrogen therefore does not replicate gold's defensive behavior; any diversification benefit relative to gold is primarily one of low covariance in stress tails. not of systematic negative correlation.

Fourthly, industrial metals, especially aluminum and steel, show clearer co-movements with HYDR at longer horizons and in upper quantiles. The long-run bands in the heatmaps are visibly redder. and the 3D surfaces rise with both horizon and quantile. This points to a shared exposure to expansionary. investment-led states (e.g., capex cycles. infrastructure spending, and policy pushes toward electrification) in which hydrogen demand narratives and metals demand for equipment/transport co-intensify. Short-run, tail-specific pockets of slightly negative WQC also appear particularly at extreme quantiles indicating transient divergences during sharp news shocks or rebalancing episodes.

Collectively, these results imply that portfolio construction with hydrogen should be state contingent. For ESG-oriented or transition-themed allocations, HYDR offers meaningful diversification against fossil fuels and modest diversification against gold, while contributing equity-like beta that strengthens in risk-on states. Risk management should therefore model hydrogen's dependence with both horizon and tails in view: WQC surfaces highlight that left-tail correlations with equities are weaker than upper-tail correlations, while metals linkages intensify at longer horizons. Over longer horizons, hydrogen the correlation increased between the industrial metals. This finding is in line with the transition economy theory: when policies back clean energy and capital flow into new infrastructure, demand rises across both metals and hydrogen supply chains. The result is pro-cyclical linkages that build over several quarters.

Regarding the practical implications of HYDR, it seems that HYDR behavior is closer to a growth-tilted equity theme than to an instrument that moves with fossil-fuel markets. For example, when an investor is exposed to U.S. growth equities, adding HYDR is likely to deepen the similar risk profile, instead of succeeding diversification gains. In contrary, spillover effects between oil and natural gas are weak, providing limited portfolio diversification benefits. Furthermore, the tail behavior differs from the average correlation, thus investors, policy makers and corporations could benefit by examining these patterns during volatile environments and minimize potential losses.

Future research can examine an extended sample (beyond 2024) and comparing HYDR with other hydrogen ETFs or broader hydrogen equity baskets. Looking ahead the WQC approach should be broadened to include more green assets (such as Green Bonds) and analyze periods tagged to specific shocks (policy changes, geopolitical events).

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