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Impact of climate risk on clean water investments: Does crude oil act as a hedge?

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ABSTRACT

Water investments play an increasingly important role in sustainable finance, yet their response to climate policy uncertainty (CPU) under different market conditions remains poorly understood. This study examines the regime-dependent influence of CPU on water equity performance using monthly data for the First Trust Water ETF (FIW) and the Invesco Global Water ETF (PIO) from 2007 to 2024. A Markov regime-switching VAR framework is employed to capture nonlinear dynamics that conventional linear models may overlook. The results reveal two distinct volatility regimes with contrasting CPU effects. In low-volatility periods, CPU is associated with higher returns, indicating that climate-policy developments can signal investment opportunities when markets are stable. During high-volatility periods, CPU exerts a negative influence, consistent with rising discount rates applied to long-term water-infrastructure cash flows. Regime persistence differs across ETFs: FIW exhibits frequent, short-lived transitions, whereas PIO displays more persistent states. A complementary DCC-GARCH analysis shows that crude oil provides a relatively cost-effective hedge for water portfolios, while technology ETFs offer substantially weaker hedging performance. Overall, the findings highlight the importance of regime-sensitive portfolio strategies for investors and emphasize that policymakers should consider prevailing market conditions when communicating climate initiatives. The study demonstrates that nonlinear models are essential for uncovering climate-finance linkages that linear approaches fail to detect.

1. Introduction

Water has become one of the most strategically important resources on the global policy agenda as population growth, rapid urbanization, and climate change intensify scarcity and deepen inequalities in access (Garrick et al., 2020). Recognizing water as a finite and increasingly valuable resource has reshaped the sector's economics, generating investment opportunities and attracting both institutional and retail capital. This transformation has repositioned water from a traditional public utility service to an emerging investable asset class with documented diversification benefits (Díaz-Mendoza and Pardo, 2023; Jin et al., 2015).

Despite growing investor interest, water-related assets remain acutely exposed to climate variability (Alavian et al., 2009). Valuing this exposure is challenging, as investors must evaluate alternative climate scenarios and their implications for returns (Elmahdi and Wang, 2022), while navigating fragmented or inconsistent national climate policies that shape capital-intensive water infrastructure decisions (Pittock, 2011). Although existing research emphasizes the relevance of uncertainty for water resource planning and infrastructure management (Adamson and Loch, 2021; Erfani et al., 2018; Fovargue et al., 2021), far less is known about how water equity markets respond to climate policy uncertainty (CPU),[1] a dimension of risk that has become increasingly salient in global financial markets.

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[1] Several recent studies consider CPU, introduced by Gavriilidis (2021), as a suitable measure of climate risk. Qiao et al. (2024), for instance, argue that CPU can proxy climate change as it is constructed based on several relevant keywords such as climate change, uncertainty, greenhouse gases, etc. In addition, Ren et al. (2022) and Liu et al. (2025) also recommend the application of CPU.

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Water investments merit special attention within the climate-finance interface due to their unique structural and regulatory characteristics. The sector operates at the core of the water-energy-food nexus, requiring investment decisions that account for complex interdependencies across resource systems (Payet-Burin et al., 2019). Moreover, water infrastructure is subject to overlapping regulatory regimes, including water quality standards, allocation frameworks, climate adaptation mandates, and energy-water nexus policies-creating multi-layered exposure to policy decisions. Coupled with high capital intensity and long asset lifecycles, this regulatory complexity generates increased sensitivity to CPU.

Theoretical advances in finance suggest that policy uncertainty is a systematic risk factor that affects expected cash flows, discount rates, and risk premiums (Pástor and Veronesi, 2013; Su et al., 2024). Real options theory further predicts that uncertainty increases the value of delaying irreversible investment (Kellogg, 2014), a mechanism particularly salient for water utilities and infrastructure firms with long-lived assets. Collectively, these frameworks imply that CPU may affect water equity valuations in nonlinear and regime-dependent ways, with investor responses varying systematically across market conditions.

We formalize these mechanisms by identifying two channels through which CPU influences water equity valuations, with their relative importance varying across underlying volatility regimes. First, real options effects operate through investment timing: during low-volatility regimes, climate policy activity signals forthcoming regulatory clarity, reducing long-term uncertainty and encouraging infrastructure investment; during high-volatility regimes, the same activity compounds short-term uncertainty, increasing the value of waiting and delaying investment (Bloom, 2009; Dixit and Pindyck, 1994a). Second, risk-premium amplification operates through discount rates: CPU commands positive risk premia, which intensify during high-volatility periods when investors apply higher discount rates to cash flows already exposed to regulatory uncertainty (Ali and Naz, 2025). The relative strength of these channels depends on investor risk appetite, which varies systematically across volatility regimes and generates nonlinear relationships that linear models cannot capture.

The objective of this study is to provide evidence-based guidance for both investors and policymakers engaged in water-sector finance. For investors, we identify regime-specific hedging instruments and optimal allocation strategies. For policymakers, we show that the timing and communication of climate policy announcements generate markedly different return sensitivities across volatility regimes. Achieving these objectives requires addressing a key methodological limitation: prior studies relying on linear frameworks often report weak or insignificant relationships between policy uncertainty and asset returns (Bekiros et al., 2016). We argue that such findings reflect model misspecification rather than economic irrelevance.

Specifically, the study examines three interrelated issues. First, how does CPU influence water equity returns, given the sector's high sensitivity to climate variability and policy uncertainty? Second, to what extent can risks associated with water investments be hedged under rising CPU, and which instruments offer the most capital-efficient protection? Third, do CPU effects vary systematically across market volatility regimes, such that linear models understate their economic relevance?

To address this gap, we employ a Markov Regime-Switching Vector Autoregressive (MRS-VAR) model that accommodates nonlinear dynamics and structural breaks associated with major events such as the global financial crisis and the COVID-19 pandemic. By allowing parameters to vary across latent volatility regimes, this framework generates regime-specific impulse responses that reveal how CPU shocks propagate differently across market conditions.

This study makes three contributions. First, it provides the first theoretically grounded and empirically validated evidence of a nonlinear, state-dependent relationship between CPU and water equity valuations. Second, it demonstrates that linear specifications systematically understate the economic relevance of CPU, offering a regime-switching framework as a methodological remedy. Third, it delivers actionable insights by identifying capital-efficient hedging strategies and highlighting how policy communication timing generates sharply different return sensitivities across volatility regimes.

The remainder of the paper is organized as follows. Section 2 reviews literature and develops testable hypotheses. Section 3 presents the data and methodology. Section 4 reports empirical results and robustness checks. Section 5 concludes with policy implications and directions for future research.

2. Literature review and hypotheses development

2.1. Theoretical framework: real options and risk premia under policy uncertainty

Uncertainty is a defining feature of long-term investment. Keynes (1937) emphasized its central role in economic decision-making, and it is particularly acute for capital intensive sectors like water (Vieira et al., 2020). CPU represents a contemporary and highly salient dimension of this uncertainty, reflecting ambiguity surrounding the timing, scope and stringency of climate-related regulations. Building on prior theoretical and empirical work, we conceptualize CPU as influencing water-sector investment and asset prices through two complementary mechanisms whose effects vary across market volatility regimes.

The first mechanism arises from real options theory, which analyzes investment behavior under conditions of irreversibility and uncertainty. When investment expenditures are at least partially irreversible and can be postponed, firms possess an option to delay commitment until additional information becomes available (Dixit and Pindyck, 1994b). In such settings, increases in uncertainty raise the value of waiting, generating "wait-and-see" behavior (Bloom, 2009). CPU is particularly potent in this regard, as it affects expectations about future regulatory standards, compliance costs, and public financing mechanisms (Fuss et al., 2008). For water utilities and infrastructure firms, characterized by substantial upfront capital requirements and multi-decade asset lifetimes, clarity regarding regulatory frameworks and funding arrangements is essential for investment planning (Haasnoot et al., 2020).

The second mechanism operates through asset pricing channels. Political and regulatory uncertainty has been shown to function as a systematic risk factor that commands positive risk premia (Pástor and Veronesi, 2012, 2013). These premia tend to increase during periods of increased market volatility, when return correlations rise and investors demand higher compensation for bearing uncertainty-related risks. Conditional asset pricing models further demonstrate that time-varying exposure to uncertainty factors is associated with significant risk premia in equity markets (Bali and Zhou, 2016). In the context of water utilities, CPU can increase uncertainty surrounding future cash flows by affecting tariff structures, cost recovery mechanisms, and infrastructure funding commitments. Behavioral finance perspectives reinforce this channel by showing that heightened policy uncertainty can increase stock price crash risk through managerial bad-news hoarding and delayed disclosure (Vo et al., 2025).

These two mechanisms operate simultaneously, but their net effect depends on investor risk appetite, which varies systematically across market volatility regimes. In low-volatility environments, greater risk tolerance increases the likelihood that CPU is interpreted as signaling forthcoming regulatory engagement or policy clarification, thereby reducing the real option value of waiting and potentially supporting positive return responses. In contrast, during high-volatility regimes, increased risk aversion amplifies both real-options delays and required risk premia, resulting in a negative relationship between CPU and asset returns.

2.2. Water as an investable asset: characteristics and market structure

The water sector has undergone a significant transformation from a predominantly public utility model toward recognition as a distinct asset class within sustainable finance. This shift has been driven by structural pressures, including aging infrastructure, rising climate adaptation needs, and persistent imbalances between water supply and demand (He et al., 2021; Jiang, 2023). In the United States, early twenty-first-century policy emphasized regulatory compliance and infrastructure renewal (Copeland and Tiemann, 2010), creating conditions that later facilitated financialization through specialized investment vehicles and exchange-traded products (Reis et al., 2024).

Several structural features distinguish water assets from other infrastructure investments and shape their sensitivity to policy uncertainty. Water infrastructure typically requires substantial upfront capital commitments, while revenues accrue gradually over long horizons. As a result, asset valuations are highly sensitive to discount rate dynamics and the stability of policy frameworks governing tariffs, cost recovery, and long-term investment incentives (Hidayatno et al., 2015; Jin et al., 2016). Ownership structure further conditions investment responses: public utilities often prioritize network expansion and regulatory compliance, whereas private operators may limit capital expenditures to protect short-term profitability (Romano et al., 2013). Relative to electricity or telecommunications utilities, water assets also face heightened exposure to environmental variability and hydrological risks, increasing operational vulnerability (Pescetto, 2008).

The financialization of the sector has expanded access to water-related investments for both institutional and retail investors through dedicated funds and exchange-traded funds (ETFs). These instruments convert fixed, capital-intensive infrastructure assets into liquid financial products, enabling portfolio-level exposure to water utilities, infrastructure firms, and water technology companies (Loftus et al., 2019; Loftus and March, 2016). Empirical evidence suggests that water equities provide diversification benefits due to historically low correlations with major asset classes (Díaz-Mendoza and Pardo, 2023).

Despite these benefits, water financial markets remain highly interconnected and vulnerable to systemic shocks. High levels of global integration imply that localized disturbances can propagate rapidly across markets (Roca and Tularam, 2012). Water equity indices exhibit persistent volatility and asymmetric responses to positive and negative shocks, particularly during periods of financial stress (Reza et al., 2018). Besides, regime-switching dynamics are also observed in water equities. For instance, Tularam and Reza (2016) identify 3 different regimes (e.g., calm, transitional, turbulent) in various water ETFs. Moreover, interdependencies with energy and food markets, reflecting the water–energy–food nexus, create additional transmission channels through which CPU can spill over from more directly regulated sectors (Peri et al., 2017). These characteristics suggest that water investments may act as sensitive indicators of broader climate policy developments, amplifying their sensitivity to CPU.

2.3. Climate policy uncertainty, hedging and sustainable investments

CPU has become a central risk factor for sustainable investments, although its specific effects on water equities remain underexplored. Evidence from related asset classes shows that CPU influences both returns and volatility. Olasehinde-Williams et al. (2023), for example, show that CPU exerts stronger effects on the volatility of U.S. sustainable investments than on mean returns, indicating that policy ambiguity operates primarily through risk channels. At the firm level, CPU reduces capital expenditures, employment, and R&D investment, particularly in clean technology sectors, while increasing equity volatility and depressing returns for carbon-intensive industries (Basaglia et al., 2025). Together, these findings highlight that CPU influences both real investment behavior and financial market dynamics through increased risk premia.

As CPU rises, effective hedging becomes increasingly important for sustainable portfolios. Portfolio theory predicts that investors adjust hedging intensity in response to changing risk environments, adopting more defensive positions as uncertainty increases (Engle et al., 2020). For water investments, characterized by long-lived assets, high regulatory exposure, and substantial capital intensity, hedging is therefore especially critical during periods of increased CPU.

Despite this importance, existing evidence offers limited guidance on hedging strategies tailored specifically to water-focused portfolios. Samitas et al. (2022) show that water assets can hedge exposures in shipping, crude oil, and fixed-income markets, implying defensive properties under certain conditions. However, this literature focuses on whether water assets hedge other markets, rather than identifying instruments that effectively hedge water investments themselves. In contrast, Ozcelebi et al. (2025) document strong connectedness between technology ETFs and policy uncertainty indices, suggesting that technology-based hedges may amplify, rather than mitigate, exposure to shared CPU shocks.

While earlier sections examine how CPU affects water equity valuations across market volatility regimes, the hedging problem faced by investors is conditional on the prevailing level of climate policy shocks. From a portfolio management perspective, hedge positions are adjusted in response to the intensity of policy uncertainty itself, regardless of broader volatility conditions. This raises a key unresolved question: does hedging effectiveness vary across CPU regimes? If CPU exerts state-dependent effects on water equity returns, as implied by real-options and risk-premium theories, then optimal hedge ratios should likewise differ between low- and high-CPU environments. During low-CPU periods, policy environments are relatively stable, reducing downside risk and limiting the benefits of aggressive hedging. In contrast, during high-CPU regimes, policy uncertainty amplifies investment irreversibility and required risk premia, increasing vulnerability and the value of effective hedging. Ignoring this regime dependence risks producing suboptimal or destabilizing hedge positions.

Traditional linear econometric models, which impose constant parameters over time, are illsuited to capture such state-dependent dynamics. Regime-switching models (Hamilton, 1989) address this limitation by allowing parameters and variances to differ across latent uncertainty states. Empirical studies show that these models uncover economically meaningful relationships obscured in linear specifications. For instance, Basher et al. (2018) and Zhu et al. (2017) demonstrate that commodity price shocks exert opposite effects on equity returns across low- and high-uncertainty states, yielding insignificant average effects in pooled regressions. These insights motivate the use of regime-switching frameworks to evaluate hedging strategies for water equities under varying CPU conditions.

Building on these insights and the mechanisms described above, we propose the following hypotheses:

H_1. CPU significantly influences clean water investments.

H_2. The magnitude and direction of this relationship vary across low- and high-volatility regimes.

H_3. Oil and technology ETFs exhibit differential hedging effectiveness for water ETFs, with hedging performance varying across low-and high-CPU regimes.

3. Data and methodology

3.1. Data

This study utilizes data on two distinct water ETFs: FIW and PIO. It is important to note that the First Trust Water ETF (FIW) invests at least 90 % of its net assets in securities comprising the ISE Clean Edge Water™ Index. Meanwhile, the Invesco Global Water ETF (PIO) tracks the Nasdaq OMX Global Water Index. Both ETFs are designed to follow companies that develop technologies and products aimed at conserving and purifying water for residential, commercial, and industrial use. Data are sourced from the Bloomberg Terminal, covering the period from July 2007 to September 2024. In addition, we collect data on the CPU Index from the Economic Policy Uncertainty website, with all variables observed on a monthly basis to match the CPU index frequency.

Fig. 1 displays the time series of ETF indices, highlighting major downturns associated with global events such as the 2008 financial crisis, the 2014 oil price collapse, and the COVID-19 pandemic. Fig. 2 presents the CPU Index, which shows a marked upward trajectory in recent years, consistent with heightened global concern over climate-related policy.

Table 1 provides the summary statistics. On average, both ETFs exhibit positive returns, with the PIO index displaying slightly higher volatility than the FIW index. Both ETF return series are negatively skewed, while the CPU index is positively skewed. Furthermore, all three-time series are leptokurtic, indicating the presence of fat tails. The Jarque–Bera test rejects the null hypothesis of normality for all variables, confirming that the distributions deviate from Gaussian assumptions.

Table 2 reports the results of unit root tests, including the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–-Phillips–Schmidt–Shin (KPSS) tests. The results show that the return series of both ETFs are stationary, while the CPU index is non-stationary in levels according to the KPSS test. Consequently, we use the first difference of the CPU index in all subsequent analyses.

3.2. Vector autoregressive (VAR) model

We begin with a standard vector autoregressive (VAR) model, a widely applied framework for analyzing multivariate time series due to its ability to capture dynamic interdependencies among multiple variables (Mutele and Carranza, 2024; Petropoulos et al., 2022). In a VAR system, each variable is expressed as a linear function of its own lagged values as well as the lagged values of all other variables in the system, thereby allowing for a comprehensive representation of feedback effects and mutual dependencies over time.

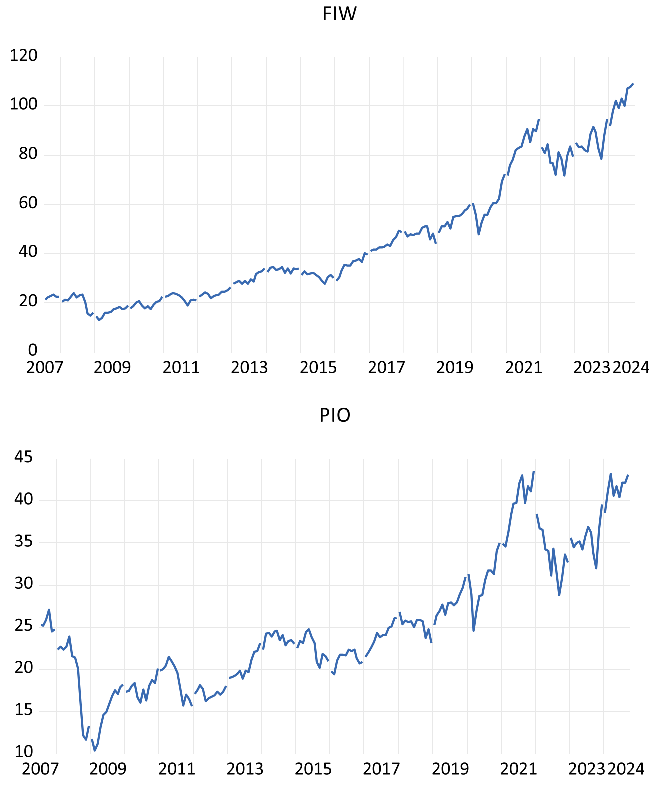

Fig. 1. Time series plots of water ETFs.

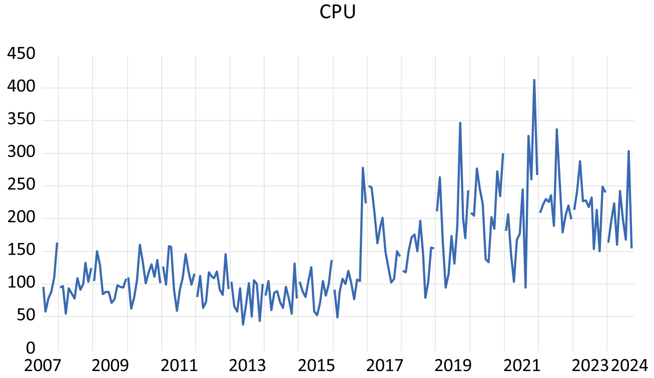

Fig. 2. Time series plot of CPU index.

Table 1
Summary statistics.

	FIW	PIO	CPU
Mean	0.0080	0.0025	144.22
Std. Dev.	0.0565	0.0594	68.30
Skewness	-0.8108	-1.0021	0.9562
Kurtosis	4.72	6.56	3.59
Jarque-Bera test	48.13***	143.58***	34.47***

Notes: ***, ** and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

Table 2
Results of unit root tests.

Unit root test ↓	FIW		PIO		CPU	
	Level	Log-difference	Level	Log-difference	Level	1st difference
ADF	1.02	-14.70***	-0.29	-12.99***	-3.98***	-15.54***
PP	1.25	-14.71***	-0.31	-13.04***	-6.00***	-63.78***
KPSS	1.67***	0.12	1.49***	0.16	1.54***	0.24

Notes: ***, ** and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

In this study, we estimate the following VAR (1) process:

$$R_t = \alpha_1 + \beta_1 R_{t-1} + \gamma_1 \Delta CPU_{t-1} + \epsilon_{1t} \tag{1}$$

$$\Delta CPU_t = \alpha_2 + \beta_2 R_{t-1} + \gamma_2 \Delta CPU_{t-1} + \epsilon_{2t} \tag{2}$$

where, R_t refers to the log-return for the water ETF at time t and ΔCPU_t indicates the first-order difference for the CPU index at time t. In addition, ϵ_{1t} and ϵ_{2t} are white noise having mean 0. Notably, the lag length is chosen based on the Akaike Information Criterion (AIC), Hannan-Quinn Criterion (HQ) and Schwarz Criterion (SC).[2]

While useful for baseline analysis, the VAR framework assumes linearity and constant parameters across time-limitations that may prevent it from capturing the structural breaks and regime-dependent effects likely present in water investment dynamics. For this reason,

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[2] There may exist bidirectional between CPU and ETF returns, which could lead to the endogeneity issue. To test for the presence of endogeneity, we first estimate the bivariate VAR system and obtain the residuals, say u_{1t} and u_{2t}. Next, we check whether the correlation between the u_{1t} and u_{2t} is statistically significant. In our case, we do not find any statistically significant correlations, implying the non-existence of endogeneity.

we extend the analysis to a Markov Regime-Switching VAR (MRS-VAR) model.

3.3. MRS-VAR model

The MRS-VAR model, first introduced by Hamilton (1989) and extended by Krolzig (1997), integrates regime-switching dynamics with a standard VAR framework. This approach is particularly suited for financial time series characterized by nonlinear dynamics, asymmetry, and structural breaks (Chen et al., 2019; Gong et al., 2021; Su et al., 2023).

Formally, let the two-dimensional vector be:

$$y_t = (R_t, \quad \Delta CPU_t)'; t = 1, 2, \cdots, T$$

where R_t is the log-return of the water ETF and ΔCPU_t is the first-differenced Climate Policy Uncertainty index. We assume the system operates under M unobserved regimes. The MRS-VAR process is then defined as:

$$y_t = v(S_t) + A_1(S_t)y_{t-1} + \ldots + A_p(S_t)y_{t-p} + e_t \tag{3}$$

where, v represents the intercept or mean for each regime, S_t refers to the regime variable ($S_t \in \{1, 2, \ldots, M\}$), $A_i (i = 1, 2, \ldots, p)$ is the regime-dependent matrix and $e_t \sim NID(0, \sum(S_t))$.

In the Markov regime switching regression, the variable S_t is assumed to be generated by the first order of the Markov chain and assuming that the state in period $t+1$ depends only on the state in period t, we can also calculate the transition probability between different states as follows:

$$p_{ij} = \Pr(S_{t+1} = j | S_t = i), \quad \sum\nolimits_{j=1}^{M} p_{ij} = 1, \quad \forall i, j \in \{1, 2, \ldots, M\} \tag{4}$$

Based on information criteria (AIC, HQ, SC) and log-likelihoods, the optimal specification is identified as an MRS(2)-VAR(1), corresponding to two distinct regimes: a low-volatility state and a high-volatility state.[3] Note that we also use the regime classification measure (RCM) for evaluating the accuracy of our regime switching process:

$$RCM(r) = 100r^2 (1 \Big/ T) \sum_{t=1}^{T} \prod_{i=1}^{r} \widehat{p}_{i,t}$$

The RCM statistic ranges from 0 to 100, with values closer to 0 indicating better regime classification accuracy.

Next, the transition probability matrix is:

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix}, \quad p_{i1} + p_{i2} = 1, \quad i \in (1, 2)$$

Model parameters are estimated via maximum likelihood optimization of the log-likelihood function. The two-regime specification enables us to examine how rising CPU influences water ETF returns under different market conditions. In particular, the model allows us to derive regime-dependent impulse responses, capturing whether CPU shocks generate opportunity effects in stable states or amplify risks during volatile periods.

4. Empirical results and discussion

The empirical analysis reveals striking differences between linear and regime-switching approaches in capturing the relationship between CPU and water ETFs performance. These findings provide strong support for our theoretical framework and offer significant contributions to the literature on CPU and water investments.

4.1. VAR model

Table 3 presents the estimates of the standard VAR model. For both ETFs, the lagged ETF returns, and lagged CPU changes are largely insignificant, except for a small positive intercept in FIW returns, significant at the 5 % level. This suggests that, under a linear framework, CPU does not exert a measurable impact on water ETF returns. While the log-likelihood values of 238.59 (FIW) and 230.35 (PIO) indicate an acceptable baseline fit, the lack of significant coefficients underscores the limitations of linear models in capturing the complex, regime-dependent dynamics of water investments, particularly under varying volatility conditions.

The inability of the VAR model to detect significant relationships aligns with Basher et al. (2018), who argue that traditional linear econometric approaches may obscure regime-dependent effects in financial time series. For climate-related financial risks, policy uncertainty may carry fundamentally different implications depending on market conditions-a nuance linear models cannot adequately capture.

4.2. MRS-VAR model

The MRS-VAR results, reported in Table 4, uncover the state-dependent relationship between CPU and water ETF returns that linear models fail to detect. Two distinct regimes are identified for each ETF, corresponding to low- and high-volatility states based on the estimated σ values. For FIW, Regime 1 (σ = 0.0007) represents low-volatility periods, while Regime 2 (σ = 0.0030) represents high-volatility periods. For PIO, Regime 1 (σ = 0.0012) corresponds to high-volatility, and Regime 2 (σ = 0.0070) to low-volatility periods. This confirms our theoretical expectation of regime-dependent dynamics and aligns with the literature on nonlinear financial time series.

In regime 1, characterized by low volatility, FIW exhibits a significant positive response to CPU ($\beta = 0.0347$, $p < 0.001$). In particular, this finding suggests that a one-unit increase in CPU corresponds to approximately 3.47 % higher monthly returns for FIW in the low-volatility state, which strongly supports our first channel hypothesis that CPU signals long-term investment opportunities during stable market conditions. Our results could be attributed to an increasing demand for clean water services during periods of high climate risk, which leads to a growth in water equity prices, indicating that investors interpret climate policy announcements as positive signals for water infrastructure and technological investments. Similarly, PIO also shows a significant positive response in Regime 2 ($\beta = 0.0149$, $p < 0.001$), consistent with the idea that low-volatility conditions allow investors to interpret policy announcements as investment opportunities. When markets are calm and investors have greater capacity for forward-looking analysis, climate policy announcements may be interpreted as catalysts for water infrastructure investment and technological innovation. This result resonates with recent work by D'Arcangelo et al. (2025), who find that stable climate policy encourages firms for green investment and technological development. In summary, with an increase in the CPU index, investors may expect stricter or more unpredictable environmental regulations. As a consequence, water-related companies such as utilities, treatment firms, infrastructure providers often benefit

Table 3
Results of VAR model.

Dependent variable →	Returns on FIW		Returns on PIO	
	Estimate	Standard error	Estimate	Standard error
Constant	0.0080**	0.0040	0.0023	0.0042
R_{t-1}	-0.0305	0.0702	0.0913	0.0700
ΔCPU_{t-1}	0.0027	0.0113	0.0025	0.0118
Log-likelihood	238.59		230.35	

Notes: This table reports the estimates of the VAR model for both ETFs. ***, ** and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

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[3] Table A1 shows the results for these model selection criteria.

Table 4
Results of MRS-VAR model.

Dependent variable →	Returns on FIW		Returns on PIO	
	Estimate	Standard error	Estimate	Standard error
Panel A: Regime 1				
Constant	-0.4135**	0.0748	0.1741	0.1322
R_{t-1}	-0.0154	0.0107	-0.0222	0.0368
ΔCPU_{t-1}	0.0347***	0.0035	-0.0140	0.0121
Sigma	0.0007		0.0070	
Durbin-Watson test	1.99		2.01	
Panel B: Regime 2				
Constant	0.4130***	0.1072	-0.2242**	0.1003
R_{t-1}	0.0112	0.0177	0.0110	0.0089
ΔCPU_{t-1}	-0.0250***	0.0076	0.0149***	0.0043
Sigma	0.0030		0.0012	
Durbin-Watson test	1.97		2.02	

Notes: This table reports the estimates of the MRS-VAR model for both ETFs. ***, ** and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

from regulatory tightening given that governments tend to increase spending on water infrastructure. In addition, compliance requirements also boost demand for water technologies. Thus, when CPU rises, investors may shift funds into water stocks as a hedge against policy-driven risks elsewhere, pushing up returns.

In regime 2, characterized by high volatility, FIW reveals a distinct pattern that confirms the second channel hypothesis, namely CPU's risk-amplifying effects during turbulent periods. The CPU coefficient for FIW turns significantly negative ($\beta = -0.0250$, $p < 0.001$), indicating that CPU depresses returns when market volatility is elevated. PIO also records a negative CPU coefficient in Regime 1 ($\beta = -0.0149$, $p > 0.1$), though the effect is statistically insignificant. This suggests that, while both ETFs are adversely affected during high-volatility periods, the impact is stronger and more robust for FIW. These findings add to the growing literature on climate risk and sustainable investment by demonstrating that policy uncertainty can be negatively associated with sustainable investment performance during periods of financial stress (Shaikh, 2022). The negative coefficient further implies that, in high-volatility states, investors apply higher discount rates to future cash flows from water assets, consistent with theoretical predictions on uncertainty and capital allocation (Segal et al., 2015).

4.3. *Regime-dependent dynamics and market structure*

The empirical analysis highlights strong regime-dependent behavior in water ETFs, demonstrating how CPU affects returns differently across volatility states. To better understand these dynamics, we examine both the cumulative impulse-response functions (Fig. 4a–b) and the filtered probabilities (Fig. 3a-b) which show the time-varying likelihood of each ETF being in a particular regime.

For the First Trust Water ETF (FIW), in the low-volatility state (Regime 1; Fig. 4a), a CPU shock generates a positive response, gradually increasing to a peak of 0.012 in the second month and stabilizing at around 0.011 thereafter. This result supports the hypothesis that CPU can act as an opportunity signal during stable periods, with climate policy announcements interpreted as catalysts for water infrastructure investment and technological innovation. Under high-volatility conditions (Regime 2), FIW exhibits a negative cumulative response, declining to -0.0075 after an initial drop of -0.07 in the second month, consistent with CPU's risk-amplifying effects during turbulent periods. The relevance of these risk-amplifying effects is underscored by the filtered probabilities for FIW (Fig. 3a), which show frequent shifts between states, with spikes in high-volatility probability aligning with major market stress events such as the 2008 financial crisis, the 2014 oil price collapse, and the COVID-19 pandemic.

For the Invesco Global Water ETF (PIO), the responses follow a similar regime-dependent pattern (Fig. 4b). In the low-volatility state, PIO records a positive response to CPU shocks, whereas in the high-volatility state, the response turns negative. These impulse-response functions confirm that CPU exerts asymmetric, state-dependent effects on water ETFs-enhancing returns in stable periods but depressing them during volatile market conditions. Notably, the dynamics of these regimes differ between ETFs. PIO's filtered probabilities (Fig. 3b) show that the low-volatility state (Regime 2) is highly persistent, with intermittent, sharp spikes into the high-volatility state (Regime 1).

Beyond these dynamic responses, the regime persistence metrics in Table 5 reveal further important contrasts in market structure. FIW operates in a relatively balanced regime environment, with Regime 1 (low-volatility) occurring at 29.36 % of the time and an average duration of 1.41 months, while Regime 2 (high-volatility) dominates 70.64 % of observations with a slightly longer duration of 1.53 months. This indicates frequent transitions between volatility states, suggesting that FIW is subject to ongoing market stress and may require nimble, short-term risk management strategies.

PIO exhibits markedly different dynamics, spending most of its time (84.10 %) in the low-volatility state (Regime 2) with an average duration of 6.28 months. Transitions to the high-volatility state (Regime 1) are less frequent but highly persistent, lasting an average of 12.44 months. This structure implies that PIO experiences long periods of relative stability punctuated by extended episodes of high volatility, reflecting the stabilizing effect of its global diversification.

Moreover, for both ETFs, the RCM statistic suggests that the MRS process appears to be a good fitting model. Collectively, the impulse-response functions and regime persistence analysis provide a comprehensive picture of how CPU propagates through water ETF markets. The results confirm our theoretical predictions that CPU operates through dual channels-signaling investment opportunities during calm periods and amplifying risk during turbulent periods-and that these effects are reinforced by the persistence and duration of market regimes.

4.4. *Portfolio implications*

This section evaluates hedging strategies for water ETFs under varying climate risk conditions. Two asset portfolios are considered: (i) water ETFs combined with oil (WTI index) and (ii) water ETFs combined with a technology ETF (SPDR NYSE Technology ETF, XNTK). Data on oil price and XNTK is also collected from the Bloomberg terminal.

Crude oil is included based on prior evidence that it effectively mitigates downside risk in sustainable assets (Dutta et al., 2020; Rubbaniy et al., 2024; Yahya et al., 2021). Given that water equities are part of the sustainable asset class, oil provides a natural hedging candidate.[4] In contrast, technology ETFs are considered for their potential synergies with water firms through innovation linkages, though their financial hedging role remains less established.

We compute hedge ratios using the DCC-GARCH model (Engle, 2002). The framework is specified as follows:

$$r_t = \mu + \gamma r_{t-1} + \varepsilon_t \tag{5}$$

$$\varepsilon_t = H_t^{\frac{1}{2}} z_t \tag{6}$$

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[4] The energy sector is a major consumer of water, particularly in oil extraction and processing (e.g., hydraulic fracturing). When oil prices rise, there may be increased investment in oil production, heightening the demand for water (Samitas et al., 2022). This interdependence can create a scenario where strong oil performance positively influences water equities, thereby improving diversification. Besides, as both oil and water are critical resources, rising oil prices due to geopolitical tensions or supply constraints may signal a similar concern for water resources, which in turn boost the valuation of water equities as essential assets.

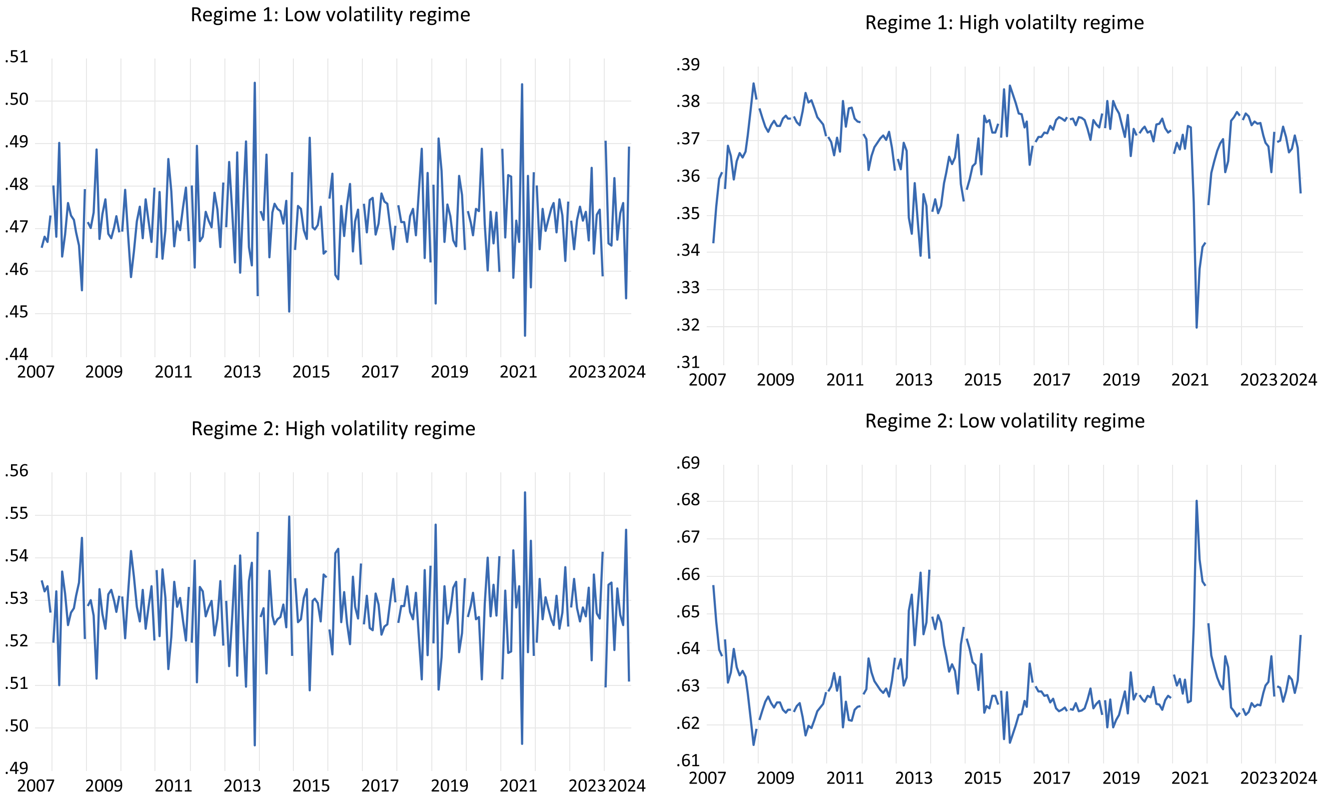

Fig. 3. a: **Filtered probabilities for the FIW index.** Notes. The filtered probabilities are derived from the Markov regime switching regression. The probabilities refer to the likelihoods of remaining in the low volatility states for the FIW index. The X-axis indicates the timeline, while the Y-axis shows the filtered probabilities. b: **Filtered probabilities for the PIO index.** Notes. The filtered probabilities are derived from the Markov regime switching regression. The probabilities refer to the likelihoods of remaining in the low volatility states for the PIO index. The X-axis indicates the timeline, while the Y-axis shows the filtered probabilities.

where, r_t denotes the return vector and H_t refers to the matrix of conditional volatilities defined as:

$$H_t = D_t R_t D_t \tag{7}$$

$$D_t = diag(\sqrt{h_t^W}, \sqrt{h_t^O}) \tag{8}$$

$$R_t = diag(Q_t)^{-1} Q_t diag(Q_t)^{-1} \tag{9}$$

here, D_t and R_t indicate the matrices of dynamic conditional correlations and the time-varying conditional variances, respectively. In addition, h_t^W and h_t^O are the conditional variances for the water ETF and oil market returns.

Note that in a univariate GARCH(1,1) process, the components of $\boldsymbol{H_t}$ are defined as

$$h_t = \omega + a\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{10}$$

Moreover, the time-varying covariance matrix, denoted as Q_t, is represented as:

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q} + \theta_1 z_{t-1} z'_{t-1} + \theta_2 Q_{t-1} \tag{11}$$

where θ_1 and θ_2 refer to the non-negative scalar parameters satisfying the condition $\theta_1 + \theta_2 < 1$, and $\overline{Q}$ denotes the unconditional matrix of standardized residuals z_t ($z_t = \varepsilon_t / \sqrt{h_t}$).[5]

Then the hedge ratios can be computed as:

$$\delta_t = \frac{h_t^{WO}}{h_t^O} \tag{12}$$

with h_t^{WO}indicating the conditional covariance between water ETF returns and returns on other assets (oil/XNTK). Portfolios with lower hedge ratios are cheaper to be hedged (López Cabrera and Schulz, 2016).

Table 6 reports average hedge ratios across high- and low-climate risk regimes (defined relative to the CPU index median). For FIW, hedging with oil requires a $7 short position in WTI per $100 long in FIW during high-risk periods, falling to $6.1 in low-risk periods. PIO displays slightly higher ratios (0.077 vs. 0.071), suggesting marginally greater hedging costs than FIW. In contrast, technology-based portfolios are far more expensive: hedge ratios range from 0.232 to 0.203, more than three times those of oil-based hedges.

Two main insights emerge. First, hedging costs rise during high CPU, reflecting investors' demand for protection in volatile regimes. Second, oil consistently outperforms technology as a hedging instrument, confirming its cost-effectiveness even for water-focused sustainable assets. Importantly, FIW is cheaper to hedge than PIO, consistent with its more frequent but shorter volatility transitions identified in Section 4.3.

Next, we calculate the optimal portfolio weights and hedging effectiveness using these assets. Such analysis offers market participants effective risk-reduction tools to manage the impact of price volatility amid high uncertainties (Papathanasiou et al., 2025). In doing so, we first compute the optimal portfolio weights using the following equation:

$$\omega_t^{wo} = \frac{h_t^w - h_t^{wo}}{h_t^o - 2h_t^{wo} + h_t^w} \tag{13}$$

with ω_t^{wo} indicating the weight of other assets (oil or XNTK) in a one-

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[5] Table A2 displays the residual diagnosis for the DCC-GARCH model

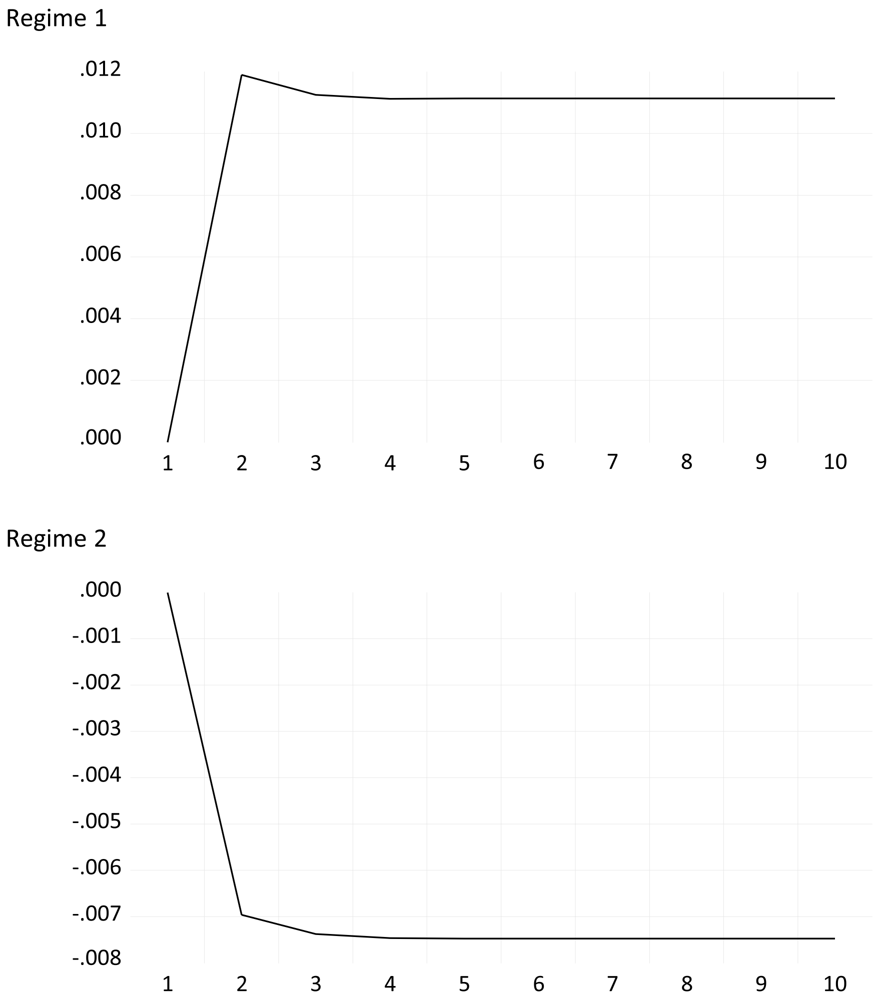


Fig. 4. a: **Cumulative response of FIW returns to CPU across various regimes.** Notes. In this graph, the x-axis indicates the time period proxied by the number of days ahead, while the y-axis shows the impulse responses of FIW returns to a one-unit shock in CPU. b: **Cumulative response of PIO returns to CPU across various regimes.** Notes. In this graph, the x-axis indicates the time period proxied by the number of days ahead, while the y-axis shows the impulse responses of PIO returns to a one-unit shock in CPU.

dollar portfolio consisting of oil/XNTK and water equity at time t. In addition, h_t^w, h_t^o and h_t^{wo} refer to the variance and covariance terms for these assets.

Next, the hedging effectiveness (HE) is computed as:

$$HE = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} \tag{14}$$

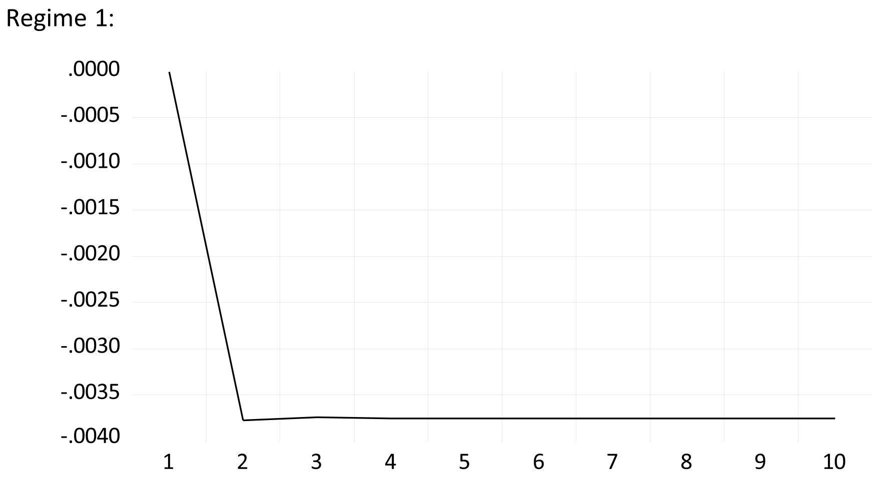
where, $Var_{unhedged}$ represents the variance of a portfolio which includes water equity only, whereas Var_{hedged} is the variance of a portfolio which includes both water and oil/XNT. A higher hedging effectiveness ratio indicates a stronger risk reduction. A higher HE of a given portfolio indicates the greater portfolio risk reduction.

Now, Table 7, which displays the optimal weights, reveal that for a $1 portfolio, an investor should put 11 cents on the WTI market and 89 cents on the FIW index when climate risk is low. During the periods of high climate risk, on the other hand, these weights are 14 % and 86 % respectively. These results lead to two important conclusions. Firstly, in order to reduce risk in a high climate risk environment, investors should allocate more funds to oil/XNTK than they would in a low-risk setting. Secondly, of the two assets, oil and XNTK, the former plays more important role in hedging the risk involved in clean water investments. Table 8 showing the results for HE analyses also conclude the same. In particular, the findings indicate that forming a portfolio using water and oil/XNTK minimizes the potential risk during the periods of high climate risk.

Overall, these results underscore the importance of regime-sensitive hedging strategies in sustainable finance. Investors should anticipate higher costs during periods of elevated climate risk and prioritize oil-based hedges, while recognizing that ETF-specific volatility dynamics shape hedging effectiveness.

5. Robustness checks

Earlier studies (Bouri et al., 2023; Sarker et al., 2022) argue that the use of CPU has several limitations. For instance, this index reflects uncertainty around climate-policy announcements and discourse (e.g., legislation, presidential statements, newspaper coverage) rather than all dimensions of policy implementation risk (such as actual regulatory enforcement, international policy linkages, or private sector adaptation). In addition, as CPU is U.S.–centric nature and the fact that coverage and media behavior may vary by country and language, the index is less suitable for comparing absolute levels of CPU across different countries. Furthermore, CPU is available only on monthly basis, whereas investors, policy makers, and regulators require to gain an understanding of the implications of climate risks, physical and transition, at a higher than monthly frequency (Bouri et al., 2023). This


Regime 1:

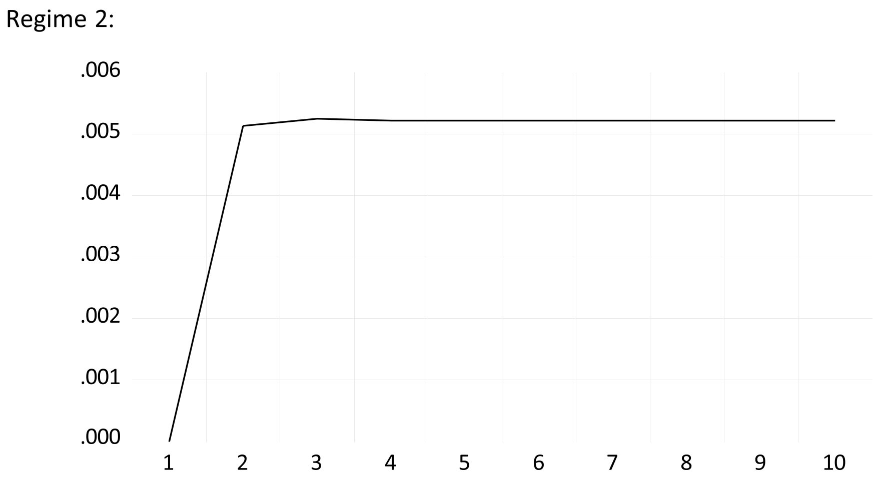

Regime 2:

Fig. 4. (*continued*).

Table 5
Regime features.

ETF ↓	p_{11}	p_{12}	p_{21}	p_{22}	DU1	DU2	RCM
FIW	0.2936	0.7064	0.6529	0.3471	1.41	1.53	12.47
PIO	0.8410	0.1590	0.0804	0.9196	6.28	12.44	13.98

Notes: This table presents the probabilities of regime switching and the durations (DU) in each state.

Table 6
Optimal hedge ratio.

Portfolio	High climate risk regime	Low climate risk regime
FIW/WTI	0.070	0.061
PIO/WTI	0.077	0.071
FIW/XNTK	0.232	0.214
PIO/XNTK	0.225	0.203

Notes: This table reports the average ratios for the water and oil/technology portfolios across the high and low climate risk regimes.

Table 7
Optimal portfolio weights.

Portfolio	High climate risk regime	Low climate risk regime
FIW/WTI	0.14	0.11
PIO/WTI	0.16	0.12
FIW/XNTK	0.10	0.06
PIO/XNTK	0.09	0.06

Notes: This table shows the average optimal weights for the water-oil/XNTK portfolios.

Table 8
Hedging effectiveness analysis.

Portfolio	High climate risk regime	Low climate risk regime
FIW/WTI	18 %	22 %
PIO/WTI	17 %	24 %
FIW/XNTK	12 %	16 %
PIO/XNTK	13 %	18 %

Notes: This table exhibits the hedging effectiveness results for the water-oil/XNTK portfolios.

is particularly important given that investors often need to quickly adjust their portfolios in response to climate risk shocks, while policymakers and regulators focus on the long-term impacts of short-term climate-related risks on financial stability and the challenges they pose to achieving climate goals.

To address these limitations, we consider an alternative measure of climate risk proposed by Bua et al. (2024). This indicator, which is available on daily basis, utilizes scientific literature on climate, along with a variety of news and press articles from Reuters News, to develop the Physical Risk Index (PRI) and Transition Risk Index (TRI). These two comprehensive climate risk indicators reflect advancements in both aspects of climate change risk. Physical risk pertains to the loss of value or increased expenses resulting from chronic hazards like sea level rise or drought, as well as acute hazards such as floods or heat waves. In contrast, transition risk refers to the risks and costs associated with the shift towards a climate-neutral economy, usually prompted by climate mitigation policies, technological innovations, and changes in public preferences. Notably, incorporating both types of climate change risk offers an advantage over earlier studies that only addressed sub-dimensions of physical and transition risks.

Moreover, to check the consistency of our findings, we use an additional water ETF called S&P Global Water ETF (CGW). In this robustness analysis, we have considered the sample period from 14 June, 2007–30 June, 2025. Notably, the use of daily data allows us to perform sub-sample analyses as well. In particular, we consider three different sub-samples to explore the relationship between climate risk and water investments under volatile market conditions. These crisis periods include the 2008 global financial crisis, COVID-19 pandemic and the 2022–2023 global energy crisis, which arises from several economic factors, including a swift post-pandemic recovery that exceeds energy supply levels. This situation escalates into a widespread global energy crisis due to the Russia-Ukraine conflict and oil prices reached their highest point since 2008 (Zhao et al., 2023). Our first subsample ranges from 2 January, 2008–30 June, 2009 to represent the financial turmoil. We determine the timeframe of the global financial crisis based on the guidelines provided by the National Bureau of Economic Research (NBER).[6] To indicate the COVID-19 pandemic era, our second subsample covers the period from 18 February, 2020–5 May, 2023.[7] Finally, the third subsample spans from 1 January, 2021 to December 31, 2022 to cover the global energy crisis.[8]

Table 9 displaying the results of our robustness analysis reveals several interesting facts. For instance, transition risks do not exert any impact on water equity returns as evidenced from the results of Panel A. This result holds irrespective of the sample periods used. While looking at the results of the full sample analysis for Panel B, we observe that all the water ETFs are sensitive to the changes in the physical risk measure. In particular, PRI has a significant negative influence across the high volatility regimes. This finding also holds for the financial crisis subsample,[9] though we notice an insignificant linkage between these variables for the COVID-19 as well as the energy crisis subsamples. Our results are consistent with earlier works (e.g., Dutta et al., 2024), which document that COVID-19 has more impact on traditional assets compared to sustainable assets such as clean energy equities. These findings also draw attention to the fact that water equity returns are influenced by the specific source of climate risk, with physical risks appearing to play a more significant role than transition risks.

6. Conclusions

This study examines the complex, regime-dependent relationship between CPU and water equity performance, addressing a critical gap in sustainable finance literature. Using a Markov Regime-Switching Vector Autoregressive (MRS-VAR) framework, we show that traditional linear VAR models fundamentally misrepresent these dynamics, failing to capture the dual-channel effects of CPU on water ETFs. Our findings highlight the importance of nonlinear, state-dependent approaches for understanding climate-finance linkages.

Empirically, we find that CPU affects the First Trust Water ETF (FIW) positively during low-volatility periods ($\beta = 0.0347$, $p < 0.001$) and negatively during high-volatility states ($\beta = -0.0250$, $p < 0.001$), confirming that policy uncertainty can signal opportunities under stable conditions while amplifying risks in turbulent markets. The Invesco Global Water ETF (PIO) exhibits a more complex response pattern, reflecting its international exposure and index composition. Regime persistence analysis reveals that FIW experiences frequent, short-lived regimes, whereas PIO's low- and high-volatility states are longer and more persistent, which has implications for tactical allocation and hedging strategies. Hedging analysis using DCC-GARCH indicates that oil (WTI) is an effective and cost-efficient hedge for water ETFs, with hedge ratios ranging from 6.1 % to 7.7 % depending on ETF and climate risk regime. Technology ETFs, despite potential business synergies, prove to be expensive and less effective hedging instruments, with ratios three times higher than oil. These results underscore the regime-dependent nature of hedging costs and the importance of aligning risk management strategies with prevailing market conditions.

Theoretical contributions of this research include demonstrating that CPU effects are inherently nonlinear and regime-dependent, extending policy uncertainty transmission literature to sustainable finance. Policy implications are equally important: during stable periods, clear and consistent climate policies can stimulate water infrastructure investment, whereas in volatile periods, well-intentioned policies may depress investment by increasing discount rates applied to long-term projects. These findings highlight the need for policymakers to consider both market conditions and communication timing when designing climate interventions. For example, the finding that when market volatility is high, CPU has a negative effect on water equity returns suggests that policymakers should refrain from making significant climate-policy shifts when financial markets are under stress. Implementing reforms during calmer periods could help sustain investor trust. Such inverse association also recommends that governments should build credible climate-policy framework including long-term targets, clear timelines and transparent regulatory process to stabilize expectations and prevent volatility-induced investment retreats. Moreover, as CPU affects investor behavior differently depending on market conditions, governments and development banks could introduce instruments to absorb climate-policy risk, smoothing investment flows into the water sector during the turmoil periods. Such asymmetric linkage across the volatility regimes further suggests that policymakers should develop forward guidance similar to monetary-policy communication, to minimize shocks that interact negatively with market volatility.

Our investigation is also important for socially responsible investors who like to maintain a low carbon portfolio through sustainable investments in global water sectors. Given that rising CPU often results in increased energy market volatility and causes delays in decarbonization policies during stress periods, this strand of research could help water market participants make appropriate asset allocation decisions to minimize portfolio risk. In particular, our research could help them adjust the portfolio to hedge uncertainties due to climate policy. More specifically, the negative influence of CPU on water equities have several implications for eco-friendly investors. For instance, they could diversify across various sectors and asset classes to mitigate risks associated with water equity returns. To this end, oil could be potential hedge as evidenced by our results. In addition, investors could also consider investments in companies that may benefit from climate policies, such as renewable energy or sustainable agriculture. Besides, they could invest in water-related equities across different regions to reduce exposure to local policy changes. It is worth noting that the water ETFs may respond differently to shifts in CPU. Our results also confirm this given that FIW and PIO do not react to CPU in the same manner. This implies that the analysis can assist investors in selecting appropriate hedging tools according to the level of climate policy shocks affecting each ETF.

Despite these contributions, the study has limitations. The analysis focuses on two major water ETFs, which may not fully capture global water equity dynamics. Future research could expand the sample to

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[6] Bouri (2015) and Dutta (2017) also use the same reference from NBER.

[7] See Bouri and Demir (2025) as a reference.

[8] See Sæther and Neumann (2024) as a reference.

[9] In the aftermath of the 2008 financial crisis, the interlinkage among the asset classes increases substantially (Gkillas et al., 2023; Papathanasiou et al., 2022), which makes them more vulnerable to uncertainties (Gheorghe et al., 2025).

Table 9
Robustness checks.

Dependent variable →	Returns on FIW		Returns on PIO		Returns on CGW	
	Low	**High**	**Low**	**High**	**Low**	**High**
Panel A: TRI						
Full sample	0.0064	-0.0197	0.0065	-0.0277	0.0050	-0.0297
Financial crisis	0.1158	-0.1981	0.0256	-0.4268	0.0753	-0.3923
COVID-19	-0.0247	0.0451	-0.0246	0.0596	-0.0187	0.0306
Energy crisis	-0.0232	-0.0063	0.0032	0.0047	-0.0051	-0.0096
Panel B: PRI						
Full sample	0.0005	-0.0505**	0.0044	-0.0566**	0.0039	-0.0730**
Financial crisis	0.0099	-0.3294**	-0.0684	-0.5874**	-0.0563	-0.4972**
COVID-19	-0.0144	0.0739	-0.0219	0.0901	-0.0119	0.0769
Energy crisis	0.0243	-0.0085	0.0136	0.0088	0.0128	0.0089

Notes: This table reports the results of our robustness analysis. Panel A shows the impacts of transition risk, while Panel B exhibits the same for the physical risk index. *Low* and *High* refer to low and high volatility regimes. In addition to the full sample (14 June, 2007–30 June, 2025), we consider several subsamples in this analysis. Our first subsample ranges from 2 January, 2008–30 June, 2009 to represent the global financial turmoil. To indicate the COVID-19 pandemic era, our second subsample covers the period from 18 February, 2020–5 May, 2023. Finally, the third subsample spans from 1 January, 2021 to December 31, 2022 to cover the global energy crisis. ***, ** and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

include additional ETFs and regional water markets, explore sector-specific regime effects, and investigate alternative climate policy measures. Incorporating macroeconomic indicators or forward-looking uncertainty indices could further enhance the robustness of regime identification.

In summary, this research demonstrates that CPU has dual, regime-dependent effects on water equity markets, with significant implications for investment, hedging, and policy design. Understanding these nonlinear dynamics is essential for mobilizing private capital toward sustainable water infrastructure and technology, ensuring that climate policies facilitate rather than hinder investment flows, and supporting global sustainability objectives.

CRediT authorship contribution statement

Gazi Salah Uddin: Writing – review & editing, Supervision, Project administration, Formal analysis. **Anupam Dutta:** Writing – original draft, Software, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ali Ahmed:** Writing – review & editing, Supervision. **Mohammad Rakib Uddin Bhuiyan:** Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization.

Ethics in publishing statement

I testify on behalf of all co-authors that our article submitted followed ethical principles in publishing.

Title: Climate policy uncertainty and clean water investment: Implications for sustainability

All authors agree that:

This research presents an accurate account of the work performed, all data presented are accurate and methodologies detailed enough to permit others to replicate the work.

This manuscript represents entirely original works and or if work and/or words of others have been used, that this has been appropriately cited or quoted and permission has been obtained where necessary.

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All authors have been personally and actively involved in substantive work leading to the manuscript and will hold themselves jointly and individually responsible for its content.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.joitmc.2025.100708.

Data availability

Data will be made available on reasonable request.

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