# Early Market Efficiency Testing among Hydrogen Players

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## Abstract

We study the stock price efficiency of companies with exposure to the hydrogen economy. As hydrogen, a pillar of the energy transition required for the global society to achieve the Sustainable Development Goals for 2030, does not trade as a commodity, we use the Solactive Hydrogen Index NTR as a proxy. Efficiency is assessed through a fractal methodology, with data from November 2018 to June 2021. Additionally, we run a time-varying approach that improves the robustness of the efficiency estimates. We find random price behavior consistent with the weak version of the market efficiency hypothesis, with only mild departures from efficiency in some companies with higher hydrogen exposure. There is also evidence of time-varying behavior of randomness during the acute pandemic period. The study validates the Solactive Hydrogen Index as an adequate proxy for the hydrogen economy.

**Keywords:** Hydrogen Economy, ESG Investment, Efficient Market Hypothesis, Fractals, Long Memory, Time Series Analysis
**JEL codes:** Q42, Q40, G14, G11, C13

## 1. Introduction

The hydrogen economy is growing because of its potential to help the global society meet some of the Sustainable Development Goals for 2030 (Goals 7 and 10, respectively, for affordable and clean energy and climate action). However, significant research and investment are required to make it more affordable, reliable, and safe (Acar & Dincer, 2019; Burton, Padilla, Rose & Habibulllah, 2021). For investment flows to increase research and development in the hydrogen economy, market efficiency is a necessary condition for better capital allocation. However, hydrogen does not trade as a commodity with a market quotation, which potentially hampers investments in the field.

In this study, we investigate the suitability of the Solactive Hydrogen Economy Index NTR (Sohydron) as a proxy for the hydrogen economy. Despite the nascent hydrogen economy, with short time-series data available, we can extract useful information from it. Suppose trading in the index follows the Efficient Market Hypothesis (EMH) (recent literature reviews can be found in Zaremba, Umutlu & Maydybura, 2020; Jacobs & Muller, 2020; Harvey, Liu & Zhu, 2016). In that case, we argue that financial frictions should not be a barrier to hydrogen as a driver of climate transition.

This study contributes to society in a few significant ways. First, we show that applying fractal methodologies to short time series can improve the robustness of market efficiency studies. Second, we find that financial frictions such as inefficient capital markets should not be a barrier to developing the hydrogen economy. Finally, we provide some guidance on the crossroads between environmental, social, and corporate governance (ESG) investments and long-term price dependence, including the effect of the global pandemic on the efficiency of hydrogen markets.

The fractal methodology is suitable because of the departures from normality of the sample under study. Furthermore, as the companies that constitute the Sohydron index show different degrees of exposure to the hydrogen economy and belong to diverse industries, we deepen the analysis by clustering stocks into four groups for more granular results.

We calculate three fractal estimators: the R/S-AL estimator developed by Annis and Lloyd (1976), Detrended Fluctuation Analysis (DFA), and multifractal Generalized Hurst Exponent (GHE) (see Di Matteo, Aste, & Dacorogna, 2003; Di Matteo, 2007; Barunik & Kristoufek, 2010; Sensoy & Hacihasanoglu, 2014). We complement the static estimation with a rolling window approach to further investigate the time-varying efficiency dynamics, which is particularly important because the data include the recent acute global pandemic.

We find evidence of random price behavior that is consistent with the weak version of market efficiency, except for some mild departures in the companies with a more substantial hydrogen exposure, which are grouped in Cluster 1 (mainly electrolyzer and fuel cell companies). This cluster displays long memory in returns, precisely, a trend-reinforcing behavior. These results are consistent with recent investor interest that, coupled with that from regulators, has fueled the momentum of several hydrogen producers' stocks. However, the aggregated result for Cluster 1 does not imply uniform behavior. Indeed, there is no evidence of a substantial deviation from the weak EMH in the evolution of the three companies classified as green hydrogen pure players (GPPs).

There is also an indication of a time-varying behavior of randomness during the acute pandemic period. The index returns exhibit steady, persistent behavior during the market crash in March 2020 but return to randomness by the second half of 2020.

The study also validates the use of the index as an adequate proxy for hydrogen investments, given its mimicking behavior of those players who are more focused on the hydrogen economy. This renders the Sohydron index a suitable underlying asset for affordable investment products, such as Exchange Traded Funds (ETFs). This allows retail and institutional investors to effortlessly invest in the hydrogen economy.

The remainder of this paper is organized as follows. Section 2 explains the relevance of the hydrogen economy, while Section 3 describes the sample that was used as a proxy for hydrogen behavior. In Section 4, the fractal methodology employed is explained. Section 5 presents the results and a discussion of the empirical estimations from the fractal analysis, while Section 6 concludes.

## 2. Hydrogen Economy

Hydrogen should play an essential role in climate transition (Shafiei, Davidsdottir, Leaver & Stefansson, 2017), as 20% of global carbon emissions could be abated by its widespread use in energy markets (BofA, 2020). Despite being in its nascence, the hydrogen economy may allow storage and transportation of renewable energy (Kalinci, Dince & Hepbasli, 2017; Beheshti, Ghassemi & Shahsavan-Markadeh, 2016), with the potential to solve the main barrier to universal adoption of renewables. Hydrogen may power 20–25% of the transportation industry by 2050 (Mostafaeipour et al., 2016). It may also be deployed as a source of heat on buildings' existing natural gas infrastructure (Alanne & Cao, 2017), and as an alternative feedstock for energy-intensive manufacturing industries (Acar & Dincer, 2014; Mehrpooya, Sayyad & Zonouz, 2017). However, several issues must be considered for its development.

On the one hand, over 99% of hydrogen output is still generated using fossil fuels, accounting for 2.2% of global carbon emissions (BofA, 2020). Therefore, the hydrogen economy will contribute to climate change mitigation only if hydrogen is produced using renewable energy sources (Göllei, Görbe & Magyar, 2016). Such hydrogen is referred to as green hydrogen, as opposed to hydrogen produced through coal gasification (brown hydrogen) or steam methane reforming (grey hydrogen). Carbon dioxide emissions are released into the atmosphere during brown and grey hydrogen production. When these emissions are captured and stored, the hydrogen obtained is denominated as "blue." Thus, energy transition entails moving from grey, through blue, to green hydrogen.

On the other hand, the technologies for green hydrogen production are not economically viable (Burton, 2021). Its production cost would have to decline by 50% for it to be economically competitive with grey hydrogen (Jia et al., 2016). However, hydrogen production methods are becoming more efficient and affordable (Salvi & Subramanian, 2015). Further advancements are expected to lower costs and increase the scale of hydrogen production (Nastasi & Basso, 2016). Falling renewable prices are also paramount in reducing hydrogen costs; public policy measures setting higher carbon prices and more stringent decarbonization mandates could be a tipping point in favor of green hydrogen (Chintala & Subramanian, 2015).

Finally, as the technology to exploit hydrogen is not fully mature, public investors are increasingly being pressed to play a role in sustainable investing (Elsenhuber & Skenderasi, 2020). Simultaneously, driven by ESG investment criteria, private investors seek hydrogen to contribute to climate change mitigation (Göllei et al., 2016).

Investment growth and attention by asset managers have been reflected in stock prices, bringing extreme volatility. Hydrogen-related stocks have increased by an average of more than 100% during 2020 (such as PowerCell, Chart Industries, Ballard Power Systems, and Nel ASA).

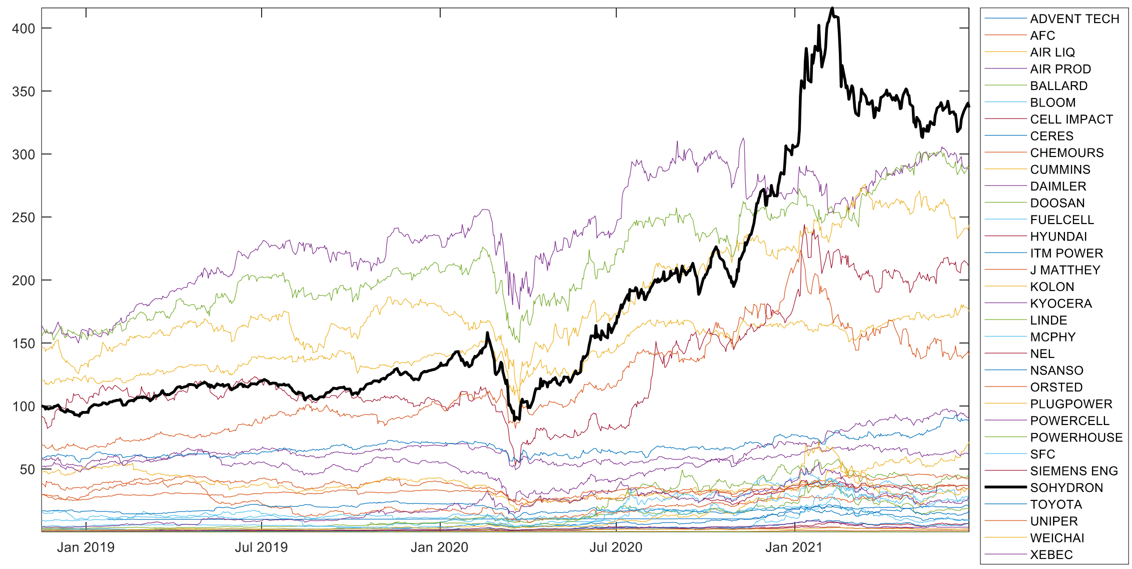
In some cases, stock prices have risen by over 300% (Bloom Energy, FuelCell Energy, and Plug Power). Although stocks have retreated from all-time highs, concerns about asset bubbles remain. Determining whether, at this stage, this is an efficient market would be valuable to investors and public authorities.

## 3. Sample description

Presently, investors cannot trade hydrogen as a commodity. The main alternative for investors who want to build positions in the hydrogen economy is through specific company stocks, mutual funds, ETFs, or indexes related to the major companies in the industry. These include the Global Hydrogen Index, the Korean FnGuide Hydrogen Economy Theme Index, and the Sohydron index. We identify the Sohydron index as the best proxy to study hydrogen price behavior, given that it has a worldwide, diversified industry exposure and the most extended time series available. Other Solactive indices, such as the Solactive Sustainability Index Europe and the Solactive Green Bond Index, have been previously used in the academic literature (Mikołajek-Gocejna, 2018; Pham & Huynh, 2020; Saeed, Bouri & Alsulami, 2021). In the appendix, we describe the other indices and the reasons for their ineligibility for efficiency study purposes.

The Sohydron index is denominated in US$ and aims to track the performance of a worldwide basket of stocks from companies involved in the hydrogen economy. The index is semiannually rebalanced and monthly adjusted. On each selection day, each index component is assigned an equal weight, subject to some constraints. We consider daily closing prices, for the Sohydron index and its components, over the period from November 16, 2018, when the index was created, to June 30, 2021. The total number of observations for the index and each of its components exceeds 600, except for three companies that started quoting at a later date (Doosan Fuel Cell Co on October 18, 2019, Advent Technologies Holdings Inc on January 23, 2019, and Siemens Energy AG on September 28, 2020). Figure 1 shows stock price changes (in nominal dollars).

**Figure 1:** Daily time series evolution of the Solactive Hydrogen Economy Index NTR (Sohydron) series and its components.




A company must meet a few requirements to qualify as this index component. The first is for the company to be part of the hydrogen production supply chain. Other requirements for inclusion are a market capitalization of at least $200 million at the time of inclusion and a three-month average daily traded value of at least $1 million. The resulting basket includes many electrolyzer and fuel cell manufacturers, industrial producers of their main components, hydrogen producers, companies from the energy, automotive, or gas industries, and even a few large conglomerates. For instance, Infinergia Consulting (2021) classifies companies as "pure-players" (focused on hydrogen activities) and "diversified" (have multiple activities, including hydrogen). According to Infinergia's hydrogen company database, 15 companies included in the Sohydron index are considered pure players.

As of June 30, 2021, the index contained the 32 stocks shown in Table 1, which also presents the main statistics of their daily logarithmic close/close increments series.

**Table 1:** Solactive Hydrogen Economy Index NTR and its components as of May 24, 2021, and descriptive statistics of the daily logarithmic close/close increments series. Jarque-Bera tests strongly reject normality of the returns in all cases at a significance level of 1% (***). The sample period is from November 16, 2018 to June 30, 2021.

| Short Name | Index component | Weighting % | Country | Num. Observ | Mean (%) | Std (%) | Max (%) | Min (%) | Skew | Kurtosis | Jarque-Bera test |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sohydron | Solactive Hydrogen Economy Index NTR | | | 660 | 0.18 | 2.02 | 10.88 | -13.00 | -0.29 | 9.04 | 1085.91*** |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Ceres | Ceres Power Holdings PLC | 2.73 | UK | 660 | 0.29 | 3.87 | 14.33 | -20.89 | -0.31 | 5.76 | 220.06*** |
| Powerhouse | Powerhouse Energy Group PLC | 0.99 | UK | 660 | 0.38 | 6.70 | 46.85 | -20.92 | 1.74 | 10.87 | 2039.29*** |
| AFC | AFC Energy PLC | 3.28 | UK | 660 | 0.38 | 6.83 | 38.86 | -22.46 | 1.22 | 8.73 | 1068.40*** |
| Cell Impact | Cell Impact AB | 3.98 | Sweden | 652 | 0.37 | 6.88 | 47.51 | -37.44 | 0.33 | 9.72 | 1238.64*** |
| FuelCell | FuelCell Energy Inc | 3.13 | US | 657 | 0.36 | 13.38 | 207.99 | -63.82 | 6.14 | 94.19 | 231758.69*** |
| PlugPower | Plug Power Inc | 4.06 | US | 657 | 0.44 | 5.53 | 30.10 | -20.26 | 0.5 | 6.01 | 274.50*** |
| Ballard | Ballard Power Systems Inc | 3.51 | Canada | 657 | 0.28 | 4.74 | 17.10 | -21.99 | -0.25 | 5.56 | 186.37*** |
| ITM Power | ITM Power PLC | 3.53 | UK | 659 | 0.43 | 6.04 | 27.01 | -23.66 | -0.01 | 5.56 | 180.35*** |
| Nel | NEL ASA | 2.97 | Norway | 651 | 0.22 | 4.48 | 13.63 | -20.91 | -0.66 | 5.78 | 257.22*** |
| Xebec | Xebec Adsorption Inc | 3.12 | Canada | 657 | 0.29 | 4.54 | 18.66 | -36.81 | -0.90 | 11.55 | 2091.91*** |
| McPhy | McPhy Energy SA | 1.95 | France | 664 | 0.27 | 4.58 | 37.61 | -18.76 | 0.94 | 11.97 | 2321.82*** |
| Orsted | Orsted AS | 3.31 | Denmark | 646 | 0.11 | 2.03 | 7.67 | -10.32 | -0.25 | 5.09 | 124.64*** |
| Bloom | Bloom Energy Corp | 3.17 | US | 657 | 0.08 | 6.86 | 36.79 | -55.34 | -0.28 | 12.69 | 2578.76*** |
| Cummins | Cummins Inc | 2.90 | US | 657 | 0.08 | 2.07 | 19.18 | -12.53 | 0.62 | 17.15 | 5525.36*** |
| Hyundai | Hyundai Motor Co | 3.19 | R. Korea | 646 | 0.13 | 2.67 | 17.88 | -10.70 | 0.99 | 9.41 | 1211.07*** |
| SFC | SFC Energy AG | 2.52 | Germany | 657 | 0.22 | 4.90 | 21.00 | -33.35 | -0.60 | 9.61 | 1236.26*** |
| PowerCell | PowerCell Sweden AB | 3.18 | Sweden | 652 | 0.29 | 5.13 | 30.04 | -26.75 | 0.02 | 7.29 | 499.43*** |
| Weichai | Weichai Power Co Ltd | 3.17 | China | 644 | 0.11 | 2.71 | 12.29 | -10.73 | 0.3 | 4.47 | 67.42*** |
| Air Liq | Air Liquide SA | 3.22 | France | 667 | 0.06 | 1.50 | 5.41 | -12.71 | -1.37 | 13.68 | 3378.47*** |
| Linde | Linde PLC | 3.09 | Ireland | 657 | 0.09 | 1.80 | 10.13 | -7.45 | 0.03 | 6.24 | 288.01*** |
| Air Prod | Air Products and Chemicals Inc | 3.19 | US | 657 | 0.09 | 2.01 | 12.86 | -13.47 | -0.52 | 13.22 | 2888.22*** |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Uniper | Uniper SE | 3.18 | Germany | 658 | 0.03 | 1.60 | 6.43 | -10.40 | -0.80 | 8.52 | 904.44*** |
| Toyota | Toyota Motor Corp | 3.68 | Japan | 632 | 0.06 | 1.50 | 10.40 | -5.76 | 0.68 | 7.67 | 621.47*** |
| Chemours | Chemours Co/The | 3.18 | US | 657 | 0.03 | 4.32 | 21.13 | -25.87 | -0.28 | 7.84 | 648.72*** |
| Daimler | Daimler AG | 3.03 | Germany | 661 | 0.07 | 2.64 | 21.42 | -19.73 | -0.27 | 17.4 | 5716.82*** |
| Kolon | Kolon Industries Inc | 3.77 | R. Korea | 646 | 0.06 | 2.96 | 15.90 | -12.12 | 0.29 | 7.24 | 492.64*** |
| J Matthey | Johnson Matthey PLC | 2.98 | UK | 660 | 0.01 | 2.27 | 12.23 | -13.46 | -0.41 | 6.65 | 384.18*** |
| Kyocera | Kyocera Corp | 3.17 | Japan | 632 | 0.03 | 1.65 | 7.46 | -10.44 | -0.72 | 8.15 | 751.8*** |
| N Sanso | Nippon Sanso Holdings Corp | 3.54 | Japan | 632 | 0.03 | 2.35 | 16.79 | -12.82 | 0.14 | 10.70 | 1564.68*** |
| Advent Tech | Advent Technologies Holdings Inc | 2.48 | US | 484 | -106.89 | 2.68 | 17.11 | -11.75 | 0.87 | 12.53 | 1895.32*** |
| Doosan | Doosan Fuel Cell Co Ltd | 3.70 | R. Korea | 420 | 0.54 | 5.53 | 26.90 | -18.04 | 1.27 | 8.40 | 624.01*** |
| Siemens Eng | Siemens Energy AG | 3.10 | Germany | 190 | 0.21 | 2.52 | 15.39 | -7.07 | 1.13 | 8.99 | 324.4*** |

The significant departures from normality in the daily returns of these stocks, shown in Table 1, support the use of the fractal methodology. The index itself experiences large movements and exhibits non-normal behavior. We also observe that the maximum and minimum returns for each stock point to broad movements.

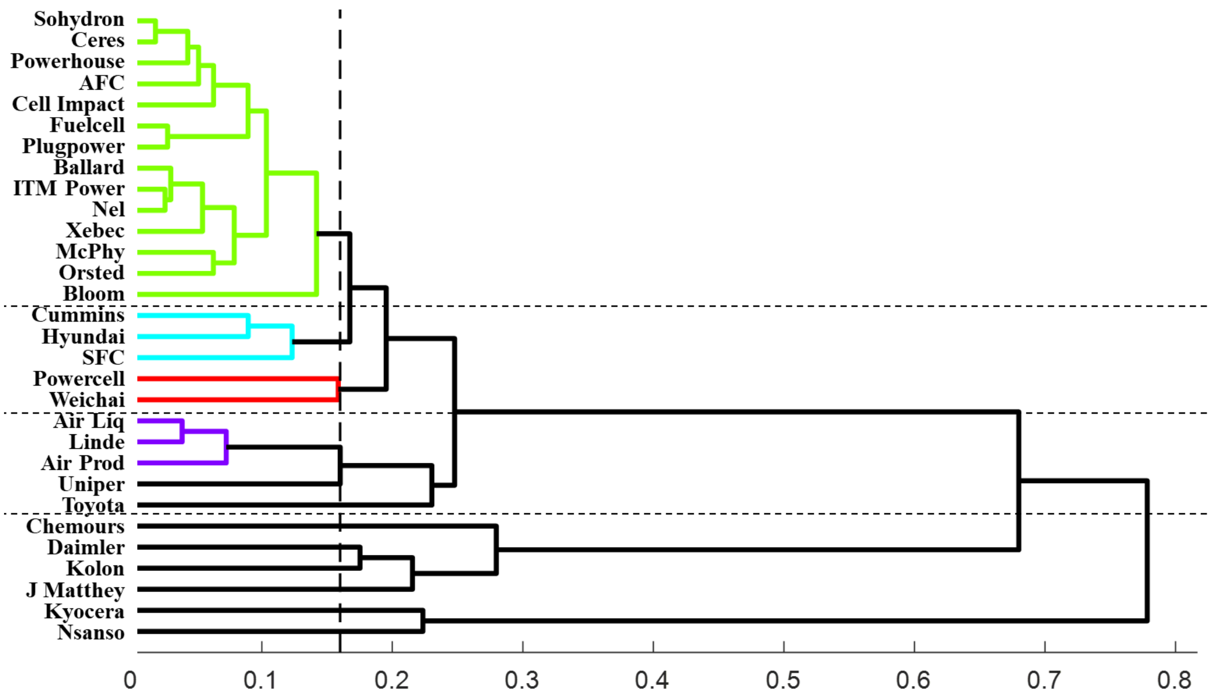
The results section shows the fractal analysis applied to each company and the index itself. However, given the diverse nature of the companies under study, we perform an initial clustering of the Sohydron components to obtain meaningful, aggregated results. We apply an average-linkage hierarchical agglomerative cluster analysis using the linear correlation between price series to measure the distance[1] between the components. We include all components but three that display shorter price series that do not allow for proper correlation analysis: Advent Tech, Doosan, and Siemens Energy. While the number of observations (above 400) will allow the further inclusion of Advent Tech and Doosan in Cluster 1, the 190 observations for Siemens

[1] See https://es.mathworks.com/help/stats/linkage.html for more information on the technique used.

Energy (which entered the Sohydron index in its last revision by May, 2021) justify the exclusion of this stock from the analysis.

The resulting clustering dendrogram is shown in Figure 2, illustrating the groupings created. Each horizontal-axis value is one minus the sample correlation between groups. Hence, time series that are highly correlated are linked on the left side of the horizontal axis. Based on the cluster analysis, we obtain four company groups.

**Figure 2:** Clusters produced by agglomerative cluster analysis using the linear correlation between price series as a measure of distance. The broken line marks the 84% correlation level. Advent Tech, Doosan, and Siemens Energy are not included due to their short price series.




According to industry sources, most of the companies clustered together at the top in Cluster 1 (C1) were those previously mentioned as pure players. Furthermore, all three green hydrogen players (GPPs) are in C1. This cluster also includes Doosan and Advent Tech (not shown in Figure 2 because of their shorter price series) due to their business activities and the fact that Infinergia Consulting (2021) considers them to be pure players.

Expectedly, the clustering analysis reveals that the Sohydron index is highly correlated with the pure players' stock prices, which supports our claim that it is a good proxy for the hydrogen economy.

Cluster 2 includes two of the companies classified as pure players by Infinergia (2021) and three that are diversified. This cluster shows proximity to C1 but a slightly weaker correlation.

The remaining two clusters in the lower part of Figure 2 (C3 and C4) include mostly diversified companies (only J Matthey in C4 is a pure player), which, as noted before, means that their hydrogen exposure represents a smaller percentage of their overall business activities.

Table 2 presents the clusters' compositions with a summary of each company's activity and degree of involvement in the hydrogen economy.

**Table 2:** Cluster groups of the Solactive Hydrogen Economy Index NTR and its components. Distinction between pure players (PP) and diversified (D) companies is according to Infinergia Consulting (2021), highlighting the three pure green hydrogen players (GPP) identified by Seeking Alpha (2021).

| Short Name | Cluster | Infinergia category | Activity |
|---|---|---|---|
| Sohydron | | | |
| Ceres | C1 | Pure Player (PP) | Fuel cell technology |
| Powerhouse | C1 | Diversified (D) | Hydrogen production process |
| AFC | C1 | Pure Player (PP) | Fuel cell (alkaline and PEM) |
| Cell Impact | C1 | Pure Player (PP) | Fuel cell components (flow plates) |
| FuelCell | C1 | Pure Player (PP) | Fuel cell and integrated hydrogen projects |
| PlugPower | C1 | Pure Player (PP) | Fuel cell systems |
| Ballard | C1 | Pure Player (PP) | Fuel cells with PEM technology |
| ITM Power | C1 | Pure Player (GPP) | Electrolyzers (PEM) and integrated projects |
| Nel | C1 | Pure Player (GPP) | Electrolyzers (alkaline and PEM) and hydrogen projects |
| Xebec | C1 | Diversified (D) | Hydrogen production process |
| McPhy | C1 | Pure Player (GPP) | Electrolyzers and integrated hydrogen projects |
| Orsted | C1 | Diversified (D) | Renewable energy (mainly wind) |
| Bloom | C1 | Pure Player (PP) | Fuel cell (solid oxide) power generators |
| Advent Tech | C1 | Pure Player (PP) | Fuel cell, flow batteries, hydrogen production |
| Doosan | C1 | Pure Player (PP) | Fuel cells |
| Cummins | C2 | Diversified (D) | Industrial engineering co. PEM electrolyzers and fuel cells |
| Hyundai | C2 | Diversified (D) | Automotive co. Fuel cell hydrogen vehicles |
| SFC | C2 | Pure Player (PP) | Fuel cells for the mobile industry |
| PowerCell | C2 | Pure Player (PP) | Fuel cells and integrated hydrogen projects |
| Weichai | C2 | Diversified (D) | Diesel engines co. Fuel cell hydrogen vehicles |

| | | | |
|---|---|---|---|
| Air Liq | C3 | Diversified (D) | Industrial gas co. Hydrogen producer (mainly gray) |
| Linde | C3 | Diversified (D) | Industrial gas co. Hydrogen producer (mainly gray) |
| Air Prod | C3 | Diversified (D) | Industrial gas co. Hydrogen producer (mainly gray) |
| Uniper | C3 | Diversified (D) | Energy co. Gas and renewables storage |
| Toyota | C3 | Diversified (D) | Automotive co. Hydrogen vehicles |
| Chemours | C4 | Diversified (D) | Chemical co. Materials for PEM membranes |
| Daimler | C4 | Diversified (D) | Automotive co. Fuel cells |
| Kolon | C4 | Diversified (D) | Chemical co. Components for fuel cells |
| J Matthey | C4 | Pure Player (PP) | Chemical co. Fuel cells. |
| Kyocera | C4 | Diversified (D) | Large conglomerate. Components for fuel cells (solid oxide) |
| N Sanso | C4 | Diversified (D) | Large conglomerate. Refueling stations for hydrogen vehicles |
| Siemens Eng | | Diversified (D) | Electrolyzers (PEM). Energy transition |

## 4. Methodology

In its weak form, the EMH assumes an inability to reach long-term, above-average, risk-adjusted profits with respect to the information contained in past prices (Fama, 1970, 1991). Long-term dependency in asset prices is inconsistent with the EMH while short-term dependencies change rapidly over time, forcing investors to adjust their trading strategies (Kristoufek, 2019).

Since Hurst's (1951) seminal paper, fractality has been applied in different areas. Authors such as Mandelbrot (2005) introduced the fractal postulates of physics into finance, in an attempt to find answers that are not provided by classical theories. Recent studies such as Di Matteo et al. (2003, 2005), Di Matteo (2007), Kristoufek (2010), Auer (2016), and Okorie and Lin (2020) are some examples of the applications of fractal analysis to financial time series. Additionally, fractality has been applied to test market efficiency in commodity markets, e.g., Kristoufek and Vosvrda (2014), Tiwari, Kumar, Pathak and Roubaud (2019), Kristoufek (2019), energy markets (e.g., Sensoy & Hacihasanoglu, 2014), or cryptocurrencies (Caporale, Gil-Alana & Plastun, 2018; Jiang, Nie & Ruan 2018). In addition to addressing the local memory issue, these studies point to the importance of correctly assessing long memory in asset returns due to the implications for asset pricing, because long-range dependency entails a violation of the weak EMH.

Therefore, to measure long-range dependence in a time series, we use the parameter H proposed by Hurst (1951), commonly known as the Hurst coefficient. Several techniques are available for computing H, including the rescaled-range (R/S) which is the traditional method.

For computing the R/S Hurst estimate, and following Weron (2002), the return time series is divided into *d* subseries of length, *n*. For each subseries, $Z_{i,m}$ ($m$ = 1,…, $d$ ; $i$=1,….., n), the sample mean ($E_m$) and standard deviation ($S_m$) are computed. The data are then normalized by subtracting the sample mean, $X_{i,m} = Z_{i,m} - E_m$, thus creating the cumulative time series, $Y_{i,m} = \sum_{j=1}^{i} X_{j,m}$. Subsequently, for each subseries, *m*, the rescaled range is obtained as follows:

$$\left(\frac{R}{S}\right)_m = \frac{max\left(Y_{1,m}, \ldots Y_{n,m}\right) - min\left(Y_{1,m}, \ldots Y_{n,m}\right)}{S_m} \qquad (1)$$

By calculating the mean value of the rescaled range for all subseries of length, *n*, the $\mathrm{R/S(n)}$ statistic is obtained. Repeating the process for divisions with different subseries lengths, *n*, the R/S(n) statistic asymptotically follows the relation (Mandelbrot, 1975):

$$\mathrm{R/S(n)} = C\, n^H, \qquad (2)$$

where C is a positive constant. By plotting log $(R/S(n))$ versus log (n) in a graph, the *H* coefficient for the series is obtained from the slope of the fitted regression line.

This Hurst coefficient (*H*) reveals long-run correlations in random processes and helps determine the existence of persistence in a given series. In independent processes, the value of *H* is expected to be approximately 0.5, representing a self-determining process in which the series observations are independent of previous observations. Values of $0 < H < 0.5$ describe an anti-persistent time series, with mean-reverting characteristics. The strength of the mean-reverting behavior increases as the Hurst exponent approaches zero (Mitra, 2012). Values of $0.5 < H < 1$ exhibit persistence, i.e., the values of the series in question increase or decrease in a broader range than could be possible from a random walk. Such series follow a trend for some time, which is later interrupted by abrupt discontinuities. The power of the trend-reinforcing behavior increases as the value of the Hurst exponent gets closer to one (Mitra, 2012).

This approach can be applied without detailed assumptions on the structure of the underlying model (thus, avoiding the normal distribution hypothesis followed by many statistical methods). Its superiority to more conventional methods of determining long-range dependence (such as autocorrelation analysis, spectral analysis, and variance ratios) has been widely demonstrated (Lo, 1991).

The method of detecting long-term dependence was modified by Annis and Lloyd (1976) to account for small sample bias, thus providing the methodology used in this work, the R/S-AL statistics.

As several authors have advised against the use of a unique technique for testing for long-memory in a given dataset (e.g., Teverovsky, Taqqu & Willinger, 1999; Willinger, Taqqu, & Teverovsky, 1999; Clark, 2005), this study applies, together with the improved estimation of H proposed by Annis and Lloyd (1976), two of the most robust methods found in the literature: the widely extended DFA, and the alternative GHE approach.

The DFA was first proposed by Peng et al. (1992) and Stanley et al. (1992) to avoid the spurious detection of correlations that are artifacts of non-stationarities in time series (Kantelhardt et al., 2002.)

We follow Weron (2002) in adapting the DFA methodology to our work:

Given a time series of log-returns, $X_i$, of N data points (i.e., $i = 1, \dots, N$), the detrended profile, $Y_i$, is obtained as the cumulative sum of $X_i$, subtracting the mean return $\left(\bar{X} = \frac{1}{N}\sum_{k=1}^{N} X_i\right)$. Hence:

$$Y_i = \sum_{j=1}^{i} \left(X_j - \bar{X}\right), \text{for } i = 1,2, \dots, N \tag{3}$$

The data series, $Y_i$, is then divided into $d$ contiguous subperiods, $y_i^m$, $m = 1, \dots, d$, each of length, $n$. For each subperiod, $m$, the local trend is found by fitting a straight line, $z_i^m$ , within the subperiod:

$$z_i^m = a\, y_i^m + b \tag{4}$$

The fluctuation is obtained using the corresponding variance between $y_i^m$ and its fitted value, $z_i^m$, as follows:

$$F_m(n) = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (y_i^m - z_i^m)^2} \tag{5}$$

The average fluctuation, $\overline{F(n)}$, is then obtained by averaging all the deviations, $F_m(n)$, obtained. The process is repeated for various time scales, $n$, while the scaling relationship is defined by

$$\bar{F}(n) = C\, n^{H}, \tag{6}$$

where *C* is the constant and *H* is the Hurst exponent. As suggested by Kristoufek (2010), a minimum subperiod length is set to 10 samples to avoid inefficient fitting and averaging.

The third method used in this study to examine long-term dependence in hydrogen-related stocks is the GHE method, which analyzes multifractal features of data and avoids the sensitivity of the original Hurst exponent to outliers.

The GHE was first introduced by Barabsi and Vicsek (1991) and generalized by Di Matteo et al. (2003, 2005) to study the degree of development of several financial markets. These studies have been followed by other authors, including Kristoufek (2010), Morales, Di Matteo, Gramatica and Aste (2012), Kristoufek and Vosvrda (2014), Sensoy (2013), and Jiang et al. (2018), among others.

Following Di Matteo (2005), we analyze the q-order moments of the distribution of the increments, which is a good characterization of the statistical evolution of a stochastic variable, *X(t)*. The $K_q(\tau)$ statistic is defined as

$$K_q(\tau) = \frac{\langle |X(t+\tau) - X(t)|^q \rangle}{\langle |X(t)|^q \rangle} \tag{7}$$

Here, the time-interval, τ, can vary between 1 and $\tau_{\max}$. According to Kristoufek (2010), the parameter, τ, can be understood as an investment horizon in financial terms.

*H(q)* is then defined for each time scale, τ, and each parameter, q, as follows (Sensoy, 2013):

$$K_q(\tau) \sim \tau^{qH(q)}, \tag{8}$$

where *H(q)* is computed from an average over a set of values corresponding to different values of $\tau_{\max}$ in $K_q(\tau)$.

In this study, the Hurst coefficient is used as a measure of the level of persistence of successive changes in hydrogen prices. Persistence (anti-persistence) refers to the probability of changes in one direction being succeeded by further changes in the same (opposite) direction (Batten & Ellis, 1996).

Together with the estimation of the three fractality coefficients for every single stock as well as for the Sohydron index, a rolling window analysis is performed on the index to detect the time evolution of its long-range dependence (Subsection 5.1). Additionally, with the aim of assessing the extent to which the observed behavior was affected by the SARS-Cov-2 pandemic, another fractal analysis is repeated for the last 242 days only, corresponding to the period from

July 2020 to June 2021 (Subsection 5.2). Finally, a rolling window analysis is also performed on each of the four clusters as well as on all the individual companies (Subsection 5.3).

To assess the statistical significance of the results, confidence intervals are obtained, following Weron's (2002) methodology, where 10,000 Gaussian white noise sequences (H=0) of a fixed length are simulated and 5% and 95% sample quantiles of the estimated Hurst coefficients are obtained. For the full study period, 660-length series are used to obtain confidence intervals. For the moving window approach, 242-length series are used.

## 5. Results and discussion

### 5.1 Stock and index fractal analysis

The Hurst coefficients obtained through the Annis-Lloyd corrected R/S analysis, extended DFA, and alternative GHE approach are presented in Table 3.

Single stocks show mixed results, most of which are in the realm of efficiency. Persistent cases mostly appear in C1, while C2, C3, and C4 display an overall random behavior. McPhy is the only company whose three estimators point to some persistency.

A first approach to the fractal structure of the Sohydron index provides two out of three Hurst coefficients just above the limit of the confidence interval. Nonetheless, the DFA estimator points to a random walk. Thus, overall, the results evidence a mild departure from the EMH for the entire period analyzed.

**Table 3:** Fractal analysis of stock and Sohydron index returns. Time series from November 16, 2018 to June 30, 2021. Grey-colored numbers refer to persistence results (1 > H > 0.5), while those in bold refer to anti-persistence results (0 < H < 0.5). Confidence intervals are shown at the bottom of the table.

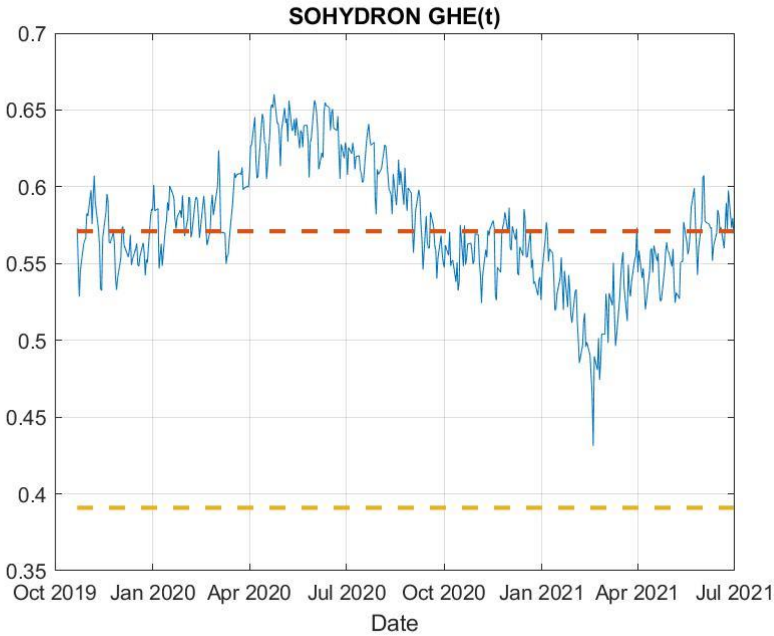
| Name | Hurst | DFA | GHE | Number Observations |
|---|---|---|---|---|
| Sohydron | 0.587 | 0.560 | 0.588 | 683 |
| *Cluster 1* | | | | |
| Ceres | 0.563 | 0.550 | 0.529 | 660 |
| Powerhouse | 0.538 | 0.530 | 0.560 | 660 |
| AFC | 0.555 | 0.587 | 0.587 | 660 |
| Cell Impact | 0.477 | 0.450 | 0.513 | 652 |
| FuelCell | 0.512 | 0.562 | 0.598 | 657 |
| PlugPower | 0.554 | 0.553 | 0.578 | 657 |
| Ballard | 0.502 | 0.501 | 0.531 | 657 |
| ITM Power | 0.498 | 0.510 | 0.460 | 659 |

| | | | | |
|---|---|---|---|---|
| Nel | 0.499 | 0.515 | 0.536 | 651 |
| Xebec | 0.542 | 0.554 | 0.551 | 657 |
| McPhy | 0.570 | 0.622 | 0.599 | 664 |
| Orsted | 0.539 | 0.498 | 0.513 | 646 |
| Bloom | 0.565 | 0.566 | 0.577 | 657 |
| Advent Tech | 0.474 | 0.520 | 0.453 | *484* |
| Doosan | 0.534 | 0.581 | 0.590 | *420* |
| *Cluster 2* | | | | |
| Cummins | 0.549 | 0.487 | 0.479 | 657 |
| Hyundai | 0.554 | 0.492 | 0.536 | 646 |
| SFC | **0.435** | 0.422 | 0.447 | 657 |
| PowerCell | 0.512 | 0.498 | 0.520 | 652 |
| Weichai | 0.540 | 0.510 | 0.521 | 644 |
| *Cluster 3* | | | | |
| Air Liq | 0.463 | 0.471 | 0.455 | 667 |
| Linde | 0.458 | 0.442 | 0.454 | 657 |
| Air Prod | 0.498 | 0.515 | 0.470 | 657 |
| Uniper | 0.527 | 0.442 | 0.495 | 658 |
| Toyota | 0.443 | **0.377** | 0.471 | 632 |
| *Cluster 4* | | | | |
| Chemours | 0.529 | 0.532 | 0.513 | 657 |
| Daimler | 0.506 | 0.486 | 0.567 | 661 |
| Kolon | 0.502 | 0.456 | 0.513 | 646 |
| J Matthey | 0.514 | 0.477 | 0.545 | 660 |
| Kyocera | 0.476 | 0.422 | **0.428** | 632 |
| N Sanso | 0.544 | 0.499 | 0.494 | 632 |
| *Insufficient observations* | | | | |
| Siemens Eng | 0.590 | 0.610 | 0.564 | *190* |

| Confidence Intervals | Hurst | DFA | GHE |
|---|---|---|---|
| 5 | 0.437 | 0.407 | 0.438 |
| 95 | 0.556 | 0.569 | 0.546 |

To better understand the dynamics of the returns, and following Kristoufek and Vosvrda (2014), we estimate the time-varying GHE estimator for the index on a moving window of 242 days, as shown in Figure 3.

**Figure 3:** Time evolution of the GHE Hurst coefficient for the Sohydron index. A rolling-window approach is used in which for each daily observation, t, H(t) is calculated using the previous-year data (242 daily observations). Confidence intervals are shown in broken lines.




Visual observation allows assessing the change in the fractal dynamics of the index' returns. The index moves from persistency at the time of the acute SARS-Cov-2 pandemic, to randomness from September 2020 on, approaching the limits of the confidence interval at the end of the analyzed period.

5.2 Fractal analysis in post-acute SARS-Cov-2 pandemic times

Like in Yaya, Ogbonna, Mudida and Abu (2021), who distinguish between a pre- and a post-crash period when testing for market efficiency, and under the suspicion that the time evolution of the fractal coefficient might be affected by the coronavirus SARS-CoV-2 (Covid-19) pandemic, a complementary analysis is conducted. Thus, the fractality analysis is repeated for the last 242 days (see Table 3).

By excluding the probable overreaction of investors during the first five months of the global pandemic (as the WHO declared the outbreak a Public Health Emergency of International Concern on January 30, 2020), we aim to obtain a clearer picture of the hydrogen players' stock price evolution.

**Table 3:** Post-acute SARS-CoV-2 pandemic Hurst coefficients for the July 2020/June 2021 period. Grey-colored numbers refer to persistence results, while those in bold type refer to anti-persistence. Confidence intervals are shown at the bottom of the table.

| Name | Hurst | DFA | GHE | Number Observations |
|---|---|---|---|---|
| Sohydron | 0.506 | 0.500 | 0.567 | 242 |
| *Cluster 1* | | | | |
| Ceres | 0.441 | 0.432 | 0.496 | 242 |
| Powerhouse | 0.509 | 0.591 | 0.542 | 242 |
| AFC | 0.574 | 0.663 | 0.629 | 242 |
| Cell Impact | 0.511 | 0.493 | 0.504 | 242 |
| FuelCell | 0.567 | 0.597 | 0.627 | 242 |
| PlugPower | 0.556 | 0.493 | 0.609 | 242 |
| Ballard | 0.540 | 0.493 | 0.591 | 242 |
| ITM Power | 0.505 | 0.467 | 0.485 | 242 |
| Nel | 0.507 | 0.544 | 0.534 | 242 |
| Xebec | 0.534 | 0.604 | 0.634 | 242 |
| McPhy | 0.466 | 0.426 | 0.450 | 242 |
| Orsted | 0.508 | 0.445 | 0.515 | 242 |
| Bloom | 0.528 | 0.494 | 0.540 | 242 |
| Advent Tech | 0.468 | 0.422 | 0.511 | 242 |
| Doosan | 0.465 | 0.425 | 0.504 | 242 |
| *Cluster 2* | | | | |
| Cummins | 0.457 | 0.442 | 0.411 | 242 |
| Hyundai | 0.503 | 0.479 | 0.485 | 242 |
| SFC | 0.482 | 0.452 | 0.422 | 242 |
| PowerCell | 0.491 | 0.456 | 0.498 | 242 |
| Weichai | 0.486 | 0.525 | 0.507 | 242 |
| *Cluster 3* | | | | |
| Air Liq | 0.504 | 0.429 | 0.457 | 242 |
| Linde | 0.529 | 0.481 | 0.459 | 242 |
| Air Prod | 0.458 | 0.443 | 0.468 | 242 |
| Uniper | 0.443 | 0.393 | 0.411 | 242 |
| Toyota | 0.487 | 0.474 | 0.482 | 242 |
| *Cluster 4* | | | | |
| Chemours | 0.455 | 0.423 | 0.393 | 242 |
| Daimler | 0.460 | 0.394 | 0.449 | 242 |

| | | | | |
|---|---|---|---|---|
| Kolon | 0.436 | 0.406 | 0.405 | 242 |
| J Matthey | 0.488 | 0.444 | 0.484 | 242 |
| Kyocera | **0.392** | **0.344** | 0.434 | 242 |
| N Sanso | 0.415 | **0.354** | **0.384** | 242 |
| *Insufficient observations* | | | | |
| Siemens Eng | 0.590 | 0.610 | 0.564 | *190* |

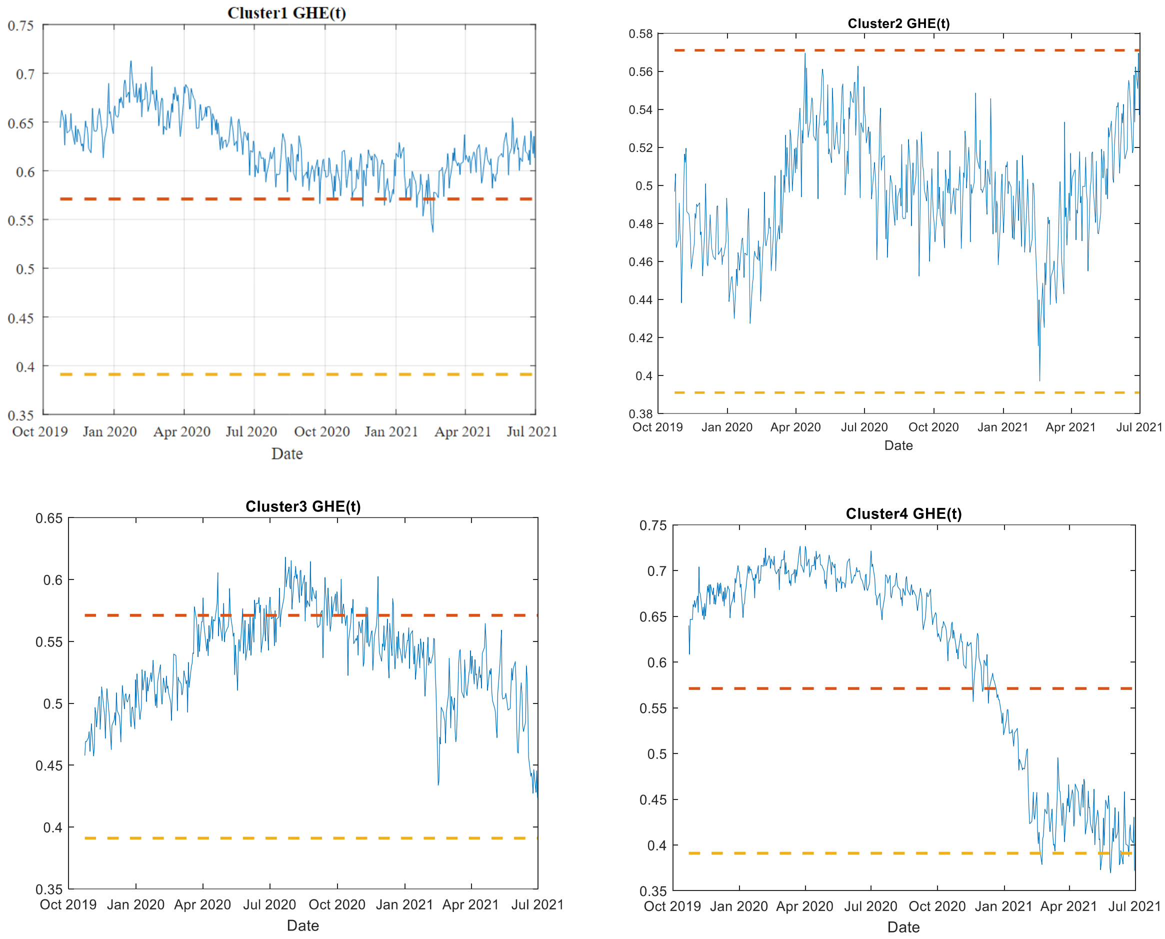
| Confidence Intervals | Hurst | DFA | GHE |
|---|---|---|---|
| 5 | 0.4069 | 0.359 | 0.390 |
| 95 | 0.588 | 0.612 | 0.571 |

The 95% confidence interval widens due to a decrease in the number of observations; however, together with the rolling window approach, the analysis evidences a return of the index to the efficiency area. The same can be said of most of the individual stocks. Thus, a persistent effect of the SARS-Cov-2 pandemic is evidenced, as well as a higher hydrogen player market efficiency during ordinary times.

### 5.3 Rolling window analysis for each cluster and their components

The results in Tables 2 and 3 point to several companies in C1 displaying persistent behavior, significant although very close to the confidence intervals, which is not the case in other clusters. To obtain a deeper understanding, we analyze the time evolution of the Hurst coefficient for each of the four clusters under study (Figure 4) together with their individual components (Figures 5 to 8). To assess the clusters' long memory evolution, the time series are obtained by summing all log-returns of the companies belonging to each of them. This allows a comparison of the groups’ dynamics.

**Figure 4:** Time evolution of the GHE Hurst coefficient for the sum of the log-returns of the stocks in each cluster obtained in Section 3. A rolling window approach is used in which for each daily observation, t, H(t) is calculated using the previous-year data (242 daily observations).

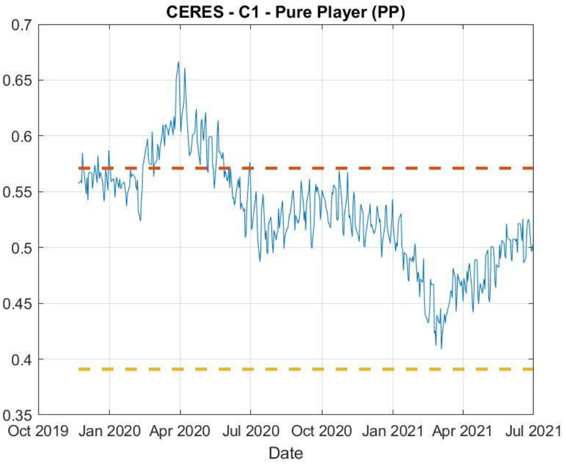


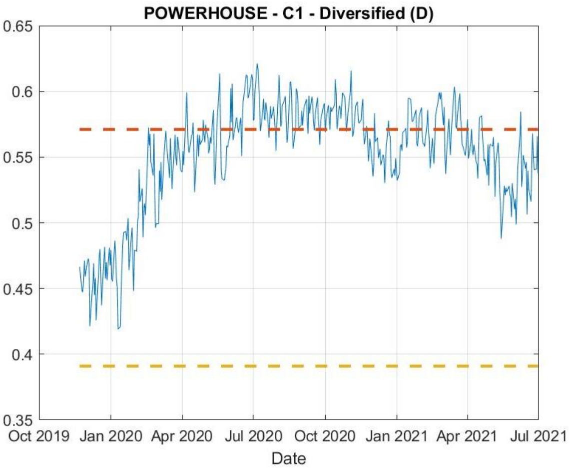

Remarkable differences are observed among the four clusters. C1 is the largest, with 10 of its 15 components being pure players, and shows distinctive persistency over the 3-year period, suggesting trending behavior.

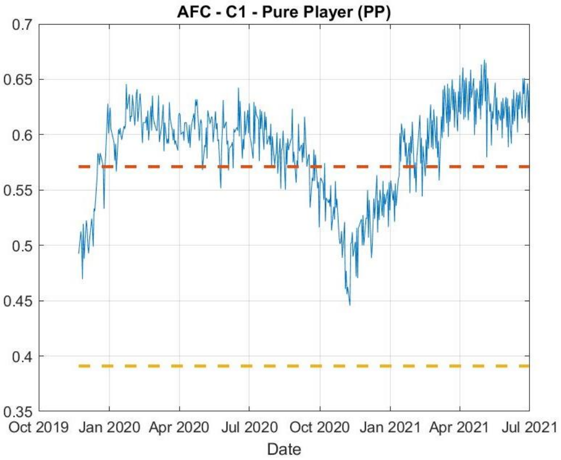
The evolution of the Sohydron index (Figure 3) resembles the time-variation of C1 (Figure 4), validating it as an adequate proxy for hydrogen investing or ESG diversification purposes. This also renders the Sohydron index a suitable underlying asset for affordable investment products, such as ETFs, enabling retail investors to get exposure to the hydrogen economy.

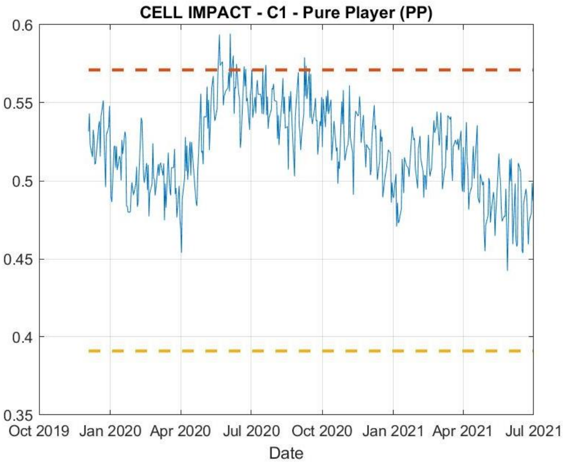
Not all the stocks in C1 behave the same, as already shown in the H parameter estimators (Tables 2 and 3). The C1 individual stocks' rolling window estimations (Figure 5) graphically evidence these differences.

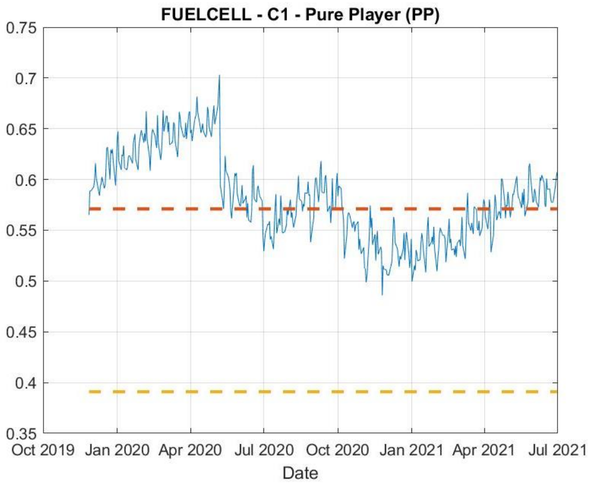
**Figure 5:** Time evolution of the GHE Hurst coefficient for the stocks in C1. A rolling-window approach is used in which for each daily observation, t, H(t) is calculated using the previous-year data (242 daily observations).

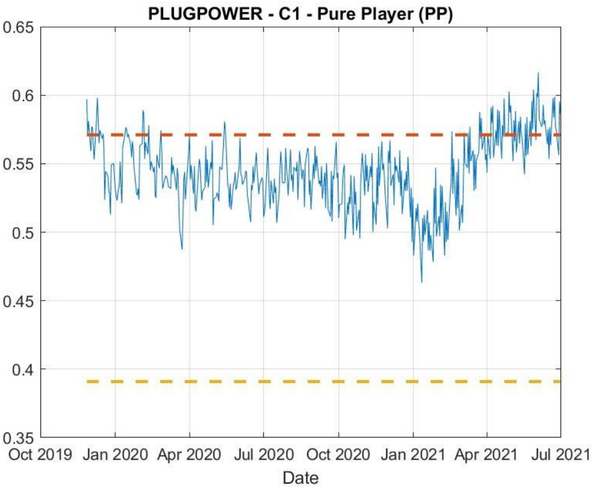

CERES - C1 - Pure Player (PP)
0.7
0.65
0.6
0.55
0.5
0.45
0.4
0.35
Oct 2019 Jan 2020 Apr 2020 Jul 2020 Oct 2020 Jan 2021 Apr 2021 Jul 2021
Date

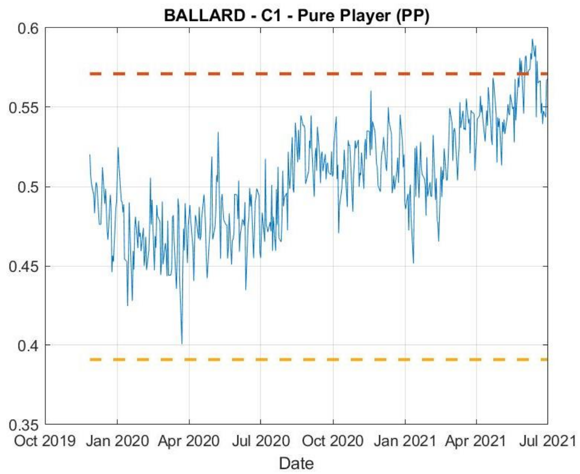

POWERHOUSE - C1 - Diversified (D)
0.65
0.6
0.55
0.5
0.45
0.4
0.35
Oct 2019 Jan 2020 Apr 2020 Jul 2020 Oct 2020 Jan 2021 Apr 2021 Jul 2021
Date

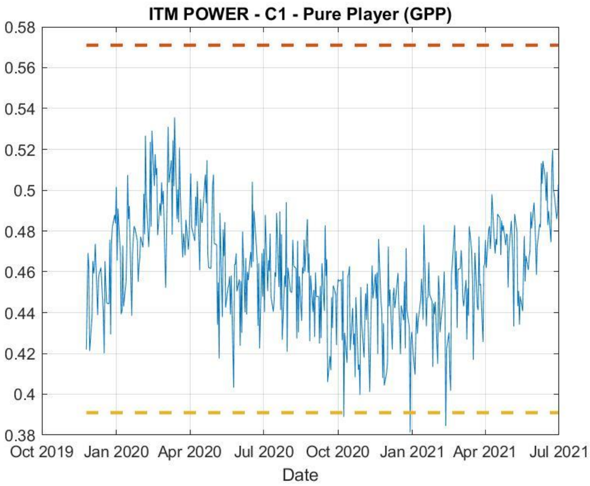

AFC - C1 - Pure Player (PP)
0.7
0.65
0.6
0.55
0.5
0.45
0.4
0.35
Oct 2019 Jan 2020 Apr 2020 Jul 2020 Oct 2020 Jan 2021 Apr 2021 Jul 2021
Date

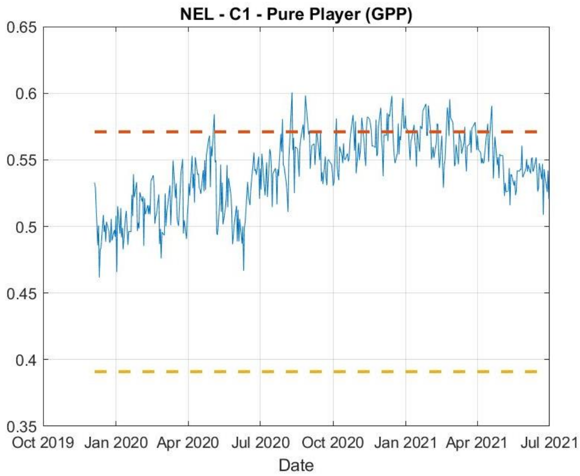

CELL IMPACT - C1 - Pure Player (PP)
0.6
0.55
0.5
0.45
0.4
0.35
Oct 2019 Jan 2020 Apr 2020 Jul 2020 Oct 2020 Jan 2021 Apr 2021 Jul 2021
Date

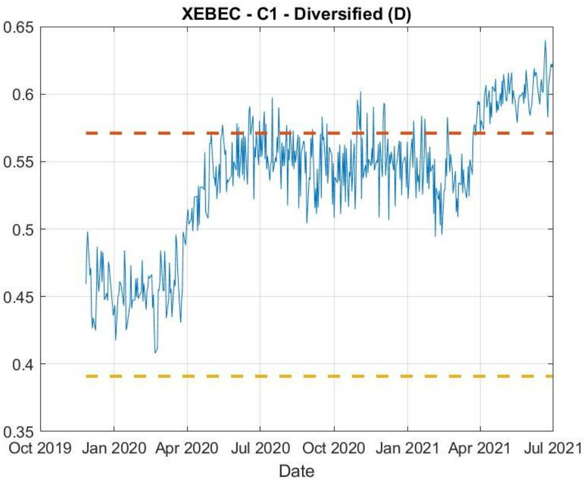

FUELCELL - C1 - Pure Player (PP)
0.75
0.7
0.65
0.6
0.55
0.5
0.45
0.4
0.35
Oct 2019 Jan 2020 Apr 2020 Jul 2020 Oct 2020 Jan 2021 Apr 2021 Jul 2021
Date

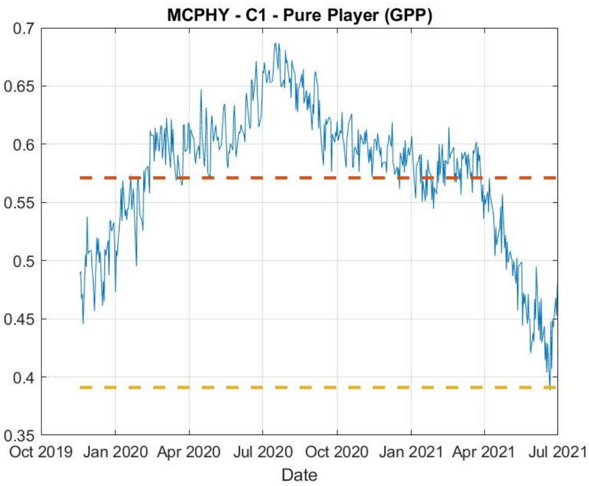

PLUGPOWER - C1 - Pure Player (PP)
0.65
0.6
0.55
0.5
0.45
0.4
0.35
Oct 2019 Jan 2020 Apr 2020 Jul 2020 Oct 2020 Jan 2021 Apr 2021 Jul 2021
Date

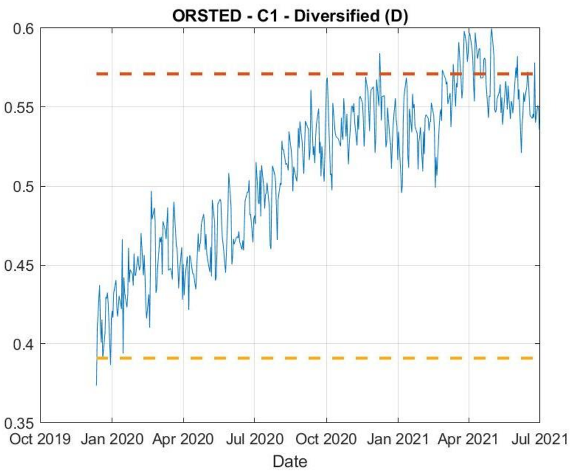

BALLARD - C1 - Pure Player (PP)
0.6
0.55
0.5
0.45
0.4
0.35
Oct 2019 Jan 2020 Apr 2020 Jul 2020 Oct 2020 Jan 2021 Apr 2021 Jul 2021
Date

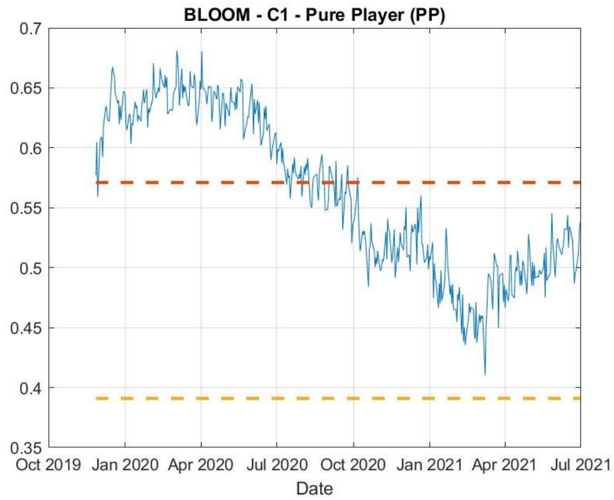

ITM POWER - C1 - Pure Player (GPP)
0.58
0.56
0.54
0.52
0.5
0.48
0.46
0.44
0.42
0.4
0.38
Oct 2019 Jan 2020 Apr 2020 Jul 2020 Oct 2020 Jan 2021 Apr 2021 Jul 2021
Date


NEL - C1 - Pure Player (GPP)
0.65
0.6
0.55
0.5
0.45
0.4
0.35
Oct 2019 Jan 2020 Apr 2020 Jul 2020 Oct 2020 Jan 2021 Apr 2021 Jul 2021
Date


XEBEC - C1 - Diversified (D)
0.65
0.6
0.55
0.5
0.45
0.4
0.35
Oct 2019 Jan 2020 Apr 2020 Jul 2020 Oct 2020 Jan 2021 Apr 2021 Jul 2021
Date


MCPHY - C1 - Pure Player (GPP)
0.7
0.65
0.6
0.55
0.5
0.45
0.4
0.35
Oct 2019 Jan 2020 Apr 2020 Jul 2020 Oct 2020 Jan 2021 Apr 2021 Jul 2021
Date

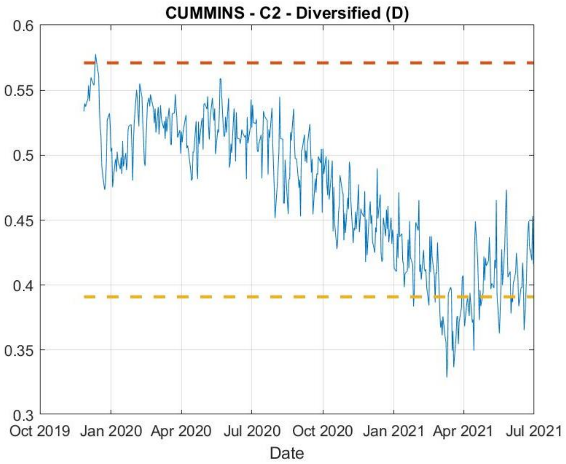

ORSTED - C1 - Diversified (D)
0.6
0.55
0.5
0.45
0.4
0.35
Oct 2019 Jan 2020 Apr 2020 Jul 2020 Oct 2020 Jan 2021 Apr 2021 Jul 2021
Date

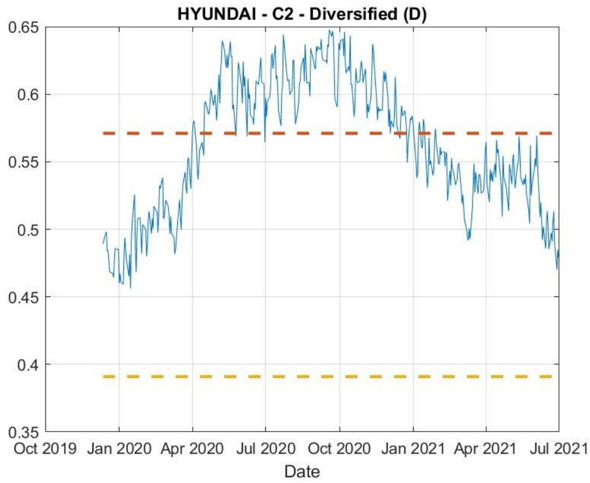


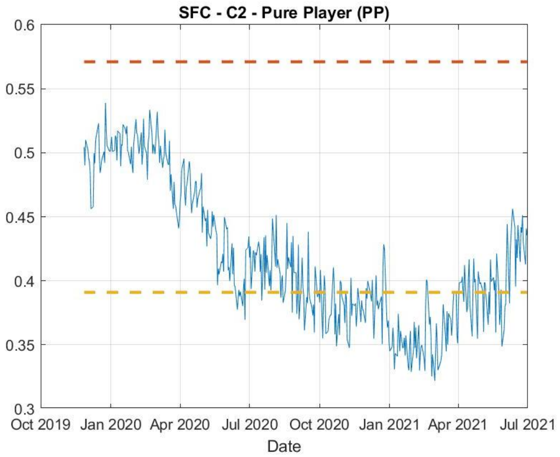

A remarkable feature of these charts is the time variation between randomness and persistency in all 15 stocks. However, this time evolution does not seem to follow the same underlying pattern. Indeed, the trend shifts neither coincide in direction nor happen simultaneously. Nevertheless, at the end of the period analyzed, 11 of the 15 companies show random behavior, including the three companies classified as GPPs. Thus, although some inefficiencies have been revealed during the stress period (SARS-Cov-2 pandemic), an overall trend to market efficiency is evidenced, confirming them as good investment options for gaining exposure to the hydrogen economy.

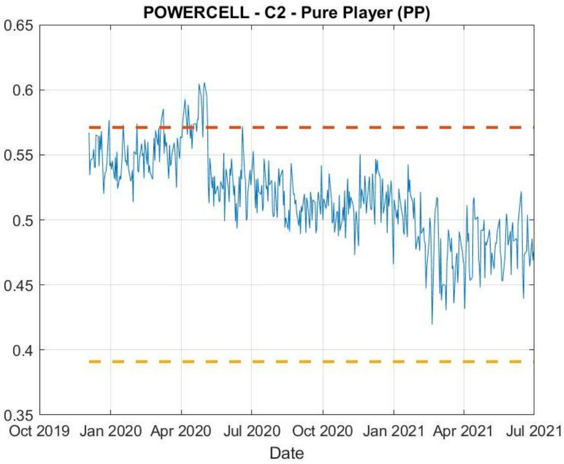
C2 remains in the efficient territory during the entire sample period, as shown in Figure 4. Despite showing a trend-reinforcing dynamic that approaches the efficiency-persistency frontier from March 2021, C2 never leaves randomness. Moreover, all five individual stocks´ returns remain in the random area and may also represent good opportunities for investors.

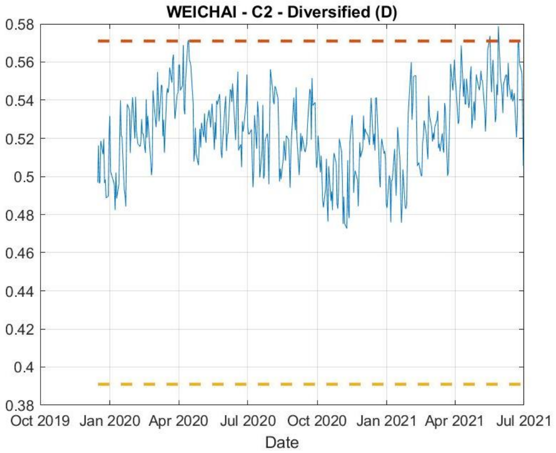
**Figure 6:** Time evolution of the GHE Hurst coefficient for the stocks in C2. A rolling window approach is used in which for each daily observation, t, *H(t)* is calculated using the previous-year data (242 daily observations).



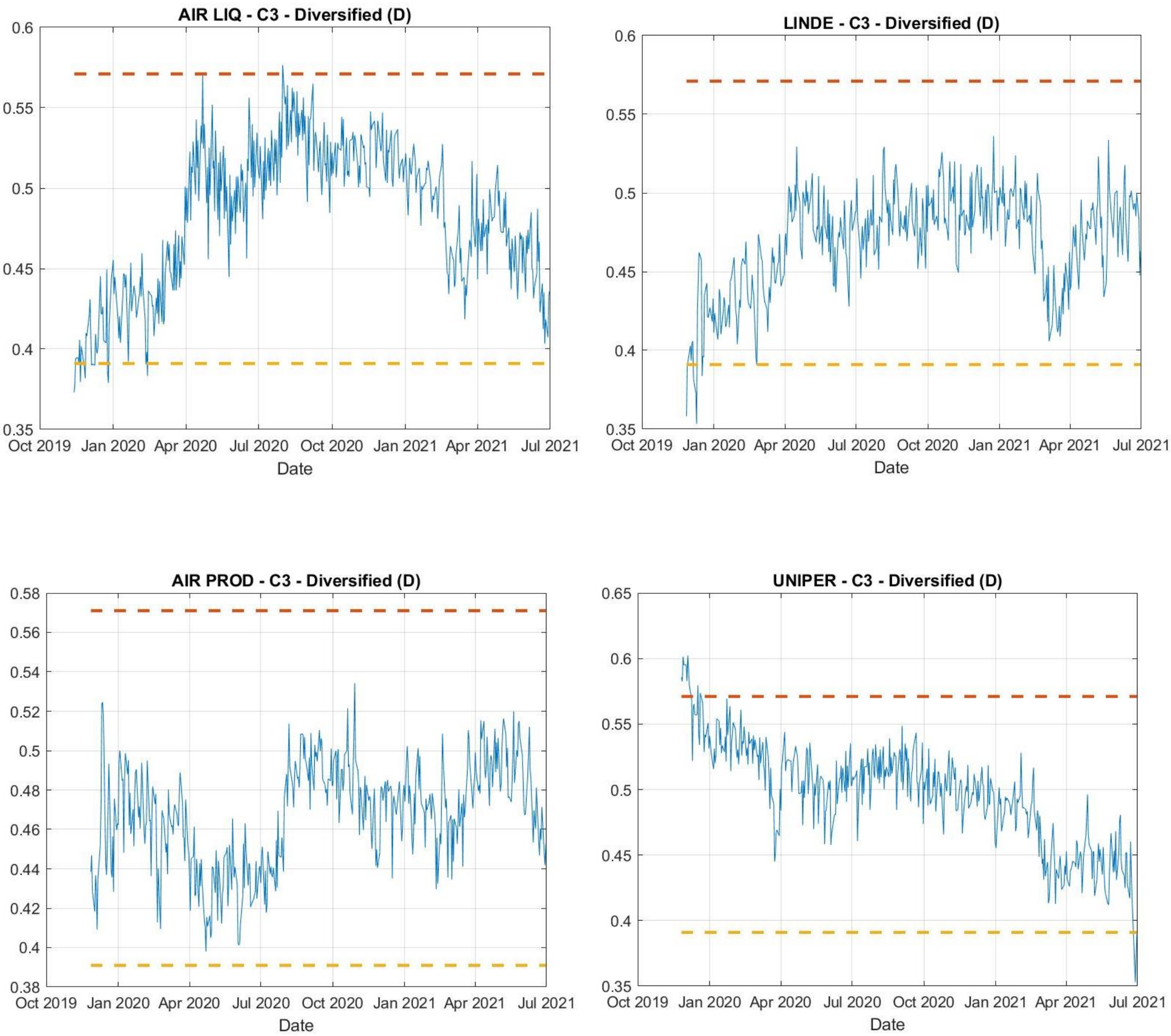



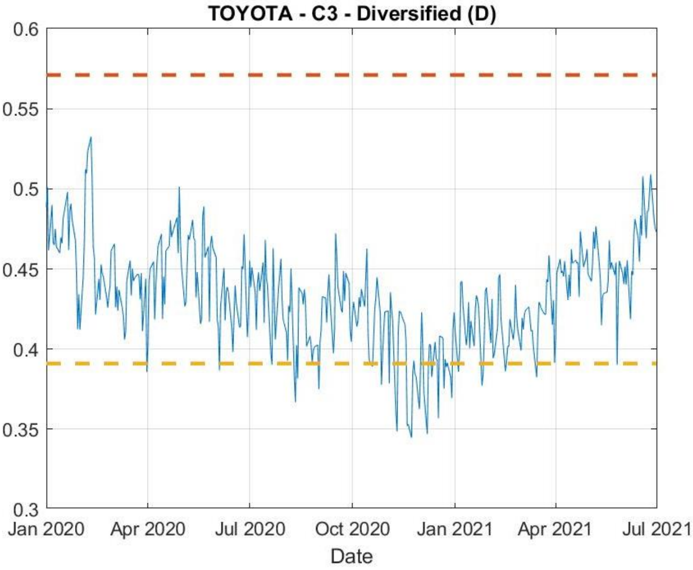




C3 shows overall market efficiency. Although it experiences persistent behavior during the acute phase of the pandemic, it ends well into random territory. These five companies are diversified multiplayers, with their hydrogen related activities still small relative to their general businesses. Individually, all predominantly show market efficiency.

**Figure 7:** Time evolution of the GHE Hurst coefficient for the stocks in C3. A rolling window approach is used in which for each daily observation, t, *H(t)* is calculated using the previous-year data (242 daily observations).

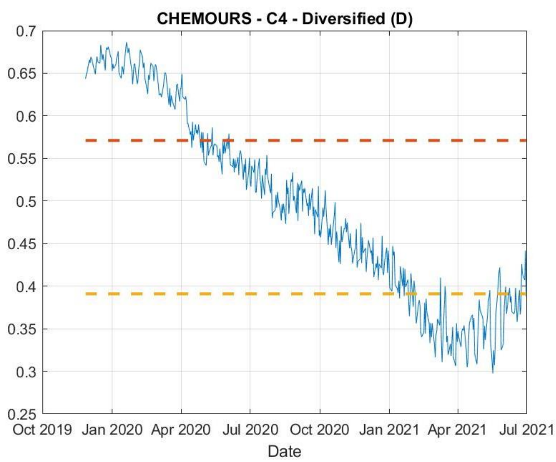


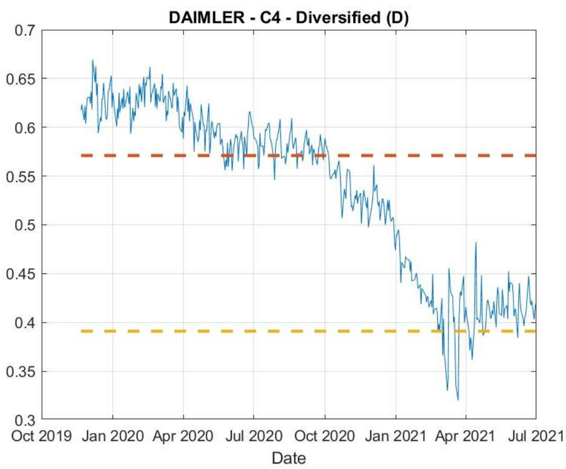


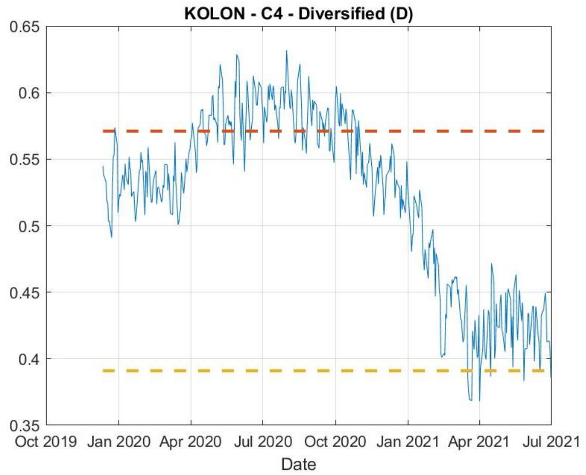

C4, similar to C3, comprises diversified multiplayer stocks with weaker exposure to hydrogen. However, as in C1, a tendency from persistency to market efficiency is evidenced during the time series analyzed.

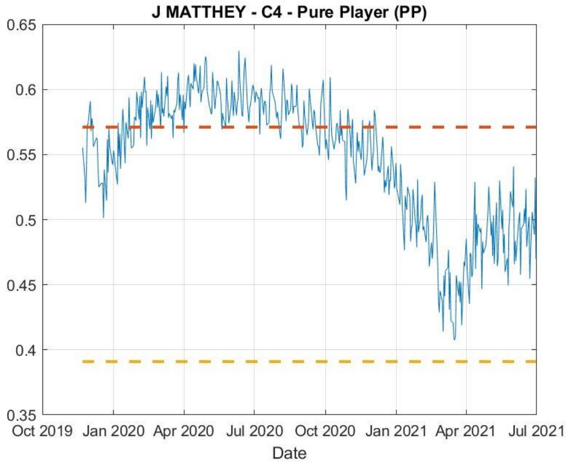
Individually, the charts of all six stocks' exhibit a downward trend, suggesting a slight mean-reverting dynamic until March 2021. However, all of them correct this movement ending within the efficiency confidence intervals.

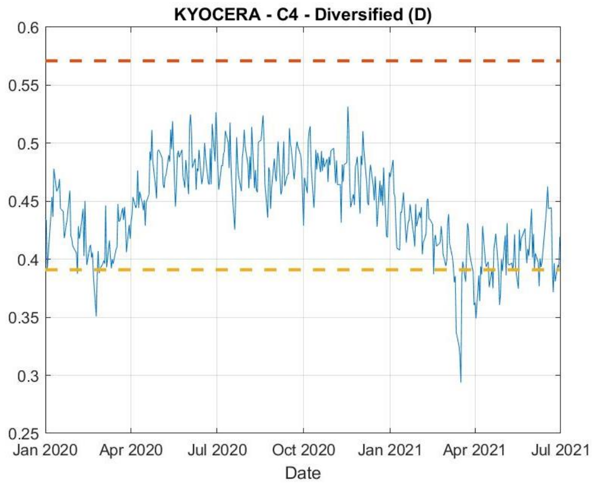
**Figure 8:** Time evolution of the GHE Hurst coefficient for C4 stocks. A rolling window approach is used in which for each daily observation, t, H(t) is calculated using the previous-year data (242 daily observations).

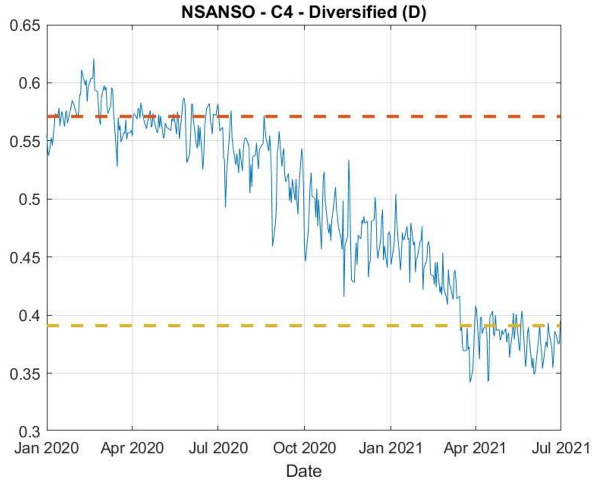





In summary, results evidence different behaviors among the Sohydron index constituents. Companies with milder exposure to hydrogen exhibit higher market efficiency. Most of the pure players show an overall slight trend-reinforcing conduct, evidenced by some of the estimators in table 2. However, the rolling-window approach and post-acute SARS-CoV-2 pandemic fractal coefficients show a time variation of market efficiency (aligned with results in Zhang (2013) for oil markets or Sensoy and Hacihasanoglu (2013) for energy futures, among others) and confirm the current trend toward randomness.

The findings are consistent with the increasing interest perceived from investors and regulators, and evidence that departures from randomness are corrected and are not permanent. Thus, the aggregated results point to early market efficiency in hydrogen players.

## 6. Concluding Remarks.

This study uses a fractal methodology to examine hydrogen players' efficient behavior. It is among the first works at the crossroads of ESG investment and efficient price behavior and is a pioneering study in hydrogen energy finance.

The analysis shows that players participating in the hydrogen economy undergo lively dynamics during the full sample and evidence an overall weak form of market efficiency.

The Sohydron index and some individual stocks (mainly pure players) show some alternating episodes of low and high random behavior in their Hurst coefficients. The mild departures from efficiency primarily occur during the acute SARS-Cov-2 pandemic, consistent with preceding studies which relate persistency to the most impactful market shocks and stock market overreaction (see Dima, Dima, & Ioan, 2022).

A possible explanation for the few stocks that maintain a trend-reinforcing behavior in the post-pandemic period (primarily players with stronger exposure to hydrogen) may be connected to investors' responses to public policy measures and incentives to boost the hydrogen economy, becoming a more demand-driven market dynamic in those cases. However, we find that financial frictions such as temporary market inefficiencies, shouldn´t be a barrier to the development of the hydrogen economy.

The worldwide Sohydron index, with its heterogenous components (which show a very different exposure grade to the hydrogen economy), is revealed as an appropriate tool. It emerges as a good proxy to track the evolution of the hydrogen economy, and as a suitable underlying asset for investment products seeking to gain exposure to this market. It therefore becomes a good vehicle for portfolios that follow ESG criteria in their diversification strategies.

To the best of our knowledge, ours is the first study to address efficiency in hydrogen-related stock prices. The results point to reassuring implications for investors and regulators, as hydrogen is attracting increasing attention from governments and policy makers pursuing carbon neutrality, and from investors interested in ESG investment opportunities.

With the hydrogen economy gaining momentum, we expect to see a hydrogen-commodity quote at some stage, which will enable efficiency studies in specific hydrogen markets.

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## Appendix: Other hydrogen indices

The Global Hydrogen Index is a EUR Net Return Index first published by ICF BANK AG[2] on February 26, 2020. The index shows the stock performance of a maximum of 25 companies involved in the development and production of green hydrogen and hydrogen transportation, as well as active fuel cell corporations. Every index component is equally weighted, while the requirements for inclusion are a market capitalization of at least €100 million at the time of inclusion and a daily average trading volume over a period of three months of at least €100,000. Since September 18, 2020, the index is composed by the 20 stocks shown in Table A.2.
Similarly, ICF BANK AG has published the Global Hydrogen Index II EUR Net Return since September 14, 2020. The latter index only differs from the former in that the daily average trading volume of the components over a period of three months is required to be at least €3,000,000. The current components are the same in the two indices (Table A.2).
These indices were discarded as hydrogen proxies due to their short time frames; however, 11 of their components are also included in the selected proxy (Sohydron).

Table A.1

| Name | Weighting % |
|---|---|
| Linde PLC | 5 |
| Umicore | 5 |
| Cummins Inc | 5 |
| Bloom Energy Corp | 5 |
| Olin corp | 5 |
| Powercell Sweden AB | 5 |
| Westlake Chemical Corp | 5 |
| Nel asa | 5 |
| Fuelcell Energy Inc | 5 |
| Air Liquide SA | 5 |

[2] www.icf-markets.de

| | |
|---|---|
| Ballard Systems Inc | 5 |
| Alstom | 5 |
| Paccar inc | 5 |
| Pbf Energy Inc | 5 |
| Worthington industries | 5 |
| Air Chemicals Inc | 5 |
| The Chemours Company | 5 |
| General Motors Co | 5 |
| Plug Power Inc | 5 |
| Chart Industries Inc | 5 |

The remaining ICF hydrogen-related indices, such as the Hydrogen Select Index EUR Net Return and the European Hydrogen Focus Index EUR Net Return, were discarded for being local portfolios.

The Korean FnGuide Hydrogen Economy Theme Index is a price return index that comprises companies listed on the KOSPI/KOSDAQ market, which is classified as a hydrogen economy industry under a keyword-score computed by text-analysis. According to Bloomberg, the index was first published on June 12, 2017, is rebalanced half-yearly, is free-float market cap weighted, and prices are set in South Korean won. Regrettably, having consulted the Bloomberg data team, there seems to be no way to establish contact with the index issuer regarding its components. Furthermore, it is a local hydrogen-related portfolio.