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Research Article

Investigating the Impact of Water, Energy, and Greenhouse Gas Uncertainty on Investment Returns: Application of Fuzzy Regression: Iran case study

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ABSTRACT

This study employs a fuzzy logic-based approach to estimate the impact of uncertainty in key sustainability-related sectors—namely water, energy, waste, greenhouse gas (GHG) emissions, and debt-to-capital ratio—on return on investment (ROI) over the period from 1993 to 2024. Given the inherently imprecise and dynamic nature of environmental and financial variables, fuzzy logic provides a robust framework to model vagueness and ambiguity in data. The analysis integrates longitudinal data across global markets, incorporating fuzzy sets to represent uncertain input variables and their nonlinear relationships with ROI. Results indicate that increased uncertainty in water and energy usage, as well as higher GHG emissions and waste production, negatively influence ROI, particularly when coupled with elevated debt-to-capital ratios. However, the application of sustainable practices that reduce these uncertainties can lead to more stable and higher investment returns. The findings offer strategic insights for investors and policymakers aiming to balance economic performance with environmental and financial risks. They also highlight the importance of investments needed to meet regulatory requirements, which are the main drivers for organizations at the financial level.

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1. Introduction

Petroleum and natural gas remain pivotal to the world economy, supplying approximately 45% and 25% of global energy needs respectively, and serving as vital stocks for petrochemical production. Green financing—through mechanisms such as energy-efficiency investments, carbon capture and storage, renewable integration and environmental remediation—is playing a central role in mobilizing capital needed for sustainable development in the oil and gas industry" (Adebayo et al., 2024). Green financing is playing a central role in mobilizing the capital required to drive sustainable development within the oil and gas industry (Fu et al., 2023).

The escalating volatility of environmental and financial variables, encompassing water scarcity, energy demand fluctuations, waste generation, greenhouse gas emissions, and corporate leverage, has precipitated a marked increase in uncertainty within investment environments over the past three decades. This burgeoning uncertainty has underscored the limitations of traditional deterministic models, which frequently fail to adequately account for the imprecise and dynamic nature of these factors, thereby highlighting the imperative for more adaptable and robust decision-making frameworks. In response, fuzzy logic has emerged as a salient approach for modeling the inherent vagueness and ambiguity present in complex systems, providing a flexible framework for representing linguistic uncertainty and human expert judgment through the utilization of membership functions and fuzzy rules. (Robati & Rezaei, 2022, Phillis et al., 2001). Fuzzy logic has garnered significant attention in environmental and energy management systems, particularly in addressing uncertain variables. Notably, numerous studies have leveraged fuzzy logic to optimize planning under conditions of unpredictability, such as renewable energy inputs and water resource constraints, within the context of the energy-water nexus. Furthermore, fuzzy evaluation indices have been employed to assess water sustainability in EU water risk hotspots, effectively capturing the multifaceted dimensions of ecological, social, and economic aspects under conditions of data uncertainty. (Pérez-Pérez et al., 2024, Ghassemi & Scott, 2020).

This study undertakes an examination of the period spanning from 1993 to 2024, a timeframe characterized by significant global environmental policy transformations, including the Kyoto Protocol and the Paris Agreement, as well as notable financial crises and escalating stakeholder expectations for sustainable performance. The primary objective of this research is to investigate the propagation of uncertainty across key sectors, namely water availability, energy consumption, waste generation, greenhouse gas (GHG) emissions, and debt-to-capital ratio, and their subsequent impacts on return on investment (ROI). To achieve this objective, each of the five sectors will be represented by fuzzy sets, which will be defined using linguistic variables such as "Low", "Medium", and "High" water stress, energy volatility, waste production, GHG emissions, and debt leverage, with corresponding membership functions. This fuzzy logic-based approach will enable the quantification of uncertainty and its effects on investment returns. Through trend analysis over time, this study will reveal how changes in uncertainty influence investment returns, providing valuable insights into the dynamic relationships between environmental, financial, and investment performance. By examining the interactions between these variables, this research aims to contribute to a deeper understanding of the complex interplay between sustainability, uncertainty, and investment decision-making.

Following this introduction, Section 2 outlines the theoretical foundations relevant to the environmental finance nexus. Section 3 details the fuzzy logic modeling framework, including model design, and fuzzification procedures. Section 4 Results and discussion takes place. Section 5 presents the main findings alongside discussion and interpretation of the results.

2. Literature review

In recent decades, the intersection of capital structure decisions, environmental performance, and firm-level investment efficiency has attracted growing academic attention, particularly as sustainability concerns reshape strategic financial planning. Capital structure theories, such as Modigliani and Miller's (1958) irrelevance theory, the trade-off theory (Kraus & Litzenberger, 1973), and the pecking order theory (Myers & Majluf, 1984), provide foundational perspectives on how firms determine their optimal mix of debt and equity. These frameworks suggest that financing choices not only influence the cost of capital and financial risk but also affect managerial behavior and investment outcomes. In the context of environmental performance, a firm's capital structure may influence its ability to invest in green technologies or meet regulatory compliance standards. For example, higher debt levels can either constrain environmental investments due to financial distress costs (Jensen, 1986), or motivate managers to improve performance—environmental and otherwise—through disciplined resource allocation (Grossman & Hart, 1982). Furthermore, studies have examined the mediating role of environmental, social, and governance (ESG) performance in the relationship between debt financing and firm profitability (Nguyen & Nguyen, 2020; Cheng et al., 2014), highlighting the complexity of capital structure's influence in sustainability-driven markets. As environmental regulations tighten and stakeholder pressure intensifies, understanding how capital structure decisions affect environmental outcomes and, in turn, impact investment returns become critical for firms striving for long-term value creation. Therefore, this study aims to explore and synthesize key theoretical perspectives that explain the dynamic linkages between capital structure, environmental performance, and investment returns, thereby providing a comprehensive foundation for further empirical analysis.

Initially, discussions will focus on capital structure and investment returns, followed by an examination of the impact of environmental factors on return on investment.

Capital Structure, Leverage, and Return on Invested Capital

According to the Trade-off Theory of Capital Structure (Kraus & Litzenberger, 1973; Ai et al., 2021), a firm balances the tax-shield benefits of debt (D) against the expected costs of financial distress to maximize firm value. In energy-sector firms, higher leverage (ratio D / E or D / (D + E)) may initially lower the Weighted Average Cost of Capital (WACC) and thus raise Return on Invested Capital (ROIC). WACC is calculated as:

$$WACC = \frac{E}{D+E}.r_e + \frac{D}{D+E}.r_d.(1 - T) \tag{1}$$

where r_e = cost of equity, r_d = cost of debt, T = corporate tax rate (IEA, 2021). When environmental risks—such as water scarcity, waste generation, or GHG emissions—increase, the resulting volatility in financial performance becomes a critical concern for investors. Consequently, we focus on the volatility of ROIC (measured as the difference in natural logarithms of ROIC, $\Delta Ln(ROIC)$) to capture how environmental and financial factors induce instability in returns. (IEA, 2021; Zhou et al., 2021)

Environmental Impact Variables and Volatility of Returns

Empirical studies show that higher GHG emissions and waste intensity—with energy consumption normalized in Joules or barrels of oil equivalent (boe)—correlate with higher borrowing costs and lower ROIC (Houqe et al, 2022; Kleimeier & Viehs, 2018; research reviewed in Zhou et al., 2021). Institutional and signaling theories explain that firms with poor environmental impact (high IR_{ghg}or IR_{waste}) face increased market penalties. (JavaScript-based European study). To reflect the impact of these factors on return instability, our model is specified as:

$$\Delta Ln(ROIC) = \beta_0 + \beta_1.\text{Debt ratio} + \beta_2.IR_{ghg} + \beta_3.IR_{waste} + \beta_4.IR_{water} + \varepsilon \tag{2}$$

Where the coefficients represent the sensitivity of ROIC volatility to environmental and financial pressures. While leverage may influence the mean return, environmental risks are hypothesized to increase the dispersion ($\beta_2, \beta_3 > 0$) of future ROIC.

Green Finance, Emissions Reduction & Financial Return Stability

Building on Transition Finance and Green Bond literature (Flammer, 2021; Fatica & Panzica, 2021), firms issuing green bonds or sustainability-linked loans signal commitments to reduce GHG emissions and invest in environmental projects. Such instruments lower cost of capital by improving ESG profiles, thereby dampening the volatility of ROIC in energy firms. (Zheng et al., 2023; Zhou et al., 2021).

Under Porter's Hypothesis (Porter & van der Linde, 1995), environmental regulation and green investment spur innovation, improving resource efficiency—measured in energy units (Joule/boe)— thereby stabilizing profitability (Zheng, 2023; Chinese panel evidence). The theoretical relationship between green financing, environmental mitigation, and the volatility of returns is modeled as:

$$\Delta Ln(ROIC) = \gamma_0 + \gamma_1.\text{Green Debt} + \gamma_2.\Delta IR_{ghg} + \gamma_3.EnvInv + \eta \qquad (3)$$

where higher Green Debt and environmental investment ($EnvInv$) are expected to reduce return volatility ($\gamma_1, \gamma_3 < 0$), as they mitigate the risk exposure associated with environmental transitions.

The theoretical frameworks of capital structure, including trade-off and pecking order theories, suggest that leverage initially enhances return on capital; however, increasing environmental risks, such as greenhouse gas (GHG) emissions, water scarcity, and waste generation, escalate the cost of capital and subsequently depress profitability. The integration of institutional and signaling theories elucidates creditor and investor responses to environmental impact, while green finance instruments and Porter's innovation compensation hypothesis illustrate pathways environmental risk, access lower-cost financing, and improve return on invested capital (ROIC) over time. This study examines the period from 1993 to 2024, marked by significant global environmental policy transformations, as well as notable financial crises and escalating stakeholder expectations for sustainable performance. By representing water availability, energy consumption, waste generation, GHG emissions, and debt-to-capital ratio as fuzzy sets, this research investigates the propagation of uncertainty across key sectors and their impacts on return on investment (ROI). The analysis aims to provide insights into the inter relationships between environmental risks, capital structure, and financial performance, ultimately contributing to the development of sustainable finance and investment strategies. The following figure illustrates the relationships between environmental risks, capital structure, and financial performance, depicting how environmental risks impact the cost of capital, profitability, and ultimately, return on investment (ROI).

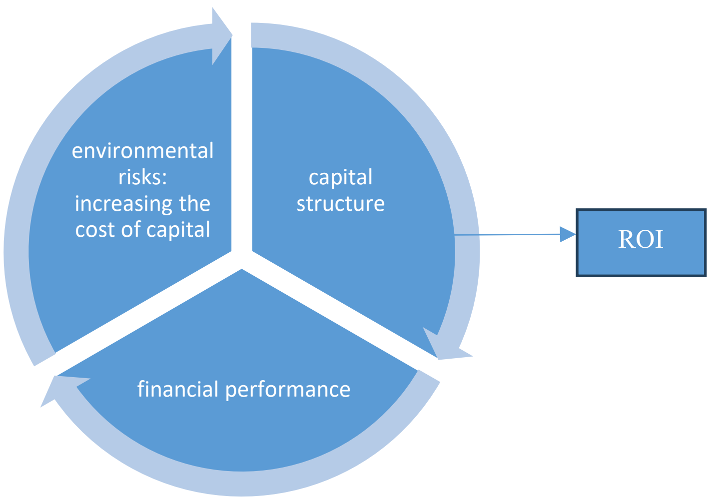

Fig 1. The Interplay between environmental risks and ROI.

The integration of green financing mechanisms into the oil and gas sector has garnered increasing scholarly attention over recent years, driven by the urgent need to align fossil fuel industries with sustainable development goals. Studies such as those by Fu et al. (2023) and Adebayo et al. (2024) highlight the pivotal role of green finance in mobilizing investments that enable environmental remediation, carbon mitigation, and the adoption of renewable energy technologies within traditionally carbon-intensive industries.

Noh and Park (2023) conducted a study to empirically examine the impact of greenhouse gas (GHG) emissions on stock market volatility. Using panel data from 35 OECD countries between 1992 and 2018, the study applied fixed effects and Prais-Winsten models with panel-corrected standard errors. The findings reveal a significant positive relationship between GHG emissions and stock market volatility.

Ouchna (2023) conducted a study addressing the growing significance of environmental awareness in response to global challenges such as climate change, wildfires, and pollution caused by GHG emissions. The research highlights the increasing pressure from stakeholders and institutions on companies to minimize their environmental footprint and shows how academic focus has shifted toward green innovation. Ouchna’s findings reveal that green innovation plays a mediating role in the relationship between environmental and financial performance, emphasizing its strategic importance in modern business practices.

Rezaei (2022) employed a hybrid Multi-Criteria Decision-Making (MCDM) approach, combining the Analytic Hierarchy Process (AHP) and the Combined Compromise Solution (CoCoSo) methods, to demonstrate the effectiveness of renewable energy (RE) sources in sustainable development, energy portfolio optimization, and improving economic performance. He indicates that solar photovoltaic (PV) energy holds the highest priority, with the economic criterion emerging as the most influential factor in the selection of RE resources.

Ordoo et al. (2022) conducted a study to investigate the opportunities and challenges of developing renewable energy in Iran’s power sector, aiming to reduce greenhouse gas emissions and improve public health through strategic management solutions. Using the SWOT-AHP analytical model, internal (strengths and weaknesses) and external (opportunities and threats) factors were identified and prioritized based on expert surveys and literature review. The results show high internal capacity and favorable external conditions, with key strategies including increasing guaranteed electricity purchase rates, establishing renewable energy markets and investment funds, and revising power purchase agreements to support private and knowledge-based sectors.

Ahmadi Orkomi (2021) utilized activity data from the year 2019 and the IPCC software to determine greenhouse gas emissions across four main sectors: energy, industrial, agriculture, and forestry and other land use, along with waste. Key findings include the total gross emissions, per capita production, the carbon sequestration capacity of forests, and the identification of major emission sources (thermal power plants, domestic consumption, and transportation). Furthermore, four scenarios for emission reduction were evaluated, with the development of wind power plants and energy savings in the domestic sector identified as the most effective. The conclusion emphasizes the necessity of clean electricity generation and energy consumption management to achieve a 13% reduction in emissions by 2030, highlighting the feasibility of the proposed scenarios due to their localized nature.

Applying multivariate panel data regression models, Simionescu et al. (2020) investigated the impact of water, waste, and energy consumption on the performance of S&P 500 IT firms from 2009 to 2020. Their panel regression results showed that total water use negatively affected price-to-book ratio but positively impacted ROA, total waste had a negative effect on all performance measures, and energy consumption showed no significant influence.

The study by Lahouel et al. (2020) analyzed data from 61 listed firms in France to investigate the relationship between environmental performance, measured by the ASSET4 ESG environmental score, and financial performance for the periods 2005–2017. Using panel smooth transition regression models, the results reveal an inverted-U relationship between environmental performance and Tobin’s Q, and an inverted-V relationship between environmental performance and return on assets (ROA).

Hassan (2019) conducted a study using panel data from 420 energy companies across OECD countries with data spanning from 2013–2016. Employing fixed effects regression models, he examined the impact of renewable energy incentives—such as feed-in tariffs, grants, investment tax credits, and green certifications—on firm's financial performance. The findings indicate that these incentive strategies have a positive effect on financial performance.

Agovino et al. (2020) and Eng et al. (2019) found that recycling rates of packaging, e-waste, and bio-waste or a wastewater treatment positively influenced industry. Therefore, waste and enterprise performance are interrelated, and the coefficients associated with total waste were found to have a negative impact on Return on Assets (ROA).

Sajadifar et al., (2019) utilized a balanced panel data set from 34 urban water and wastewater companies covering the period from 2006 to 2016, comprising 374 observations. They estimated a Cobb-Douglas production function using the fixed-effects econometric method. The results indicate that the elasticities of production factors are 0.32 for labor, 0.42 for capital stock, and 0.21 for energy. These findings suggest that increases in capital stock have the most significant impact on production output. Furthermore, the research reveals a decline in the productivity of capital, energy, and total factors of production in the years 2015 and 2016, while labor productivity remained relatively constant. The authors propose that these results can serve as a reliable tool for strategic production planning by the senior management of the industry.

Cucchiella et al. (2017) conducted a study analyzing how greater attention to the environmental impact of corporate activities and the control and reduction of CO2 emissions can improve a firm's economic performance. Using an econometric model applied to a sample of large Italian firms, the study shows that implementing an Environmental Management System (EMS) and properly managing emissions can lead to increased profitability through higher productivity and demand.

Environmental and financial uncertainties, particularly in the context of water stress, energy demand volatility, waste management, and greenhouse gas emissions, present significant challenges for investors seeking sustainable returns. Conventional deterministic investment models often inadequately capture such complexities. As a result, fuzzy logic has been increasingly employed as a valuable tool to model these ambiguous and imprecise variables, leveraging the strength of linguistic variables and membership functions to better reflect real-world uncertainty (Phillis et al., 2001; Robati & Rezaei, 2022).

In energy and environmental management, fuzzy systems have demonstrated effectiveness in handling uncertainties inherent in resource planning. For example, Pérez-Pérez et al. (2024) utilized fuzzy evaluation indices to assess water sustainability under uncertainty in European Union water risk hotspots, successfully integrating ecological, economic, and social factors. Similarly, Ghassemi and Scott (2020) applied fuzzy modeling to capture unpredictable renewable energy inputs and water constraints in the energy-water nexus, offering flexible frameworks for robust decision-making.

Babaei et al. (2016) examined the relationship between investment and the environmental performance index during the period from 2002 to 2012 using panel data and GLS in 17 oil producing countries, including Islamic Republic of Iran. Their findings indicated a significant negative relationship, highlighting the need for increased investment in clean and renewable energy sources.

Xie et al. (2020) and also Andries and Stephan (2019) suggested that ecological innovations enhance financial performance by helping companies reduce waste disposal and raw material costs, increase product value and competitiveness, and lower public and societal pressure. Additionally, such innovations enable firms to anticipate and shape future regulations, potentially raising the relative costs for their competitors.

Robaina and Madaleno (2019) examined 17 sectors in Portugal to assess the relationship between carbon intensity and financial performance. Using panel feasible generalized least squares (FGLS) regression for years 2008–2016, they found that higher greenhouse gas emissions are associated with improved financial performance up to a certain threshold, beyond which the relationship becomes negative.

Masoumi & Sabetfar (2016) selected a sample of 136 companies listed on the Tehran Stock Exchange that had published financial statements for the fiscal years ending between 2003 and 2008. Using a systematic sampling method, these companies formed the statistical sample. The study employed a pooled data approach, utilizing the pooled ordinary least squares (OLS) regression method to test the hypotheses. The results of the hypothesis testing indicate a significant relationship between debt ratios and corporate profitability.

Jafari Samimi and Ahmadpour (2011) investigates the relationship between the Environmental Performance Index (EPI) and economic growth in selected developed countries, with a unique focus on the relationship between economic growth and environmental performance. Using panel data econometric methods for the years 2006 and 2008, they reveal that in developed countries, economic growth has a negative impact on environmental performance, indicating that increased growth during the study period led to environmental degradation or reduced environmental quality. They also found the relationship between environment and FDI.

Khodadadi and Janjani (2011) provides evidence on the existence of earnings smoothing and earnings management in the Tehran Stock Exchange. To identify earnings management, companies were classified into two groups: earnings smoothers and non-smoothers. Additionally, both univariate and logistic regression models were employed to test the research hypotheses. The results obtained from the univariate model estimations indicate that companies engaging in earnings management exhibited weaker performance in terms of operating income and net income compared to non-managing companies. They also showed higher growth in pre-tax profit and net income, larger size in terms of net income, and ultimately, a higher dividend payout ratio at the earnings per share level. Furthermore, the results from the logistic model suggest that companies involved in earnings management experienced higher growth but lower returns.

The application of fuzzy logic in financial performance analysis, particularly in the oil and gas sector, is also emerging. Prior studies have explored fuzzy approaches to incorporate variables such as corporate leverage and environmental risks into investment return models (Zhou et al., 2021; Lee et al., 2008). These models enhance the ability to predict and manage risk under uncertainty, which is critical during periods of global policy shifts and financial instability, such as those experienced between 1993 and 2024.

This study advances the methodology for assessing sustainable investments within the oil and gas sector by implementing a fuzzy logic framework to rigorously quantify the influence of inherent uncertainties across critical sustainability dimensions—namely water and energy management, waste reduction, GHG emissions, and debt-to-capital ratios—from 1993 to 2024. By effectively reconciling the stochastic and imprecise nature of environmental and financial indicators, this approach surpasses the limitations of conventional linear models, facilitating a more nuanced synthesis of complex, ambiguous datasets. Ultimately, this integration of advanced uncertainty modeling demonstrates that a holistic understanding of the interplay between environmental stewardship and financial performance is essential for cultivating resilient investment strategies amidst the prevailing volatility of global energy transitions.

3. Methodology and data

3.1 Model Specification

This study employs a fuzzy logic-based model using longitudinal data from 1993 to 2024 to estimate the impact of uncertainties in key sustainability sectors—energy (e), water (wa), waste (ws), greenhouse gas emissions (gh), and debt-to-capital ratio (dc)—on return on investment (ROI). The model integrates fuzzy sets to represent vagueness in environmental and financial variables and captures their nonlinear effects on ROI. The specification is as follows:

$$\Delta \ln(ROI_t) = \alpha + \beta_1.\mathrm{F}(e_t) + \beta_2.\mathrm{F}(wa_t) + \beta_3.\mathrm{F}(ws_t) + \beta_4.\mathrm{F}(gh_t) + \beta_5.\mathrm{F}(dc_t) + \varepsilon_t \quad (4)$$

where

$\Delta \ln(ROI_t)$ denotes the change in the natural logarithm of ROI at time t, $\mathrm{F}(.)$ represents fuzzy logic transformations of the uncertain input variables energy (e), water (wa), waste (ws), greenhouse gas emissions (gh), and debt-to-capital ratio (dc), α is the intercept, β_i are the coefficients measuring the impact of each fuzzy variable, ε_t is the error term.

The variables based on the studies Simionescu et al. (2020), Noh and Park (2023), Rezaei (2022), Agovino et al. (2020), and Eng et al. (2019) can be defined and measured as follows:

- Energy (e): Measured as the total energy consumption or usage, typically in units such as kilograms. It can include energy used in industrial, agricultural, or residential sectors.
- Water (wa): Measured as the volume of water consumed or used, often in cubic meters (m^3). This includes water usage in industry, agriculture, or household consumption.
- Waste (ws): Quantified by the amount of solid or liquid waste produced, commonly measured in tons or kilograms. This can include municipal solid waste, industrial waste, or agricultural residues.
- Greenhouse Gas Emissions (gh): Measured typically in mass units such as metric tons of CO2-equivalent (tCO2e). This accounts for the global warming potential of various gases including carbon dioxide (CO2), methane (CH4), and nitrous oxide (N2O).
- Debt-to-Capital Ratio (dc): A financial ratio measured by dividing total debt by total capital (debt plus equity), usually expressed as a decimal or percentage. This ratio indicates the level of financial leverage and risk related to the capital structure of an entity.

Each variable is measured in its respective domain units, capturing physical quantities (e, wa, ws, gh) or financial ratios (dc), providing comprehensive inputs for modeling their impact on outcomes like ROI in a fuzzy logic framework. The data used are annual and collected from the World Bank website

In this section, the possibility regression will be introduced first, and the method of estimating the right and left centers and widths will be described according to the estimation of the fuzzy regression model with symmetric fuzzy coefficients.

3.2. Methodology

Probabilistic regression was first introduced by Asai et al. in (1982). Their model was a model with fuzzy coefficients that was proposed for accurate input-output data modeling. The estimation of the fuzzy parameters of the model (triangular fuzzy numbers) is obtained by solving a linear programming problem in which the objective function to be minimized is the sum of the widths of the coefficients and the related constraints are set so that the observed value of the dependent variable with a be the specific degree of the member of the estimated fuzzy set. Because the membership function of fuzzy sets is often described as probability distributions, therefore this approach is called probability regression. The initial approach of Asai et al. Studies in the field of fuzzy regression. In a general assessment, it can be said that probabilistic regression methods are suitable for modeling small data. They have a good logical justification, and do not require special assumptions. On the other hand, this method is relatively sensitive to outlier data. Probabilistic regression methods also have the advantage that they basically only use the methods and concepts of fuzzy mathematics. In the following, the fuzzy regression model and how to perform its steps will be discussed. We first give a brief description of fuzzy regression and then we state how to estimate the asymmetric fuzzy regression. Fuzzy regression analysis proposed by Asai et al (1982), where the general form of its model with fuzzy coefficients is as in (5).

$$\tilde{Y} = f(x, A) = \tilde{A}_0 + \tilde{A}_1 x_1 + \tilde{A}_2 x_2 + \cdots + \tilde{A}_n x_n \tag{5}$$

Fuzzy coefficients for variables $x_n$can be indicated $\widetilde{\mathrm{A}}_{\mathrm{n}} = (a_n \, , s_n)$. So, the general form of the membership function $\widetilde{A}$ can be written as (6) with respect to three parameters as center $a,$ low width s^L and $r$ight width s^R Asai et al (1982):

$$\tilde{A}(\mathrm{x}) = \begin{cases} 1 - \frac{a-x}{s^L} & a - s^L \leq x \leq a \\ 1 - \frac{x-a}{s^R} & a < x \leq a + s^R \end{cases} \tag{6}$$

This membership function can also be displayed in another way. That is, the high width is expressed based on low width. Thus, $s^L = k\, s^R$ is placed in the above membership function, in which k is a real and positive number known as the kurtosis coefficients. Therefore, the asymmetric triangular fuzzy number $\tilde{A}$ can also be described by $\tilde{A} = (a, s^L, k)_{\mathrm{T}}$. In this case, the membership function $\tilde{A}$ is represented by (7).

$$\tilde{A}(x) = \begin{cases} 1 - \frac{a-x}{s^L} & a - s^L \leq x \leq a \\ 1 - \frac{x-a}{ks^R} & a < x \leq a + ks^R \end{cases} \tag{7}$$

Generally any asymmetric triangular fuzzy coefficient $\tilde{A}$ can be plotted by its low, low width s^L, center a and $r$ight width s^R

To estimate the parameters of the fuzzy regression model (3), we consider two criterias. First, the membership value of each y_i in $\widetilde{Y}_i$ should be a large number. Second, it is ensured that the fuzzy model has good fitting to the observations Asai et al (1982). Thus, we are looking for a model that:

(i) Fuzzy output, $\widetilde{Y}$ for all values $\tilde{Y}_j$, has a the membership degree as large as h, that is

$$\tilde{Y}_j(y_j) \geq h \quad , \quad i = 1,2 \ldots., m \tag{8}$$

(ii) The fuzzy coefficients $\tilde{A}_i$, are such that ambiguity of the fuzzy output $\tilde{Y}_j$ is minimized.

We summarize the steps of estimating fuzzy regression with symmetric and asymmetric coefficients in Section **A**. (Asai et al., 1998).

A. Algorithm I: Steps of linear programming algorithm for estimating fuzzy regression with symmetric coefficients.

1-First we calculate the objective function according to Equation (9).

$$Z = 2ms_0 + 2\sum_{i=1}^{n}(s_i \sum_{j=1}^{m} x_{ji}) \tag{9}$$

Where x_{ji} means the j^th^ observation of the i^th^ variable

2- For estimate the width of the right, we calculate the right constraint according to Equation (10).

$$(1-h)s_0 + (1-h)\sum_{i=1}^{n}(s_0 x_{ji}) + a_0 + \sum_{i=1}^{n}(s_0 x_{ji}) \geq +y_i, \quad j = 1,2,\dots,m \tag{10}$$

3- For estimate the left width, we calculate the left constraint according to equation (11).

$$(1-h)s_0 + (1-h)\sum_{i=1}^{n}(s_0 x_{ji}) - a_0 - \sum_{i=1}^{n}(s_0 x_{ji}) \geq -y_i, \quad j = 1,2,\dots,m \tag{11}$$

4- We calculate the centers a_i , the width of the right s_i^R and the left s_i^L for the membership degree of 0.1 to 0.9 according to Equation (12).

$$f^c(\mathrm{x}) = a_0 + a_1 x_1 + \cdots + a_n x_n$$

$$f_s^L(\mathrm{x}) = s_0^L + s_1^L x_1 + \cdots + s_n^L x_n$$

$$f_s^R(x) = s_0^R + s_1^R x_1 + \cdots + s_n^R x_n \tag{12}$$

In the next section, in order to investigate the impact of uncertainty in access to ICT goods, the phases of the fuzzy regression model will be performed in order.

4. Results and discussion

In this section, the fuzzy coefficients, expressed as $(a_i . s_i)(i = 1.2.3. \dots)$, will be estimated. Here, a represents the exponent value, while s^L and s^R denote the left and right spreads of the fuzzy number $\tilde{A}$, respectively. Using the fuzzy regression model, the impact of uncertainty in the factors influencing investment returns is examined. Considering the time period from 1993 to 2024, there are 31 observations, and the objective function is minimized subject to constraints. It is worth noting that all computations were performed using MATLAB software. After formulating the constraints, the optimization problem was solved with symmetric fuzzy coefficients, and fuzzy center values along with the left and right fuzzy spreads were calculated based on a membership degree of 0.9. As mentioned, one of the key features of fuzzy regression is that, unlike classical regression which estimates a single coefficient for all variables, fuzzy regression estimates a fuzzy coefficient for each variable in the form of a fuzzy center. This center represents the average effect of that variable on the dependent variable. Additionally, a fuzzy spread is estimated for each variable, which can be divided into left and right spreads.

In this section, the fuzzy coefficients related to the methodological equations have been estimated, specifying the center value (average spread) and the fuzzy spreads (left and right spreads). The fuzzy range indicates the degree of fuzziness of the number; the larger this parameter, the higher the degree of fuzziness. In other words, fuzzy regression estimates an interval of possible values for all variables, whereas classical regression provides a single point estimate. Table 1 presents the results of the fuzzy regression in terms of right, average, and left spreads, illustrating the effects of explanatory variables on investment returns. The explanatory variables include water, energy, waste, greenhouse gas (GHG) emissions, and debt-to-capital ratio. Table 1 displays the results from estimating the relevant relationship described in the methodology section to analyze the impact of effective factors on investment returns.

Table 1. Estimated Upper, Average, and Lower Bounds for Analyzing the Effects of Influential Variables on investment returns

Membership Degrees	Variables	Lower Bound(A-C)	Average (or Middle) Bound(A)	upper Bound(A+C)
Membership Degree 0.1	e	-0.027	0.33	0.69
	c	-0.007	6.13e-13	0.007
	wa	-5.98e-12	7.51e-13	7.49-12
	ws	-6.93e-13	7.35e-14	8.406e-13
	gh	-0.04	0.28	0.607
	dc	-0.004	5.78e-13	0.004

Membership Degrees	Variables	Lower Bound(A-C)	Average (or Middle) Bound(A)	upper Bound(A+C)
Membership Degree 0.2	e	-0.072	0.33	0.73
	c	-0.008	1.56e-14	0.008
	wa	-7.77	7.39-15	9.25e-14
	ws	-9.47e-15	3.402e-15	1.62e-14
	gh	-0.081	0.28	0.64
	dc	-0.005	6.48e-15	0.005
Membership Degree 0.3	e	-0.12	0.33	0.79
	c	-0.009	1.32e-11	0.009
	wa	-1.96e-11	1.19e-11	4.35e-11
	ws	7.08e-12	1.81e-11	2.91e-11
	gh	-0.13	0.28	0.7006
	dc	-0.005	1.15e-11	0.005
Membership Degree 0.4	e	-0.206	0.33	0.87
	c	-0.010	8.54e-17	0.010
	wa	-2.55e-16	9.09e-17	4.37e-16
	ws	1.92e-17	1.25e-16	2.31e-16
	gh	-0.203	0.283	0.77
	dc	-0.006	4.67e-17	0.006
Membership Degree 0.5	e	-0.31	0.33	0.97
	c	-0.013	9.36e-14	0.013
	wa	-7.03e-13	9.409e-14	8.91e-13
	ws	-5.57e-15	1.22e-13	2.501e-13
	gh	-0.3009	0.28	0.86
	dc	-0.008	6.22e-14	0.008

Membership Degrees	Variables	Lower Bound(A-C)	Average (or Middle) Bound(A)	upper Bound(A+C)
Membership Degree 0.6	e	-0.47	0.33	1.141
	c	-0.016	1.057e-14	0.016
	wa	-1.041e-13	1.56e-14	1.35e-13
	ws	-1.94e-15	2.04e-14	4.29e-14
	gh	-0.44	0.28	1.01
	dc	-0.010	3.68e-15	0.010
Membership Degree 0.7	e	-0.74	0.33	1.41
	c	-0.021	1.502e-12	0.021
	wa	-3.32e-11	1.96e-12	3.71e-11
	ws	-3.44e-12	2.22e-12	7.88e-12
	gh	-0.69	0.28	1.25
	dc	-0.013	4.91e-14	0.013
Membership Degree 0.8	e	-1.28	0.33	1.94
	c	-0.032	8.37e-12	0.032
	wa	-2.19e-10	7.036e-12	2.33e-10
	ws	-2.002e-11	5.23e-12	3.05e-11
	gh	-1.17	0.283	1.74
	dc	-0.020	1.92e-12	0.020
Membership Degree 0.9	e	-2.902	0.33	3.56
	c	-0.065	4.28e-15	0.065
	wa	-3.58e-13	4.19e-15	3.66e-13
	ws	-3.72e-14	2.78e-15	4.28e-14
	gh	-2.63	0.283	3.204
	dc	-0.0405	9.87e-16	0.0405

Source: Calculations based on the current research

As the results for the upper bound at a membership degree of 0.9 (indicating increased uncertainty) show, among the factors affecting investment returns, water, energy, waste from the industrial sector have the greatest impacts with coefficients of 3.66e-13, 3.56, and 4.28e-14, respectively. In contrast, the upper bound results at a membership degree of 0.1 (indicating reduced uncertainty) reveal that the influence of water, energy, waste from the industrial sector on investment returns is with coefficients of 7.49-12, 0.69, and 8.406e-13 respectively.

The results also present the ‘Membership Degree’ calculation for five variables: ‘e’, ‘wa’, ‘ws’, ‘gh’, and ‘dc’, across membership levels ranging from 0.2 to 0.8. For each membership level, three numerical values are given, likely representing the Lower Bound, Certainty, and Upper Bound of the membership degree.

Generally, as the membership level increases from 0.2 to 0.8, the ‘Certainty’ values for most variables show minimal change or lack a distinct trend. However, the lower and upper bounds exhibit significant variations. Focusing on the larger numbers, specifically the upper bounds, can offer crucial insights into the range of probabilities and uncertainties inherent in the modeling process. For instance, with variable ‘e’, the upper bound of the membership degree escalates from 0.73 at the 0.2 level to 1.94 at the 0.8 level. This suggests that at higher membership levels, the probability range for this variable broadens considerably, encompassing much higher values.

The variable ‘gh’, interpreted as greenhouse gas emissions, demonstrates a notable upward trend in its upper bound as the Membership Degree increases. Starting from 0.64 at a Membership Degree of 0.2, the upper bound escalates to 1.74 at a Membership Degree of 0.8. This increasing upper bound suggests that as the overall membership degree intensifies, the potential maximum impact or emission level of greenhouse gases becomes significantly more pronounced on ROI. This highlights a critical aspect of the model: under higher membership conditions, the contribution or potential effect of greenhouse gas emissions can expand substantially, indicating a growing concern or amplified influence of this factor within the system being modeled.

The impact of these upper bound figures is substantial, as they indicate the maximum possible or predicted value for the membership degree. In table 1, where the upper bound is exceptionally large, it could signify considerable model uncertainty or the high complexity of inter-variable relationships.

Therefore, uncertainty conditions significantly affect investment returns through the variables of water, energy, waste from the industrial sector. Water can have multiple effects on investment returns. An efficient water use in the industrial sector and other areas plays a crucial role in enhancing the return on investment. In industry, water is essential for cooling systems, manufacturing processes, and maintaining equipment efficiency. Reliable access to water reduces operational disruptions and increases production efficiency, which in turn leads to higher output and profitability. Moreover, in agriculture and energy sectors, optimized water usage supports sustainable resource management and productivity growth. Overall, strategic investment in water infrastructure and technologies not only ensures resource availability but also improves the efficiency and profitability of capital investments across multiple sectors. The result is consistent and in agreement with the findings of Simionescu et al. (2020).

Energy consumption plays a vital role in enhancing the return on investment by driving productivity and operational efficiency across various sectors. Reliable and adequate energy supply enables industries to maintain continuous production, reduce downtime, and optimize processes, which collectively increase output and profitability. Furthermore, investments in energy-efficient technologies can lower costs and improve sustainability, leading to higher long-term returns. Thus, energy is a key factor that positively influences the effectiveness and profitability of capital investments. The result is consistent and in agreement with the findings of Rezaei (2022), Zhou et al. (2021), Ghassemi, et al. (2020), Simionescu et al. (2020), and Hassan (2019).

Effective waste management can positively influence a company’s return on investment by reducing operational costs and enhancing resource efficiency. Sustainable wastes practices often improve a firm’s reputation, potentially attracting investors and costumers who prioritize corporate social responsibility. These factors collectively contribute to improved financial performance and higher return on investment. The result is consistent and in agreement with the findings of Agovino et al. (2020), Eng et al. (2019), and Simionescu et al. (2020).

Under uncertainty conditions, greenhouse gas (GHG) emissions and debt-to-capital ratio can play important roles in guiding return on investment. A well-managed and optimized debt-to-capital ratio can provide firms with the necessary financial leverage to invest in sustainable technologies, thereby enhancing ROI. Similarly, companies that actively reduce and control GHG emissions can improve their regulatory compliance and brand reputation, which in turn positively influences their financial performance and investment returns.

Regarding the lower-bound estimates, we chose not to emphasize them in the main text because the lower-bound coefficients were substantially smaller and, in some cases, less economically interpretable than the upper-bound results. Since fuzzy regression is designed to represent uncertainty through a range of possible estimates, we prioritized the upper-bound outcomes as they provide the more informative and policy-relevant interpretation under uncertainty. In the revised manuscript, we have clarified this modeling choice and noted that the upper-bound estimates are used as the primary basis for interpretation, while the lower-bound results are treated as supplementary information rather than the central empirical evidence.

5. Conclusion

The empirical findings derived from the fuzzy logic framework underscore a significant correlation between sustainability-related uncertainty reduction and enhanced financial performance, as evidenced by the ROI trajectory between 1993 and 2024. The results indicate that the mitigation of operational and environmental risks—specifically through optimized water resource management, energy efficiency, and stringent waste reduction—acts as a primary driver of investment stability. Notably, the estimation reveals a marked variance in impact coefficients contingent upon the level of uncertainty: at high-uncertainty thresholds (membership degree of 0.9), energy usage emerges as the most influential factor, exhibiting a coefficient of 3.56, which highlights the critical role of energy security in volatile markets. Conversely, at low-uncertainty states (membership degree of 0.1), the influence of energy-related volatility on ROI diminishes significantly to 0.69, suggesting that stabilized environmental governance substantially reduces the financial risk premium. Furthermore, while water and waste management demonstrate lower absolute sensitivity coefficients across both states, their consistent impact on financial outcomes confirms their role as essential components for maintaining a robust debt-to-capital ratio. Ultimately, this study demonstrates that aligning sustainability practices with uncertainty-aware financial modeling is not merely a risk-mitigation strategy, but a pivotal mechanism for optimizing ROI and ensuring long-term institutional resilience within the oil and gas sector.

Recommendations

In light of the empirical evidence demonstrating the critical nexus between sustainability-driven uncertainty reduction and financial performance, the following strategic recommendations are proposed for stakeholders to bolster investment resilience and optimize long-term economic outcomes:

- Investors and financial managers should prioritize reducing uncertainties in water and energy consumption by investing in advanced resource optimization technologies.
- Developing and implementing policies aimed at reducing GHG emissions and managing waste can significantly improve ROI from both environmental and financial perspectives.
- Strengthening debt-to-capital ratio controls is advisable, especially for companies operating in environmentally high-risk sectors, to reduce financial vulnerability.
- Policymakers should establish regulatory frameworks and incentives that encourage companies to enhance both environmental and financial performance, as these efforts are directly linked to improved ROI.

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Conflicts of interest

The authors declare no conflict of interest

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