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MODELLING VOLATILITY OF GREEN INVESTMENT: EVIDENCE FROM HYDROGEN FINANCING

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ABSTRACT:

The global clean energy demand has increased in recent years to address sustainability. At present, hydrogen is considered a cornerstone of sustainable energy solutions. Due to the increased demand for global sustainability, hydrogen has experienced significant growth in demand, production, and research. To ensure its viability and widespread adoption, understanding and managing the inherent risks associated with hydrogen investments is crucial for fostering a stable and attractive environment for continued growth and innovation in this vital sector. Moreover, the hydrogen investment can be influenced by the financial market condition represented by the Volatility Index (VIX). Surprisingly, the volatility dynamics and risk profiles of this growing sector, particularly the influence of broader financial market conditions as reflected by the VIX, remain largely unexplored. This gap in understanding presents a challenge to investors and policymakers seeking to foster stable and sustainable growth in hydrogen financing. To rectify this situation, this research addresses the gap in understanding and predicting hydrogen return volatility by applying various GARCH-type models to the S&P hydrogen economy index and CBOE Volatility Index (VIX) from May 2019 to May 2025. By applying a set of GARCH (generalized autoregressive conditional heteroskedasticity) approaches, the study reveals strong proof of volatility clustering and unequal effects of shocks on hydrogen returns. The TGARCH model highlights the prominence of negative shocks, while the EGARCH model indicates a larger impact from positive shocks. Furthermore, the study shows that the content of information in the Volatility Index (VIX) is an essential determinant to explain the variation in the hydrogen return. The incorporation of the Volatility Index (VIX) into the GARCH variance equation also improves the volatility forecasts of the hydrogen return.

The outcomes of the analysis could be helpful for investors, decision-makers, and stakeholders in developing effective risk management strategies for green energy projects within the emerging hydrogen financing sector. In the future, to contribute to the existing literature, the researchers can explore this area by expanding datasets, adding more macroeconomic factors, investigating specific event impacts, analysing interdependencies with other renewable energy sectors, employing advanced econometric techniques, and considering behavioural influences to further refine our understanding and forecasting capabilities.

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KEYWORDS: Volatility, Green investment, Hydrogen, clean energy, Sustainability,

JEL Classification: C58, Q41, Q48

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Abbreviations

IEA	International Energy Agency
VIX	Volatility Index
PCA	Paris Climate Agreement
IRENA	International Renewable Energy Agency
COVAR	Covariance
ARCH	Autoregressive Conditional Heteroskedasticity.
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
TGARCH	Threshold Generalized Autoregressive Conditional Heteroskedasticity
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
CGARCH	Component GARCH
IGARCH	Integrated GARCH
APGARCH	Asymmetric Power GARCH
OLS	Ordinary Least Squares
CBOE	Chicago Board Options Exchange
ADF	The Augmented Dickey Fuller and
PP	Phillips Perron

1 INTRODUCTION

1.1 Background and motivation

Hydrogen has recently garnered significant attention worldwide, driven by increasing apprehensions regarding global warming (Hosseini & Wahid, 2016). Based on the prediction of the IEA, the energy demand of the world will escalate by up to 30 % by 2030, resulting in increased CO2 discharge for the dependence of the economies on fossil fuels, especially oil and coal. This increased energy demand will intensify catastrophic climate disruption (Reuter et al., 2020). To address these issues, many countries throughout the world have proposed a low-emission strategy for 2050 to ensure growth and socioeconomic stability (Noussan et al., 2021). These approaches have steered the focus of decision-makers, governments, regulators, and investors towards the importance of green investment activities, from traditional carbon-focused investment to green investment in renewable energy resources (Naeem et al., 2023).

Recently, the global focus on green energy has strengthened, motivated by the Paris Climate Agreement (PCA) enforced in 2016. This agreement intends to reduce carbon emissions collaboratively, with all parties committing to achieve zero carbon emissions by 2050. The agreement's inclusive goal is to threshold global warming to well below 2 degrees Celsius through a reduction in fossil fuel based energy by increasing the reliance on renewable energy sources (Rubbaniy et al., 2024). Hydrogen is perceived as a foundation of the energy transition essential for the global society to achieve the Sustainable Development Goals for 2030 (Corzo Santamaría et al., 2022). As a result, the renewable energy sector is undergoing significant expansion, with the International Renewable Energy Agency (IRENA) forecasting an increase from 16% in 2020 to a targeted 77% in the global energy mix by 2050 (Rubbaniy et al., 2024).

Hydrogen is a pristine and vibrant source of fuel and possibly one of the most promising fuel sources of the future. This is thanks to its global availability and the fact that water

is its only by-product (Demirbas & Bamufleh, 2017). Hydrogen is considered a vital element of a low-carbon economic system due to its potential as a clean energy source and its adaptability to a wide range of uses, such as industrial operations, transportation, and heating globally. The approach of sustainable development has developed into a strategy that intends to address human needs while preserving harmony with the Earth's environment (Barreto et al., 2003). The IEA offers the Sustainable Development Scenario, which aims to model and promote pathways for energy production and consumption that balance economic growth with environmental protection. This framework emphasises the essential contribution of countries in formulating plans and outlines for the global energy system in the future. Furthermore, it evaluates additional key elements, including insights, technological expenses, resource availability, corporate responsibilities to sustainability, and energy costs. Hydrogen has obtained particular concentration in this evaluation for its high-quality, optimal, harmless, and tidy applications. Hence, a framework based on hydrogen is acknowledged as a positive and doable choice to meet sustainability goals in the long term (Barreto et al., 2003).

As a sustainable energy source, the performance of hydrogen depends on the various production methods. Comprehending its contribution to eco-friendliness necessitates distinguishing its three primary forms: blue, grey, and green. Each type is featured by its distinct ecological impact, acting differently from the eco-friendly initiative (Lucey et al., 2024).

The predominant type of Grey hydrogen is produced by steam processing of fossil gas, which emits considerable amounts of CO2. A similar method is applied in Blue hydrogen production, but it intends to seize and stockpile the carbon discharge underground. This process has the potential to minimise CO2 release, but it has yet to be revealed at a meaningful scale. Due to the high dependence on fossil fuels, these two methods could be more correctly identified as ’fossil hydrogen’. Conversely, green hydrogen acts as an environmentally sustainable choice, which is produced from sustainable energy sources, such as water, by electrolysing, and brings considerably lower carbon outputs. Multiple

cutting-edge methods are designed to generate eco-friendly green hydrogen. To produce green hydrogen cost-effectively and efficiently, the advanced electrolysis methods have already emerged as the best method (Lucey et al., 2024).

At present, hydrogen is considered as a versatile and clean energy carrier with significant potential to transform the global energy landscape. The ability to be produced from diverse sources and decarbonizing, hydrogen has potential as a sustainable energy solution. All the nations of the world are concerned about environmental hazards and working on sustainability. Consequently, hydrogen could be a promising pathway towards sustainability and sustainable development.

To ensure a sustainable energy future, a forward-thinking investment in clean technologies like hydrogen is highly demanded because it has enormous potential as a green energy carrier. Moreover, the investment in hydrogen largely depends on the risk pattern in the hydrogen sector. These days, the financial marketplace of hydrogen projects is still immature and often characterized by high volatility and uncertainty.

Understanding the volatility dynamics and the factors that drive this volatility is essential for investors, decision-makers, and interested parties to make optimal decisions, allocate resources efficiently, and foster stable investment environments. Furthermore, investigating the volatility of hydrogen financing is crucial in order to recognize the patterns of risks to make outcomes of the investment more predictable and find effective ways to minimize the risks in the hydrogen economy. The understanding of the risk dynamics of hydrogen investment will facilitate a more robust growth of the hydrogen sector, driving the globe towards adopting renewable energies, cutting greenhouse gas emissions, and aiding long-term climate goals. The motivation of the study is to provide some worthwhile insights into the risk dynamics of hydrogen return. Furthermore, the study will explore the association between macroeconomic shocks and the volatility in the return of hydrogen that will boost the financial stability and resilience in the emerging green hydrogen economy.

There have been studies carried out about the green investment, particularly in hydrogen, by a select number of researchers, focusing on the inter-relationship and risk dynamics of hydrogen with major asset classes, hydrogen-related assets performance, and risks mitigation success of the hydrogen economy, hydrogen production, role of hydrogen economy, and significance of hydrogen as an eco-friendly clean energy. Most of them examine the role of hydrogen as an energy solution and the connection of hydrogen to traditional asset classes. To date, the volatility dynamics of hydrogen as a green investment still remain unclear. Therefore, this volatility modelling issue will be considered in the thesis. The main research papers in leading journals are Lucey et al. (2024) in the Journal of Renewable and Sustainable Energy Reviews, Rubbaniy et al. (2024) in the Journal of Cleaner Production, as well as Noussan and Raimondi (2021) in the Journal of Sustainability. Further details about their contribution and studies will be examined in the literature review section.

1.2 Purpose of the study

The study aims to model the volatility of hydrogen return and identify the best-fitted model to represent the volatility dynamics of the hydrogen return. The analysis employs the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approaches (Bollerslev, 1986; Glosten et al., 1993; Nelson, 1991; Ding et al., 1993) to model the volatility in hydrogen return. Furthermore, the study identifies the influence, forecast ability, and explanatory power of market instability represented by the volatility index (VIX) on the hydrogen return volatility.

To quantify the influence and explanatory power of the volatility index (VIX) on the volatility of hydrogen return, the study incorporates the volatility index (VIX) into the variance equations of the GARCH models.

The potential hypotheses guiding this research are H1: the volatility clustering exists in the hydrogen return. H2: The market instability represented by the volatility index (VIX)

has an association with the volatility of hydrogen return and helps to improve the forecasting power of the models. This study will test these hypotheses through empirical analysis of relevant data points.

1.3 Niche of the Research

Although green finance has received growing attention, most studies focus on established sectors like solar and wind energy. While governments and private companies throughout the world are putting significant resources into the development of hydrogen technologies, there remains a high number of unsolved issues (Noussan et al., 2021). Research on the financial behaviour and volatility of emerging green technologies—particularly hydrogen financing—remains scarce. The current knowledge base on green finance predominantly concentrates on well-established renewable energy sources such as wind power and solar. Therefore, a noticeable gap exists in the understanding of risk profiles of emerging green technologies, like hydrogen. This research gap presents a problem, as high volatility in hydrogen financing poses a significant concern for investors, potentially hindering the flow of capital required for a sustainable energy transition.

To address the research gap, this study seeks to answer the following question:
RQ1: Does volatility clustering exist in hydrogen return? Investigating this question relates to exploring the risk nature of green investments. If volatility clustering exists, it indicates that periods of high risk tend to persist, which is crucial for modelling and forecasting hydrogen investment risks accurately. This insight can help investors and policymakers develop better risk management strategies.

RQ2: Is the investment in hydrogen risky? This question will investigate the overall risk or volatility of hydrogen investments to understand their level of risk.

RQ3: How do macroeconomic factors influence hydrogen financing volatility? This question aims to quantify the impact of broader economic conditions on hydrogen investment risk.

RQ4: What are the factors that influence hydrogen return? This question aims to identify some elements or conditions that affect hydrogen return.

RQ5: What are the potential policy significances of this research for attracting investment into the hydrogen sector and mitigating financial risks associated with hydrogen financing? This research question will explore the potential for policy interventions to stabilize hydrogen markets and incentivize green investment.

The sustainability largely depends on green investments like hydrogen. A better understanding of the volatility in the hydrogen sector is essential. This understanding of the risk profile in hydrogen can attract more investment, boost the adoption of sustainable technologies, and help to realize the broader objectives in mitigating climate change. Therefore, this research intends to enhance the understanding of the volatility dynamics within the hydrogen financing landscape for donating to the growth and stability of the sector.

1.4 Intended contribution

The study will contribute to filling a critical gap in the understanding of volatility dynamics in hydrogen-related investments, which are crucial for the shift to an eco-friendly energy future. By evolving and deploying sophisticated modelling approaches, the study will offer important insight into the risks and uncertainties within the hydrogen financing. The findings will help investors, policymakers, and other stakeholders to develop better risk avoidance strategies to improve the stability and attractiveness of the investment ecosystem for green and sustainable energy projects. Additionally, this research will add insights to the current knowledge base related to green finance and renewable energy investment, providing empirics as well as methodologies that can be generalized into other emerging green sectors and assist in reaching sustainability goals.

1.5 Thesis structure

The thesis is organised as follows:

Part 1 introduces the study by representing the background and motivation, previous primary studies, purpose of the study, niche of the study, intended contributions, and an overview of the thesis structure.

Part 2 reviews the theoretical background relevant to the study.

Part 3 presents prior studies on the volatility modelling of green investment, focusing on hydrogen, as well as presents hypotheses.

Part 4 illustrates the data sources, the time period of data, variables related to the study, indices, and descriptive statistics.

Part 5 presents the methodology with all econometric models employed in the analysis.

Part 6 presents the study's main findings, their robustness, recommendations, and proposes directions for future research.

2 Theoretical Background

This section examines key theoretical frameworks that have shaped the understanding of the returns from green investment, market risk, risk profile of assets, psychological influence on investment, and modelling the fluctuation of investment returns. It also addresses the growing importance of sustainable investment in the future energy carrier and sustainability.

2.1 Sustainable finance theory

This study is centered on some established theories and models in sustainable finance and volatility analysis, encompassing sustainable finance theory, modern portfolio theory, the GARCH model, and behavioral finance. Core to this analysis is sustainable finance theory, which strengthens the significance of favouring investments in green energy sources like hydrogen. This theory draws attention to the unification of ecological, communal, and supervision issues into financial decisions and incorporates social as well as financial objectives (Edmans & Kacperczyk, 2022). It focuses on the long-term ecological and economic benefits of transitioning from carbon-based energy to green energy systems. By considering green investments through this viewpoint, the study underlines the conditions and drivers influencing financial decisions in eco-friendly energy markets.

2.2 Modern portfolio theory (MPT)

Professor Markowitz, in 1952, first introduced the modern portfolio theory, which offers a way to minimize risk while having the highest return of sustainable energy investments (Yu & Zhang, 2023). This theory highlights the significance of portfolio broadening in mitigating the uncertainty associated with a portfolio. It explains how investing in hydrogen and other green technologies can be strategically balanced against traditional energy assets to enhance returns while mitigating risk. It also drives the investor's intent

to accomplish green portfolio diversification and stability in an emerging energy landscape.

2.3 The generalized autoregressive conditional heteroskedasticity (GARCH) model

The GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model and its variants, such as EGARCH, TGARCH, APGARCH, are widely adopted to address the volatility aspect (Society, 1991). To capture the volatility patterns within the hydrogen financing, the GARCH model is crucial. It presents a complete methodical framework for estimating, forecasting, and analyzing the inherent risks. This analysis explores the unique volatility dynamics of the green investment to provide exact insights into the green sector by incorporating these models.

2.4 Behavioral finance theory

The behavioral finance theory attempts to explain how the sentimental and cognitive forces influence financiers and market participants in the capital markets (Ricciardi & Simon, 2008). Behavioral finance integrates diverse theories, schools of thought and fields, including behavioral economics, psychology, sociology, anthropology, economics, management, marketing, finance, technology, and accounting. This field of study determines the psychological factors influencing investment decisions correlated to volatility dynamics in hydrogen energy. These theories and models offer a theoretical framework for the research methodology and layout of this research.

3 LITERATURE REVIEW AND HYPOTHESIS

The research builds upon three major studies: the green investments, hydrogen as the cleanest energy carrier asset class, and the volatility dynamics of returns of the green assets.

3.1 Previous studies

Sustainability through green investment has been an interesting topic for scholars and policymakers for the last few decades. However, in the recent trend, scholars and policymakers have focused on hydrogen financing as a sustainable energy solution for the future.

In this regard, Lucey et al. (2024) examined the inter-relationship and risk dynamics of hydrogen compared to other assets by employing a dynamic copula approach. The findings of the study showed that the relationship of hydrogen with conventional assets and market changes notably in the times of excessive uncertainty. The pandemic period had a significant repercussion on hydrogen industry linkages. The study concluded that hydrogen did not continuously reinforce connections. It showed a distinctive profile as an energy resource. Moreover, hydrogen was sensitive to crises; its reactions were varied, which demands customized interpretations. Furthermore, the estimation of conditional VAR, VAR, and Delta CoVAR confirmed the least investment risks of green bonds across frequencies. The government support and growing demand facilitate lower investment risks.

In addition, Rubbaniy et al. (2024) investigated the dynamic interconnections, portfolio performance, and hedging effectiveness across the hydrogen economy, renewable energy markets, equities, and energy commodities employing a Time-Varying Parameter Vector Auto Regressive (TVP-VAR) connectedness approach amidst the backdrop of the COVID-19 pandemic and the Russia-Ukraine conflict. Their findings revealed a consistent

degree of average linkage during both black swan events, with dynamic connectivity reaching its peak during the COVID-19 crisis. The study also concluded that certain assets, like the hydrogen economy index, clean technology index, renewable energy, and solar, consistently function as net transmitters. In contrast, others, such as the geothermal index, biofuel, natural gas, crude oil and gold, persistently act as net receivers. The results showed that the hydrogen economy generally serves as a shock transmitter for the commodities and equity market indices.

Noussan et al. (2021) analyzed the challenges and opportunities of green and blue hydrogen as the basis of a potential hydrogen society. They concluded that though many governments and private companies across the globe are putting substantial assets into the progress of hydrogen technology, nonetheless, so many unaddressed issues exist in hydrogen, including economic issues, technical challenges, and geopolitical implications. They also found that a hydrogen economy offers promising possibilities to combat climate change, enhance energy security, and foster local industries in many countries.

Dutta (2019) modeled and forecasted the US ethanol market volatility using the recently published corn price implied volatility (CIV) index. The study employed a set of GARCH (generalized autoregressive conditional heteroskedasticity) volatility approaches and concluded that the CIV index is a key element in explaining the variation in the ethanol price. The study also showed that including the CIV index improves the volatility forecasts of the US ethanol price index.

Zhang et al. (2022) investigated the instability in earth capital, energy financing, and eco-investing with a data set from 1990 to 2020. This study employed the autoregressive conditional heteroscedasticity (ARCH) and the threshold GARCH (TGARCH (1, 1) models to analyze volatility and shocks asymmetry, respectively. Their findings uncovered that the negative shock in natural resources leads to higher volatility than the positive shock, and no asymmetry exists between the positive and negative shocks in energy investment.

They recommended diversifying energy investment by expanding other energy materials, and eco-friendly financing must be enhanced.

Zhao et al. (2024) studied the effect of eco-friendly finance, fuel price instability and geostrategic uncertainty on replenishable energy capital allocation. They utilised a rich dataset of Chinese listed companies. The study used OLS, instrumental variables and GMM evaluation approaches to consider the relationship patterns and endogeneity between the concerned variables. The findings underline the significance of eco-friendly capitalisation and ecological taxes to boost investment in sustainable power suppliers. Furthermore, the study suggested a stronger attachment between eco-friendly capital provision and sustainable energy capitalisation and encouraged China to prioritize the eco-friendly businesses growth to increase investment in renewable energy sources.

Pham (2016) analyzed the volatility dynamics of the green bond market with a data set the S&P green bond indices. The study applied a multivariate GARCH framework. The outcomes of the analysis showed the high volatility clustering experience in the certified segment of the green bond market, while the pattern of volatility clustering was weaker in the uncertified segment of the market. The study also concluded that a shock in the overall traditional bond market is likely to spread over into the green bond market, and the spillover effect is dynamic over time.

Dutta et al. (2023) examined the ramifications of unrefined oil instability jumps on the RV of green and dirty stocks in India. To do so, they estimated the time-varying jumps in the OVX index and then extended the HAR process using the information on such jumps. They found that unrefined oil instability jumps offer supplemental details, which are not incorporated even in the OVX index itself.

Yaya et al. (2022) analyzed the influence of oil surprise on the volatility of green investments. They applied GARCH and MIDAS approaches to examine the influences. Their findings revealed that the oil shocks influence the volatility of green investments

homogeneously and heterogeneously. Furthermore, the study confirmed the asymmetry effect of positive and negative oil shocks on the volatility of green investments.

Tumala et al. (2023) examined the relationship between atmospheric shift and the price fluctuation of carbon-based fuels. They applied the GARCH-MIDAS framework to analyze the linkage between variables. The study found a strong and positive association between climate change and the price volatility of fossil fuels. Their findings revealed that climate change amplifies the instability in the carbon-based fuels market and confirmed that inflationary pressures do not affect the dynamics between the variability of carbon-based fuel prices and climate change.

Lu et al. (2023) inspected the return and uncertainty interconnection among sustainable capital markets by using the TVP-VAR extended joint connectedness approach. The study presented the Green Bond index (GBI) as the main net recipient of return externalities, succeeded by the Global 1200 ESG index (ESGI), Global 1200 Carbon Efficient Index (CEI) and Global 1200 Fossil Fuel Free Index (FFFI) and showed S&P Global Clean Energy index (GCEI) as the main radiator of return during the full observed period. They recognized the volatility connectedness among ESGI, CEI, and FFFI as net emitters of volatility spillovers during the full, pre-COVID-19, and post-COVID-19 periods.

Olaoluwa (2022) examined how market volatility of green investments reacts to oil shocks by applying the Generalized Autoregressive Conditional Heteroscedasticity with Mixed Data Sampling (GARCH-MIDAS) methodological structure. Their outcomes confirmed uniform and mixed responses of green investments' volatility to variants of oil shocks. Alongside the positive and negative effects of oil shocks on the volatility of green investments, the asymmetric effects of oil shocks are also presented.

Li et al. (2022) carried out a study to examine the contribution of green funding, volatility, and geopolitical instability to the investment in renewable energy sources by applying

benchmarks and regression analysis to determine the association between the concerned variables. The findings of the study validated that green financing, especially green bonds and eco-friendly policies, exerts a considerable positive influence in stimulating capitalisation in regenerative energy sources. Conversely, fuel price instability and international political uncertainty have detrimental ramifications on the capitalisation trend for eco-friendly energy sources.

The asymmetry and extreme volatility effects were examined for modelling and predicting stock volatility by Wang et al. (2020). To do so, they employed the GARCH–MIDAS approach and concluded that the extreme shocks considerably influenced the stock fluctuation, and the unequal effect on the fluctuation was stronger than the extreme instability effect in both immediate and extended horizons. Further, they verified the results with out-of-sample and some robustness checks.

Ghani et al. (2023) studied the contribution of the oil shock in forecasting the U.S. stock market volatility. They included ANP(asymmetric net price change), NPI (net price increase), LPI (significant price increase), SNP (symmetric net price change), and NPI2 (net price increase) indicators to measure oil shocks. The study applied the GARCH—MIDAS model to assess the volatility. This study confirmed that symmetrical net oil price change data in the case of all oil shocks contribute significantly to anticipating the fluctuation of the U.S. stock market.

By the combination of the time-varying parameter vector autoregression model (TVP-VAR) and the Diebold-Yilmaz spillover index, Y. Wang et al. (2025) investigated the time-varying risk transmission effects in the green financial markets. The study concentrated on the eco-bond market, environmentally responsible stock market, carbon credit market, and crude oil futures market of China based on return data from 2018 to 2024. The findings of this study revealed that green financial markets experienced cyclical risk transmission and were notably influenced by leading risk incidents like pandemics as well as adverse climate conditions. According to the outcomes of the analysis, the most

robust risk infection market within the green financial system was the green stock market, with a higher potential for disseminating risk than receiving it. The researchers confirmed notable impacts of market sentiment on the overall contagion effect of risk in green financial markets in the short run, while the fear sentiment was more prominent in the long run.

Fang et al. (2023) investigated the global economic policy impacts on the volatility of crude oil futures by applying a two-factor GARCH-MIDAS approach. The researchers were trying to comprehend the channels through which economic policy influences the volatility of crude oil futures, which considerably benefits decision-makers, investors, and market participants. This study intended to figure out the association between pivotal worldwide economic policy variables and the volatility of crude oil futures. This study ensured a complex nexus between crude oil futures volatility and universal economic policy. Furthermore, the study's findings provided valuable insights into how altering fiscal policies, trade policies, and interest rates influences crude oil futures volatility.

A study was carried out by Salisu et al. (2022) to figure out the association between geopolitical risk and stock market volatility in evolving economies by applying the GARCH-MIDAS framework. This study aimed to estimate the forecastability and economic benefits of the subject, thereby enhancing the decision-making of investors and practitioners. The findings of the study showed a positive association between stock market volatility and geopolitical risks in emerging economies, with better forecastability of the act-related geopolitical index than hazard-linked geopolitical risk. Alongside this, the study confirmed the importance of global economic factors in the case of forecastability analysis for reliable outcomes. Finally, the study identified improvements in utility by incorporating geopolitical risks into the volatility model.

Hoon et al. (2009) examined the volatility models' effectiveness across three crude oil markets—Dubai, West Texas Intermediate (WTI), and Brent. The study focused on forecasting future volatility and the volatility patterns detection capacity of different GARCH models, especially persistence or long memory effects. To do so, the researchers employed different types of GARCH models. The study concluded that the CGARCH and FIGARCH models are more effective at capturing persistence in volatility compared to the GARCH and IGARCH models, and perform better in out-of-sample volatility projection. Finally, the researchers considered the FIGARCH and CGARCH models as the best-fitted models and advantageous for framing and projecting the volatility of crude oil.

Glosten et al. (1993) found an inverse relationship between conditional expected return and conditional variance, applying the modified GARCH-M model. They also concluded that the conditional volatility was not as persistent as thought, and an unexpected positive return seems to lead to a reduction in the estimated conditional volatility. In contrast, an unanticipated negative return seems to lead to an increase in the estimated conditional volatility.

Barreto et al. (2003) studied the essential function of hydrogen in a hydrogen economy for a prolonged shift toward a tidy and ecological energy future. The study did quantitative and qualitative analyses to contribute insights to the existing literature. The study suggests that in a wealthy, equity and sustainability-driven world, the hydrogen technologies experience significant improvements in their performance and costs over time. Hence, the hydrogen technologies are viable to become widely adopted and used extensively in the future. To be transformed in the direction of a more elastic, protected, and dispersed energy system, hydrogen technologies serve an essential function in meeting energy needs in a tidy, optimal, and economical way. The transformed global energy system delivers considerable progress in power consumption and supply safeguard by accelerating and decarbonizing the power generation mix, with low climate

impacts. Furthermore, the study concluded that the current hydrogen energy system path is insufficient to mitigate the risk of high climate sensitivities; however, it would be a prime candidate for a risk management strategy against an uncertain climate future.

3.2 Hypotheses development

This study models the volatility of hydrogen return with a specific focus on the role of risk dynamics of green assets as the potential driver of global sustainability.

It donates to the evolving literature on green investment, particularly in the hydrogen sector, by examining how risk dynamics of hydrogen investment influence the world's transition to a hydrogen economy. Moreover, the study explores the relationship between the overall market instability and the volatility of the hydrogen returns, and the explanatory power of the volatility index. Based on the purpose and intended contribution, the hypotheses are as follows:

Hypothesis 1: There is a significant volatility clustering in the case of hydrogen returns. The existence of the phenomenon that the large price fluctuations are followed by larger swings, and small moves are followed by small moves.

Hypothesis 2: Macroeconomic factors influence the return volatility of the hydrogen investment.

Hypothesis 3: The Volatility Index (VIX) is positively related to the return volatility of hydrogen investment. Any increase in the market uncertainty will lead to higher perceived volatility in hydrogen returns.

Hypothesis 4: Incorporating the Volatility Index (VIX) as an explanatory variable in the model improves the forecasting power of the model.

4 DATA AND DESCRIPTIVE STATISTICS

4.1 Data

In the empirical analysis, this study considers the S&P hydrogen economy index and the CBOE Volatility Index (VIX). The sample data covers daily data from May 2019 to May 2025. The observation period was chosen based on the data accessibility. The study has chosen daily data over monthly or quarterly data because day-to-day data provides a timely understanding of market motions and economic patterns, crucial for decision-making in quickly evolving environments like financial markets (Claessens & Schmukler, 2007). Furthermore, more frequent data collection catches more comprehensive information and enables researchers to discover subtle trends and fluctuations, contributing to higher precision in analyses (Bekaert & Harvey, 2000).

Day-to-day data also assists in lowering noise and improving signal-to-noise ratios, particularly significant in the financial markets' instability. Moreover, stakeholders can also use within-day data, like data on hourly, minute-by-minute, to observe the market fluctuations, but it can result in lower performance due to unequal information. Furthermore, it may introduce issues in analysing the market dynamics and also may require a complex modelling approach for analysing the investment strategies (*Trading Halts and Market Activity : An Analysis of Volume at the Open and the Close Author (s): Mason S . Gerety and J . Harold Mulherin Source : The Journal of Finance , Dec ., 1992 , Vol . 47 , No . 5 (Dec ., 1992), Pp . 1765-1784 Published by : Wil*, 1992). This study collects data from the Refinitiv Eikon Database, investing.com, and Bloomberg as data sources.

4.2 Descriptive statistics

To provide a clear and concise overview of the data set, the study summarises the main features of the data, including measures such as mean, median, standard deviation, frequency distributions, trends in the data, and stationarity of the data. These statistics facilitate understanding the distribution, central tendency, and variability of the data, identify patterns or outliers, and set the foundation for further analysis.

Figure 1: Trend line of Hydrogen Index (line and symbol plot)

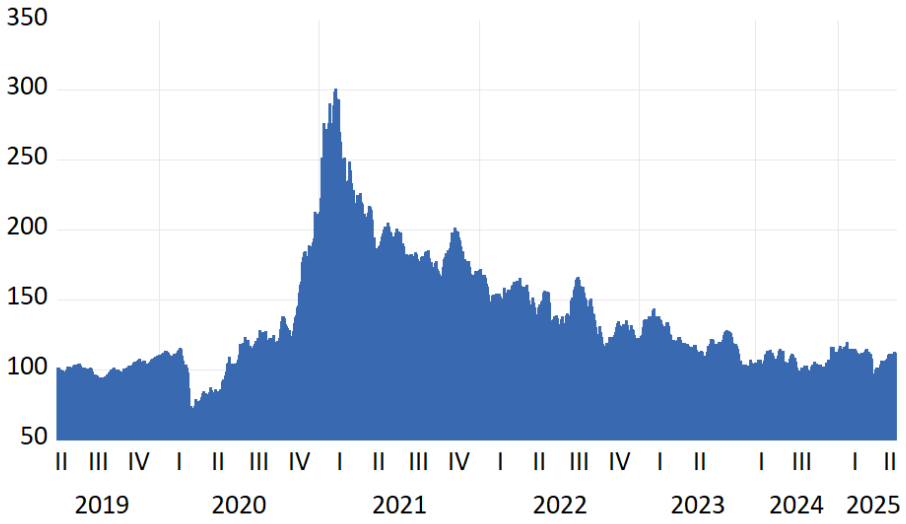

Figure 2: Trend line of Hydrogen Index (Spike plot)

The trend graphs in Figures 1 and 2 display a clear visualization of the dynamics of the hydrogen index over several years. The graphs underscore the significant events and periods of stability. The period of 2019 shows a phase of relative stability because the values of the hydrogen index variable fluctuate within a narrow range. On the other hand, a dramatic spike is observed at the beginning of 2020, where the value of the hydrogen index rapidly climbs to over 300. The sudden fluctuation of the values suggests an unusual event or change in an economic, political, technological, or environmental factor associated with hydrogen. Later in 2021, a rapid decline in the values was noticed, which indicates the resolution of the event or a market correction. However, from 2021 onwards, the values fluctuate within a narrow range that reflects a return to consistent conditions up to 2025.

The graphs represented in Figures 3 and 4 plot the fluctuations in values of the Volatility Index (VIX) over the years, depicting a clear view of how market uncertainty has changed across these years. In 2019, the values of the VIX index remained relatively stable and fluctuated within a minimum range. At the beginning of 2020, a sharp spike was ob-

served in the VIX index values, indicating a period of extreme market stress or uncertainty. This large fluctuation aligns with global financial turmoil during events like the COVID-19 pandemic, which caused heightened fears and volatility in the markets. During 2021, the oscillation was within a narrow range, but in 2022 onwards, the VIX shows a decreasing trend. Again, at the beginning of 2025, a large spike appears.

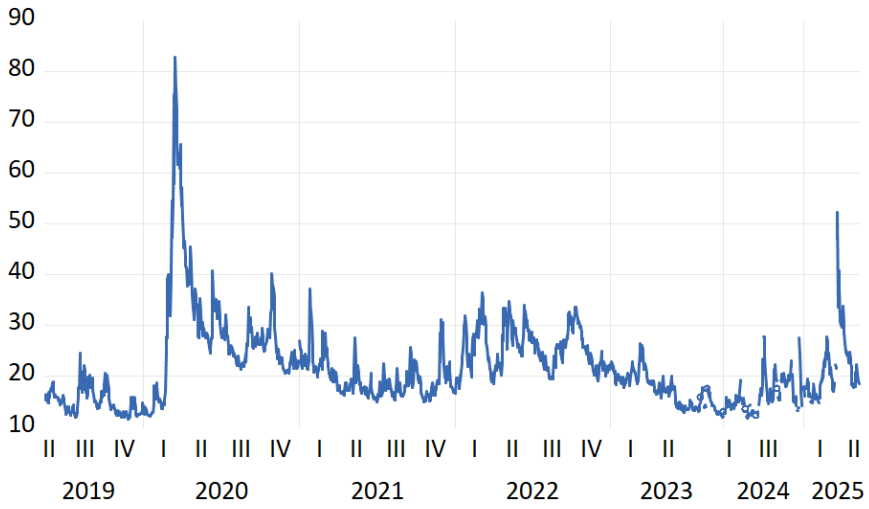

Figure 3: Trend line of the Volatility Index (VIX) (Line and symbol plot)

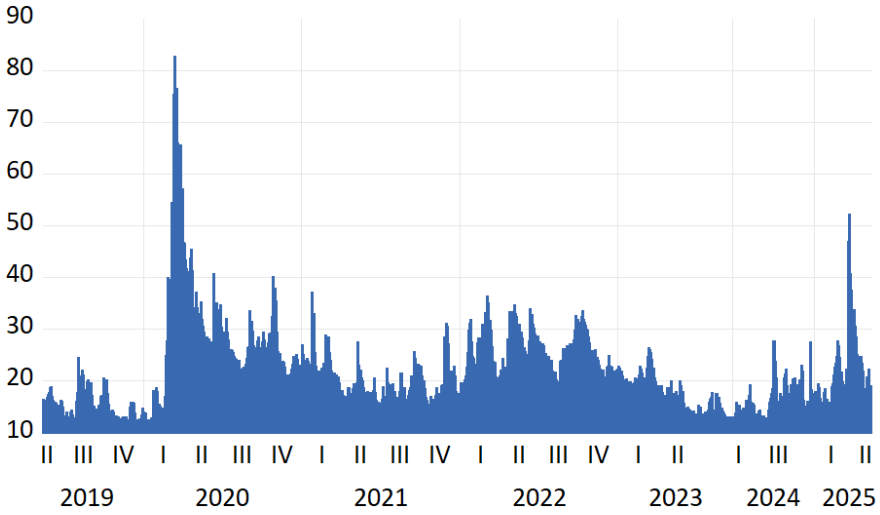

Figure 4: Trend line of the Volatility Index (VIX) (Spike plot)

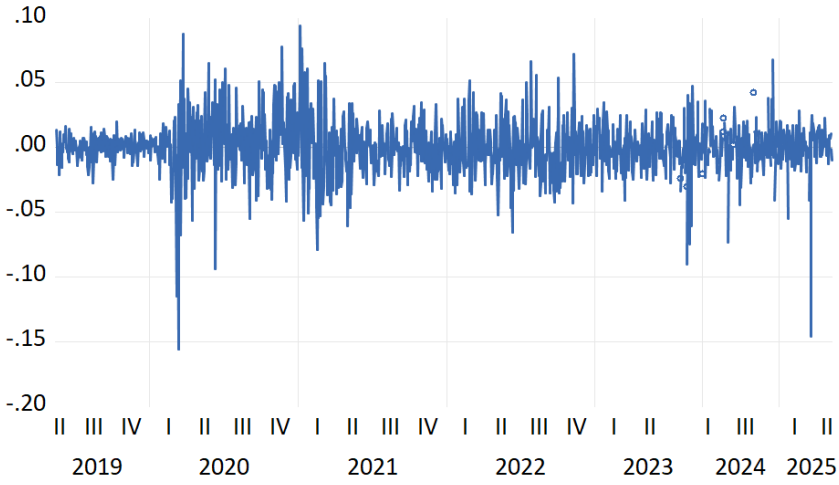

Figure 5: Hydrogen price returns

Figure 5 depicts the fluctuations in hydrogen return from 2019 to 2025. Every data point on the graph represents the return rate of hydrogen prices and illustrates the change in price compared to the previous period. The volatile pattern is noticeable in the graph with numerous sharp peaks and troughs over the entire sample period. This volatility is a common feature of the asset market and is influenced by supply and demand dynamics, technological advancements, and geopolitical events. Initially, the minor fluctuations in 2019 indicate relative stability in hydrogen prices. Later, from 2020 to 2025, a significant level of volatility is noticeable. These significant spikes (upward and downward) indicate periods of uncertainty or rapid market changes. The COVID-19 pandemic, market risks, and market expectations might be possible reasons for this instability in hydrogen return.

The visual evidence of return series spans from the second quarter (II) of 2019 to the second quarter (II) of 2025, suggesting that there's strong evidence of volatility clustering. In early 2020, a period of high volatility was noticeable and marked by substantial positive and negative return variability. This volatility potentially indicates a significant market event. This visual observation warrants further statistical investigation to confirm and model the volatility dynamics.

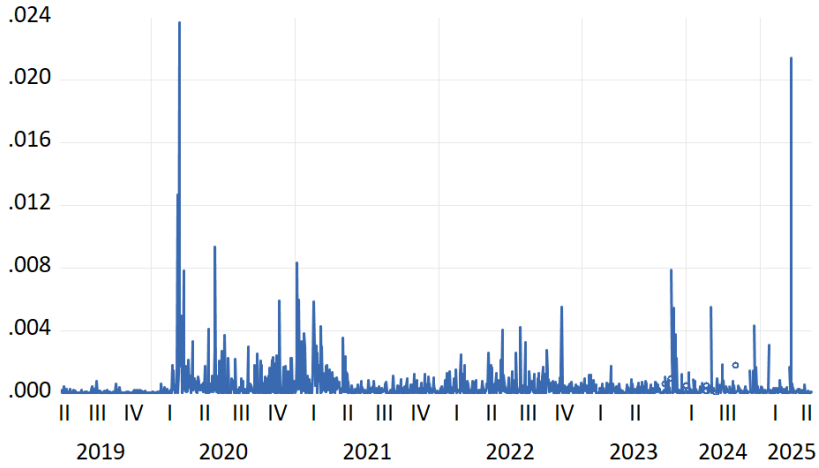

Figure 6: Heteroskedasticity in Residuals

Figure 6 depicts the squared residuals over the time span from 2019 to 2025. The spikes in squared residuals at different points indicate the existence of volatility in the hydrogen return. The lower squared residuals during the period from 2021 to 2023, with minimal spikes, indicate a period of stability. Moreover, in 2020, 2024, and 2025, the significant spikes in the squared residuals confirm significant volatility in hydrogen return. The global instability and the COVID-19 pandemic might be associated with the fluctuation in the hydrogen sector.

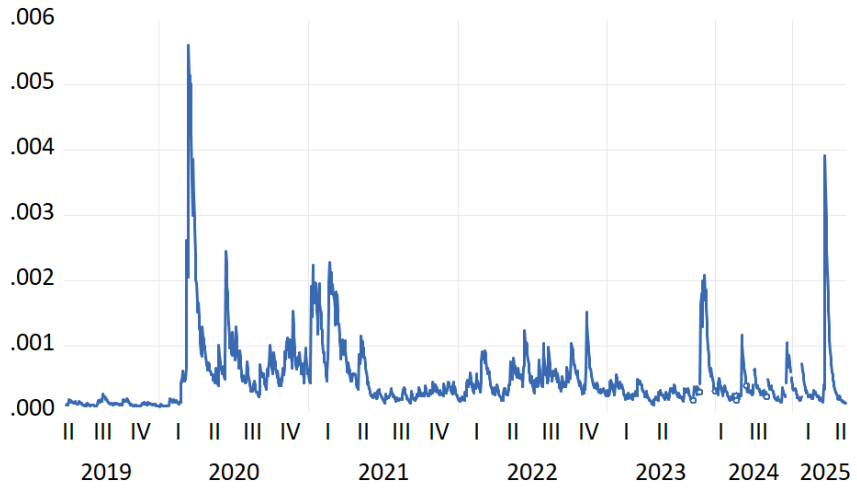

Figure 7: Hydrogen Return Volatility

Figure 7 illustrates the fluctuation in the volatility series of hydrogen return for the entire sample period from 2019 to 2025. The volatility of hydrogen return demonstrates significant variability throughout the observed period. It highlights the dynamic nature of the hydrogen market. In 2020 and 2024-2025, the noticeable spikes suggest a period of extreme market uncertainty in the hydrogen sector. Furthermore, the volatile nature of hydrogen return signals the influence of external shocks, geopolitical events, technological breakthroughs, and significant policy shifts on the hydrogen industry during the studied period. Corresponding to the previous graphical representation, the fluctuation in the volatility series of hydrogen return confirms the existence of volatility clustering in hydrogen return.

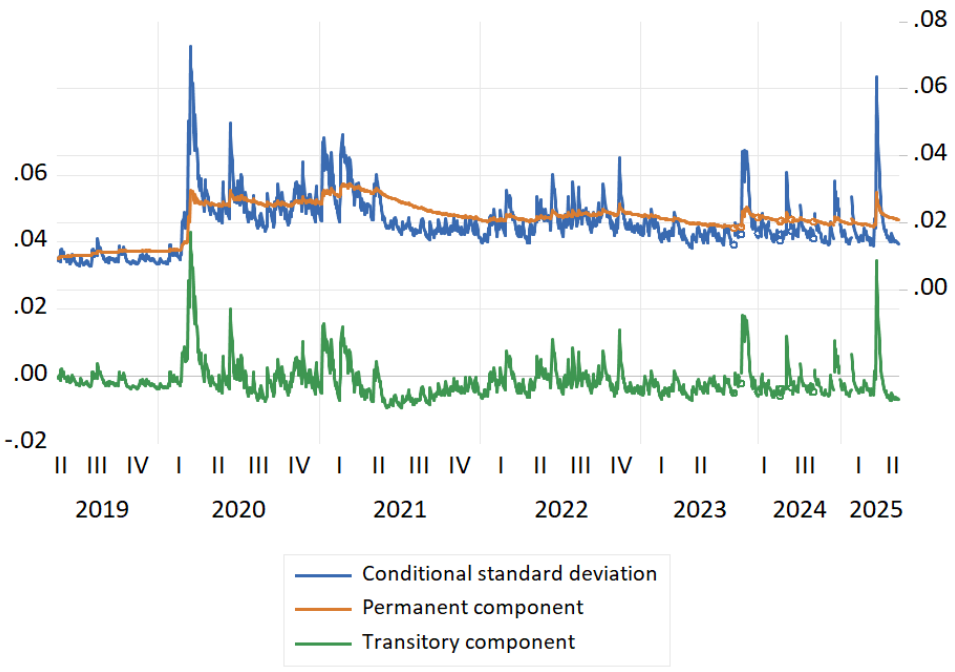

Figure 8: Decomposition of Volatility: Conditional Standard Deviation, Permanent, and Transitory Components

Figure 8 depicts the volatility decomposition into three components: conditional standard deviation, permanent, and transitory components. The blue line in the graph represents the overall fluctuations at any given point in time as the conditional standard deviation. The significant fluctuation of this component around 2020 and 2024-2025 suggests a period of heightened market uncertainty. This component remains sensitive to shocks that cause sudden increases in volatility

The orange line in the graph denotes the permanent component of volatility. It captures the long-term, persistent effects influencing return oscillation. The smoothness of this component compared to the conditional standard deviation indicates the sustainability of some influences on hydrogen return volatility over longer periods. Moreover, the gradual decline of the component to lower levels reflects the market's adaptation over time. Finally, the green line represents the transitory component. It represents short-lived shocks or temporary deviations from the long-term trend. The frequent and sharp

spikes of this component occur during periods of market turmoil, implying extreme market uncertainty. Moreover, the high frequency of the transitory component highlights standard sudden short-term shocks that increase in overall volatility temporarily.

Overall, it is clear that the short-term shocks (transitory component) experience intense fluctuations, while the long-term influences (permanent component) tend to be more stable. The conditional standard deviation captures the overall market uncertainty at any given time, influenced by both short-term shocks and long-term trends.

Table -1: Descriptive statistics

	Hydrogen	VIX
Mean	135.0378	20.72499
Median	119.7763	18.84000
Maximum	300.9740	82.69000
Minimum	67.27530	11.54000
Standard Deviation	41.46519	7.95971
Skewness	1.357398	2.562184
Kurtosis	4.797444	14.52407
Jarque-Bera	602.0443***	10299.36***
Q (24)	2.003***	850***

Notes: *** Indicates statistical significance at 1% level. The null hypothesis of the Jarque-Bera test, (H_o): The data is normally distributed, and the alternative hypothesis (H_1): The data is not normally distributed. Q(24) is the Box–Pierce statistics of the return series and the VIX series for up to 24th order serial correlation. The null hypothesis of the test (H_o): there is no autocorrelation up to lag 24.

Table -1 shows the summary statistics of the time series under consideration. The findings confirm the significant deviations of the Hydrogen and the volatility index (VIX)

datasets from normality, exhibiting notable skewness and kurtosis. The positive values of the skewness of the concerned variables indicate the right-skewness and asymmetry of both distributions with longer tails extending towards higher values. Furthermore, the kurtosis values of both variables are notably greater than 3, suggesting heavier tails and the presence of significant outliers. The Jarque-Bera test also confirms that none of the series follow normal distribution with highly significant statistics (p-values less than 0.01). Moreover, the Q(24) test indicates the existence of strong autocorrelation between the values of the series. Moreover the values of standard deviation of the series confirm the existance of volatility in hydrogen market.

Table -2: Unit root tests of the series

Variables	Hydrogen		VIX	
	First Difference		First Difference	
	With trend	Without trend	With trend	Without trend
ADF	-34.008***	-34.003***	-48.589***	-48.603***
PP	-34.067***	-34.087***	-48.715***	-48.730***

Notes: *** Indicates statistical significance at 1% level. The null hypothesis of Augmented Dickey Fuller (ADF) and Phillips Perron (PP) tests, (H_o): The variable has a unit root, and the alternative hypothesis (H_1): the variable does not have a unit root.

Table -2 presents the outcomes of stationarity tests of the variables under different conditions, like with trend, without trend, and first differencing. The tests aim to detect the unit root problem of the series, which has implications for time series analysis and modelling. The ADF and PP test values for both variables show compelling evidence to reject the null hypothesis of the tests related to the existence of a unit root problem at the 1% significance level. The outcomes of the tests confirm the integrated order of one (I(1)) of the variables. The integrated order of one (I(1)) of the variables further suggests that the

series has a unit root problem, meaning that all series are not stationary in their original form but become stationary after taking the first difference. Overall, the application of Augmented Dickey Fuller (ADF) and Phillips Perron (PP) tests ensures that both indices are stationary at the first difference.

5 METHODOLOGY

In the empirical segment, this study utilized a series of GARCH approaches to analyze and predict the instability of green investment. As an augmentation of the ARCH model built by Robert Engle in 1982, Tim Bollerslev first introduced the GARCH model in 1986. Due to its viability in calculating and predicting the volatility clustering observed in financial markets, the GARCH has become a crucial device in risk management and financial econometrics. In the case of modelling and forecasting volatility, GARCH-type frameworks are quite frequent in current literature (SH et al., 2009). The GARCH-type frameworks incorporate a symmetric GARCH model (Bollerslev, 1986) as well as some distinct asymmetric models encompassing the exponential GARCH (EGARCH) model (Society, 1991). the threshold GARCH (TGARCH) model (GLOSTEN et al., 1993), and the asymmetric power GARCH (APGARCH) model (Ding et al., 1993).

5.1 The GARCH (1,1) Model

As an expansion of the ARCH model built by Robert Engle in 1982, Tim Bollerslev first introduced the GARCH in 1986 (Bollerslev, 1986). The main idea of the GARCH(1,1) model was related to the facts that the conditional variance of the returns at time t depends on the squared error term from the previous period (ARCH term) and the conditional variance from the previous period (GARCH term).

The preliminary stage of utilizing the GARCH models involves specifying the conditional mean equation as follows:

$$r_t = \pi + \phi r_{t-1} + \varepsilon_t \quad (1)$$

Where r_t indicates the daily log return of green investment (hydrogen) at time t. π symbolizes an intercept term that denotes the level of the return when the return of the previous period approaches zero with no shock. ϕ represents the coefficient of the earlier period's return, which measures the influence of the previous period's return on

the current period's return. r_{t-1} denotes the previous period's return. ε_t represents the error term at time t, which illustrates the unanticipated surprise or new information that affects the return. It is expected that the disturbance term sticks to a symmetrical distribution.

The GARCH (1,1) model appears as follows:

$$h_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2 \quad (2)$$

In the GARCH (1,1) equation, h_t^2 denotes the conditional variance of at time t, and ω , represents the constant or base level of variance that must be greater than zero. α symbolizes the coefficient of the previous period squared error term as "ARCH" part of the model and quantifies the influence of recent news or shocks on volatility. β indicates the coefficient on the lagged conditional variance, and as a GARCH part of the model. It quantifies the effect of earlier volatility on present volatility. ε_{t-1}^2 indicates the shock or surprise at the period of t-1 and h_{t-1}^2 represents the conditional dispersion at time t–1.

5.2 The TGARCH Model

Glosten, Jagannathan, and Runkle 1993 proposed the threshold GARCH model (TGARCH) to integrate unevenness by facilitating negative and positive surprises to have a distinct influence on future volatility (GLOSTEN et al., 1993).

The TGARCH model takes the following structure:

$$h_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 S_{t-1} + \beta h_{t-1}^2 \quad (3)$$

The TGARCH model is an enlargement of the standard GARCH model. This model was developed to capture the asymmetric effects of shocks on volatility. Evidence points out that financial markets respond more distinctly to bad news than good news. A negative shock influences volatility more than a positive shock, and TGARCH is viable to account for this. In equation (3), S_{t-1} represents a dummy variable. This dummy variable takes the worth 1 if ε_{t-1} is negative and 0 in different circumstances. γ denotes the impact of negative shocks on volatility. If the value of γ is greater than 0, and statistically significant, the adverse shocks escalate volatility over the positive surprises of equal in size. More specifically- $H_0 : \gamma = 0$ is rejected, then asymmetry arises.

5.3 The Exponential GARCH (EGARCH) Model

The EGARCH model was developed by Nelson in 1991 to deal with some drawbacks of the GARCH model. This model allows for the uneven consequences of positive and negative surprises on volatility (Society, 1991). The EGARCH specification takes the following form :

$$h_t^2 = \omega + \alpha \left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta h_{t-1}^2 \qquad (4)$$

h_t^2 represents the conditional variance at t time, ω denotes the constant term or the average variance in the long run. α indicates the coefficient of standardized residual and measures the impact of previous surprise on current volatility, $\frac{\varepsilon_{t-1}}{h_{t-1}}$ stand for the absolute value of the standardized residual at time t-1. Standardizing the residual facilitates to scale the impact of the shock. γ symbolizes the coefficient of the standardized residual at time t-1 t, which is the main term to capture asymmetry. If $\gamma = 0$, then the model becomes symmetric, meaning that the negative and positive shocks with the same magnitude will have the same influence on volatility. If γ is less than 0, the positive news raises volatility over the bad news.

5.4 The Asymmetric Power GARCH Model (APGARCH)

Ding, Engle, and Granger (1993) developed the Asymmetric Power GARCH (APGARCH) model to expand GARCH models by incorporating a power parameter, enabling flexible modeling of volatility persistence and asymmetric effects in time series data (Ding et al., 1993). This model facilitates capturing both asymmetry and a power transformation of the conditional variance and error terms. This is an effective model for modelling volatility where volatility may react distinctly to negative and positive shocks, and where the association between previous surprise and present volatility may not be linear. The APGARCH model is structured as :

$$h_t^{\delta} = \omega + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^{\delta} + \beta h_{t-1}^{\delta} \qquad (5)$$

In equation (5), ω, α, γ, β, and δ are the parameters, ω denotes long-run average variance, α symbolizes the coefficient of past shock, γ represents the asymmetric parameter. If γ is greater than 0, then the negative surprise intensifies volatility beyond the positive shocks. δ indicates the parameter for the power term that allows a flexible relationship between previous surprise and present volatility. β represents the coefficient of the GARCH term.

5.5 The Component GARCH Model (CGARCH)

The Component GARCH (CGARCH) model was developed by Thomas P.M. McCurdy and Ieuan G. Morgan in 1999 to consider the long-run and the short-run volatility effects.

The CGARCH model can be structured as follows:

$$h_t = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(h_{t-1} - q_{t-1}) \quad (6)$$

$$q_t = \omega + \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - h_{t-1}) \quad (7)$$

In expression (6), h_t represents the conditional variance at time t, q_t denotes the time-varying long-run component of variance at time t. It is the "base level" of volatility that the short-term volatility tends to revert to. α indicates the sensitivity of the conditional variance to shocks in the previous period (t-1), relative to the long-run component. A higher α means a bigger impact on volatility above and beyond the long-run level. $\varepsilon_{t-1}^2 - q_{t-1}$ represents the deviation of the shock from the long-run level. β indicates the coefficient that measures the persistence of the short-run component. $h_{t-1} - q_{t-1}$ denotes the difference between the conditional variance and the long-run component in the previous period.

In equation (7), ω denotes the long-run variance in the absence of any shocks, ρ indicates the coefficient of the persistence of the long-run component. It measures how much the previous period's long-run component affects the current long-run component. Typically, $0 < \rho < 1$, meaning the long-run component is mean-reverting. ϕ denotes the sensitivity of the long-run component to shocks in the previous period. $\varepsilon_{t-1}^2 - h_{t-1}$ represents the difference between the squared error term and the conditional variance in the previous period and indicating the unexpected shock to volatility relative to the total volatility.

5.6 Integrated GARCH Model (IGARCH)

Engle and Bollerslev (1986) cultivated the IGARCH representation to capture endless endurance in the conditional variance. The IGARCH framework proposes a permanent impact of a shock on volatility, and the volatility process is non-stationary, meaning it doesn't revert to a long-run mean. This variant of the GARCH model enforces the restriction that the sum of the coefficients is equal to one.

The IGARCH model specification is as follows :

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (8)$$

$$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j = 1 \quad (9)$$

Equation (9) denotes the constraint of the IGARCH model, indicating that the ramification of shocks to volatility is permanent and does not decay over time. In the GARCH model, without this restriction, the influence of a shock on the volatility gradually reduces as time progresses.

To evaluate the impact of the stock market's expected volatility shock, the VIX is incorporated in all the GARCH Equations from (2) to (8). The coefficient θ represents the ramification of the VIX. To illustrate, Equation (2) is widened as :

$$h_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^2 + \theta VIX_{t-1}^2 \quad (10)$$

A similar augmentation is employed for other GARCH variants.

6 EMPIRICAL FINDINGS AND DISCUSSION

6.1 Estimation of the model excluding VIX as a predictor

Now, the study discusses the findings of all the GARCH models employed without incorporating the VIX as an explanatory variable in the GARCH variance equations.

Table 3- Testing for the ARCH effect

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000401***	3.5605	11.25207	0.0000
(RSD (-1)) ^2	0.096714***	0.027009	3.580878	0.0004
F-statistic	12.82269	Prob. F(1,1358)		0.0004
Obs*R^2	12.72145	Prob. Chi-Square(1)		0.0004

Notes: The independent variable used here is Residual Squared RSD (-1), and *** indicates statistical significance at 1% level.

Table 3 presents the findings of the test for the ARCH effect. As a key focus, the significant coefficient of the lag residual squared ((RSD (-1)) ^2) indicates that past residuals significantly influence current variance. The highly significant F-statistic and the Chi-Square test statistic further confirm the presence of ARCH effects. Moreover, the findings clarify the time variant variance of the residuals that depends on the past residuals, suggesting the existence of conditional heteroskedasticity. These findings indicate the importance of the ARCH or the GARCH model as a suitable method for accurately capturing the data's characteristics. The existence of the ARCH effect in the eturn of hydrogen provides a basis for applying the GARCH frameworks to modelling the volatility of hydrogen return in the study.

Table 4: The outcomes of the GARCH model

Coefficients	Values	Std. Error	z-Statistic	Prob.
ω	7.9306***	2.2906	3.4582	0.0005
α	0.1688***	0.0134	12.547	0.0000
β	0.8350***	0.0148	56.248	0.0000

Notes: The dependent variables used here are Residual Squared (RSD(-1)^2) and GARCH(-1). *** indicates statistical significance at 1% level.

Table 4 shows the findings of the GARCH(1,1) model. The findings provide strong evidence of the GARCH effect's presence. The significant GARCH coefficient underscores the persistence of volatility over time as well as identifies the past variances as a strong predictor of future variances and notably influences current variance, emphasizing the tendency of volatility to cluster over time. Furthermore, the significant ARCH term suggests that recent shocks or unexpected returns have a direct and noteworthy impact on current volatility. The strongly significant ARCH term confirms the dependency of current variance on the immediate past surprise. On the other side, the GARCH term captures the longer-term persistence of volatility. The significant ARCH and GARCH terms confirm the dynamic nature of volatility, where both recent shocks and past volatility levels shape current market risk. Therefore, based on the outcomes of the GARCH model, it is justified that the previous surprise and volatility influence the volatility of the hydrogen return.

Table 5: The findings of the TGARCH Model

Coefficients	Values	Std. Error	z-Statistic	Prob.
ω	7.2706***	2.2706	3.19805	0.0014
α	0.13246***	0.01840	7.1969	0.0000
γ	0.07730***	0.01817	4.2535	0.0000
β	0.8357***	0.0157	53.0084	0.0000

Notes: The dependent variables used here are Residual Squared RSD (-1) ^2, RSD(-1)^2*RSD (-1), and GARCH(-1). *** indicates 1% level of statistical significance.

Table 5 summarizes the findings of the TGARCH model. The highly significant coefficients in the TGARCH model provide strong evidence of the asymmetric impact of news on volatility. The significant coefficient of past squared residuals confirms that the recent shocks indeed influence future volatility. Furthermore, the highly significant coefficient of the interaction term also highlights the combined effect of past shocks and their magnitude on present volatility. The TGARCH model justifies the asymmetry through its parameters and indicates that negative surprises have a greater impact on subsequent volatility. The high significance and magnitude of these coefficients uphold the idea that the negative shocks influence volatility more than positive shocks of similar size. Overall, the outcomes of the TGARCH model validate the prominence of negative shocks over the positive surprise in modelling hydrogen return volatility.

Table 6: The results of the EGARCH Model

Coefficients	Values	Std. Error	z-Statistic	Prob.
ω	-0.4730***	0.07015	-6.6159	0.0000
α	0.2783***	0.0227	12.2614	0.0000
γ	-0.0587***	0.0090	-6.5088	0.0000
β	0.9664***	0.0078	122.873	0.0000

Notes: *** indicates 1% level of statistical significance.

Table 6 presents the findings of the EGARCH model, showing all statistically significant estimated coefficients. The statistically significant value of α and β indicates the contribution of previous shocks to current volatility and the persistence of volatility over time. On the other hand, the strongly significant negative value of the coefficient γ confirms the asymmetry or leverage effect and indicates that the impact of positive shocks on volatility outweighs the ramifications of adverse shocks. Though the EGARCH model provides evidence for the prominence of positive shocks over negative shocks, both models affirm the asymmetric influence of the surprises. Later, the study will identify the best-fitted model.

Table 7: The result of the APGARCH Model

Coefficients	Values	Std. Error	z-Statistic	Prob.
ω	8.0705	5.5705	1.4479	0.1476
α	0.1565***	0.0149	10.4391	0.0000
γ	0.1770***	0.0443	3.9948	0.0001
β	0.8618***	0.0143	60.2298	0.0000
δ	1.4035***	0.1413	9.9320	0.0000

Notes: *** indicates statistical significance at 1% level.

Table 7 shows the results of the APGARCH model. The highly significant past shock coefficient confirms that the market is more sensitive to the size of past shocks. Any surprises in returns, either positive or negative, lead to a larger increase in volatility. Further, the significance of the asymmetry coefficient ensures that the negative shocks (bad news) influence the hydrogen return volatility more than positive shocks (good news) of the same magnitude and indicates that the market responds differently to positive and negative information. The persistence of the volatility coefficient also confirms the phenomenon of volatility grouping. The statistical significance of the power term of the model further underlines the necessity of a non-proportional linkage between shocks and volatility, and allows the model greater flexibility in capturing complex dynamics.

Table 8: The results of the CGARCH Model

Coefficients	Values	Std. Error	z-Statistic	Prob.
ω	0.0017	0.0009	1.8622	0.0626
ρ	0.9995***	0.0002	4554.2	0.0000
ϕ	0.0216***	0.0069	3.1364	0.0017
α	0.1517***	0.0196	7.7273	0.0000
β	0.7580***	0.0408	18.553	0.0000

Notes: *** indicates statistical significance at 1% level.

Table 8 summarizes the results of the CGARCH model and reveals significant dynamics in the volatility. The findings decompose the overall volatility into a long-run component and a transitory component effectively, and provide valuable insights beyond a standard GARCH model. Particularly, the highly significant coefficient of the persistent component indicates that shocks to long-run volatility have a lasting impact and suggesting the presence of underlying structural factors influencing volatility. Furthermore, the significant

coefficient for the transitory component underscores the role of short-term news and market fluctuations in driving temporary volatility spikes.

Table 9: The results of the Integrated GARCH Model (IGARCH)

Coefficients	Values	Std. Error	z-Statistic	Prob.
ω	-5.9705	0.0003	-0.1958	0.8447
α	0.0933***	0.0059	15.6614	0.0000
β	0.9066***	0.0059	152.0311	0.0000

Notes: The dependent variables used here are Residual Squared (RSD(-1)^2) and GARCH(-1). *** indicates statistical significance at 1% level.

Table 9 shows the results of the IGARCH model. With the consideration of the IGARCH restriction, the sum of the statistically significant coefficients approaches one, indicating a highly persistent volatility process. The findings confirm that shocks to volatility decay very slowly over time, indicating that previous instability has a prolonged influence on present fluctuation.

Table 10: The findings of all the GARCH models by excluding VIX from the models: Error distribution is normal

	GARCH	TGARCH	EGARCH	APGARCH	CGARCH	IGARCH
ω	7.9306***	7.2706***	-0.473***	8.0705	0.0017	-5.970
α	0.1688***	0.1324***	0.2783***	0.1565***	0.1517***	0.0933***
β	0.8350***	0.8357***	0.9664***	0.8618***	0.7580***	0.9066***
γ		0.0773***	-0.058***	0.1770***		
δ				1.4035***		
ρ					0.9995***	
ϕ					0.0216***	
AC	-5.1000	-5.1031	-5.0991	-5.1049	-5.1043	-5.0696
LL	3475.6	3478.7	3477.5	3480.8	3482.0	3452.9

Notes: In this table, AC and LL represent Akaike Information Criterion and the log-likelihood, respectively; *** and * suggest that the parameters are significant at the 1% and 10% levels, respectively.

The statistically significant GARCH parameters (β) in all models signal the existence of robust ARCH and GARCH consequences. Moreover, the aggregation of the ARCH and GARCH parameters confirms a considerable intensity of volatility endurance in hydrogen returns. The fluctuation persistence illustrates that present instability shocks dominate the future expectation of volatility for a long duration. More specifically, the persistence of variability validates a substantial influence of present return on future volatility. Consequently, the future volatility predictions of the hydrogen market largely depend on the present hydrogen returns.

Furthermore, the notable statistical significance of the asymmetric surprise coefficient (γ) in all models suggests unequal ramifications of bad and good news surprises on the hydrogen market. Therefore, the negative shock and positive shock asymmetrically affect volatility.

To validate whether bad news influences on volatility outweigh the impacts of good news, the study computes the extent of news ramifications on the return fluctuation in the hydrogen market using the TGARCH, EGARCH, and APGARCH models. These findings, presented in Table 11, illustrate that the negative shocks influence the volatility beyond the influence of good news. In the case of the normal error distribution, the findings of the TGARCH model confirm approximately two times more effect of bad news on conditional volatility than that of good news. Furthermore, in the case of Student's t error distribution, the EGARCH model also ensures approximately twice the effect of bad news on conditional volatility than that of good news.

Table 11: The extent of the shock's impact on volatility

	TGARCH	EGARCH
Panel A: Normal error distribution		
Negative shocks	0.2097	0.3363
Positive shocks	0.1324	0.2203
Panel B: Student's t error distribution		
Negative shocks	0.0978	0.2018
Positive shocks	0.0753	0.1208
Note: In the case of the TGARCH process, a positive shock has the consequence of α, while a negative surprise has the ramification of α + γ. In the case of the EGARCH model, positive surprise has the ramification of α + γ, while negative surprise has the ramification of α – γ.		

The findings of the study confirm the existence of asymmetric effects in the hydrogen market. The existence of asymmetric effects may have crucial implications for investigators, analysts and regulators. For investigators, the existence of asymmetry in the hydrogen industry would encourage them to develop more sophisticated models that can capture asymmetric responses to market shocks, policy changes, or technological advancements. Moreover, the researchers would be inspired to emphasize studying non-linear relationships and threshold effects within the hydrogen market. On the other hand, the understanding of the asymmetry will help policymakers to take better policies regarding the asymmetric nature of the hydrogen market because it affects how the market responds to different policies and economic factors. If they ignore these uneven responses, they might underestimate or overestimate the market's reaction, leading to ineffective or even harmful policies. The ineffective policy without considering asymmetric effects may increase risks, market volatility, and hinder sustainable growth. By recognizing and accounting for asymmetries, policymakers can

design better strategies that promote stability and encourage steady development of the hydrogen sector.

6.2 In-sample fitting of the model incorporating VIX as a predictor

Now, the study discusses the findings of the GARCH models by incorporating the VIX as an explanatory variable in the GARCH variance equations.

Table 12: The findings of the GARCH models by incorporating VIX into the models: Error distribution is Normal

	GARCH	TGARCH	EGARCH	APGARCH	CGARCH	IGARCH
ω	-3.2505***	-3.5305***	-0.6938***	-1.9505	-0.0005***	6.6905
α	0.1550***	0.1245***	0.2831***	0.1668***	-0.0053	0.1862***
β	0.7820***	0.7673***	0.9459***	0.7518***	0.2497	0.8137***
γ		0.0887***	-0.0596***	0.1236***		
δ				2.2044***		
θ	3.2006***	3.4206***	0.0024**	1.7806	3.4206***	6.3107***
ρ					0.9333***	
ϕ					0.1642***	
AC	-5.1078	-5.1202	-5.1091	-5.1189	-5.1148	-5.1083
LL	3483.4	3491.3	3483.8	3491.4	3488.6	3480.2

Notes: In this table, AC and LL represent Akaike Information Criterion and the log-likelihood, respectively; ***, **, and * suggest that the parameters are significant at the 1%, 5%, and 10% levels, respectively.

The main intention of presenting the findings of the various GARCH models by incorporating VIX into the models is to demonstrate that the lagged values of the VIX have a notable impact on the hydrogen return fluctuation. The study finds statistically significant positive lagged VIX coefficients (θ) in all GARCH variants (except APGARCH) models, which further confirms a substantial impact of the volatility index (VIX) on the volatility of hydrogen returns. The rejection of the null hypothesis for H0: $\theta = 0$ at the 1% level

verifies that the information provided by the VIX should not be ignored when modeling and predicting hydrogen market volatility.

The positive association between the volatility index (VIX) and hydrogen return volatility is expected because a rising VIX increases risk aversion, uncertainty, and pessimistic sentiment, leading to tighter financial conditions and liquidity crises in the market, which can reduce funding availability, cause project delays, bankruptcies, and increased volatility in hydrogen-related assets.

To assess the most appropriate model, the study considers two different indicators: Akaike information criteria and the log-likelihood (AIC and LL). Based on the values of Akaike information criteria and the log-likelihood (AIC and LL), the TGARCH, APGARCH, and CGARCH frameworks emerge as the principal models for structuring the conditional instability of hydrogen returns.

Table 13: The findings of the extended GARCH-type models by incorporating VIX into the models: **Error distribution is Student's t**

	GARCH	TGARCH	EGARCH	APGARCH	CGARCH	IGARCH
ω	-2.3605***	-2.5405***	-0.2890***	-1.6205	-0.0004***	0.0003
α	0.0913***	0.0773***	0.1573***	0.0893***	-1.1462***	0.0941***
β	0.8583***	0.8995***	0.9808***	0.9063***	2.0424***	0.9058***
γ		0.0378	-0.0416***	0.3232***		
δ				1.0092***		
θ	2.2406***	2.4006***	0.0008	2.3505	3.9306***	2.6407***
ρ					0.9003***	
ϕ					1.2289***	
AC	-5.1956	-5.1950	-5.1091	-5.1981	-5.1927	-5.1905
LL	3542.6	3543.2	3483.8	3546.3	3542.6	3537.2

Notes: In this table, AC and LL represent Akaike Information Criterion and the log-likelihood, respectively; ***,**, and * suggest that the parameters are significant at the 1%, 5% and 10% levels, respectively.

To examine the resilience of the results, the study further estimates the GARCH models, supposing a Student's t distribution followed by the error term. The findings of the GARCH models with this assumption (a Student's t distribution is followed by the error term) are presented in Table 13. These outcomes are mostly coherent with the findings (supposing the normal distribution is followed by the error term) documented in Table 12. Hence, volatility clustering exists in the hydrogen market, and the volatility index (VIX) maintains meaningful ramifications on hydrogen return fluctuation. Moreover, the GARCH, the APGARCH, and the TGARCH frameworks outperform the rest of the models. The results of the study are therefore reliable because they are not affected by the different methods employed.

Table 14: Approximated error metrics for various GARCH processes

	GARCH	TGARCH	EGARCH	APGARCH	CGARCH	IGARCH
Q-Statistics	0.0121 (0.912)	5.E-07 (0.999)	0.1018 (0.750)	0.0272 (0.869)	0.0143 (0.905)	0.0035 (0.953)
ARCH (LM)	0.102253 (0.7491)	0.042239 (0.8372)	0.000250 (0.9874)	2.10E-06 (0.9988)	0.101078 (0.7505)	0.012419 (0.9113)

Notes: In this table, Q-statistics demonstrates the Ljung–Box serial correlation test applied to scrutinize the hypothesis that there is no serial correlation, and ARCH (LM) denotes Autoregressive Conditional Heteroskedasticity Lagrange Multiplier (LM) Test used to investigate the null hypothesis of no presence of ARCH effects, which are a form of heteroskedasticity (changing variance) in a time series. Values in parentheses are p-values. ***, **, and * highlights the significance level of parameters at 1%, 5% and 10% levels, respectively.

The findings presented in Table 14 report the results of the Ljung–Box serial correlation test and Autoregressive Conditional Heteroskedasticity Lagrange Multiplier (LM) Test for

ARCH effect. The Q-statistics check the null hypothesis of no serial correlation, while the ARCH (LM) test investigates the null hypothesis of no ARCH effects (heteroskedasticity). The p-values of these diagnostic tests confirm the insignificance of the tests and suggest that serial correlations as well as heteroskedasticity are absent in the standardized error term for all the GARCH frameworks. Hence, the study can summarize that the GARCH processes can capture volatility persistence.

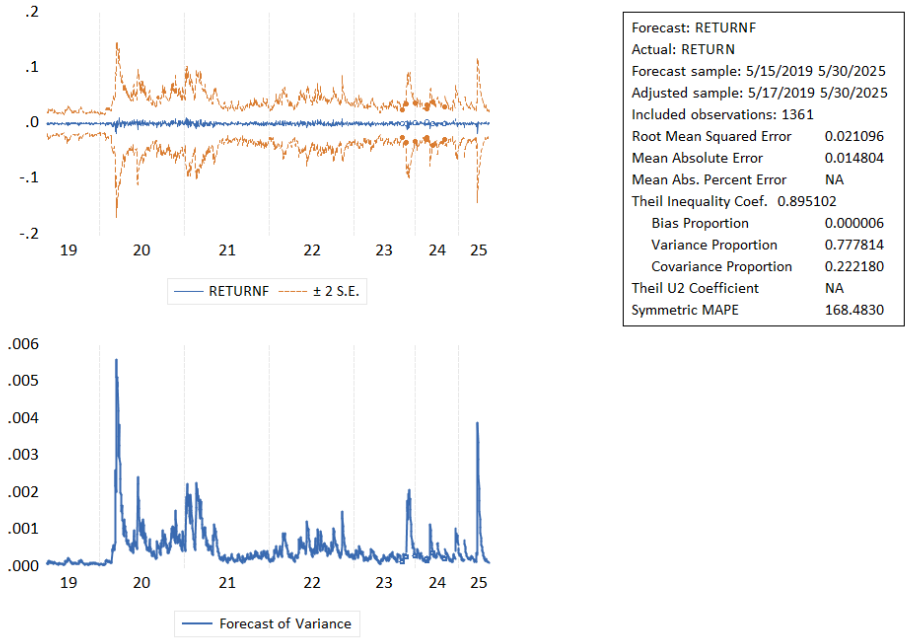

Figure 9: Static Forecast of Return for Entire Sample

The top graph presented in Figure 7 depicts the forecasted returns (RETURNF) for the entire sample coupled with the upper and lower confidence intervals, shown by the ±2 standard errors (S.E.). The returns seem to fluctuate close to zero, with confidence intervals remaining relatively narrow, indicating stable predictions with small variability over time. The graph below illustrates the Forecasts of Variance by presenting how the variance changes over the forecast period. Notably, there are peaks in variance during certain periods, suggesting potential volatility.

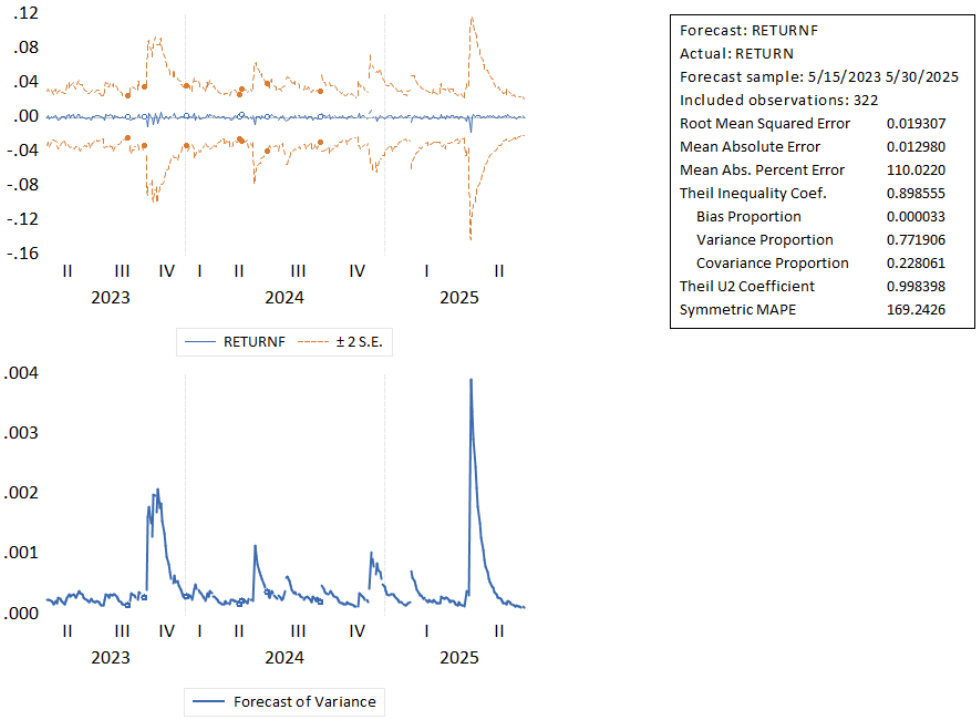

Figure 10: Static Forecast of Return for Sub-Sample

The above graph, shown in Figure 8, displays the forecasted returns (RETURNF) for the sub-sample along with confidence intervals. The fluctuation of returns around zero, and the tight confidence intervals indicate consistent predictions of returns with minimal variability over this period. Furthermore, the graph underneath shows the forecast of variance by indicating how variance shifts throughout the forecast period. There are notable spikes in variance at certain times, signifying periods of increased volatility.

6.3 In-Sample Performance of GARCH Models

With two main goals, the study evaluates the forecasting performance of various GARCH models. First, the study determines whether incorporating the information from the volatility index (VIX) enhances the GARCH forecasts. Second, the study identifies which of the models yields the most accurate predicted outcomes. The objective functions below are utilized in this analysis.

$$\text{Mean Squared Error: } MSE = \frac{1}{n}\sum_{i=1}^{n} \left(\sigma_{a,t}^2 - \sigma_{f,t}^2\right)^2$$

$$\text{Mean Absolute Error: } MAE = \frac{1}{n}\sum_{i=1}^{n} \left|\sigma_{a,t}^2 - \sigma_{f,t}^2\right|$$

In the aforementioned equations, n denotes the quantity of data points to be predicted., $\sigma_{a,t}^2$ indicates the actual volatility on day t, and $\sigma_{f,t}^2$ symbolizes the fluctuation prediction for day t.

Table 14 represents the calculated error metrics for different GARCH approaches. These findings indicate that incorporating the volatility index (VIX) as an explanatory variable in the model improves the forecasting power of the GARCH specifications. For each model, the MSE and MAE values are lower when the volatility index (VIX) is included as an influencing variable compared to the standard model without the VIX. Although the MSE and MAE values decrease slightly, this suggests that VIX provides valuable information that helps the models make more accurate predictions. While accomplishing the second goal, both the mean square error (MSE) and the mean absolute error (MAE) statistics confirm the earlier findings of the study, where the asymmetric GARCH models perform better than the standard symmetric GARCH model, with the TGARCH and the APGARCH showing the best performance.

Table 15:Mean Squared Error and Mean Absolute Error metrics

Model	Standard GARCH model	Volatility index (VIX) is included as an influencing variable in the GARCH processes
GARCH		
MSE	0.021096	0.020996
MAE	0.014804	0.014732
TGARCH		
MSE	0.021090	0.021018
MAE	0.014805	0.014745
EGARCH		
MSE	0.021095	0.021033
MAE	0.014807	0.014747
APGARCH		
MSE	0.021092	0.021019
MAE	0.014805	0.014746
CGARCH		
MSE	0.021098	0.020988
MAE	0.014804	0.014736
IGARCH		
MSE	0.021098	0.020996
MAE	0.014806	0.014730

Notes: These results are derived under the assumption that the errors follow a normal distribution.

7 CONCLUSION

Understanding the inherent risks associated with hydrogen investments is crucial for fostering a stable and attractive environment for continued growth and innovation in the hydrogen sector. This study explores the volatility dynamics of hydrogen investment, which is considered a key area of sustainable energy. To do so, the study uses the GRACH-type models on the S&P hydrogen index and the VIX to analyze data from May 2019 to May 2025. The study reveals strong evidence of volatility clustering and asymmetric effects of shocks on hydrogen returns. Furthermore, the research confirms the explanatory power of the Volatility Index (VIX) and demonstrates that the VIX contains essential information for explaining variations in hydrogen returns and improves the accuracy of volatility forecasts. The findings provide valuable insights for investors, policymakers, and stakeholders to manage risks associated with green energy projects within the evolving hydrogen financing sector efficiently.

7.1 Implications

A precise measure of financial market volatility is crucial because the hydrogen return is heavily influenced by the overall financial market condition. Expected future uncertainties in the financial market can create an adverse effect on the hydrogen return by rising pessimistic sentiment among investors and reducing funding availability for hydrogen-related projects. Notwithstanding, modelling and forecasting the volatility of hydrogen return, incorporating the financial market expectation of future volatility (VIX), has been overlooked or given little attention in previous studies. To address this research gap, the current research has endeavored to structure and anticipate the hydrogen return fluctuation by utilizing the Volatility Index (VIX).

Employing various GARCH (generalized autoregressive conditional heteroskedasticity) -type models, the study investigates the volatility of green investments, explicitly focusing on hydrogen financing. This research aims to model the volatility of hydrogen returns and identify the best-fitting model to capture the volatility dynamics. Alongside, the

study further explores the influence of macroeconomic factors, particularly the financial market instability represented by the Volatility Index (VIX), on the hydrogen return volatility.

The empirical analysis considers the S&P hydrogen economy index and CBOE Volatility Index (VIX), covering daily data from May 2019 to May 2025. With the help of GARCH(1,1), TGARCH, EGARCH, APGARCH, CGARCH, and Integrated GARCH (IGARCH) models, the study analyzes and forecasts the hydrogen return volatility. The findings reveal strong evidence of volatility clustering in hydrogen returns. The significant GARCH coefficients underscore the persistence of volatility over time, identifying past variances as strong predictors of future variances. The ARCH term suggests that recent shocks or unexpected returns have a direct impact on current volatility.

The study also finds asymmetric effects of news on volatility. According to the TGARCH model the negative shocks impact is more powerful than the positive surprises on the hydrogen return volatility, while the EGARCH model indicates that positive shocks have a larger impact on volatility. The APGARCH model confirms that the market is more sensitive to the size of past shocks, with any surprises in returns leading to a larger increase in volatility. Furthermore, the results show that the information content of the Volatility Index (VIX) is a notable factor in explaining the variation in the hydrogen return. The incorporation of the VIX also improves the volatility forecasts of the hydrogen return.
The research demonstrates that incorporating the VIX in the model significantly influences hydrogen return volatility. The past values of the VIX index have notable ramifications on the fluctuation of the hydrogen return. The study verifies that the information provided by the VIX can be used when modeling and predicting hydrogen market volatility.

Overall, the research contributes to filling a critical gap in the understanding of volatility dynamics in hydrogen-related investments. The findings of the study will be helpful for investors, policymakers, and stakeholders in developing effective risk management strategies for green energy projects within the emerging hydrogen financing sector to improve the attractiveness and stability of the investment environment for green energy projects..

7.2 Limitations and future research directions

The quality and availability of data on hydrogen investment are the main limitations of the study. The emerging hydrogen industry is still evolving, so the scarcity of historical data can impact the reliability of the analysis. Furthermore, due to the early stage development of the hydrogen industry in terms of investment, the findings of the study may not be widely adaptable across extended periods or in different market environments. In addition, the study applies the GARCH model to capture the volatility dynamics that may not fully represent the intricacies of actual market dynamics, particularly in the light of possible structural breaks or regime shifts. Additionally, external shocks like policy changes, technological advancements, macroeconomic surprises, and international incidents can notably influence market volatility and might not be completely represented through financial data alone. Finally, the study focuses exclusively on financial and market-based indexes, which may ignore broader societal, economic, and ecological determinants relevant to green investments. These limitations highlight the difficulty of simulating the whole range of influences on the hydrogen financing market.

By following the efficient market hypothesis, the study assumes that the market for hydrogen investments represents all available information and the asset prices integrate anticipations about risks and returns correctly. It also assumes that the data used in the models are stationary or appropriately transformed to meet stationarity conditions, ensuring valid statistical inferences. Furthermore, the study believes that the applied volatility models to capture the volatility dynamics of hydrogen financing markets are reliable.

Finally, the study posits that external conditions, such as macroeconomic variables and regulatory landscapes, remain stable and their effects are constant throughout the study period.

Future research stemming from this work could explore several promising ways. The research with a larger dataset to capture a longer time horizon and broader geographical scope can increase the reliability and applicability of the current findings. As the hydrogen market develops and more data becomes available, future studies can incorporate this information to refine volatility models and capture evolving market dynamics.
Upcoming research may analyze the influence and explanatory power of other indexes and factors in shaping hydrogen market volatility in the future. Incorporating these variables into the analysis could provide a more comprehensive understanding of the external forces driving market behavior.

Moreover, to find out the impact of a major policy announcements, geopolitical shifts and technological breakthroughs, the researcher can consider event study in future. Employing event study methodologies could help isolate and quantify the effect of these events on hydrogen market volatility, informing investment strategies and risk management practices. The interdependencies between hydrogen financing and other renewable energy sectors could also be explored in the future to understand how volatility in one industry spills over to others. Future researchers may apply more sophisticated econometric tools and machine learning algorithms for capturing non-linear relationships and improving forecasting accuracy, leading to more effective risk management strategies.

Finally, investigating the role of investor sentiment and behavioral biases in shaping hydrogen market volatility is a promising area for future inquiry. Understanding how psychological factors influence investment decisions provides valuable insights into market dynamics and informs strategies for managing investor expectations. To contribute to

the understanding of hydrogen market volatility and inform strategies for promoting sustainable and resilient green investments, the future research directions mentioned above can build upon the foundations laid by this work.

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