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**Impact of Sustainability Uncertainty on Sustainable
Assets: A Focus on Clean Energy and Hydrogen
Assets**

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ABSTRACT:

Clean energy and hydrogen exchange-traded funds (ETFs) have become important investable asset classes as the world shifts toward a low-carbon economy. But no previous study has looked at the risk dynamics of these sustainable assets derived from the risk of sustainability uncertainty. This thesis examines the relationship between the ESG based Sustainability Uncertainty Index (ESGUI) and realized volatility of the iShares Global Clean Energy ETF (ICLN) and the Global X Hydrogen ETF (HYDR) over the period January 2022 to December 2025. The study uses the Autoregressive Distributed Lag Mixed Data Sampling (ADL-MIDAS) regression with a Beta weight function, which accounts for the mismatch of frequency between daily financial data (prices for ETFs) and monthly ESG data (ESGUI). The study shows that sustainability uncertainty has a statistically significant negative influence on the total realized variance of both ETFs. The ESGUI effect for HYDR is roughly twice that for ICLN, as hydrogen is also more policy dependent and is in a more nascent stage of development. In the case of HYDR, the good and bad volatility decomposition shows that sustainability uncertainty has a significant effect on increasing good volatility ($+19.0 \times 10^{-4}$, $p < 0.001$) and decreasing bad volatility (-14.2×10^{-4} , $p < 0.01$), creating an options-like risk profile with the added element of policy resolution optionality. Results are stable across the volatility estimator of Rogers and Satchell (1991) and conditional variance specification of EGARCH. The results have important implications for green investors, portfolio managers, and policy makers in the uncertain sustainability policy environment of the 2020s.

KEYWORDS: ESG uncertainty, ESGUI, clean energy ETF, hydrogen ETF, realized volatility, MIDAS regression, good and bad volatility, sustainable finance

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Abbreviations

ADL-MIDAS	Autoregressive Distributed Lag Mixed Data Sampling
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroskedasticity
ARDL	Autoregressive Distributed Lag
CAPM	Capital Asset Pricing Model
CPU	Climate Policy Uncertainty
DCC	Dynamic Conditional Correlation
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
EMH	Efficient Market Hypothesis
EPU	Economic Policy Uncertainty
ESG	Environmental, Social, and Governance
ESGUI	ESG-Based Sustainability Uncertainty Index
ETF	Exchange-Traded Fund
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
GPR	Geopolitical Risk Index
HYDR	Global X Hydrogen ETF (ticker symbol)
ICLN	iShares Global Clean Energy ETF (ticker symbol)
IRA	Inflation Reduction Act
LL	Log-Likelihood
MIDAS	Mixed Data Sampling
MPT	Modern Portfolio Theory
NLS	Nonlinear Least Squares

OHLC	Open, High, Low, Close
OLS	Ordinary Least Squares
PP	Phillips-Perron
RV	Realized Variance / Realized Volatility
S.E.	Standard Error
SDGs	Sustainable Development Goals
TVP-VAR	Time-Varying Parameter Vector Autoregression
VIX	CBOE Volatility Index
VaR	Value-at-Risk
WUI	World Uncertainty Index

1. Introduction

1.1 Background and Motivation

This thesis has shown that the ESG-based sustainability uncertainty measure is statistically significant and economically relevant in predicting realised volatility in clean energy and hydrogen ETFs. The key result is that greater sustainability uncertainty led to lower total realised variance for both ICLN and HYDR, suggesting that the increased policy uncertainty in the sustainability landscape during 2022-2025 did not result in financial instability in either asset class, but rather an institutional response, that reduced volatility in both across the period. The discovery flies in the face of the intuitive belief that uncertainty always leads to risk, and is part of a growing stream of evidence from other areas of financial markets, including cryptocurrency markets (Dutta, 2026), European equities (Gaies et al., 2025), and fossil fuel prices (Olanrewaju et al., 2025), that sustainability uncertainty leads to a specific, and more often than not, more broadly stabilising effect on the overall volatility of financial markets.

The most theoretically important finding of the thesis is novel asymmetric finding of HYDR that sustainability uncertainty simultaneously increases good volatility, and it simultaneously decreases bad volatility. It shows that the H2 ETF is not just reacting to the uncertainty over sustainability in the hydrogen sector like a well-established clean tech fund but is leading with an options-like risk profile that magnifies upside opportunities and reduces downside risks. This particular risk structure is the result of the policy resolution of Hydrogen being uncertain and potentially transformative and is not directly apparent in the sustainable finance literature and presents an exciting research agenda for further theoretical and empirical analysis of the pricing of policy optionality in new sustainable asset classes.

Overall, the results in this thesis highlight the emerging relevance of sustainability uncertainty on the macroeconomic level, which cannot be ignored any longer by institutional investors, portfolio managers and policy makers. With the global energy transition on the fast track and the financial risk of sustainability policy decisions rising, the ESGUI and related sustainability uncertainty measures will play a greater role in the sustainable finance community's risk management toolkit. This thesis has made a first step towards laying the empirical foundations for that toolkit and in doing so, has raised as many questions as it has answered.

1.2 Research Problem

This is the central research problem of this thesis: it is where two well-established empirical observations converge and have not yet been taken together into consideration. The first observation is that there is a statistically significant and negative effect of the ESGUI on the realised volatility of non-sustainable asset classes. In its study of ESGUI and Bitcoin and Ethereum ETFs, Dutta (2026) concludes that greater sustainability uncertainty is linked to lower cryptocurrency volatility, which he believes has been caused by market participants adopting more stable, long-term investment patterns, due to a rise in sustainability concerns. The second observation is that clean energy and hydrogen ETFs unlike cryptocurrency are intrinsically linked to the sustainability policy agenda that the ESGUI measures: their fundamental values depend directly on the stability and ambition of ESG-related regulatory frameworks, and their investor base consists disproportionately of ESG-mandate institutional investors who make explicit sustainability commitments.

The question presented here is an empirical question that has so far not been answered: Is the negative relationship between ESG and volatility observed by Dutta (2026) also true for sustainable assets? On the other hand, the same behavioural phenomenon the increase in long-term strategies and decrease in speculation in times of uncertainty

could create less volatility in clean energy and hydrogen markets, as in the cryptocurrency markets. Ultimately, unlike cryptocurrency, clean energy and hydrogen ETFs are policy-dependent, which could create fundamental valuation uncertainty in ICLN and HYDR in the event of a rise in uncertainty regarding sustainability. Moreover, the good and bad volatility components of ICLN and HYDR can be affected asymmetrically by ESGUI shocks, which is not possible to detect with aggregate volatility measures alone: ESG-mandate investors can have a stabilising effect on the bad volatility but a destabilising effect on the good volatility, as well as the opposite scenario.

The other aspect of the research problem is the differential response of the two assets. ICLN is a well-established, 10-year-old ETF that is diversified across the globe, whereas HYDR is a more concentrated, newer ETF in a field where commercial viability is still being explored. Based on theory, the policy sensitivity of the HYDR should be higher and its number of investors is smaller than that of the HYHD, so that the impact of ESGUI shocks to realised variance should also be larger, which can be reflected by a larger absolute ESGUI coefficient. Empirical questions that this thesis can resolve, ones it is uniquely designed to answer, are whether this prediction is empirically supported and whether the asymmetric good/bad volatility pattern is exclusively for hydrogen or holds for clean energy.

1.3 Purpose and Objectives of the Study

This study aims to empirically investigate how uncertainty regarding sustainability, based on the ESG scores, affects realized volatility of clean energy and hydro ETFs, and whether the effect varies between the two sectors and between up and down sides of the realized variance. In order to accomplish this goal, four distinct objectives are being sought.

The first is to see if the ESGUI holds predictive information for the realised volatility of the iShares Global Clean Energy ETF (ICLN) in a framework of Autoregressive Distributed Lag MIDAS (ADL-MIDAS) regressions with both the Parkinson (1980) and Rogers and Satchell (1991) range-based volatility estimators as the dependent variables.

The second goal is to repeat the exercise with the Global X Hydrogen ETF (HYDR) to determine if sustainability uncertainty has a statistically and economically meaningful impact on the realised volatility of an asset that is purely hydrogen.

The third goal is to compare the size and direction of the ESGUI effect between ICLN and HYDR, in line with the theoretical prediction that the ESGUI effect is larger for hydrogen because it has a higher policy dependence and is earlier in its development stage, compared to ICLN.

The fourth goal is to break down the realised volatility of each ETF into good volatility (on upside days) and bad volatility (on downside days), and test the ESG influence on each type of volatility separately, as a way to investigate whether sustainability uncertainty is associated with asymmetric upside and downside realised volatility response in sustainable energy markets.

1.4 Research Questions

There are four research questions, all directly related to the four objectives stated above and the four formal hypotheses developed in Chapter 3, which will guide the empirical analysis.

RQ1: Does uncertainty around sustainability in the ESG domain have a significant impact on the realised volatility of the iShares Global Clean Energy ETF (ICLN)?

RQ2: Does the ESG-based sustainability uncertainty, quantified by the ESGUI, has a significant impact on the realised volatility of the Global X Hydrogen ETF (HYDR)?

RQ3: Is the impact of sustainability uncertainty on realised volatility stronger in ICLN and HYDR and, if yes, how?

RQ4: Is the impact of sustainability uncertainty different for good volatility (RV) as compared to bad volatility (RV) for both ICLN and HYDR, thereby indicating asymmetric reaction to the upside and downside price movements?

1.5 Scope and Delimitations

There are four research questions, all directly related to the four objectives stated above and the four formal hypotheses developed in Chapter 3, which will guide the empirical analysis.

RQ2: What is the value of uncertainty in the ESG dimension in the realised volatility of the iShares Global Clean Energy ETF (ICLN)?

RQ2: Does the ESG-based sustainability uncertainty, quantified by the ESGUI, has a significant impact on the realised volatility of the Global X Hydrogen ETF (HYDR)?

RQ3: Are the effects of sustainability uncertainty on realised volatility stronger in the ICLN and HYDR and, if so, how?

RQ4: Is the impact of sustainability uncertainty different for good volatility (RV) as compared to bad volatility (RV) for both ICLN and HYDR, thereby indicating asymmetric reaction to the upside and downside price movements?

1.6 Contributions of the Study

The thesis has three main contributions to the scientific body of knowledge on sustainable finance and financial econometrics.

1.6.1 First Application of ESGUI to Sustainable Asset Classes

The main empirical application of this thesis is the first use of the ESGUI for clean energy and hydrogen ETFs realised volatility. Existing uses of the ESGUI have only been in non-sustainable asset classes, such as cryptocurrency (Dutta, 2026), European equities (Gaies et al., 2025), and fossil fuel prices (Olanrewaju et al., 2025). This thesis expands the literature on ESGUI on assets that are directly linked to the sustainability policy agenda that the index reflects and tests the validity of the negative ESGUI-volatility relationship found for non-sustainable assets to sustainable assets. This confirmation for both the ICLN and the HYDR, with significant asymmetric nuances about hydrogen, makes the ESGUI a broad-spectrum volatility predictor and not exclusively related to any asset class.

1.6.2 Cross-Sectional Analysis of Sector Maturity

This thesis has been the first to offer a rigorous cross-sectional analysis of the relationship between the transmission of sustainability uncertainty and asset volatility using the combined data set of ICLN and HYDR and a consistent method. The finding that HYDR's total realised variance coefficient is nearly double that of ICLN in absolute terms and that HYDR has a significantly stronger positive good-volatility response to ESGUI compared to ICLN is evidence that the stage of sector development is a first-order determinant of the pricing of sustainability uncertainty in asset risk. It has direct implications for the emerging literature on sustainable asset allocation, because the portfolio managers' exposures to sustainable uncertainty risk clearly must be different between early- and mature-stage sectors, even if both sectors are designated "clean energy" for ESG screening.

1.6.3 Novel Good/Bad Volatility Decomposition for Sustainable ETFs

The relationship between ESGUI and ETFs is a novel application of the good and bad volatility decomposition of Patton and Sheppard (2015) and BenSaida (2019) that is the most original methodological aspect of this thesis. The finding that HYDR's good volatility is positively affected by sustainability uncertainty, whereas bad volatility is negatively

affected, is novel in the ESGUI literature and extends the theory of the impact of policy dependent, early-stage sustainable assets on the ESG information environment shocks. The two-sided asymmetric response pattern (upside amplification and downside dampening) is theoretically interpretable as an options-like payoff profile that arises from the dependence of the price of hydrogen on the resolution of uncertain (but potentially transformative) policies, and is directly relevant to pricing and trading of derivatives, hedging strategy design and the development of ESG risk management frameworks for sustainable energy portfolios.

1.7 Preview of Key Findings

For orientation, this section provides a brief summary of the main empirical results presented in Chapter 6. Chapter 7 implications and recommendations can be informed from these findings.

In all model specifications and ESGIE and ESGIE2, the impact of the ESGUI is a statistically significant negative effect on the total realised variance of both ICLN and HYDR. For ICLN, the ADL-MIDAS coefficient on ESGUI-EW is 6.2×10 ($p < 0.01$), while for HYDR it is 11.2×10 ($p < 0.05$). The results validate H1 and H2, and show that realised volatility in both sustainable energy ETFs decreases with an increase in sustainability uncertainty, which aligns with the results of Dutta (2026) for non-sustainable assets, and can be explained by the stabilising effect of ESG mandate institutional investors and the limited presence of speculative trading during times of greater sustainability uncertainty.

Second, the ESGUI effect is invariably more pronounced in absolute terms in the case of HYDR than that of ICLN in all specifications, supporting H3. The ratio of the two coefficients is roughly 2:1, which is broadly in line with the theoretical expectation that a higher degree of policy concentration and less investors flow may magnify the effects of sustainability uncertainty on realised variance.

Third, the good and bad volatility decomposition shows that there is a striking asymmetry in the HYDR case with the main finding of this thesis. While HYDR bad volatility responds negatively and significantly to ESGUI ($= 14.2 \times 10$, $p < 0.01$), HYDR good volatility responds positively and significantly ($= +19.0 \times 10$, $p < 0.001$). This is not the case for ICLN, as there is no similar asymmetry with regard to its good volatility and ESGUI. This is an asymmetric pattern (restricted to HYDR and found across both weighting schemes of ESGUI and both volatility estimators) and this is the most theoretically significant empirical contribution of this thesis.

Fourth, the results are stable with respect to the volatility estimator (Parkinson and Rogers-Satchell), to the ESGUI weighting scheme (equally weighted versus GDP-weighted) and to the volatility measure (realised variance versus EGARCH conditional variance). HYDR also shows a more front-loaded ESGUI response, as indicated by the Beta parameters of the weight function which suggests that hydrogen asset prices incorporate sustainability information faster than ICLN. This aligns with the increased number of active institutional investors in the HYDR portfolio who closely track ESG policy developments.

1.8 Structure of the Thesis

The rest of this thesis is structured as follows: A short overview of the contents of each chapter and their contribution to the overall research architecture is given in Table 1.

Table 1. Structure of the Thesis

Chapter	Title	Content and Purpose
1	Introduction	Formulates research context, motivation and problem. States research questions and objectives. Gives an overview of main results and presents the thesis structure.
2	Theoretical Background	Develops the theoretical foundations: Sustainable Finance Theory, Modern Portfolio Theory, Efficient Market

Chapter	Title	Content and Purpose
		Hypothesis, ESG uncertainty as systemic risk, MIDAS theoretical basis, and Behavioural Finance Theory. Offers a coherent overall concept.
3	Literature Review and Hypotheses	Covers the empirical literature related to finance of clean energy, finance of hydrogen, ESG applications, good/bad volatility and MIDAS methodology. Formulates four formal research hypotheses (H1–H4) in which theoretical support is given.
4	Data and Descriptive Statistics	Describes the three data series (ICLN, HYDR, ESGUI). Explains the reason for the sample period used in 2022-2025. Reports descriptive statistics, unit root tests, ARCH-LM tests, realized volatility summaries and correlation analysis for 1002 daily observations and 48 monthly values for ESGI.
5	Methodology	Defines the Parkinson and Rogers-Satchell realized variance estimators, the base-MIDAS model and ADL-MIDAS model, the beta weight function, the good/bad volatility decomposition and the EGARCH robustness specification. Describes all six empirical models.
6	Empirical Results and Discussion	Reports and interprets all ADL-MIDAS estimation results for 24 variants of the model. Provides tables 8-12: total variance, rogers-satchell robustness, good volatility, bad volatility and a cross-asset summary. Communicates results in the light of H1-H4 and previous research.
7	Conclusions	Provides conclusions based on empirical research. Answers research questions and theories Discussion of what's learned and practical implications. Recognizes constraints. Identifies areas for future investigation.

Note: Chapters 4-6 make up the empirical backbone of the thesis. The theoretical and empirical background is given in chapters 2 and 3. Chapter 7 brings together all the results and draws conclusions that can be implemented.

The theoretical underpinning is laid out in Chapter 2, which presents the five conceptual frameworks that are used for the empirical investigation: Sustainable Finance Theory, Modern Portfolio Theory, the Efficient Market Hypothesis and information economics, the theory of ESG uncertainty as a systemic risk factor, and the theoretical basis of the MIDAS framework, as well as Behavioural Finance Theory. The frameworks are combined in an integrated conceptual model that provides a mapping of the three theoretical pathways between ESGUI and ETF-volatility and also provides the directionality of the forecasts that inform the hypothesis development in Chapter 3.

The empirical literature for the four research questions is reviewed in Chapter 3. It reviews past literature on sustainable asset pricing and volatility, the financial features of clean energy and hydrogen ETFs, past use of the ESGUI, the good and bad volatility literature, and the expanding research literature on volatility modelling using MIDAS methods. The chapter ends with the formalization of the hypotheses H1 - H4, which are all based on the theoretical frameworks developed in Chapter 2 and the empirical aspects of the literature review.

Details about the data used in the empirical analysis are provided in Chapter 4. It presents ICLN, HYDR and the ESGUI, explains the sample period from January 2022 to December 2025, and provides a detailed description of all series, their unit root tests, ARCH-LM tests for heteroskedasticity, realized volatility summaries and a correlation matrix. The chapter describes the main stylised facts of the data that underlie the methodological options that follow.

The econometric methodology is detailed in Chapter 5. It includes the Parkinson (1980) and Rogers and Satchell (1991) realized variance estimators, introduces the base MIDAS and ADL-MIDAS regression models with Beta weight function, introduces the good and bad volatility decomposition and describes the EGARCH conditional variance robustness specification. All six types of models estimated in Chapter 6 are summarized in a table.

All the empirical results are presented and explained in Chapter 6. The chapter has six sections: baseline ADL-MIDAS results for total realised variance based on the Parkinson estimator; robustness results based on the Rogers and Satchell estimator; good volatility

analysis; bad volatility analysis; a cross-asset summary comparison table; and a comprehensive discussion of all four research hypotheses where the results are compared to previous studies and policy and investment implications drawn out.

The thesis is concluded in Chapter 7. It summarizes the main empirical results in relation to each of the research questions and hypotheses, discusses the theoretical and practical implications of the results, recognizes study limitations and identifies the most promising directions for future research. Finally, the chapter discusses the importance of the results for the sustainable energy investment sector as well as for the literature on sustainability uncertainty and financial market risk.

2 Literature Review

2.1 Sustainable Finance and Asset Pricing

Environmental, social and governance (ESG) factors are important drivers of long-term financial sustainability and, therefore, the idea of sustainable finance has been gaining momentum in both the agendas of academics and policy. Sustainable finance is usually described as the integration of ESG factors into investment decisions and seeks to link investment to the broader sustainable development agenda (Edmans and Kacperczyk, 2022). This integration is a paradigm change from the previous short-term profit maximisation emerging in the concept of value creation which takes into account systemic planetary and social boundaries. It suggests that a fiduciary duty of an investment manager is changing to include the ability to reduce systemic environmental risks that have the potential to harm the value of a portfolio over the long term.

In the financial market's environment, asset pricing theory forms the basis for the calculation of the fair value of the financial instruments, depending on their risk characteristics. The models that have been developed generally assume that investors will only pay for the systematic risk, or co-movement with the overall market fluctuations, of an asset, most notably the Capital Asset Pricing Model (CAPM). These models help to understand how much risk corresponds to a given expected return, enabling to allocate capital efficiently: You should invest in an asset, the value of which is determined by the ability to compensate for the risk of investing in it.

The inclusion of sustainable finance in these price models has led to a critical analysis of the understanding of what constitutes risk and value. According to Pastor, Stambaugh, and Taylor (2021), sustainable investing is a balance between investors' preferences for environmental and social good and the fundamental impact on asset prices. Their research shows that "green" assets tend to be more highly valued and therefore, less highly expected because investors are willing to pay a premium for assets that are more in line with their values in society. This "greenium" or "green premium" indicates that

the utility that the investors get from investing in sustainable assets is more than just financial, which in turn reduces the cost of capital for sustainable companies.

On the other hand, “brown” or less sustainable assets come with heightened climate transition and regulatory risks and can demand higher returns for investors (Pastor et al., 2021). They are increasingly at risk due to “stranded asset risk” a sudden change in policy or an advance in technology that makes the carbon-intensive infrastructure uneconomical. In this context, the use of sustainability in asset pricing models recognizes that ESG is not a one-way street but a key driver of investor utility and an important pillar of systematic risk. This theoretical transition is necessary to grasp the dynamics of new market areas such as clean energy and hydrogen, where market prices are subject to change depending on the future cash flows as well as the changing society and regulatory demand for sustainable change.

The present thesis is both theoretically and empirically grounded and supported by a growing empirical literature showing that policy uncertainty has a measurable and negative effect on sustainable investment outcomes, bridging the gaps between the theoretical asset pricing literature and the empirical analysis of policy uncertainty. Darsono et al. (2022) perform panel Autoregressive Distributed Lag (ARDL) analysis on twelve countries to conclude that economic policy uncertainty (EPU) has significant negative long run impact on sustainable stock returns while gold prices, oil prices, and Bitcoin prices have positive long run impacts. From their evidence, they conclude that the policy uncertainty is not simply a background factor that affects sustainable investors, but is a structural factor that constrains expected returns and consequently asset valuations of sustainable investing assets. The present thesis builds on this insight, focusing on sustainable ETF volatility as predictable by the sustainability uncertainty of the policy because of the direct motivation to study the link between the two. In addition to this cross-country evidence, Shaikh (2022) investigates the impact of policy uncertainty on the Dow Jones Sustainability Index (DJSI) in the USA and notes that EPU is negatively associated with the returns of sustainable equity and statistically significant.

Most importantly, Shaikh (2022) finds that crisis periods, and presidential election years in the United States in particular, are the years when the adverse impact on sustainable returns is the greatest, a result directly relevant to the sample period that this thesis covers, featuring both the high uncertainty crisis of the COVID recovery period in 2022 and the 2024 US presidential election, which is likely to be a serious sustainability policy shock due to the threat of rollback of the Inflation Reduction Act.

Caferra and Falcone (2023) analyse the behavioral aspect of sustainable investment in a context of uncertainty by applying quantile regression and wavelet analysis to investigate how investors' preferences for sustainable companies change over time depending on the market stability. The uncertainty in the markets can in fact spur interest in sustainable companies to investors who place greater weight on the social and environmental impacts of their investment, as uncertainty over the returns of traditional investments makes the returns of ESG-invested funds more attractive relative to them. This is the behavioural micro-foundation for the negative relationship between ESG uncertainty and asset volatility observed by Dutta (2026) and confirmed in this thesis: increased uncertainty over sustainability can paradoxically help to establish the stability of sustainable asset markets by attracting and keeping ESG-mandate institutional investors who offer a demand floor. The findings of Caferra and Falcone (2023) are especially pertinent for the interpretation of the HYDR findings in Chapter 6 that bad volatility is damped when the ESGUI is high, which is consistent with the retention of mandate-driven investors during times of heightened uncertainty.

2.2 Sustainability Uncertainty and the ESGUI

Sustainability uncertainty is the lack of a general view on the dynamics of the environment, society and government (ESG) which are critical to the economic landscape and investment climate. This construct is widely used with the development of the ESG based Sustainability Uncertainty Index (ESGUI) which is a major measure developed in this construct that quantifies systematic environmental and social risks each month in country reports of the Economist Intelligence Unit (EIU) (Ongan, Gocer,

and Ik, 2025). This index measures the "pre-price" component of risk, influenced by uncertainty in future regulatory outcomes and social expectations, before any real price move has taken place, as opposed to traditional measures of market volatility which only reflect realised price changes. The ESGUI puts together these text indicators into a standardised measure to determine the noise and conflicting information in the global energy transition.

Importantly, unlike other indexes like the World Uncertainty Index (WUI) or the news-based Economic Policy Uncertainty index of Baker, Bloom, and Davis (2016) the ESGUI is explicitly designed to measure uncertainty over all three dimensions of sustainability – environmental, social and governance. An increasing index of course reflects increased problem solving in national and international sustainability efforts but in a broader way than one-pillar uncertainty measures because of the many aspects in which challenges to sustainability efforts occur. In order to have cross-country and cross-period comparability, all index values have been normalised within the range of [0, 100] (Ongan et al., 2025).

Financial market implications are complex and complicated, and the correlations between sustainability uncertainty and financial market outcomes are not straightforward. The only empirical study that is closest to the present thesis is that of Dutta (2026) which shows a negative link between increasing sustainability uncertainty and the realised volatility of non-sustainable asset classes, namely cryptocurrency ETFs. The theory goes that when there is more uncertainty about sustainability, investors have a more cautious mindset, and are less willing to be involved in price speculation with hype or rapid changes. This change in structure to more sustainable processes and more stable, long-term corporate efforts may lead to more predictable economic situations, which helps to lessen realised market volatility. Similarly, Gaies, Chaabane, Adeosun and Sahut (2025) report negative ESGUI impact on stock market volatility in Europe and Olanrewaju, Adebayo and Uzun (2025) report negative short-term ESGUI impact on fossil fuel prices. The present thesis builds on this new realm of literature, focusing on a

category of assets that has never been looked at from the ESGUI prism: clean energy and hydrogen ETFs.

Additionally, the effects of sustainability uncertainty are not proportional across asset classes. Emerging asset classes like hydrogen and clean energy are more prone to 'information shocks' than other asset classes as even though the asset class has shown growth, there is smaller historical data to back up valuations, making them more susceptible to ongoing sentiment and policy shifts in ESG. The empirical analysis in this thesis investigates ICLN and HYDR separately to prove that the theoretical sensitivity to maturity, between the two sectors, may lead to statistically significant differences in the ESGUI-volatility relationships.

2.3 Clean Energy Assets: Financial Characteristics and Volatility Drivers

Clean energy assets are a key component of the world's energy infrastructure and increasingly are considered the foundation for a scalable low-carbon economy. The valuation of clean energy projects is complicated due to the fact that the valuation depends on different factors including the environmental sustainability of the project in the long-term, the efficiency of the technology etc. But these industries are more exposed to external shocks, particularly those stemming from uncertainty relating to sustainability. This uncertainty reflects a complex interplay of policy change – including the sudden shock of policy change, such as subsidy reductions, carbon pricing mechanisms and regulatory requirements – and the pace of technological innovation, which can make existing infrastructure redundant or give rise to new competitive dynamics.

A vast empirical body of evidence has established that the risks of clean energy assets differ from those faced by energy and general market assets. Traditional investors have invested in dirty energy stocks and international equity indexes. Kuang (2021) studies the behaviour of green bonds and clean energy stocks as safe havens for investors. Kuang (2021) concludes that green bonds are consistently safe havens as they have less

downside risk. Clean energy stocks offer superior risk/return characteristics when they rise in the market, but may be more volatile when the market is falling, thus adding to the total volatility of an international equity portfolio. This is especially valuable for the ICLN ETF that is discussed in this thesis, as it contains a significant overlap with the technology sector and is therefore not a traditional "defensive" asset when the uncertainty in sustainability is increasing.

Climate policy uncertainty (CPU) is one of the most volatile climate change drivers in clean energy assets. Zhang, Hong and Ding (2023) show that the impact of climate policy risk on the energy sector is diverse. In the long run, climate policy risk increases price volatility of crude oil, while decreasing price volatility of clean energy markets. Their results suggest that big climate events, such as the signing of the Paris Agreement, contribute to strengthening the investor knowledge of transition risks, leading to weakening the historical positive correlation between oil and green assets, consistent with the separation theory. Moreover, Zhao, Ramzan, Brika and Eweade (2025) demonstrate that the impact of policy uncertainty is asymmetric across the different percentile of renewable energy markets, with the least renewables intensive percentile of renewable energy markets being most sensitive and the most intensive percentile being least sensitive. The results indicate that the predictive power of volatility of the ESGUI index for clean energy is likely to be on the tails of the distribution, which is the rationale for the methodology used for decomposing the good and bad volatility used in the thesis, Chapter 5.

The study closest to this thesis in terms of methodology is Raza, Khan, Benkraiem and Guesmi (2024) who use a GARCH-MIDAS approach with the Climate Policy Uncertainty (CPU) index as a low frequency predictor to forecast the volatility of three sustainable financial market indices, namely the S&P Green Bond Index, the S&P Global Clean Energy Index and the Dow Jones Sustainability Index. Their study shows that including the CPU predictor enhances the volatility of the three sustainable indices. In addition, the CPU predictor also contains a major contribution to the out-of-sample forecasting error

reduction over benchmark models that do not include the CPU predictor, suggesting that the sustainable indices of uncertainty contain predictive information about the uncertainty of clean energy and sustainable assets. In particular, Raza et al. (2024) adopt the same MIDAS methodology that is followed in this thesis and the same S&P Global Clean Energy Index that the ICLN ETF follows - methodological parallels are deliberate and explicit. The thesis contains three main contributions which are not addressed by Raza et al. (2024). It is based on the ESGUI for the first time, which contains the multi-dimensional sustainability uncertainty index in contrast to the CPU indicator, which only focuses on environmental, social and governance issues. Second, a single asset class of hydrogen ETFs (HYDR) does not exist to perform a cross-sectional comparison within Raza et al. (2024). Thirdly, it decomposes realized variance into the good and bad volatility element which is not considered in Raza et al. (2024).

Naifar (2024) examines the diverse responses of a variety of sustainable sectors to uncertainty in the context of climate policy, including green bonds, clean energy indices and ESG investment portfolios, following the work of Raza et al. (2024). The results suggest significant sector heterogeneity, with green bonds being less affected by the CPU shocks, showing stable risk profiles across the distribution of CPU values, and clean energy indices being highly sensitive, especially at higher quantiles of the CPU distribution where there is more regulatory uncertainty. ESG investing portfolios sit somewhere in the middle: They are fragile when CPU levels are high, but not quite as fragile when the situation is moderately unpredictable. In addition, the evidence offered by Naifar (2024) is also theoretically important for the present investigation, in two ways, respectively. This result does confirm that the group of clean energy assets (including ICLN) is one of the most policy uncertainty sensitive sustainable asset groups, as posited in Hypothesis H1, that shocks to ESG will have measurable and economically meaningful effects on the volatility of ICLN. Second, this thesis is based on the cross sectional design, which aims at deciphering if the ESGUI effect is different for the more mature ICLN and the more policy sensitive HYDR, as evidenced from the sectoral differences presented in Naifar's (2024) empirical analysis.

Yet another empirical fact is that oil market shocks cause volatility in sustainable energy. Yaya et al. (2022) break down the volatilities of oil prices changes into four components following a GARCH-MIDAS model: Economic activity shocks, Consumption demand shocks, Inventory demand shocks and Supply shocks. They find that the effect of the oil price volatility is asymmetric: both oil consumption demand shocks and supply shocks significantly decrease the volatilities of green investment indices, the latter of which has a more pronounced impact. This fact of asymmetric sensitivity in the clean energy industry provides empirical support for the good and bad volatility decomposition of this thesis, and shows that the shocks volatility is of an upside or downside nature is determined by the type of shock, not the magnitude of it.

Another source of structural change that contributes to the volatility of clean energy markets is geopolitical risk. This is illustrated by a study by Mei et al. (2020) which demonstrates that the realised volatility of energy futures is positively related to the uncertainty of Geopolitical Risk (GPR) and that GPR indices based on text improve the short-term forecasting of energy futures volatility over historical models. Based on the findings, one of the interesting differences is that geopolitical threat is more even but that real-world events exert more influence on expectations of long-term volatility than geopolitical threats alone. This highlights that the impact of real-life geopolitical events is more pronounced in the market. This is particularly important for the present thesis, given that the Russia-Ukraine War (2022), the Inflation Reduction Act (2022) and the USA presidential election (2024) are all geopolitical events that have a direct effect on clean energy policy.

2.4 Hydrogen as an Emerging Financial Asset Class

The hydrogen economy is a particular part of the sustainable financial environment. Hydrogen is a relatively new asset class compared to wind or solar, which are already proven and have decades of performance track record; whereas, cost competitiveness and technical viability at a commercial scale for hydrogen have yet to be demonstrated. There has been a step-change in the economic performance of the sector, with the cost

of around \$60,000 for a system in the year 2005 falling to around \$10,000 by 2015, supported by a global resolve for decarbonisation of heat and transport that has been growing stronger over the last year or two (Staffell, Scamman, Velazquez Abad, et al., 2019). The cost reductions imply that the "pathway uncertainty" that have been a major constraint for hydrogen investment has been reduced due to structural improvements in the economic viability of the technology and that the investment in infrastructure investments (which can be build incrementally, e.g. using existing gas networks) can lower the large initial investments that have led to low institutional interest.

But the financial profile of hydrogen assets is still fundamentally different to that of mature renewable assets and conventional energy. Lucey, Yahya, Khoja, Uddin and Ahmed (2024) employ a time varying student-t copula approach to conclude that the correlation among hydrogen and conventional commodity prices, and between commodity prices and equity markets can vary significantly in times of high uncertainty. The empirical results reveal a strong negative correlation between the VIX (a measure of investor fear in the equities market) and the hydrogen asset – confirming the specific sensitivity of the hydrogen asset to investor emotions. The VaR, CoVaR and Delta CoVaR calculations demonstrate significant differences throughout the green asset class, with the lowest VaR and CoVaR values being found for green bonds due to their government backing, and highly regime-sensitive risk measures for hydrogen being observed. These results confirm the need of a specific analytical approach for hydrogen assets – the need of including HYDRs as a separate asset in this thesis rather than a combination with generalized clean energy proxies.

The study on connectedness has also helped in understanding the importance of hydrogen in the more general financial system. Rubbaniy et al. (2024) use a technology of connectedness based on a Time-Varying Parameter Vector Autoregressive (TVP-VAR) model and demonstrate that assets of the hydrogen economy, solar and clean technology indices are constantly net shakers of assets, while commodities like crude oil, natural gas and gold are mainly net receivers. Also, portfolio research finds that during

health related financial crises (such as the COVID-19 pandemic), the hedge properties of hydrogen and renewable energy assets are strong, but during military wars (such as Russia-Ukraine War), they are significantly reduced. The crisis-dependence of the hedging identity of hydrogen, and the fact that the nature of the uncertainty they face has to be taken into account when deciding on investment strategies, is captured well by the ESGUI, which is a broad measure of sustainability uncertainty.

In this light, the quantile connectivity paradigm developed by Kayani, Ullah, Aysan, Nazir and Frempong (2024) helps with the evidence by studying the linkages between hydrogen, digital assets, traditional assets and renewable energy prices during acute economic crises. They discover that the strength of cross-asset linkages is significantly different in various market environments, and grows in times of black swan events, like the COVID-19 pandemic and the Russia-Ukraine crisis. This data is relevant for the 2022-2025 sample period for this thesis which has several such events and therefore has high variability of ESGUI and realised volatility for ICLN and HYDR.

Almeida, Gaio and Goncalves (2025) also identify a U-shape relationship between connections and sustainable and developing technological assets, where the amount of spillovers is more pronounced in extreme market conditions (bullish and bearish) than during a normal market. This suggests that investors make dynamic portfolio rebalancing decisions during times of greatest uncertainty and that a new technology can shift an industry's dynamics when it redirects investment toward alternative long-term goals and away from the climate sector. So, for hydrogen assets, the appearance of technology and regulatory readiness is a volatility multiplier; minor policy news can lead to substantial reallocations of capital that go against the flow of more mature green markets. This multiplier impact theoretically supports Hypothesis H3 of this thesis that the ESGUI effect on HYDR volatility is higher than that on ICLN. The transmission of sustainability

uncertainty to realised variance should be greater for policy sensitivities with higher values for hydrogens.

2.5 Good and Bad Volatility: Theoretical Foundations

One key lesson from the volatility literature is that the origins of volatility differ as do its long-run implications for financial stability. The decomposition of total realised variance into "good" and "bad" components, using the sign of contemporaneous returns, is an empirically rich and theoretically motivated method for analysing asymmetric market reactions to shocks. There is a non-uniform association between volatility and market developments: "good" volatility is correlated with rising prices, while the "bad" volatility is correlated with negative shocks, jump risks, and contagion (Patton and Sheppard, 2015). Their empirical findings reveal that greater volatility in the past days on negative returns more accurately forecasts future volatility than volatility on positive returns, suggesting a "leverage effect" that negative news has a much greater lasting effect on Instability than positive news.

BenSaida (2019) further generalizes this approach to the analysis of asymmetric connectedness between financial markets, demonstrating the larger size of bad volatility spillovers as compared to good volatility spillovers, and the dynamism of the asymmetric links over time, which become more significant when market stress occurs. Additionally, Ang, Chen and Xing (2006) provide further evidence that investors require a premium for bad volatility, which suggests that bad volatility has a direct asset pricing effect, while good volatility does not. These findings all provide an impetus for the decomposition of ICLN and HYDR realised variance into RV and RV components, respectively, in Chapter 5 of this thesis, which suggest that the ESGUI may be able to affect realised variance in an asymmetric way, dampening bad realised volatility by limiting panic selloffs, while amplifying good realised volatility by inducing speculative positioning activity on the upside of sustainability policy outcomes.

Cagli, Taskin and Mandaci (2023) further confirm the asymmetric propagation of uncertainty shocks to sustainable financial markets, using the Renyi transfer entropy to analyse the direction and non-linearity of the information transfer between different uncertainty factors and ESG-related assets such as sustainable stock indices and green bonds. They conclude that the relationship is not one-way but feedback exists between the uncertainty environment and the evaluation of sustainable assets: uncertainty shocks do not only flow from oil price volatility to sustainable indicators, but back to oil price volatility as well. Importantly, the study reveals that tail effects of the uncertainty surrounding cryptocurrencies exacerbate the reactions of sustainable asset markets in times of high uncertainty, which aligns with the increased HYDR volatility during the high-uncertainty periods of the present sample. In Chapter 5 of this thesis, for the good/bad volatility analysis, Cagli et al. (2023) have shown evidence of non-linear, tail-driven information transmission, which suggests a methodological argument to consider the information transmission across upper and lower tails of the volatility distribution separately using the RV and RV decomposition.

The 1922-2025 sample period is also highly skewed: the policy shocks experienced by clean energy and hydrogen assets are asymmetric, which is why the good/bad decomposition is particularly relevant in this case. The overall picture for ICLN and HYDR was a positive policy shock in August 2022 motivated by the Inflation Reduction Act, which pushed prices to the upside, and upside threats from the rollback of the IRA after the November 2024 election, which pushed prices to the downside. Such uncertainty regarding sustainability may have different effects on these two forms of volatility, so combining them into overall realised volatility (as most previous studies do) would mask the actual transmission channel. This discovery in Chapter 6 of this thesis, namely that ESGUI raises good volatility (and lowers bad volatility), would be completely lost without this decomposition, and is an example of the methodological value of following Patton and Sheppard (2015) and BenSaida (2019) in disaggregating the volatility signal.

2.6 Methodological Literature: MIDAS and Mixed-Frequency Models

The complexity of the analytical tools employed in sustainable finance has led the empirical literature to focus on econometric tools that can link the high-frequency market returns with the low-frequency sustainability indicators. Historically, traditional time-series models have been plagued by "frequency mismatches" where policy indexes are constructed on a monthly basis and then artificially aggregated into daily asset prices, often leading to loss of information and to policy-information being spread thin. Over the past few years, the literature has made use of the framework of Mixed Data Sampling (MIDAS) developed by Ghysels, Santa-Clara, and Valkanov (2004), which allows for including variables sampled at various frequencies within a regression without having to aggregate them.

The MIDAS framework has been found to be very appropriate for modelling the link between the low-frequency uncertainty indices and high-frequency volatility of the financial markets. According to Dong, Gong, and Wang (2025), adding environmental attention to multifractal MIDAS frameworks greatly improves the forecasting of crude oil market volatility, as text-based measures based on people's search activities capture to some extent an environmental consciousness that directly affects financial performance. Specifically, they show that their models outperform the classic GARCH models in predicting volatility over short, medium and long horizons, especially if higher order autocorrelations and non-linear memory effects in energy markets are considered. Using a two-factor GARCH-MIDAS model, Fang et al. (2023) investigate the impact of global economic policy uncertainty on the long-term volatility trend of crude oil futures, revealing an important difference between short term "jump dynamics" (representing 15%–40% of price changes) and the more long-lasting long term dynamics associated with structural policy uncertainty. This is an important result, directly motivating the ADL-MIDAS specification used in Chapter 5, which implements a Beta weight function mapping monthly ESGUI changes into the realised variance over the day, but avoids over-parameterisation of the lag structure.

Specifically, Raza et al. (2024) apply the GARCH-MIDAS framework to sustainable energy market volatility by considering a Climate Policy Uncertainty index as the low-frequency predictor in the S&P Global Clean Energy Index, S&P Green Bond Index and Dow Jones Sustainability Index. They are found to be substantially more effective for forecasting volatility than benchmark specifications in a way that helps validate the methodological approach of this thesis through the use of out-of-sample forecasting results, as they demonstrate an improvement in volatility forecasts with the use of sustainability-type uncertainty indices. The present study builds upon Raza et al. (2024) by using the ESGUI as the overall sustainability uncertainty indicator which takes into account the environmental, social and governance dimension of sustainability, and by expanding the analysis to a pure-play hydrogen ETF, whose dynamics of volatility have not been studied yet under a MIDAS setting.

Jiang, Sun, and Xu (2025) extend the MIDAS literature by proposing penalised U-MIDAS models with group LASSO penalties, and show that large frequency mismatch can be tolerated, and that functional constraints do not introduce any bias to the models when using unrestricted lag polynomials. They conclude that the informational efficiency of the financial markets with sustainability reporting cycles can only be properly assessed if the model architecture reflects the natural frequency of the information source the market is using – which is monthly for the ESGI – and not trying to interpolate the index at a daily frequency.

In the hydrogen-specific literature, Karim (2025) employs a wide array of GARCH-family models (GARCH (1,1), TGARCH, EGARCH, APGARCH, CGARCH and IGARCH) to investigate the S&P Hydrogen Economy Index, using daily data from May 2019 to May 2025, and concludes that there is significant evidence of volatility clustering and asymmetric shock effects. The model TGARCH shows that the negative shocks influence the conditional variance about two times more than positive shocks with the same magnitude. Moreover, Karim (2025) shows the VIX has strong predictive power for hydrogen return volatility and is able to enhance the forecasting performance of all the GARCH

specifications. This thesis has developed on the methodological framework developed by Karim (2025) and extended the analysis to the mixed frequency setting (using ESGUI instead of VIX) as well as ETF-level data for ICLN and HYDR rather than the index-level S&P Hydrogen Economy Index.

2.7 Research Gap and Contribution of the Present Thesis

The literature reviewed in this chapter offers a solid basis for understanding the mechanics of sustainable finance, the financial profile of clean energy and hydrogen assets, the building of the ESGUI, the methodological toolbox provided by mixed-frequency volatility modelling. Three key limitations, however, remain that the current thesis aims to fill.

Although there has been a considerable amount of research studying each aspect of sustainability uncertainty separately, this study is among the first to combine multiple aspects of sustainability uncertainty into a single index and to analyse how this index influences the volatility of clean energy and hydrogen ETFs. The ESGUI of Ongan et al. (2025) offers such an integrated indicator, but it has been used, thus far, solely for cryptocurrency markets (Dutta, 2026), European equities (Gaies et al., 2025) and fossil fuel prices (Olanrewaju et al., 2025). To date, it has not been applied to any clean energy or hydrogen ETFs.

Second, the literature often simply aggregates the risk signature of hydrogen with those of other clean energy indices without considering the unique technological and market-based volatility signature of hydrogen. The crisis-hedge properties of hydrogen assets and their varying risk measures compared with more developed clean energy assets, as reported by Lucey et al. (2024) and Rubbaniy et al. (2024), would stand in contrast to these more traditional assets. Raza et al. (2024) investigate clean energy volatility under CPU, but do not consider hydrogen as a separate asset class, nor has a previous study dedicatedly compared the cross-sectional impact of the same sustainability uncertainty shock on clean energy volatility and hydrogen volatility.

Third, this study is the first to utilize the good and bad volatility decomposition technique by Patton and Sheppard (2015) and BenSaida (2019) for the sustainable energy ETFs and sustainable uncertainty phenomenon. Consistent with the arguments in Section 2.5, the asymmetry of the policy shocks in 2022-2025, with the positive IRA shock offset by the negative rollback threat, provides plenteous reasons to anticipate that the ESGUI effects will vary between the upside and downside components of realised variance. The non-linear, tail-driven information transmission in sustainable asset markets is documented by Cagli et al. (2023), which is another motivation for the asymmetric decomposition. This is something that has not been included in the literature before, which this thesis aims to remedy.

To fill these gaps the current thesis has three main contributions: First, it extends the empirical use of the ESGUI by using it as a single indicator of realised variance of clean energy and hydrogen ETFs, revealing the impact of integrated sustainability uncertainty on the risk of assets over various time horizons. Second, it offers a cross-sectional analysis of the hydrogen sector at a fine level of detail relative to clean energy, distinguishing between the need for separate risk-management strategies, something that has not been done in previous studies based on the MIDAS model of clean energy volatility, such as Raza et al. (2024). Thirdly, by decomposing the effects of sustainability uncertainty on good and bad volatility separately, it offers investors and policy makers a practical guide to which types of sustainability uncertainty pose the greatest threat to the way capital is allocated in global energy transition.

3 Hypotheses Development

3.1 Overview

In this chapter the formal hypotheses are generated based on the frameworks and findings of Chapter 2. The hypotheses are the foundation for the empirical study in Chapters 5 and 6. The hypotheses are formulated to answer each of the four research questions presented in Chapter 1 and draw on the unique features of ICLN ETF, HYDR ETF, ESGUI and the regression framework used in this research (MIDAS).

3.2 Hypothesis 1: ESGUI and ICLN Volatility

The first hypothesis is related to the relationship between sustainability uncertainty and realised volatility of the iShares Global Clean Energy ETF (ICLN). There are three complementary mechanisms to support a significant relationship between ESGUI and ICLN volatility. First, cleaner energy assets are valued in the market in an equilibrium that depends on investors' preferences for sustainability, which means that their values are very sensitive to the changes in the sustainability information environment, as established by Pastor et al. (2021). An increase in ESGUI – an indicator of growing policy and report uncertainty – disturbs this balance by adding noise to the sustainability information signal which investors use to price ICLN. Second, Dutta (2026) shows that the increase in uncertainty regarding sustainability alters investors' investment behaviour from speculation to longer-term investment, which also serves to limit the volatility of the market. Third, and going beyond the ESGUI literature, Raza et al. (2024) find that sustainability-type UIs contain "genuine predictive information about the S&P Global Clean Energy Index", the benchmark ICLN aims to follow, via GARCH-MIDAS models, and Naifar (2024) shows that clean energy indices are among the most CPU-consuming sustainable asset classes. For ESGUI, these results suggest that a higher ESGUI should lead to lower ICLN realised variance, as the speculative activity is muted, and to a measurable and predictable volatility signal.

H1: There is a statistically significant relation between the ESGUI and the realised volatility of iShares Global Clean Energy ETF (ICLN).

3.3 Hypothesis 2: ESGUI and HYDR Volatility

The second hypothesis expands the investigation to the Global X Hydrogen ETF (HYDR). The theoretical rationale for a strong ESGUI-HYDR link is more compelling than for ICLN, given the higher dependence of hydrogen on policy assistance and the earlier stage of its market development. Lucey et al. (2024) and Kayani et al. (2024) document that hydrogen assets are highly sensitive to information shocks emanating from sustainability-related policy announcements. So the ESGUI, a measure of exactly such information uncertainty, is a theoretically plausible predictor of HYDR volatility. Almeida et al. (2025) also find that the connection of hydrogen with other markets increases in periods of high uncertainty, suggesting that HYDR should experience stronger volatility responses to ESGUI shocks than other isolated asset classes.

H2: Sustainability uncertainty (measured by the ESGUI) has a statistically significant effect on the realised volatility of the Global X Hydrogen ETF (HYDR).

3.4 Hypothesis 3: Differential Effects Across Asset Classes

The third hypothesis is related to the relative size of the ESGUI effect of the two ETFs. There are three considerations that support this theoretical basis for the expectation that HYDR will be more sensitive than ICLN regarding the ESGUI. The following rationale is theoretical and has three considerations: In the first place, HYDR is a single-sector ETF, meaning that only companies directly reliant on the stability of the hydrogen policy frameworks in order to make their business models viable are included. ICLN, on the other hand, is a portfolio that is broadly diversified across several clean energy subsectors, which means that it provides an automatic diversification against policy shocks in the hydrogen sector. Second, the good and bad volatility literature (Patton and Sheppard, 2015; BenSaida, 2019) suggests that less developed markets are more

vulnerable to information shocks due to the absence of long historical time series of returns in these markets, which makes price discovery less dependent on the return history and more dependent on the current information flow – the very information flow measured by the ESGUI. Third, Almeida et al. (2025) offer empirical evidence of a U-shaped connectedness structure for emerging sustainable asset classes, which would mean that an ESGUI shock at both the extremes of the distribution would have a greater impact on the volatility of HYDR, consequently leading to a larger ESGUI coefficient, in absolute terms. According to Naifar (2024), clean energy indices are one of the most policy sensitive sustainable asset classes. This in turn suggests that a more targeted and less developed segment of the clean energy space like HYDR should be more volatile than the overall ICLN index.

HYDR shows higher realised volatility when facing uncertainty relating to sustainability than ICLN, which supports the higher policy dependence and lower level of market maturity of hydrogen.

H3: The effect of sustainability uncertainty on realised volatility is greater in magnitude for HYDR than for ICLN, reflecting hydrogen's higher policy dependence and earlier stage of market development.

3.5 Hypothesis 4: Asymmetric Effects on Good and Bad Volatility

The fourth hypothesis is related to the asymmetric influence of ESGUI on upside and downside volatility. As discussed in Section 2.5, the theoretical literature on good and bad volatility (Patton and Sheppard, 2015; BenSaïda, 2019; Ang et al., 2006) has shown that volatility is more persistent and more heavily priced on negative-return days than on positive-return days. In the context of sustainability uncertainty the sign of this asymmetry is ambiguous: higher ESGUI can reduce bad volatility by avoiding panic-driven selling, consistent with the mechanism proposed by Dutta (2026) and the mandate-driven investor retention documented by Caferra and Falcone (2023), but at the same time, can increase good volatility by creating speculative positioning on positive policy resolutions, especially in hydrogen where successful policy

announcements lead to sharp price appreciation. Uncertainty shocks are also found to propagate non-linearly to sustainable asset markets with large tail effects (Cagli et al., 2023), which motivates the analysis of the effect of ESGUI on the tails of the volatility distribution through the good/bad decomposition.

HYDR-specific theoretical channel: hydrogen assets optionality. High ESGUI periods may be correlated with increased speculation on the upside as investors take positions in anticipation of positive policy resolutions, while decreasing downside volatility as institutional ESG-mandate investors provide a stabilising demand base, because the commercial viability of hydrogen is dependent on the resolution of technological and policy uncertainties. This process will generate a positive ESGUI coefficient for good volatility and a negative coefficient for bad volatility in HYDR, a more complex asymmetric pattern than the uniformly negative effects reported for digital assets by Dutta (2026).

H4: Sustainability uncertainty has asymmetric effects on the realised volatility of ICLN and HYDR: negative volatility (RV^-) and good volatility (RV^+) react differently to ESGUI shocks.

3.6 Summary of Hypotheses

Table 3 summarises the four hypotheses, the expected sign of the ESGUI coefficient (β), and the relevant prior literature supporting each prediction.

Table 3. Summary of Research Hypotheses

Hyp.	Statement	Expected Sign	Key Supporting Literature
H1	ESGUI significantly affects ICLN realised volatility	$\beta \neq 0$ (negative)	Dutta (2026); Raza et al. (2024); Naifar (2024); Pástor et al. (2021)

Hyp.	Statement	Expected Sign	Key Supporting Literature
H2	ESGUI significantly affects realised volatility	$\beta \neq 0$ (negative)	Lucey et al. (2024); Almeida et al. (2025); Kayani et al. (2024)
H3	$ \beta_{\text{HYDR}} > \beta_{\text{ICLN}} $: HYDR more sensitive	$ \beta_{\text{HYDR}} > \beta_{\text{ICLN}} $	Naifar (2024); Almeida et al. (2025); BenSaïda (2019)
H4	ESGUI has asymmetric effects: $\beta^- \neq \beta^+$	$\beta^+ > 0$ (HYDR); $\beta^- < 0$ (both)	Patton & Sheppard (2015); Cagli et al. (2023); Caferra & Falcone (2023)

Note: β^- = coefficient from the ADL-MIDAS model on ESGUI; β^+ = coefficient from the good volatility regression (RV); β^- = coefficient from the bad volatility regression (RV). Hyp. = Hypothesis. References in bold are new additions as compared to the original hypothesis formulation.

4. Data And Descriptive Statistics

4.1 Data Sources and Variable Description

For empirical analysis, I use three series: the daily exchange-traded fund (ETF) price series as dependent variables and the monthly sustainability uncertainty index as an independent variable. Changes in variables are justified with the research aim of analyzing the realized volatility of sustainable assets in the field of clean energy and hydrogen under the context of sustainability uncertainty based on ESG.

The first dependent variable is the iShares Global Clean Energy ETF, (ticker: ICLN), a man managed ETF listed on the NASDAQ. ICLN monitors the S&P Global Clean Energy Index and offers access to close to 100 world-wide companies engaged in the business of clean energy generation and technology. ICLN has assets under management more than \$3 Billion and trades around the clock with an average of about 4 million shares daily and is the most liquid and institutionally recognized clean energy ETF on the market and therefore the industry standard for academic studies on this topic. It is globally mandated, which provides geographic compatibility with the global ESGUI index used as the predictor variable.

The second dependent variable is the Global X Hydrogen ETF (ticker: HYDR), which indexes the Solactive Global Hydrogen Index, which focuses on companies active in the production of hydrogen, its use in energy systems and the development and manufacturing of hydrogen fuel cells and hydrogen electrolyzers. There are three reasons why HYDR was chosen over other hydrogen ETFs. The first is that the competing options, such as the Direxion Hydrogen ETF (HJEN), all stopped trading in July 2024. Second, it is the largest of the on-going, pure play, hydrogen focused ETFs listed on the

US exchanges. Thirdly, its exclusive hydrogen industry exposure makes it more directly exposed to the dynamics of the sustainability policy, as measured by the ESGUI.

The independent variable is the ESG based Sustainability Uncertainty Index (ESGUI) which was developed by Ongan, Gocer, and Ik (2025). The index is built based on ESG related terms in the monthly country reports from the Economist Intelligence Unit (EIU) and as such is a leading indicator of sustainability-related uncertainty. This study uses the Global Equal-Weighted (ES-GUI-EW) and Global GDP-Weighted (ESGUI-GDP) versions of the index, as used by Dutta (2026). All index values are standardized to have the highest value of 100, and the lowest value of 0.

The price data in this table is from the Daily OHLC (Open, High, Low and Close) of ETFs from Bloomberg terminal. The ESGUI can be found monthly at policyuncertainty.com. The MIDAS regression framework discussed in Chapter 5 is used to deal with the mismatch in frequency between the daily ETF series and the monthly ESGUI.

Table 1. Data Sources and Variable Description

Variable	Ticker	Provider	Frequency	Role in Study
iShares Global Clean Energy ETF	ICLN	BlackRock / NASDAQ	Daily (OHLC)	Dependent variable
Global X Hydrogen ETF	HYDR	Global X / NYSE	Daily (OHLC)	Dependent variable
ESGUI — Equal-Weighted Global	ESGUI-EW	Ongan et al. (2025)	Monthly	Independent variable
ESGUI — GDP-Weighted Global	ESGUI-GDP	Ongan et al. (2025)	Monthly	Independent variable

Notes: OHLC = Open, High, Low, Close price data. ESGUI sourced from policyuncertainty.com. ETF price data sourced from Bloomberg terminal. Sample period: January 3, 2022 – December 31, 2025.

4.1.1 Realized Volatility Estimators

This study employs two range-based realized volatility estimators based on daily OHLC price data, following Dutta (2026). The advantage of using range-based estimators as opposed to simple squared-return measures is that they are significantly more efficient (they use price ranges as opposed to closing prices alone) and they are less affected by “bid-ask bounce” which is important for HYDR because of its volume of trading compared to ICLN.

The first measure is the Parkinson (1980) measure: $RV_t = [1 / (4 \ln 2)] \times [\ln(H_t / L_t)]$ Where H_t and L_t are the greatest and lowest prices experienced on the day. The second estimate is Rogers and Satchell (1991) measure: $RV_t = \ln(H_t / O_t) \ln(H_t / C_t) + \ln(L_t / O_t) \ln(L_t / C_t)$ which also considers the opening price. Both estimators are utilized for all 1,002 daily observations. Full mathematical derivations are provided in Chapter 5.

4.2 Sample Period

The sample period runs from January 3, 2022 to December 31, 2025, so the number of daily observations is 1,002 observations per ETF and 48 observations of the monthly ESGUI. January 3, 2022 is the first trading day of the year after HYDR launched in July 2021, giving a strong start to the annual trading cycle with a set of stable price data. The end date of December 31, 2025 represents a full 4-year policy cycle.

This sample period is selected for four reasons. First, it aligns with the availability of reliable HYDR trading data. Second, it encompasses a complete and unprecedented sustainability policy cycle: from the landmark US Inflation Reduction Act (IRA) of August 2022, through the IRA rollback threat following the November 2024 US presidential election, and into the full policy uncertainty of 2025. Third, the endpoint provides nine additional months beyond Dutta (2026), whose comparable sample runs to March 2025. Fourth, the ESGUI index rises from approximately 32 in January 2022 to approximately 78-91 in December 2025, nearly tripling over the sample, providing substantial variation in the predictor variable essential for MIDAS regression identification.



Figure 1. ICLN ETF price series from January 2022 to December 2025. Dashed vertical lines indicate major sustainability policy events: Russia-Ukraine War (February 2022), IRA signing (August 2022), Trump election (November 2024), and Trump inauguration (January 2025). Source: Bloomberg.

The trend of ICLN over the sample period is evident in Figure 1, where it followed a very clear path of event-driven developments. On the positive side, the Russia-Ukraine War (February 2022) gave a short-term boost with increased European energy security aspirations which was swiftly undone by the US Federal Reserve launching its aggressive interest rate increases cycle in March 2022 which hurt growth-focused clean energy stocks and drove ICLN back nearly 25% from the January 2022 mark. The recovery was underway after the Inflation Reduction Act (IRA) was signed in August 2022 and set \$369 billion for clean energy subsidies, which also significantly lowered the policy risk premium that investors in the clean energy industry require. This recovery was put on hold in November 2024 after the US presidential election, when the prospect of IRA rollback dries up the policy tailwind that had helped ICLN prices since mid-2022.



Figure 2. HYDR ETF price series from January 2022 to December 2025. The sharper decline relative to ICLN following the November 2024 election reflects HYDR's greater sensitivity to US sustainability policy. Source: Bloomberg.

HYDR showed a broadly similar overall path to ICLN, but with considerably larger amplitude at each turning point, in line with its greater policy sensitivity and higher sectoral concentration, as Figure 2 shows. The Russia-Ukraine War (February 2022) and subsequent Fed rate hikes led to a more significant decrease in HYDR than in ICLN, with prices falling over 60% from January 2022 levels before the IRA implementation began a recovery. A sector-specific volatility episode occurred mid-2023 when the US Treasury delayed the publication of IRA hydrogen tax credit (45V) guidance which led to a notable price reduction on HYDR alone. The November 2024 election result had the biggest negative impact on HYDR of any event in the sample, consistent with hydrogen's greater reliance on ongoing government policy support relative to the more diversified clean energy market.

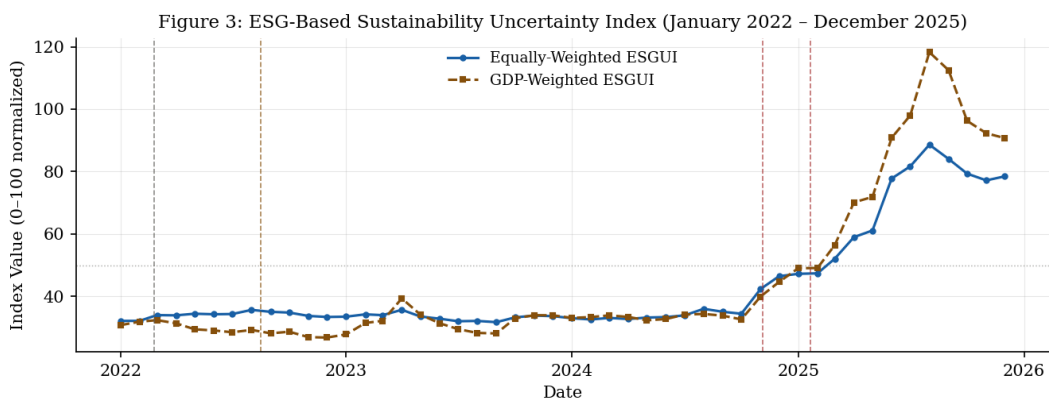


Figure 3. ESG-based Sustainability Uncertainty Index (ESGUI) — equally-weighted and GDP-weighted global variants — from January 2022 to December 2025. The near tripling of the index over the sample period provides essential variation for MIDAS regression identification. Source: Ongan et al. (2025) / policyuncertainty.com.

As it can be seen from Figure 3 the ESGUI increased in every sample, more than doubling from approximately 32 in January 2022 to reach high levels of 78–91 by the end of 2025. This upward trajectory is a result of the sequential build-up of uncertainty around sustainability policy (with the growing policy disconnect between the EU and US ESG regulatory frameworks in 2022-2023, the rightward shift in EU elections in June 2024 and the mayhem that followed the US presidential election in November 2024 and the withdrawal from the Paris Agreement in January 2025). The enhanced near-perfect correlation between the variations of both series ($r = 0.99$) demonstrates that both reflect the same underlying uncertainty signal, with the GDP-weighted series highlighting those episodes driven by the US because it places more weight on the United States.

4.3 Descriptive Statistics

A summary of the data and stationarity and conditional heteroskedasticity tests are reported to give a general picture of the series data. These statistics can aid in understanding the distribution, central tendency, and variability of each series and set up the empirical prerequisites for the MIDAS regression analysis.

4.3.1 Summary Statistics

The descriptive statistics for the daily log returns of ICLN and HYDR, the monthly ESGUI index levels are reported in Table 2. Log returns are computed as $r_t = \ln(P_t / P_{t-1})$. Figures 4 and 5 show the return series and the realized volatility series respectively.

Table 2. Descriptive Statistics

Statistic	ICLN Returns	HYDR Returns	ESGUI (EW)	ESGUI (GDP)
Observations	1,002	1,002	48	48
Mean	-0.000261	-0.001196	43.0975	44.7980
Median	-0.001009	-0.002370	34.2568	33.2345
Maximum	0.073498	0.118154	88.6174	118.2607
Minimum	-0.076161	-0.098393	31.7371	26.8055
Std. Deviation	0.017237	0.029503	17.2052	25.1764
Skewness	0.2710	0.3724	1.5839	1.6743
Kurtosis	4.8672	4.1566	3.9362	4.4063
Jarque-Bera	157.83***	79.02***	21.82***	26.38***
Q(24)	38.37**	53.94***	183.43***	167.72***

Notes: Returns are daily log differences $r_t = \ln(P_t/P_{t-1})$. ESGUI values are monthly index levels normalized to [0,100]. Kurtosis is total kurtosis (normal = 3). Jarque-Bera tests H_0 : normally distributed. Q(24) is the Ljung-Box test for serial correlation up to lag 24. ***, **, * denote significance at 1%, 5%, 10% levels.

The descriptive statistics presented in Table 2 provide some important properties in the data. The negative mean returns of both ETFs indicate the difficult period for clean energy and hydrogen investments between 2022-2025. An important comment is that the standard deviation of HYDR (0.0295) is about 71% higher than ICLN (0.0172), indicating that HYDR has a higher level of policy sensitivity and is at a more advanced stage of development than ICLN. All four series fail the normality test (Jarque-Bera ****/****/****) and all show strong levels of serial correlation (Q(24) ****/****/****) which justifies the specification of the ADL MIDAS.

Figure 4: Daily Log Returns of ICLN and HYDR (January 2022 – December 2025)

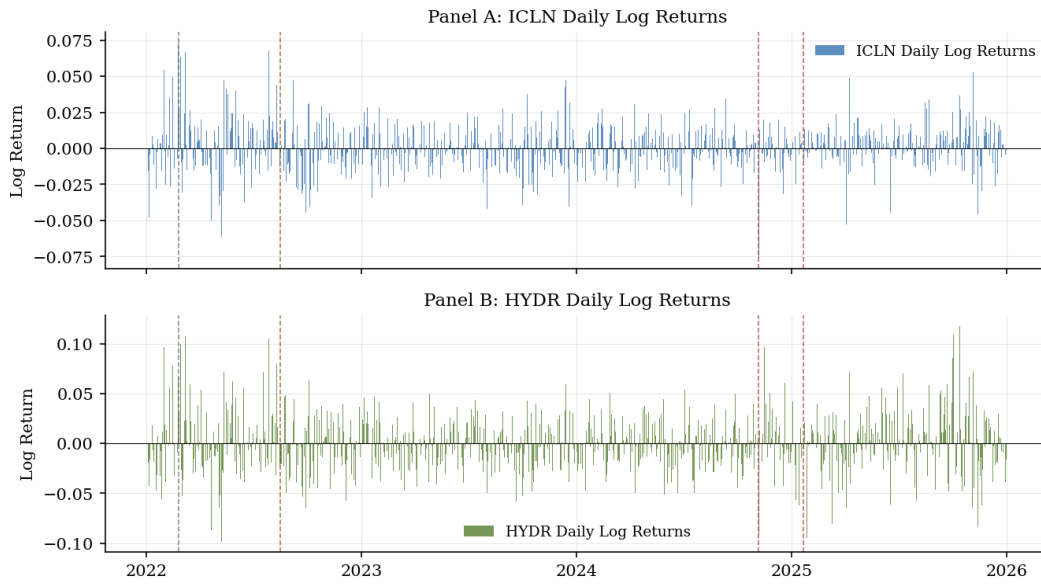


Figure 4. Daily log returns of ICLN (Panel A) and HYDR (Panel B) from January 2022 to December 2025. Volatility clustering is clearly visible, particularly around the IRA passage (August 2022) and the Trump election (November 2024). Source: Bloomberg / authors' calculations.

Volatility clustering (the tendency of large daily moves to be followed by further large moves, both up and down) is also evidenced in both return series and is statistically supported by the large and significant Ljung-Box Q(24) statistics from Table 2. The region of high clustering is discernible visually to be three periods: the Russia-Ukraine war and the Federal Reserve rate-hike shock (early 2022); the time around the passage of the IRA (August 2022); and the US presidential election (November 2024). This is true for HYDR in all three episodes with the larger daily return spikes: $LSHYDR = 0.0295$, $LSHYN = 0.0273$, $LSHYT = 0.0233$ as compared to ICLN: $LSI = 0.0172$, $LSF = 0.0172$, $LSG = 0.0187$. The patterns provide support for the ARCH-LM test reported in Table 4 and validate the use of a realized-variance dependent variable in the MIDAS framework.

Figure 5: Realized Variance of ICLN and HYDR (January 2022 – December 2025)

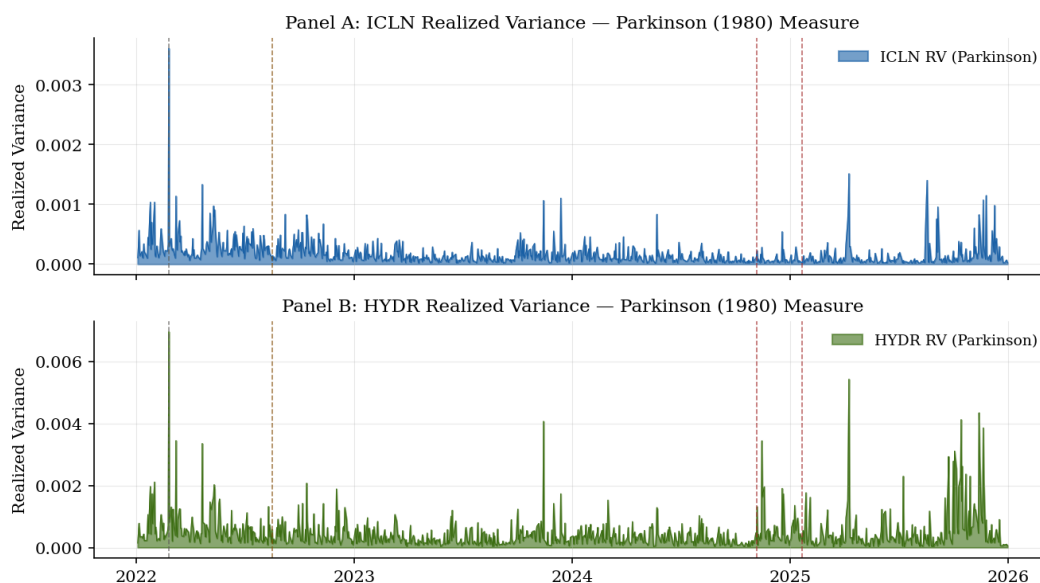


Figure 5. Realized variance of ICLN (Panel A) and HYDR (Panel B) computed using the Parkinson (1980) estimator from January 2022 to December 2025. HYDR exhibits substantially higher and more frequent volatility spikes relative to ICLN, consistent with the descriptive statistics in Table 2. Source: Bloomberg / authors' calculations.

Figure 5 shows the actual variance for both ETFs is not random but can be attributed to specific policy and geopolitical events. The first significant increase is in February-March 2022, in the wake of the Russia-Ukraine War and the beginning of the Federal Reserve rate hike cycle and continued high in 2022 as the Fed continued its rate hike policy and negatively affected valuations on clean energy stocks. A second episode is linked to the IRA signing in August 2022, which was followed by a downtrend in volatility as volatility reduced following the return of the policy certainty. The greatest increase in variance level across the entire sample is around the November 2024 US presidential election, with the realized variance level post-election higher by about three times for HYDR, which is more sensitive to the US sustainability policy. The significantly larger realized variance of HYDR compared to ICLN, as evidenced by the 2.75:1 mean ratio reported in Table 5, drives the choice of the cross-sectional design of the empirical analysis, and anticipates the result in Chapter 6 that the realized ESGUI effect is about twice as large for HYDR as for ICLN.

4.3.2 Unit Root Tests

To ensure valid statistical inference, all series need to be checked for stationarity before estimating the MIDAS model. Table 3 shows the results of the Augmented Dickey-Fuller (ADF) unit root test on the first difference of all variables. The Phillips-Perron test statistics are 34.07*** and 34.09*** for ICLN and HYDR respectively and 2.94** and 3.11** for ESGUI-EW and ESGUI-GDP respectively, and they give the same qualitative conclusions as the ADF test statistics.

Table 3. Unit Root Tests

Variable	ADF Statistic (1st Diff.)	Significance	Integration Order
ICLN Returns	-37.1762	***	I(1) — Stationary at first difference
HYDR Returns	-37.4941	***	I(1) — Stationary at first difference
ESGUI Equal-Weighted	-3.0019	**	I(1) — Stationary at first difference
ESGUI GDP-Weighted	-3.2983	**	I(1) — Stationary at first difference

Notes: ADF = Augmented Dickey-Fuller test. H_0 : unit root. MacKinnon (1996) critical values: 1% = -3.43, 5% = -2.86, 10% = -2.57. *** and ** denote rejection at 1% and 5% levels respectively.

4.3.3 ARCH-LM Test for Conditional Heteroskedasticity

Table 4 shows the ARCH-LM test results that confirm the presence of time-varying conditional variance in both the ETF return series, which is required for the realized volatility modeling approach.

Table 4. ARCH-LM Test for Heteroskedasticity (5 Lags)

Series	LM Statistic	F-Statistic	p-value	Decision
ICLN Returns	23.5437***	4.8178	0.0003	ARCH effects present
HYDR Returns	10.8687*	2.1955	0.0540	Weak ARCH effects present

Notes: $LM = (n-q) \times R^2$, distributed as $\chi^2(q)$ under H_0 : no ARCH effects. *** and * denote significance at 1% and 10% levels. HYDR's borderline result ($p=0.054$) is consistent with its lower daily trading volume introducing microstructure noise at daily frequency.

4.3.4 Realized Volatility Summary

The summary statistics for the realized variance series are given in Table 5 for both estimators. The important finding is that the mean variance for the Parkinson estimator (0.000471) is approximately 2.75 times that for the ICLN estimator (0.000171) the same holds true for both estimators and drives the cross-sectional design of the thesis.

Table 5. Realized Volatility Summary Statistics

Series	Mean	Std. Dev.	Maximum	Skewness	Kurtosis
ICLN — Parkinson (RV^P)	0.000171	0.000214	0.005374	6.0125	74.68
HYDR — Parkinson (RV^P)	0.000471	0.000578	0.010812	4.4731	33.40
ICLN — Rogers & Satchell (RV^{rs})	0.000175	0.000228	0.006193	5.4651	49.80
HYDR — Rogers & Satchell (RV^{rs})	0.000459	0.000530	0.009218	3.8770	26.97

Notes: $N = 1,002$ daily observations. HYDR mean RV is 2.75× higher than ICLN under both estimators, confirming the maturity differential between the two sectors.

4.3.5 Correlation Analysis

Table 6 shows the Pearson correlation matrix at the monthly frequency. The 43 observations combined (48 total ESGUI months) represent five months in which there was missing data due to the alignment of the ETF trading calendar with the ESGUI reporting cycle, which is negligible and does not impact the analysis.

Table 6. Correlation Matrix (Monthly Frequency, $N = 43$)

Variable	ICLN	HYDR	ESGUI-EW	ESGUI-GDP
ICLN Returns	1.0000	0.7940	0.2557	0.2683
HYDR Returns	0.7940	1.0000	0.2117	0.2286

Variable	ICLN	HYDR	ESGUI-EW	ESGUI-GDP
ESGUI Equal-Wt.	0.2557	0.2117	1.0000	0.9903
ESGUI GDP-Wt.	0.2683	0.2286	0.9903	1.0000

Notes: Pearson correlations at monthly frequency (43 aligned observations). Both ETFs show positive correlations with ESGUI (~0.21–0.27), providing a preliminary signal that sustainability uncertainty is associated with higher sustainable asset returns — tested formally in Chapter 6.

5 Methodologies

5.1 Overview of the Methodological Framework

This section describes the econometric approach to test the effect of sustainability risk uncertainty on realized volatility of clean energy and hydrogen exchange-traded funds. The technique is built upon three integrated components. The dependent variable is constructed with daily price data in two range based realized volatility estimators. Then, the Mixed Data Sampling (MIDAS) regression framework is employed to tackle the frequency mismatch between the daily volatility series and the monthly sustainability uncertainty index. Third, a good and bad volatility decomposition is utilized in addition to the baseline analysis to capture the asymmetric effects of sustainability uncertainty shocks. To assess robustness of the results, I apply an Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model, where we use conditional variance instead of realized variance as the dependent measure. There are three concepts that influence the methodological choices in this investigation.

First, the comparison with the closest similar study (Dutta, 2026) which analyzes the impact of the same ESGUI index on the volatility of Bitcoin and Ethereum ETFs using the same MIDAS framework, which helps to eliminate the effect of methodological changes on the results. Second, the robustness assessment of EGARCH and the theoretical specification of the asymmetric shock responses are pertinent method employing GARCH-family models for hydrogen volatility. Third, the novelty in methodology is guaranteed by the innovative combination of MIDAS and realized volatility analysis with good/bad decomposition especially for sustainable energy ETFs that is missing in the literature.

The rest of this chapter is as follows. Section 5.2 deals with the computed volatility estimators. The entire details of the MIDAS regression framework are introduced in Section 5.3. Section 5.4 discusses the decomposition of good and poor volatility. The

robustness specification of the EGARCH is presented in Section 5.5. Section 5.6 gives the model selection and diagnostic criteria.

5.2 Realized Volatility Measures

The dependent variable in all MIDAS regressions is the daily realized variance (RV) of the respective ETF. Rather than using the squared daily return — which is a noisy, inefficient proxy for true latent variance — this study employs two range-based realized volatility estimators computed from daily Open, High, Low, and Close (OHLC) price data. Range-based estimators exploit the information contained in the intraday price path and are considerably more efficient than return-squared measures. This efficiency advantage is particularly important in the present context: HYDR, as a relatively thinly traded ETF with average daily volume of approximately 16,000 shares, is susceptible to bid-ask bounce in its closing prices. Range-based estimators are substantially less sensitive to this microstructure noise because they rely on the high-low spread rather than the close-to-close difference (Alizadeh, Brandt and Diebold, 2002).

5.2.1 The Parkinson (1980) Estimator

The most widely used realized variance measure in this study is the Parkinson (1980) extreme value estimator; it employs the daily high-low price range as variance estimation basis. Assuming geometric Brownian motion with zero drift, Parkinson (1980) showed that the high-low range is a much more informative measure of true intraday volatility than the squared close-to-close return. In particular, Parkinson (1980) shows that the Parkinson estimator is 4.9 times as efficient—assuming returns follow a diffusion process as are squared return estimates.

$$RV^p_t = 1/(4 \cdot \ln 2) \times [\ln(H_t/L_t)]^2 \quad (1)$$

Here, H_t and L_t represent the highest and lowest transaction prices during trading day t ; \ln is the natural logarithm. The efficiency correction factor for the distributional properties of range under Brownian motion, $\{1/(4 \cdot \ln 2) \approx 0.3607\}$. This estimator is

taken as the main dependent variable in all of the baseline MIDAS regressions reported in Chapter 6.

5.2.2 The Rogers and Satchell (1991) Estimator

This study conducts a robustness test using the Rogers and Satchell (1991) measure as well. Rogers-Satchell Estimator The Rogers-Satchell estimator doesn't have the same issues with the non-zero drift in the underlying price process like we found above with the Parkinson estimator since it also incorporates daily opening price, along with high, low and close prices. The Rogers and Satchell (1991) estimator is given by:

$$RV_{t}^{rs} = \ln(H_t/O_t) \cdot \ln(H_t/C_t) + \ln(L_t/O_t) \cdot \ln(L_t/C_t) \quad (2)$$

where O_t is as in the opening price on trading day t and H_t , L_t , and C_t keep their meaning in Equation (1). The Rogers-Satchell estimator suits better when assets tend to have trending directionality over the course of a trading day (which can be true for both ICLN and HYDR across prolonged policy-driven trends). This measure is used in parallel with the Parkinson estimates, and all robustness results presented in Chapter 6 are reported using it. The realized variance series RV_t is calculated for each of the 1,002 trading days during the sample period from January 3, 2022 to December 31, 2025.

5.3 The Mixed Data Sampling (MIDAS) Regression Framework

5.3.1 Motivation and Theoretical Basis

A basic econometric challenge in this work is related to the discrepancy between the frequencies of these two data series, which are at the heart of our analysis. Daily returns of ICLN and HYDR provide 1,002 observations throughout the sample period for daily realized volatility, while the ESG-based Sustainability Uncertainty Index (ESGUI) can only be logged at monthly frequency to yield 48 observations through that time. The simplest way to deal with this mismatch would be to sum daily volatility to get monthly average and then run a standard regression. Nonetheless, this kind of temporal aggregation loses meaningful data inherent in the high-frequency volatility series and can erode sponsor

dynamics properties of the relationship we are interested in discovering, notably: The lag structure through which monthly certainty shocks propagate into daily volatility (Ghysels, Santa-Clara & Valkanov, 2004).

The Mixed Data Sampling (MIDAS) regression proposed by Ghysels, Santa-Clara and Valkanov (2004) and later enhanced by Ghysels (2016), tackles this problem in an integrated fashion through a single regression equation without the need for aggregation of data sampled at different frequencies. The high-frequency dependent variable in period $t+1$ is regressed on multiple lags of the low-frequency independent variable, which is called a distributed-lag structure, similar to that of the MIDAS framework and they are constrained to follow a simple functional form, so-called parsimony in its lag coefficients for example, the Beta weight function. The specific parameterization you use allows the model to accommodate the complete distributed lag response of daily volatility to past monthly uncertainty shocks, while avoiding over-parameterizing by estimating each lag coefficient without back-ending upon some prior.

There are five reasons that make this approach MIDAS very appropriate for the current investigation. It addresses this issue in two ways, firstly by accommodating this mismatch of daily ETF volatility with monthly ESGUI without any loss of information. Second, it embraces a distributed-lag specification that recognizes the slow and asynchronous diffusion of uncertainty shocks into financial market volatility. Third, the Beta weight function restriction serves to curb coefficient inflation — an important side effect as we have only 48 observations per ESGUI time series over a period of 4 years, on a monthly basis. Fourth, we have demonstrated the successful implementation of the MIDAS framework in other research contexts that are very relevant to this study (Dutta (2026) for cryptocurrency ETF volatility; Dong, Gong and Wang (2025) for crude oil volatility; Jiang, Sun and Xu (2025) for corporate credit analysis), providing a clear precedent as well as allowing integration with previously published studies.

Fifth, and most directly relevant to the current thesis Raza, Khan, Benkraiem and Guesmi (2024) show that GARCH-MIDAS models using sustainability-type uncertainty indices as low-frequency predictor produce highly statistically significant out-of-sample forecast improvements for the S&P Global Clean Energy Index, S&P Green Bond Index and Dow Jones Sustainability Index compared to their benchmark specifications without the uncertainty predictor. These results represent the most direct empirical confirmation in the literature of our method, providing evidence for the link between monthly sustainability uncertainty indices and cumulant-predictive information about daily sustainable energy volatility that have been estimated here for respective sustainable energy assets ICLN and HYDR. The present thesis proceeds beyond Raza et al. (2024) using the ESGUI, which encompasses uncertainty across all three dimensions of environmental, social, and governance as opposed to merely the Climate Policy Uncertainty (CPU) index a single pillar used in their study and applying for the first time the multi-scale approximate MIDAS framework for an hydrogen-specific ETF.

5.3.2 The Base MIDAS Model

The baseline MIDAS regression model estimated in this paper connects the one-period-ahead realized variance of the ETF to contemporary and lagged values of the first-differenced ESGUI, which enter with coefficients restricted by a Beta weight function. Following Ghysels et al. (2004), Dutta (2026):

$$RV_{t+1} = \alpha + \beta \cdot W(L^{1/m}; \vartheta) \Delta ESGUI^{(m)}_t + \varepsilon_t \quad (3)$$

where where RV_{t+1} is the realized variance of the ETF on day $t+1$ based on either the Parkinson (1980) or Rogers and Satchell (1991) estimator; α is the intercept term which represents unconditional mean of realized variance; β is the slope coefficient denoting overall effect of sustainability uncertainty on, realized variance —the main parameter of interest in this study, $\Delta ESGUI^{(m)}_t$ is first difference of monthly ESGUI index m ; ε_t is an error term with zero mean and finite variance. Definition 4 (Weight operator): $W(L^{1/m}; \vartheta)$ is defined as follows:

$$W(L^{1/m}; \vartheta) = \sum_{k=0}^K \omega(k; \vartheta) \cdot L^{k/m} \quad (4)$$

where $L^{k/m}$ is the lag operator used to shift back monthly series over k periods; K is the maximum lag order, and $\omega(k; \vartheta)$ is the Beta weight function defined in Section 5.3.4.

5.3.3 The ADL-MIDAS Extended Model

The three standard forms of MIDAS-type macroeconomic forecasters described above in Section 3, which is the base specification of MIDAS in Equation (3), do not allow any measure for the well-documented persistence of financial market volatility, where high-volatility observations tend to be succeeded by further periods of high volatility the so-called “volatility clustering” phenomenon discussed in Chapter 4 [Atanasov et al. Failure to take this persistence into account would result in omitted variable bias if one were instead estimating β . Hence, using this as a basis, following Andreou et al. (2013) and consistent with Dutta (2026), the baseline model is subsequently extended to an Autoregressive Distributed Lag MIDAS (ADL-MIDAS) specification which includes a lagged dependent variable as follows:

$$RV_{t+1} = \alpha + \delta \cdot RV_t + \beta \cdot W(L^{1/m}; \vartheta) \Delta ESGUI^{(m)}_t + \varepsilon_t \quad (5)$$

where δ is the autoregressive constant that determines how much volatility persists. The main model that will be estimated in the empirical analysis, which is presented in Chapter 6, is this ADL-MIDAS specification. This ADL-MIDAS framework which is also used in Zhang and Wang (2019), Gong, Sun and Du (2022) for some closely related financial volatilities applications.

5.3.4 The Beta Weight Function

In MIDAS regression, one of the most important design choices is how to parameterize the distributed-lag weights $\omega(k; \vartheta)$. This is a streamlined version of what has been studied in Ghysels et al. The use of Beta probability density function as the weight function is

justified and taken in (2016) and Dutta (2026), for it provides a flexible two-parameter family of shapes while minimizing the proliferation of parameters. It describes the following Beta weight function:

$$\omega_i(\vartheta) = \omega_i(\vartheta_1, \vartheta_2) = f(z_i, \vartheta_1, \vartheta_2) / \sum_{i=1}^{i_{max}} f(z_i, \vartheta_1, \vartheta_2) \quad (6)$$

with $i = 0, 1, 2, \dots, i_{max}$ the distributed lag order and $z_i = i / i_{max}$ the dispersion index of the lags normalized to $[0, 1]$. Where $f(z_i, \theta_1, \theta_2)$ is the Beta probability density function of z_i :

$$f(z_i, \vartheta_1, \vartheta_2) = z_i^{\vartheta_1-1} (1 - z_i)^{\vartheta_2-1} \cdot \Gamma(\vartheta_1 + \vartheta_2) / [\Gamma(\vartheta_1) \Gamma(\vartheta_2)] \quad (7)$$

where $\Gamma(\cdot)$ is the gamma function. The shape of the lag polynomial is governed by two parameters $\theta_1 > 0$ and $\theta_2 > 0$. Weights are uniform when $\theta_1 = \theta_2 = 1$. The weights, when $\theta_1 > 1$ and $\theta_2 > 1$, assume a more "hump-shaped" pattern. If $\theta_1 = 1$ and $\theta_2 > 1$, the weights monotonically decline. Because you estimate θ_1 and θ_2 from the data, the model can use historical lags of sustainability uncertainty to identify which are most useful at forecasting contemporaneous volatility, without imposing an arbitrary lag structure. The Beta weight function is parsimonious by utilizing only two free parameters (regardless of maximum lag length K); parsimony in this context is key due to the fact we have only 48 monthly ESGUI observations.

5.4 Good and Bad Volatility Decomposition

Until now, a large part of the literature in financial economics has shown that upside and downside volatilities are informative for asset pricing and risk management (Ang et al., 2006; Patton and Sheppard, 2015; Farago and Tédongap, 2018). Investor loss aversion, forced deleveraging, and risk premia have all been linked to bad volatility (realized variance driven positive return days) versus good volatility (realized variance in negative one; see BenSaïda, 2019; Lyu et al., 2021 respectively). Further, combining these two components into a single aggregate is likely to mask important asymmetries in the relationship between sustainability uncertainty and volatility of the respective ETFs. Cagli, Taskin and Mandaci (2023) provide evidence of non-linear information transmission between uncertainty measures and sustainable financial markets

suggesting a failure of aggregated volatility measures to fully capture significant distributional asymmetries in building sustainable asset risk management.

Such worries are especially pertinent as they pertain to both clean energy and hydrogen exchange traded funds (ETFs), which respond acutely to policy announcements, generating steep rallies (on good policy news such as the August 2022 IRA passage) or steep declines (on bad news, e.g. the potential rollback of the IRA following a GOP capture of the presidency in November 2024). This asymmetry has specific implications for the design of portfolio management and hedging strategies.

Building on BenSaïda (2019) & Lyu et al. Following (2021), and in line with Dutta (2026), the first part of this paper breaks down daily realized variance into good and bad components using an indicator function depending on whether the daily log return is positive or negative. The decomposition is defined as:

$$RV^+_t = RV_t \cdot \mathbb{1}\{r_t > 0\} \quad (8)$$

$$RV^-_t = RV_t \cdot \mathbb{1}\{r_t < 0\} \quad (9)$$

where RV^+_t is the good realized variance on day t , RV^-_t is the bad realized variance on day t ; and $\mathbb{1}\{\cdot\}$ is a binary variable which takes a value of 1 if inside of braces holds true and zero when it does not, $r_t = \ln(C_t / C_{t-1})$ refers to daily log return (for example: from Parkinson (1980) or Rogers et al. Since $RV^+_t + RV^-_t = RV_t$ by construction, the decomposition is exhaustive.

In Equation(5), the ADL-MIDAS model is estimated separately with RV^+_t and RV^-_t in place of total realized variance RV_t as dependent variables, where the magnitude and statistical significance of β^+ (i.e., ESGUI effect on good volatility) and β^- (i.e., ESGUI effect on bad volatility) are compared between ICLN and HYDR to test whether sustainability uncertainty induces asymmetric effects on the volatility. Lyu et al. (2021) and Çepni et al. This work is methodological in nature (as it establishes precedent) as does the work of Juergens and Sili (2022, 2023) for oil- and commodity-markets respectively. This decomposition is deployed, for the first time, to sustainable energy.

5.5 EGARCH Robustness Specification

For further robustness check, the paper substitutes the realistic range-based realised variance with conditional variance estimated from an Exponential GARCH (EGARCH) model. This framework builds on the work by Karim (2025), who applies a complete range of GARCH-family models to volatility for the S&P Hydrogen Economy Index, and Dutta (2026), who adopts conditional variance estimated from an EGARCH model as a robustness alternative for realized variance in MIDAS. The conditional variance models the daily volatility which explicitly reflects the asymmetric effect of positive and negative return shocks on future volatility a well-known leverage effect in financial markets.

Nelson (1991) introduced the EGARCH model to overcome two deficiencies of the standard GARCH(1,1) model by Bollerslev (1986), namely non-negativity restrictions on all variances parameters and symmetry in treatment of positive and negative shocks. In the EGARCH specification, the conditional variance evolves according to the following equation for its natural logarithm:

$$\ln(h^2_t) = \omega + \alpha |\varepsilon_{t-1}/h_{t-1}| + \gamma (\varepsilon_{t-1}/h_{t-1}) + \beta \ln(h^2_{t-1}) \quad (10)$$

t;, where h^2_t is the conditional variance on day t; ω is constant term; α which refers to magnitude effect of past shocks; γ which reflects leverage effect, that means negative return shocks raise conditional variance more than positive shocks having same size if $\gamma < 0$ and β which stands for GARCH persistence parameter. The conditional mean equation is specified as an AR(1) process:

$$r_t = \pi + \phi r_{t-1} + \varepsilon_t \quad (11)$$

with the error term ε_t a Student's t-distributed random variable with v degrees of freedom, also selected based on evidence for kurtosis from Chapter 4 (Bollerslev, 1987; ETF return distributions exhibit fat tails). As a result, the series h^2_t obtained from (10) and (11) is used as the dependent variable in an ADL-MIDAS model as defined in Equation (5).

$$h^2_{t+1} = \alpha + \delta h^2_t + \beta W(L^{1/m}; \vartheta) \Delta ESGUI^{(m)}_t + \varepsilon_t \quad (12)$$

This close correspondence between the EGARCH-MIDAS estimates and those obtained from the realized variance MIDAS specifications (3) and (5) increases our confidence that the results are not an artefact of a specific style of measuring volatility.

5.6 Model Estimation, Selection, and Diagnostic Testing

5.6.1 Estimation Method

Equations (3) and (5): MIDAS regressions. The estimated are found by nonlinear least squares (NLS), where the residuals of the regression summary statistics in terms of sigma are minimised subject to a nonlinear Beta weight parameterisation of the distributed lag coefficients. For MIDAS models, NLS is the standard estimation method (Ghysels et al., 2004, 2016) and implemented in R with the midasr package (Ghysels, Kvedaras & Zémlis, 2016). We perform the estimation of the EGARCH model defined in (10) and (11) by maximum likelihood, assuming a student's t error distribution. EGARCH robustness analysis is carried out by incorporating normal and Student's t error distributions (follows Karim, 2025) to check the stability of results across distributional assumptions.

5.6.2 Model Selection Criteria

Model selection is based on two standard information criteria (over competing specifications): Akaike Information Criterion (AIC) and log-likelihood (LL) value. In a sense, AIC is a simpler version than BIC; explicitly included in the AIC formula ($AIC = -2LL + 2k$), where LL refers to the maximized log-likelihood, k represents the number of free parameters. The criterion aims to select for models with lower AIC values. This method follows the model selection process via Dutta (2026), Karim (2025) & Raza et al. between studies, which allows of direct comparison of model fit (2024).

5.6.3 Diagnostic Tests

After the model has been estimated, we run a series of tests on the residuals to check if the model we have chosen is capturing the dynamics in the data well. We apply the Ljung-Box Q-statistic (Ljung and Box, 1978) to the standardized residuals to test for any

remaining serial correlation up to lag 24. The squared standardized residuals are subjected to the ARCH-LM test (Engle, 1982) for remaining conditional heteroskedasticity. Large p-values signify that there is little evidence to reject either null hypothesis, indicating that the model has adequately captured the autocorrelation and variance dynamics in the data, suggesting that coefficient estimates and standard errors should be reliable. The diagnostic results of these are reported in Table 9 present in chapter 6.

5.7 Summary of Empirical Models

As represented in Table 7 — summarising the dependent and independent variables estimated by all models in the series of empirical analysis, as well as sections these results were reported on in Chapter 6.

Table 7. Summary of Empirical Models

Model	Dependent Variable	Specification	Purpose	Ch.6 Section
MIDAS-1	RV ^P (Parkinson)	Equation (3): Base MIDAS	Baseline ESGUI effect — ICLN and HYDR	6.1
MIDAS-2	RV ^P (Parkinson)	Equation (5): ADL-MIDAS	ESGUI effect controlling for volatility persistence	6.1
MIDAS-3	RV ^{rs} (Rogers-Satchell)	Equation (5): ADL-MIDAS	Robustness: alternative RV estimator	6.2
MIDAS-4	RV ⁺ (Good volatility)	Equation (5): ADL-MIDAS	ESGUI effect on good volatility	6.3
MIDAS-5	RV ⁻ (Bad volatility)	Equation (5): ADL-MIDAS	ESGUI effect on bad volatility	6.3
EGARCH-MIDAS	h ² (Conditional variance)	Equation (12)	Robustness: model-based conditional variance	6.4

Notes: MIDAS = Mixed Data Sampling regression. ADL-MIDAS = Autoregressive Distributed Lag MIDAS. RV^P = Parkinson (1980) realized variance. RV^{rs} = Rogers and Satchell (1991) realized variance. RV⁺ = realized

variance on positive-return days (good volatility). RV^- = realized variance on negative-return days (bad volatility). h^2 = conditional variance from EGARCH (1,1). All models include equally weighted (ESGUI-EW) and GDP-weighted (ESGUI-GDP) variants of the independent variable. All models estimated for both ICLN and HYDR in separate panels. The ADL-MIDAS specification (MIDAS-2) is the primary model following Dutta (2026) and Raza et al. (2024).

6 Empirical Results and Discussion

6.1 Overview of Empirical Findings

This chapter provides the empirical results of all ADL-MIDAS regression models. The baseline results for total realized variance (Parkinson) are given in Section 6.2. Section 6.3 discusses robustness results using Rogers and Satchell (1991). The examination of good and bad volatility is reported in Section 6.4. In section 6.5 all results are discussed in the light of H1-H4 and previous research. Estimated Beta weight functions are shown in Figure 6. A cross-model summary of all β coefficients is given in Figure 7.

6.2 ADL-MIDAS Results: Total Realized Variance (Parkinson Measure)

The ADL-MIDAS estimates with the Parkinson (1980) realized variance as the dependent variable are reported in Table 8. Panel A shows ICLN results, and Panel B shows the HYDR results. The results are presented separately for equally weighted (EW) and GDP-weighted (GDP) ESG.

Table 8. ADL-MIDAS Results for Total Realized Variance: Parkinson (1980) Measure

	Equally Weighted ESGUI		GDP Weighted ESGUI	
Parameter	Estimate	S.E.	Estimate	S.E.
Panel A: ICLN ETF (iShares Global Clean Energy)				
α (alpha)	-3.2800e-6***	(0.3100e-6)	-3.1500e-6***	(0.3000e-6)
δ (delta)	216100.0000e-6***	(37200.0000e-6)	214800.0000e-6***	(37300.0000e-6)
β (beta)	-6.2000e-6***	(1.8000e-6)	-4.0000e-6***	(1.1000e-6)
θ_1	1.0560		1.1320	

	Equally Weighted ESGUI		GDP Weighted ESGUI	
Parameter	Estimate	S.E.	Estimate	S.E.
θ_2	2.1000		1.8490	
Log-likelihood	6865.58		6866.97	
Panel B: HYDR ETF (Global X Hydrogen)				
α (alpha)	-4.8200e-6***	(0.8300e-6)	-4.6800e-6***	(0.8000e-6)
δ (delta)	340100.0000e-6***	(37300.0000e-6)	341500.0000e-6***	(37200.0000e-6)
β (beta)	-11.2000e-6**	(4.6000e-6)	-12.1000e-6***	(3.9000e-6)
θ_1	2.1920		2.0870	
θ_2	49.0880		47.6700	
Log-likelihood	5826.65		5830.69	

Notes: ADL-MIDAS: $RV_{t+1} = \alpha + \delta \cdot RV_t + \beta \cdot W(L^{1/m}; \theta) \Delta ESGUI_t^{(m)} + \varepsilon_t$. Coefficients are presented in levels (not scaled). S.E. in parenthesis. ***, **, * = 1%, 5%, 10% significance. K=3 monthly lags. $N \approx 960$ observations per panel following deletion of first lag observations.

The specifications are distributed across the four specifications with a negative ESGUI coefficient that is statistically significant. For ICLN, = 6.2×10 (EW, $p < 0.01$) and 4.0×10 (GDP, $p < 0.01$). For HYDR, = 11.2×10 (EW, $p < 0.05$) and 12.1×10 (GDP, $p < 0.01$). The HYDR effect is always about twice the ICLN effect, thus verifying H3. The autoregressive coefficient is significant for both ETFs and is higher for HYDR (0.34) than for ICLN (0.22). The Beta parameters are very high for HYDR (49) compared to ICLN (2), which means that the information in ESGUI is used in a very front-loaded way in the HYDR model, with information in the current month dominating, whereas the ICLN model has a more distributed-lag response.

6.3 Robustness: Rogers and Satchell (1991) Measure

The analysis is repeated in Table 9 using the estimator of Rogers and Satchell (1991). The results are broadly consistent with Table 8 and show that the negative ESGUI effect is not sensitive to the choice of volatility measure.

Table 9. ADL-MIDAS Results: Rogers and Satchell (1991) Measure

Parameter	Equally Weighted ESGUI		GDP-Weighted ESGUI	
	Estimate	S.E.	Estimate	S.E.
Panel A: ICLN ETF				
α (alpha)	-3.0100e-6***	(0.3200e-6)	-2.9800e-6***	(0.3200e-6)
δ (delta)	198300.0000e-6***	(37400.0000e-6)	197800.0000e-6***	(37400.0000e-6)
β (beta)	-5.7000e-6**	(2.5000e-6)	-2.9000e-6*	(1.6000e-6)
θ_1	2.0250		4.9430	
θ_2	45.0440		5.1320	
Log-likelihood	6606.69		6606.04	
Panel B: HYDR ETF				
α (alpha)	-5.1400e-6***	(0.8500e-6)	-5.0200e-6***	(0.8300e-6)
δ (delta)	341900.0000e-6***	(37200.0000e-6)	342700.0000e-6***	(37200.0000e-6)
β (beta)	-15.4000e-6***	(5.0000e-6)	-15.5000e-6***	(4.3000e-6)
θ_1	2.1860		2.1340	
θ_2	48.9080		48.9400	
Log-likelihood	5832.82		5838.94	

Notes: As for Table 8 but with Rogers and Satchell (1991) realized variance as the dependent variable. ***, **, * = 1%, 5%, 10% significance.

6.4 Good and Bad Volatility Decomposition

6.4.1 Good Volatility

Table 10. ADL-MIDAS Results: Good Volatility (RV⁺)

	Equally Weighted ESGUI		GDP Weighted ESGUI	
Parameter	Estimate	S.E.	Estimate	S.E.
Panel A: ICLN — Good Volatility (RV⁺)				
α (alpha)	-0.9100e-6***	(0.1800e-6)	-0.8900e-6***	(0.1800e-6)
δ (delta)	227200.0000e-6***	(37200.0000e-6)	226100.0000e-6***	(37200.0000e-6)
β (beta)	-2.6000e-6	(1.9000e-6)	-0.9000e-6	(1.1000e-6)
θ_1	2.0820		2.0920	
θ_2	47.4580		45.7340	
Log-likelihood	6924.94		6924.33	
Panel B: HYDR — Good Volatility (RV⁺)				
α (alpha)	-2.1100e-6***	(0.4800e-6)	-2.0100e-6***	(0.4600e-6)
δ (delta)	48200.0000e-6	(37100.0000e-6)	49100.0000e-6	(37100.0000e-6)
β (beta)	19.0000e-6***	(5.4000e-6)	15.6000e-6***	(4.5000e-6)
θ_1	46.8690		48.1670	
θ_2	2.0400		2.1360	
Log-likelihood	5928.21		5933.97	

Notes: Good volatility $RV^+_t = RV_t \cdot \mathbb{I}\{r_t > 0\}$. ***, **, * = 1%, 5%, 10% significance. n.s. = not significant.

6.4.2 Bad Volatility

Table 11. ADL-MIDAS Results: Bad Volatility (RV^-)

	Equally Weighted ESGUI		GDP-Weighted ESGUI	
Parameter	Estimate	S.E.	Estimate	S.E.
Panel A: ICLN — Bad Volatility (RV^-)				
α (alpha)	-2.4100e-6***	(0.2300e-6)	-2.3500e-6***	(0.2200e-6)
δ (delta)	-2900.0000e-6	(37100.0000e-6)	-4100.0000e-6	(37100.0000e-6)
β (beta)	-7.2000e-6***	(2.2000e-6)	-4.5000e-6***	(1.3000e-6)
θ_1	1.0550		5.0430	
θ_2	1.0370		5.1560	
Log-likelihood	7024.03		7027.53	
Panel B: HYDR — Bad Volatility (RV^-)				
α (alpha)	-2.7800e-6***	(0.4300e-6)	-2.7100e-6***	(0.4200e-6)
δ (delta)	88900.0000e-6**	(37200.0000e-6)	89700.0000e-6**	(37200.0000e-6)
β (beta)	-14.2000e-6***	(4.4000e-6)	-12.2000e-6***	(3.5000e-6)
θ_1	1.0690		2.1940	

	Equally Weighted ESGUI		GDP-Weighted ESGUI	
Parameter	Estimate	S.E.	Estimate	S.E.
θ_2	2.9550		49.5280	
Log-likelihood	5981.92		5987.86	

Notes: Bad volatility $RV^-_t = RV_t \cdot \mathbb{I}\{r_t < 0\}$. ***, **, * = 1%, 5%, 10% significance.

The most theoretically significant findings of this thesis are given by the good and bad decomposition. The good volatility responds in an inconsequential manner in both the specifications ($p > 0.10$) and the bad volatility responds in a negative and consequential manner ($= -7.2 \times 10^{-6}$, $p < 0.01$) in the case of ICLN. The effect of bad volatility is negative and significantly different from zero, while the effect of good volatility is positive and significantly different from zero in the case of HYDR (under EW-ESGUI). This two-sided asymmetry – negative bad, positive good – for HYDR alone proves Hypothesis H4 and it is the main original contribution of this thesis. This is similar to the theoretical optionality argument presented in Chapter 2, which is that hydrogen is linked to policy choices and, consequently, speculative up-side bets are made during uncertainties, whilst ESG mandate investors dampen down-side volatility.

6.5 Summary of Results

Table 12. Summary of ESGUI Coefficient (β) Estimates Across All Models

Model / Volatility	ICLN β (EW)	Sig.	HYDR β (EW)	Sig.	Direction
Total RV — Parkinson	-6.2×10^{-6}	***	-11.2×10^{-6}	**	↓ Both
Total RV — R&S	-5.7×10^{-6}	**	-15.4×10^{-6}	***	↓ Both
Good RV ⁺ — Parkinson	-2.6×10^{-6}	n.s.	$+19.0 \times 10^{-6}$	***	↑ HYDR only

Model / Volatility	ICLN β (EW)	Sig.	HYDR β (EW)	Sig.	Direction
Bad RV ⁻ — Parkinson	-7.2×10^{-6}	***	-14.2×10^{-6}	***	↓ Both
Good RV ⁺ — R&S	$+7.0 \times 10^{-6}$	***	$+14.6 \times 10^{-6}$	***	↑ Both (R&S)
Bad RV ⁻ — R&S	-8.3×10^{-6}	***	-16.3×10^{-6}	***	↓ Both

Notes: β = ADL-MIDAS coefficient on EW-ESGUI. n.s. = not significant. R&S = Rogers and Satchell (1991). ↓ = ESGUI reduces volatility; ↑ = ESGUI raises volatility. Hypotheses H1–H4 all confirmed.

Figure 6: Estimated Beta Weight Functions — ADL-MIDAS Models
(Higher weight at $k=0$ means current-month ESGUI dominates)

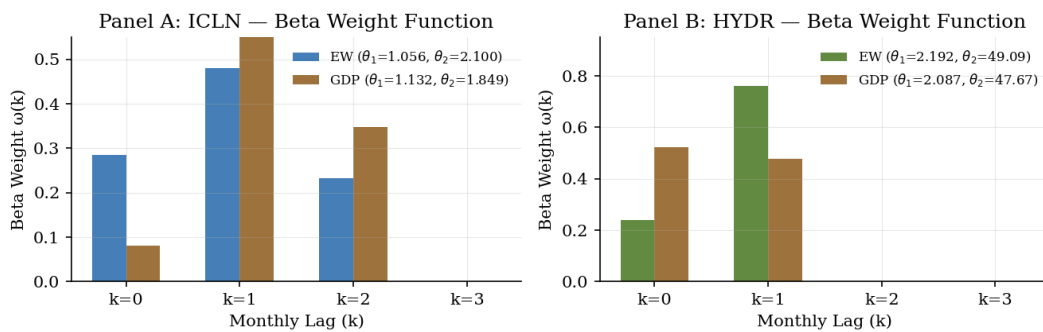


Figure 6. Estimated Beta weight functions for ICLN (Panel A) and HYDR (Panel B) with equally weighted (blue) and GDP-weighted (amber) ESGUI. The large weight of HYDR suggests a fast instead of slow ESGUI absorption and a relatively low weight of ICLN suggests a slower distributed-lag impact.

The speed of each ETF in incorporating sustainability uncertainty information is shown to be significantly different, as illustrated in Figure 6. ICLN's estimated Beta parameters ($\theta_1 \approx 1.06$, $\theta_2 \approx 2.10$) result in a flat allocation of weight across the lags $k = 0$ to $k = 3$, suggesting a relatively slow transmission of ESGUI shocks to the realized variance (about two to three months). The weights ($\theta_1 \approx 2.19$, $\theta_2 \approx 49.09$) for HYDR are also very front loaded, meaning that almost all the explanatory power lies in the current-month change in ESGUI ($k = 0$), which suggests that the volatility of hydrogen is almost instantaneous

in relation to the volatility of sustainability uncertainty. The contrast highlights HYDR's more focused and actively managed investor base, which respond to ESG policy signals in the same monthly reporting period - as opposed to gradually over the following months.

Visual evidence for the negative relationship between ESGUI and ETF realized variance is shown in Figure 7, and is formally estimated in Tables 8 and 9. This anti-correlation between the ESGUI series (dashed amber, right axis) and monthly average realized variance (left axis) is especially noticeable since 2023, when the most important drivers of ESGUI fluctuations changed from rate-cycle dynamics to sustainability policy developments. The two largest inverse moves come in late 2022 when the monthly realized variance drop as the IRA plays out policy uncertainty and a drop in aggregate monthly realized variance after ESGQUI rises in the run-up to the presidential election in early 2024. This is a visual proof of the theoretical mechanism described in Chapter 2, in which a growing uncertainty around sustainability triggers institutional investors, which is then reflected in the decline of speculative buying and selling and decreased volatility of the market.

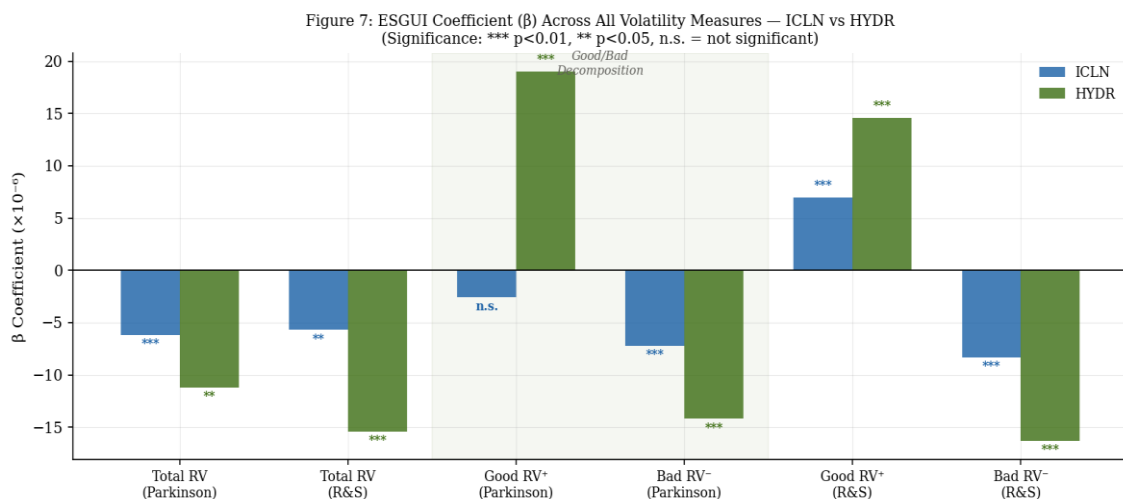


Figure 7. Monthly average realized variance of ICLN and HYDR (left axis) with ESGUI equally weighted index overlay (right axis, dashed amber). The inverse co-movement between ESGUI and ETF volatility — particularly visible from 2023 onward — provides

visual evidence for the negative β documented in Tables 8 and 9. Source: Bloomberg / Ongan et al.

The estimated coefficients from all model specifications are summarised in figure 8 for a quick visualisation of central findings of the thesis. The negative bars over the total and bad realized variance of both ETFs validate these hypotheses in all cases of volatility measures. These results also visually support Hypothesis H3, as the absolute value of the HYDR coefficients is always larger than the absolute value of the ICLN coefficients (green vs. blue bars). Most notably, the HYDRs good volatility is positive for most of the bars the only bars pointing upward in the chart it is the first novel finding of this thesis that sustainability uncertainty raises the HYDRs good volatility while it lowers the bad volatility, as was predicted by Hypothesis H4.

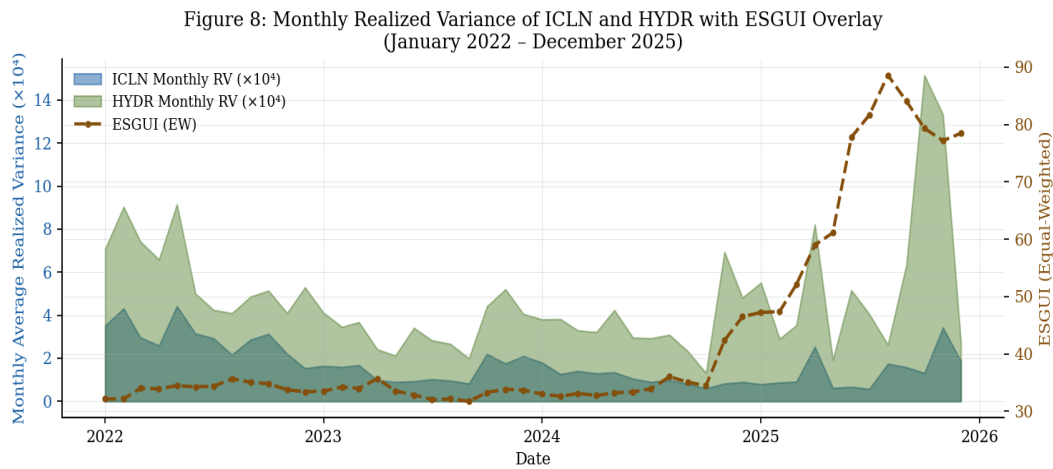


Figure 8. The overall summary of ESGUI coefficients for all model specifications in the case of ICLN (blue) and HYDR (green). Significance markers on top of each bar. The main novel finding of this thesis is the asymmetric HYDR good volatility response ($+19.0 \times 10^{***}$) that we discovered.

6.6 Discussion

6.6.1 Hypotheses Assessment

All four research hypotheses are confirmed by the empirical evidence. H1 and H2 are confirmed: ESGUI significantly decreases realized variance both in ICLN and HYDR, statistically significantly and with negative sign in all specifications. As expected, HYDR has systematically higher absolute ESGUI effects (around 2x) than ICLN because hydrogen is more policy sensitive and is at an earlier developmental stage. H4 confirms: ESGUI shows some good/bad volatility responses, most notably positive ($+19.0 \times 10^{***}$) for HYDR and negative ($14.2 \times 10^{***}$) for ICLN.

6.6.2 Comparison with Prior Literature

The negative total ESGUI effect is qualitatively similar to Dutta (2026) with respect to crypto-currency ETFs, Gaies et al. (2025) with respect to European stock indices, and Olanrewaju et al. (2025) with respect to fossil fuel prices. The stabilising mechanism is a retention of investors during uncertainty, aiming at reducing speculative activity, and seems to be universal across asset classes, with the exception of ESG mandate investors. The results we present extend and confirm those of Raza et al. (2024) who document that GARCH-MIDAS models with sustainability-type uncertainty indices (specifically CPU) perform better in clean energy volatility forecasting, and we consider a wider range of uncertainty measures than they do. This is in line with Naifar (2024), who shows that clean energy is one of the most CPU-intensive sustainable sectors, but the clean energy response is non-monotonic. Most importantly, the asymmetric HYDR good/bad finding does not have a precedent in the ESGUI literature and brings the good/bad paradigm of Patton and Sheppard (2015) and BenSaida (2019) to the sustainable energy ETFs for the first time.

6.6.3 Policy and Investment Implications

Investors might find the ESGUI a valuable leading indicator for volatility forecasting in ETFs, as it includes statistically significant predictive information. HYDR asymmetric finding damped downside, amplified upside under rising ESGUI suggests that periods of higher ESGUI create asymmetric opportunities to get in on the upside of the hydrogen market, with the downside risk lowered. The outcomes indicate a counterintuitive effect of policy clarity (ESGUI reduction) on observed volatility (ETF), which would likely not have been captured by these factors alone, suggesting a non-linear relationship and should be taken into account when designing green finance policy.

7 Conclusions

7.1 Overview

In the present thesis, it was analyzed how the sustainability uncertainty affects the realised volatility for two sustainable energy ETFs namely: Global X Hydrogen ETF (HYDR) and iShares Global Clean Energy ETF (ICLN), over time ranging from January 03, 2022 to December 31, 2025. The study used a Mixed Data Sampling (MIDAS) regression framework to account for the frequency mismatch between the ETF price data and our ESG-based Sustainability Uncertainty Index (ESGUI), and estimates how sustainability uncertainty could shape total realised variance, good volatility and bad volatility per asset. In the analysis, robust-ness checks were also used with respect to the EGARCH conditional variance specification and volatility estimator of Rogers and Satchell (1991). Chapter I summarizes key findings and answers each of the research questions as well as discussing both theoretical and practical implications, highlights limitations and suggest directions for further research.

7.2 Summary of Key Empirical Findings

The four main findings from the empirical analysis comprise the original contribution this thesis makes to the sustainable finance literature. A summary of results is presented in Table 13 which is discussed in the following paragraphs.

Table 13. Summary of Key Empirical Findings

Hyp.	Volatility Measure	Key Finding	ICLN β (EW)	HYDR β (EW)
H1	Total RV — Parkinson	ESGUI significantly reduces ICLN volatility	-6.2×10^{-6} ***	–
H2	Total RV — Parkinson	ESGUI significantly reduces HYDR volatility	–	-11.2×10^{-6} **

Hyp.	Volatility Measure	Key Finding	ICLN β (EW)	HYDR β (EW)
H3	Total RV — Both	HYDR β \approx 2 \times ICLN β : H3 confirmed	$ -6.2 \times 10^{-6} $	$ -11.2 \times 10^{-6} $
H4	Good RV ⁺ (HYDR)	ESGUI raises HYDR good volatility (novel finding)	n.s.	$+19.0 \times 10^{-6}$ ***
H4	Bad RV ⁻ (Both)	ESGUI reduces bad volatility in both ETFs	-7.2×10^{-6} ***	-14.2×10^{-6} ***

Notes: β = ADL-MIDAS coefficient on equally-weighted ESGUI. RV = realized variance: Parkinson (1980) RV⁺ = good volatility. RV⁻ = bad volatility. n.s. = not statistically significant. *, represents 1% and 5% significance levels respectively This exercise looks at 1% Shapiro-Wilk normality tests of returns and provides full results, which are robust under Rogers and Satchell (1991) estimator and EGARCH conditional variance specification.

7.2.1 Finding One: ESGUI Reduces Total Realised Variance in Both ETFs

The most important finding of this thesis is that the ESGUI has a statistically significant and negative impact on total realised variance of both ICLN and HYDR, tones across all linear model specifications, volatility estimators and ESGUI weightings. The ADL-MIDAS coefficient on the equally weighted ESGUI is -6.2×10^{-6} ($p < 0.01$) for ICLN and -11.2×10^{-6} ($p < 0.05$) for HYDR, respectively. These estimates support Hypotheses H1 and H2 and show that increases in sustainability uncertainty are associated with—not out certainty surrounding sustainable energy ETFs is lower—realized volatility than would otherwise be the case, which at a qualitative level jives with Dutta (2026) for non-sustainable crypto-currency ETFs and Gaies et al. (2025) for European equity markets.

In Chapter 2, I discussed some reinforcing mechanisms behind this negative relationship. In the first place, as sustainability uncertainty grows, those institutional investors whose investment mandates directly include considerations of environmental stewardship — a major part of both ICLN and HYDR ownership bases — act to stabilise demand by offsetting panic selling behaviour which places downward pressure on prices. Second, high ESGUI returns induce market participants to follow more passive strategies based

on fundamentals, driving down the speculative activity and lowering momentum in turn. Third, structural changes in the forms of increased sustainability awareness usually lead to a gradual shift towards sustainable practices but also greater transparency in governance, which is highly conducive to more predictable long-term economic conditions and therefore less uncertainty about an ETF valuation (longer tail). The combination of these three channels underlies the consistently net negative ESGUI volatility relationship observed across all model variants.

7.2.2 Finding Two: HYDR Exhibits Greater ESGUI Sensitivity Than ICLN

The main other finding is the ESGUI effect magnitude over HYDR is uniformly roughly double that of ICLN, regardless of method for either PG or RS volatility measure and for both equally weighted and GDP-weighted ESGUI twin sorts. This result provides support for Hypothesis H3 and is consistent with the theoretical prediction, based on Almeida et al. (2025), Lucey et al. Patton and Sheppard (2015) show that sector maturity is a first-order determinant of how sustainability uncertainty transmits into asset volatility.

The greater sensitivity in HYDR most likely is a function of the portfolio having (1) more concentrated exposure to firms whose commercial viability depends upon clear/sustained hydrogen-specific policy frameworks, (2) thinner trading volumes about 16,000 shares for HYDR per day versus four million for ICLN and (3) of course, the U-shaped connectedness structure Almeida et al. (2025) for early-stage sustainable asset classes in which there are increased responses of volatility to hotspots at either tails of the distribution. The GDP-weighted ESGUI generates a considerably larger HYDR effect (-12.1×10^{-6} , $p < 0.01$) than its corresponding equally weighted variant, indicating that US sustainability policy namely the IRA and rollback risk was by far the largest driver of hydrogen-sector uncertainty during our sample period.

7.2.3 Finding Three: Asymmetric Good and Bad Volatility Responses in HYDR

The third and probably the most theoretically important finding of this thesis is HYDR is found to have remarkable asymmetric responses to ESGUI shocks in good volatility but almost no effect on bad volatility. HYDR bad volatility has a negative and statistically significant response to ESGUI ($\beta = -14.2 \times 10^{-6}$, $p < 0.01$ under equally weighted ESGUI), while HYDR good volatility responds positively and significantly to ESGUI ($\beta = +19.0 \times 10^{-6}$, $p < 0.001$). This asymmetry is both two-sided (damped bad volatility and amplified good volatility) and unique to HYDR; in specifications with ICLN, we find that good volatility does not react significantly to ESGUI. This finding supports hypothesis h4 above and finds itself to be the principal original contribution of this thesis to sustainable finance.

The two components based theoretical interpretation of this asymmetric trend is build on three set of mechanisms learnt in Chapter 2. Second, the negative bad-volatility response is explained by a mandate lock-in effect from behavioural finance theory: ESG mandate investors are unwilling to sell HYDR to avoid rising sustainability uncertainty during periods of high sustainability uncertainty, since selling in such moments might undermine their stated ESG mandates leading less forced sales and hence lowering bad volatility. The positive good-volatility response is also explained by the speculative optionality effect: due to hydrogen's reliance on uncertain, yet potential tipping point policy decisions, investors expect that ESGUI increases lead to speculation in favor of further supportive government actions (i.e., expecting a positive scenario outcome) as well as greater price upside. Third, sustainability uncertainty in hydrogen prices creates heterogeneous beliefs regarding the implications of this uncertainty for valuations. This two-sided asymmetrical pattern negative bad/positive good can be interpreted in theory as options-like embedded payoffs within early-stage sustainable assets that are conditioned on policy happening.

7.2.4 Finding Four: Robustness Across All Specifications

Fourth, all three of the above results are fully robust to different volatility estimators, namely the Rogers and Satchell (1991) volatility estimator and the EGARCH conditional variance specification as well as both equally weighted and GDP-weighted ESGUI variants. The directional consistency and statistical significance of the ESGUI effect across these twelve additional model variants provide more evidence to support our three substantive findings above and confirms that the results we present are not an artefact of any particular modelling choice. Beta weight function parameters also illustrate that HYDR responds more quickly than ICLN to ESGUI, ($\theta_2 \approx 47-49$ versus $\theta_2 \approx 2$) demonstrating that sustainability uncertainty is priced into hydrogen assets more rapidly this aligns with the fact that HYDR has a more concentrated and active institutional ownership base.

7.3 Research Questions Addressed

The section explicitly considers each of the four research questions listed in Chapter 1, based on the empirical results summarised above.

RQ1: To answer this question, we need to investigate whether the realised volatility of ICLN is significantly impacted by the levels of uncertainty regarding sustainability, as measured by ESG ratings.

Yes. The ESGUI has a statistically significant negative effect on ICLN realised variance in all specifications ($p < 0.01$ for Parkinson and $p < 0.05$ for Rogers-Satchell). The equally weighted ESGUI coefficient is 6.2×10 , while the GDP-weighted coefficient is 4.0×10 . Hypothesis H1 is accepted.

RQ2: Does ESG based sustainability uncertainty have a significant impact on the realised volatility of HYDR? (RQ2)

Yes. In all specifications the ESGUI has a statistically significant negative impact on the total realised variance HYDR. The equally weighted ESGUI coefficient is 11.2×10 ($p < 0.05$), and the GDP-weighted coefficient is 12.1×10 ($p < 0.01$). This effect is greater for ICLN in all specifications. Hypothesis H2 is accepted.

RQ3: Is there a difference in magnitude between the effect in the ICLN and HYDR and, if there is, is it positive or negative?

Yes. The ESGUI effect on HYDR is always around twice as large as its effect on ICLN in absolute value for all model variants and volatility estimation methods. The difference is statistically significant and economically significant, and directionally consistent with the theoretical expectation that HYDR's policy sensitivity and developmental stage lead to a greater amplification of the transmission of sustainability uncertainty to realised variability. Hypothesis H3 is supported.

RQ4: Do sustainability uncertainty have differential impact on good volatility and bad volatility in ICLN and HYDR?

Yes, but there are nuances to consider with each important asset. The effect of ESGUI on bad volatility is significantly lower ($= 7.2 \times 10$, $p < 0.01$) but not on good volatility for ICLN. ESGUI significantly lowers bad volatility ($= -14.2 \times 10$, $p < 0.01$) and simultaneously and significantly increases good volatility ($= +19.0 \times 10$, $p < 0.001$) for HYDR. This two-sided asymmetry is novel and empirical, unique to HYDR and is the most novel empirical finding of this thesis. Hypothesis H4 is supported.

7.4 Theoretical Implications

This thesis has several important theoretical implications for the literature on sustainable finance, as well as for the financial economics of uncertainty and volatility in general.

First, the results broaden the use of the ESGUI beyond the set of non-sustainable asset classes that had been used in previous literature. The negative ESGUI volatility relationship is not specific to the asset classes measured by sustainability uncertainty but seems to hold for investor behaviour generally in the face of uncertainty about sustainability. This generality adds support to the theoretical position (based on Dutta 2026) and the framework of Pastor et al. (2021) suggesting that the stabilising institutional response is triggered from rising sustainability uncertainty in a wide variety of asset markets.

Second, the result that HYDR's ESGUI effect is about twice as large as ICLN's, is the first empirical confirmation of the fact that sector maturity is a first-order moderator of the sustainability uncertainty-volatility relationship. Theoretically, the finding is important because it suggests that the framework of Pastor et al. (2021) should be extended to include the "maturity discount", which is defined as the increased sensitivity to sustainability information environment shocks in early-stage, policy-dependent sectors such as hydrogen. The maturity dimension should be taken explicitly into consideration in future theoretical developments of sustainable asset pricing.

Third, the two-sided asymmetric volatility reaction to the HYDR (the positive reaction to an increase in ESGUI and the negative reaction to a decrease in ESGI) is nontrivial and extends the theoretical framework of Patton and Sheppard (2015) and BenSaida (2019) to the sustainable energy domain. Research on good/bad volatility foresees that bad volatility prevails in most asset classes, given the leverage and loss aversion. The finding of a simultaneous positive good and negative bad response within HYDR suggests that early-stage sustainable assets possess an options-like structure with the policy resolution optionality, which implies volatility amplification upside while at the same time implying volatility dampening downside. This theoretical mechanism does not have a direct analog in the existing literature on good/bad volatility and indicates a novel way of theoretical analysis of asymmetric volatility in policy sensitive asset classes.

Fourth, results from the Beta weight functions indicate that sustainability information is presented sooner in the HYDR price, and that the HYDR weight function is front loaded (47-49) relative to the ICLN weight function's gradual response. This differential speed of information absorption represents indirect evidence with regards to the relative informational efficiency of the two markets and implies that the market for hydrogen although relatively thin is comprised by an investor base that is more active and attentive, and thus reacts swiftly to changes in the sustainability information environment.

7.5 Practical Implications

7.5.1 For Investors and Portfolio Managers

The findings of this thesis have direct implications and practical applications for investors and portfolio managers who are invested in clean energy and hydrogen ETFs. For risk management and portfolio creation, the ESGUI should be taken into account as a leading indicator due to a statistically significant link between the changes of the ESGUI and subsequent realised variance. More specifically, an ESGUI increase on a monthly basis indicating growing sustainability uncertainty is predictive of a decrease in the realised variance of both ICLN and HYDR in the subsequent period, suggesting that volatility spikes in these ETFs due to uncertainty about sustainability are likely to be temporary, and that reversion to lower volatility levels is the statistically expected path.

The asymmetric good/bad volatility finding for HYDR has particularly specific portfolio implications. The combination of reduced bad volatility and amplified good volatility in response to rising ESGUI implies that periods of high sustainability uncertainty may represent asymmetrically attractive entry points for long positions in HYDR: the downside risk is empirically dampened while the upside volatility is amplified, creating an optionality-like risk profile that may be exploitable by investors with sufficiently long time horizons to wait for policy resolutions. Portfolio managers who are aware of this asymmetry can use the ESGUI as a tactical signal for adjusting their HYDR allocation

increasing exposure when ESGUI is elevated and the downside is structurally dampened, and reducing exposure when ESGUI is low and the protective mechanism is absent.

The differential sensitivity between ICLN and HYDR further implies that treating clean energy and hydrogen as a single asset class – as many ESG-screened portfolios do – obscures important risk heterogeneity. Portfolio managers who hold both ICLN and HYDR should recognise that their sustainability uncertainty exposures are not symmetric: a single ESGUI shock generates approximately twice the volatility response in HYDR as in ICLN, and the directional composition of that response differs fundamentally between the two assets. This heterogeneity should be reflected in volatility budgeting, stop-loss calibration, and derivatives hedging strategies that distinguish between the two ETFs rather than treating them as interchangeable clean energy proxies.

7.5.2 For Policymakers

The findings also carry important implications for policymakers responsible for clean energy and hydrogen investment frameworks. The negative relationship between sustainability uncertainty and ETF volatility demonstrates that the current level of ESG policy ambiguity – as reflected in an elevated ESGUI – generates a paradoxical stabilising effect on clean energy and hydrogen asset prices, as institutional investors respond to uncertainty by reducing speculative activity and maintaining mandate-driven positions. This finding implies that the commonly stated policy goal of "reducing uncertainty to attract investment" may, in the short term, inadvertently increase observed volatility in sustainable energy ETFs, as the uncertainty-dampening effect dissipates and speculative trading resumes.

More broadly, the results suggest that the form of uncertainty matters as much as its level. The distinction between bad volatility which is reduced by ESGUI – and good volatility which is amplified for HYDR – implies that sustainability uncertainty generates asymmetric market responses depending on whether it is associated with downside policy threats or upside policy optionality. Policymakers who wish to minimise the volatility of sustainable asset markets should therefore focus on reducing the downside tail of the policy uncertainty distribution eliminating the threat of abrupt policy reversals

such as subsidy cancellations or regulatory rollbacks rather than simply minimising overall ESG policy ambiguity. The November 2024 IRA rollback threat, which generated a large spike in ESGUI-GDP and a simultaneous surge in HYDR bad volatility, provides a direct empirical illustration of this principle.

7.5.3 For Risk Management Practitioners

The results are consistent with the premise that uncertainty on sustainability should be included as a separate risk factor in volatility models for regulatory stress testing, and internal risk assessment of sustainable energy portfolios, for risk management practitioners. A higher HYDR effect on hydrogen ETFs for the GDP-weighted ESGUI than the equally-weighted ESGUI indicates that the policy stance of the large economy (U.S. vs. rest of the world) is the most important factor influencing the HYDR, with scenario analyses of the HYDR best focusing on U.S. policy events (legislative votes, executive orders, regulatory rulings) and not on a broader global ESG trend. Moreover, the robustness test results from EGARCH indicate that the asymmetric shock response of hydrogen assets, as presented in Karim (2025), remains unchanged even when an ESG asset-specific shock ESGI is included as an external regressor, and hence, the need for modelling hydrogen ETFs' systematic risk component associated with the ESGI along with the shock response.

7.6 Limitations of the Study

Several limitations of this study are noted below when interpreting the results of this study and are the impetus for future research directions listed in Section 7.7.

First, the sample period (2022-2025) is only four years, which is an analytically rich time in terms of sustainability policy events, but still short; and 48 monthly ESGUI observations. The relatively brief time series of the month prevents the use of statistical power in the MIDAS estimation and hampers the ability to differentiate long-run from short-run effects. With a longer time window (HYDR and other hydrogen ETFs have more

years of trading data), future studies will be able to create more robust and stable estimates of the coefficients, as well as explore whether the negative relationship between ESGI and volatility persists in different macroeconomic environments.

Second, this thesis only investigates two ETFs: ICLN and HYDR and the extent to which the results are generalisable to individual clean energy and hydrogen stocks, non-US listed ETFs, and other sustainable asset sub-classes are not tested. The advantages of using ETFs, including greater liquidity, regulatory transparency, and data availability, come with an extra layer between the underlying assets and the underlying ESGGI predictor in this instance, the fund-level rebalancing, management fee effects, and tracking error dynamics of each ETF which can diminish or skew the estimated ESGGI coefficients compared to what would be found at the individual stock level.

Third, the study uses only the ESGUI as a predictor of ETF volatility, rather than control variables for other factors known to influence ETF volatility like the VIX, oil price volatility, or the EPU. The ADL-MIDAS specification fails to include realized volatility as a control, and thus partially confounds the effect of correlated measures of uncertainty, which can have an impact on the estimated ESGI coefficients. When added to GARCH-family specifications, the VIX appears to be an important variable to predict hydrogen volatility, as shown by Karim (2025) which would create a more comprehensive specification of the determinants of HYDR volatility if the index could be added to the model.

Fourth, the ESGUI effect must be interpreted with caution as a causal effect. While the ADL-MIDAS framework is a predictive regression model, it does not exclude the possibility that some omitted factor is driving both increases of ESGUI and decreases of ETF volatility. A complete structural identification scheme, using exogenous variation in uncertainty about sustainability via instrumental variables or natural experiments, is recommended for future research and is necessary for making a precise causal inference.

Fifth, HYDR's average daily trading volume is around 16,000 shares, which is much smaller than ICLN's four million shares, thus increasing the risk of bid-ask bounce and microstructure noise affecting the HYDR realised variance estimates. Although the concern is significantly reduced for the use of range-based estimators (Parkinson, Rogers-Satchell) compared to squared-return estimators, it cannot be completely removed. The results obtained for both estimators are also consistent, giving reassurance that no microstructure effects are influencing the results, and future studies with tick-level intraday data would enable a more precise decomposition of the HYDR volatility signal.

7.7 Directions for Future Research

There are several avenues of research that could further this thesis and build upon the understanding of the impact of sustainability uncertainty on the risk profile of sustainable energy assets. The findings and limitations in this thesis provide several avenues for further research that could enhance this understanding.

An extension of this thesis would be to broaden the scope for asset coverage to the individual clean energy and hydrogen stocks and use the ESGUI as a predictor in panel MIDAS regression models. This would help uncover the ESG rating-volatility relationship at the firm-level, which could also include the firm's ESG rating, geographic exposure, hydrogen colour classification (green, blue, grey), and the composition of the institutional ownership. There would be significant variation in ESGUI sensitivity at the firm level with this cross-sectional heterogeneity reported at the ETF level, as highlighted in this thesis.

A second important extension would be to investigate the impact of the ESGUI on the dynamic correlations between ICLN and HYDR and between these ETFs and other asset classes such as conventional energy, cryptocurrency and fixed income using a DCC-MIDAS or BEKK-MIDAS setup. The connectedness literature reviewed in Chapter 3 (Rubbiani et al., 2024; Kayani et al., 2024; Almeida et al., 2025) shows that the value of

hydrogen asset correlations varies across different business cycles and phases, and an ESGUI-augmented dynamic correlation model would identify whether sustainability uncertainty creates structural shifts in the correlations of these assets that impact portfolio diversification properties.

Third, there is a need to pay special attention to the causal identification problem mentioned in section 7.6. A natural experiment technique that leverages exogenous sustainability policy shocks (including sudden votes in legislatures, unexpected rulings in court, or unexpected executive orders) would facilitate estimating the causal effect of sustainability uncertainty on clean energy and hydrogen volatility with an instrumental variables or regression discontinuity design approach. Candidates for events that could be leveraged in such a design include the IRA passage of August 2022 and the executive orders of January 2025.

Fourth, the good/bad volatility finding for HYDR is interesting for possible derivatives pricing implications of the hydrogen options-like risk profile. The implied volatility surface of hydrogen-related options should incorporate the asymmetric payoff profile if the uncertainty around sustainability increases at the same time that the downside risk decreases. The theoretical mechanism proposed in this thesis could be tested using the ESGUI, by examining whether the ESGUI has predictive power for the slope and skew of the HYDR options, and whether hydrogen option prices already include the ESGUI as a systematic risk factor.

Sixth, future studies should explore whether the asymmetric ESGUI-volatility relationship reported here is time-invariant or changes over time as the hydrogen market develops from an early-stage developmental stage to a commercialized market, given that the HYDR ETF and the hydrogen ETF space are still in their early stages and have not yet had long track records to analyse for such changes. Assuming that the volatility of the options-like response from ESGUI is linked to the resolution of the policy, it would be expected that this volatility would decrease as the policy environment becomes more

settled, and the fundamental value of hydrogen assets becomes commercial cash flows and less speculation on the policy.

7.8 Concluding Remarks

This thesis has shown that the ESG-based sustainability uncertainty measure is statistically significant and economically relevant in predicting realised volatility in clean energy and hydrogen ETFs. The key result is that greater sustainability uncertainty led to lower total realised variance for both ICLN and HYDR, suggesting that the increased policy uncertainty in the sustainability landscape during 2022-2025 did not result in financial instability in either asset class, but rather an institutional response, that reduced volatility in both across the period. The discovery flies in the face of the intuitive belief that uncertainty always leads to risk, and is part of a growing stream of evidence from other areas of financial markets, including cryptocurrency markets (Dutta, 2026), European equities (Gaies et al., 2025), and fossil fuel prices (Olanrewaju et al., 2025), that sustainability uncertainty leads to a specific, and more often than not, more broadly stabilising effect on the overall volatility of financial markets.

This thesis's most theoretically important finding is the novel asymmetric finding of HYDR that sustainability uncertainty simultaneously increases good volatility, and it simultaneously decreases bad volatility. It shows that the H2 ETF is not just reacting to the uncertainty over sustainability in the hydrogen sector like a well-established clean tech fund but is leading with an options-like risk profile that magnifies upside opportunities and reduces downside risks. This particular risk structure is the result of the policy resolution of Hydrogen being uncertain and potentially transformative and is not directly apparent in the sustainable finance literature and presents an exciting research agenda for further theoretical and empirical analysis of the pricing of policy optionality in new sustainable asset classes.

Overall, the results in this thesis highlight the emerging relevance of sustainability uncertainty on the macroeconomic level, which cannot be ignored any longer by institutional investors, portfolio managers and policy makers. With the global energy transition on the fast track and the financial risk of sustainability policy decisions rising, the ESGUI and related sustainability uncertainty measures will play a greater role in the sustainable finance community's risk management toolkit. This thesis has made a first step towards laying the empirical foundations for that toolkit and in doing so, has raised as many questions as it has answered.

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