Impact of Climate Water Risk on Corporate Operational and Capital Markets Performance: A Machine Learning Approach

by

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Glossary

Term	Unit	Definition
Alpha		Stock return in excess of a benchmark, meaning the average return unexplained by exposure to risk factors.
Annual Growth of Water Consumption		Annual growth ratio of Water Use.
Annual Stock Return		Returns the last price provided by the exchange.
Annual Stock Volatility		Volatility is a statistical measure of the dispersion of returns. In most cases, the higher the volatility, the riskier the security.
Beta		Beta is the volatility of a security or portfolio against its benchmark.
Cash Flow Growth	%	Long term growth of operating cash, the money that is actually coming from business operations.
Dividend Yield		Sum of gross dividend per share amounts that have gone ex-dividend over the prior 12 months, divided by the current stock price.
Earnings before Interest Expenses and Income Taxes (EBIT)	$M	Company’s operating profit and its profitability.
Earnings-per-Share (EPS) Growth	%	Earnings per share (EPS) is a company's net profit divided by the number of common shares it has outstanding.
Financial Leverage		Measures the average assets to average equity. Average Total Assets / Average Total Common Equity
Fix Asset Turnover		Financial ratio of net sales to net fixed assets
Inventory Turnover		A ratio that reveals the number of times a firm sells and replaces its inventory during a given period.
Momentum		Momentum refers to the capacity for a price trend to sustain itself going forward.
Operating Margin	%	An important profitability ratio measuring revenue after the deduction of operating expenses.

Operating Return on Invested Capital (ROIC)	%	Return on invested capital (ROIC) is the amount of money a company makes that is above the average cost it pays for its debt and equity capital.
Price-to-Book Ratio		The P/B ratio measures the market's valuation of a company relative to its book value. It's calculated by dividing the company's stock price per share by its book value per share (BVPS).
Private Equity (PE)		Private equity (PE) refers to capital investment made into companies that are not publicly traded.
Profit Margin		Profit margin is the percentage of sales that a business retains after all expenses have been deducted.
Property, Plant, and Equipment (PP&E)		A company asset that is vital to business operations but cannot be easily liquidated.
Return on Asset (ROA)	%	ROA refers to a financial ratio that indicates how profitable a company is in relation to its total assets.
Return on Equity (ROE)	%	ROE is a gauge of a corporation's profitability and how efficiently it generates those profits.
Revenue (Sales)		Amount of sales generated by a company after the deduction of sales returns, allowances, discounts, and sales-based taxes.
Sales Growth	%	Sales growth is the percent growth in the net sales of a business from one fiscal period to another.
Size	$M	Size is log of market cap. Market cap is total current market value of all of a company's outstanding shares stated in the pricing currency.
Tobin's Q	%	Ratio of the market value of a firm to the replacement cost of the firm's assets.
Total Water Consumption (WC)	10^3m^3	Total amount of water used to support a company's operational process.
Volume		Total number of shares traded on security on the current day.
Water Intensity per EBIT (WIPE)	10^3m^3/$M	Annual Total Water Use/ EBIT
Water Intensity per PP&E (WIPPE)	10^3m^3/$M	Annual Total Water Use/ PP&E
Water Intensity per Sales (WIPS)	10^3m^3/$M	Annual Total Water Use/ Sales

Abstract

Climate change and water availability impacts on corporate operational performance pose substantial risks to investors, shareholders, and the broader capital markets. Financial risks associated with climate and water are linked to short or long-term opportunity costs that are not disclosed in corporate accounting and formed the basis for the Task Force on Climate-Related Disclosures (TCFD), which forces corporations to disclose their financial risk exposures. The disclosure regulation aims to incentivize investment in corporate climate resilience through stewardship of natural resources. Given the knowledge gaps in water risk disclosure, quantitative approaches were developed to understand the financial materiality of water risk to corporate accounting and market performance.

An exploration was conducted to test the hypothesis regarding the pricing of corporate water use intensity in the market and the potential quantification of this price premium using statistical tools and machine learning approaches. Indicators including water intensity relative to revenue, operating profit and net fixed assets were evaluated for representative companies from nine industry sectors. Using the statistical inference tool, propensity score matching (PSM), the analysis delved into the connection between water intensity and market metrics, accounting for corporate fundamentals. It showed that low water intensity results in improved returns over the benchmark (alpha), return on equity and long-term valuation (Tobin's Q). In addition, water intensity based on corporate classification based on its activity was shown to be a poor proxy for water intensity benefits tied to financial metrics.

The next step was to develop and test an imputation methodology combining econometric models and machine learning techniques to predict water intensity metrics for companies that are not disclosing water use risks. This methodology includes recursive feature elimination (RFE) method for feature selection, and the development of factor models using linear regression (OLS), generalized linear model (GLM), Lasso (LASSO), Random Forest (RF), and Adaptive boosting model (ADA). Random Forest models yielded the highest accuracy to impute water intensity indicators standardized to sales, operating profit and fixed assets from financial fundamentals, and allowed me to expand my testing universe from 500 to 2,525 company-years.

Then, it explores the impact of water use indicators on market metrics, including share price return, short term operational (return on assets, ROA) and financial (return on equity, ROE) metrics, as well as long-term corporate valuation (using Tobin's Q as a proxy). The difference between high- and low-water dependent companies, disclosing and non-disclosing (using imputed data) companies, as well as the impact of TCFD promulgation (2017) was tested. The results show that markets are rewarding companies exhibiting high water intensities with higher returns, though the effect is attenuated after TCFD implementation. Water intensity relative to sales and operating profit have a positive correlation with ROA and ROE, and a negative correlation to long term value. Again, the coefficients for ROA and ROE are decreasing post-TCFD, while those for Tobin's Q are increasing. Taken together, empirical evidence shows that markets are starting to price in water risk to companies. Interestingly, water intensity normalized to fixed asset investments exhibits a negative correlation to share price returns, indicating that investors are worried about capital-intensive companies delivering reduced returns. Using data science tools, my research offers new and valuable insights for business strategy and financial decision-making, emphasizing the need for managers to explore effective corporate water strategies to sustain or enhance competitiveness.

Chapter 1 Introduction

Climate change and access to water impact corporate operational performance and thus expose investors and shareholders to excess (and poorly quantified) risks. Recently, the Securities and Exchange Commission (SEC) recognized that this risk should be disclosed, as proposed in its climate disclosure document which states that "a company must provide the location by zip code of properties subject to flooding risk and must provide such location and book value of assets located in regions of high-water stress". Financial risks associated with water including impacts on supply chains, operations and logistics tend to be linked to short or long-term opportunity costs that have not generally been disclosed in corporate accounting and thus this information is difficult for investors and other stakeholders to evaluate. While research has been conducted on the impact of climate change on water quality and quantity, there is a dearth of research on the analysis of the relationship between climate change uncertainties and water risk exposures or water use intensities of companies. Given the requirement for future disclosure and the broader discussion around the cost climate transitioning under the Task Force on Climate-Related Financial Disclosures (TCFD), this research focuses on the understanding of financial materiality of water risk to corporate operations to inform risk management solutions. It is imperative for companies to understand their financial risk exposures to help with strategic decision-making to invest in risk management, depreciate stranded assets, or transfer climate water risk to insurance underwriters (Larson et al., 2012).

Climate change exacerbates water uncertainty around the world. The most recent Intergovernmental Panel on Climate Change (IPCC) report states that the temperature rises would bring big changes in the planet's water cycle, including increasing extreme flooding incidence, severe drought, and water scarcity impacting society and the broader economy. In regard to flooding, as estimated by thermodynamic relationships, each additional one-degree Celsius of global warming is projected to increase extreme rainfall intensities by 7%. By 2050, the number of people at risk of floods will increase from its current level of 1.2 billion to 1.6 billion (United Nations, 2020). Regarding water scarcity, over 60 million Americans are living under drought conditions. During the early to mid-2010s, approximately 1.9 billion people, accounting for 27% of the global population, resided in regions potentially facing severe water scarcity. Projections indicate a significant rise in this figure, from 2.7 to 3.2 billion people by 2050 (United Nations, 2020). This impact will lead to increased competition for water resources, not only socially but also economically. Further, when considering the combined effects of growing populations, rising incomes, and expanding cities, we will see demand for water rising exponentially, while supply becomes more erratic and uncertain for individuals, communities, and corporate operations. The latter is expected to increase volatility in the capital markets.

Climate change has become an economically disruptive force for companies (CDP, 2016; Daniel and Sojamo, 2012; Christ, 2017). In recent years, many companies have suffered operational losses due to various types of water risk exposures, including water scarcity, revoking of licenses to operate, flood impacts on operations, and reputational damage from poor water stewardship (Ceres, 2015; Ceres n.d.). The UK non-profit CDP Water Security, which annually aggregates corporate water risk data, noted that in 2018 alone there were US$38.5 billion in reported operational losses due to water risks. In addition, ING, an investment bank, published an estimate of financial assets under management (AUM) exposed to water risk to be $145 trn, including stocks, loans, private equity, and insurance portfolios. Insurance companies alone have seen over $7 trn in water risk exposures in their portfolios and from claim payouts. Just in 2020, companies reported financial impacts of water risks reaching US$301 billion due to poor water management and globally distributed risks for businesses. In the Investor Water Toolkit (Ceres n.d.) published by Ceres, a non-profit focused on corporate environmental disclosures to shareholders and stakeholders, the financial materiality resulting from water dependency and related risks are shown to vary significantly by sector and industry (Figure 1.1). The figure illustrates a color-coded water risk classification based on water footprint data (water used per unit product produced) and by industry sector. The mining and energy industry are mainly impacted by water resulting from cooling and extractive processes, while the semiconductor manufacturer may find its water risks are related to the inability to source large volumes of high-quality water for circuit production.

The water issues occur in different stages of their respective value chains and are therefore a widely distributed risk to corporations. As a result, water issues are increasingly viewed as financially-material business risks and are either transferred to insurance companies, addressed using new capital investments to 'harden' the plant or operations, or through accelerated asset depreciation. Importantly, business insurers are experiencing water as the medium through which they will be exposed to climate change (Moorcraft, 2021).

This dissertation will develop a methodology to quantify the financial materiality of water risk exposures for public companies across multiple industry sectors by employing advanced data science tools aimed at understanding the impact of water intensity on financial accounting and market metrics. Since management of financial materiality of water risk falls under the fiduciary requirements of corporate actors and their investors, it is my objective to help catalyze corporate water stewardship and stimulate investments in climate transitioning.

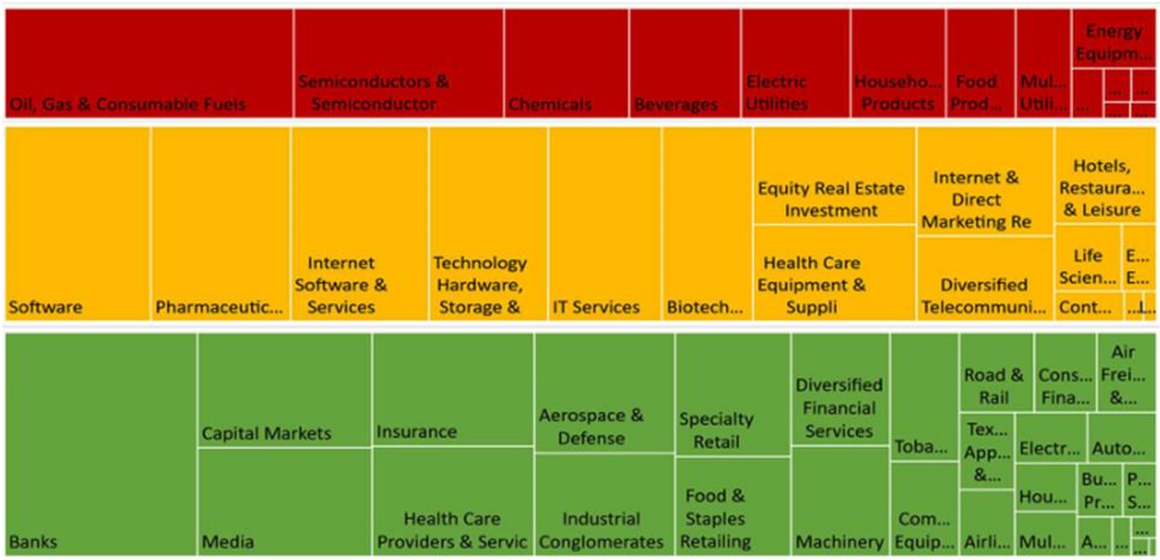


Figure 1.1: Heat map of industry water risk hotspots for S&P 500 sectors and subsectors. The size of the rectangle indicates weight of industry in the index and color indicates high, medium, or low water risk classification using classification of SASB (Sustainable Accounting Standards Board) materiality indicators (Source. Ceres)

Chapter 2 Background and Motivation

Businesses are presently encountering financially significant effects stemming from the competition for water resources and the resulting degradation of ecosystems. For corporations, water is an important part of the natural resource inventory available to their operations, as articulated in the ‘natural resource-based view of the firm’ (Hart, 1995; Hart et al. 2011). It is a critical material and natural capital for successful operations (Christ and Burritt, 2015The theory asserts that limitations imposed by the natural environment introduce disruptions that pose a threat to the current resources and capabilities of firms, which limit the capabilities to maintain a competitive advantage (Hart, 1995).

The nexus between a secure water resource and strong financial performance can be elucidated using the framework of instrumental stakeholder theory (Jones et al., 1995), According to this theoretical framework, achieving enduring success in the business world necessitates a conscientious focus on the interests of stakeholders. These stakeholders encompass a broad array of groups and individuals who possess the ability to exert influence on, or experience the consequences of, the organization's pursuit of its objectives (Freeman et al., 1984, p. 46). Disregarding the interests of stakeholders can pose a formidable impediment to a firm's endeavors in realizing its strategic goals (Jensen et al., 2001), as the unfavorable responses from stakeholders have the potential to escalate operational costs. (Berman et al., 1999). Conversely, these strategic choices directed at the overarching goal of "maximizing firm value" by means of elevating financial performance may exert a significant influence on market indicators and the overall financial performance of the organization.

2.1 Assessing the Materiality of Water Risks

Water risk factors drive basin-level adaptation to climate change, water pollution, or regulatory issues, and are starting to become accounted for in corporate financials. Financial material risks include operational risk, capital markets risk, reputational risk, and regulatory as well as litigation risks. A few examples serve to illustrate each of these risk vectors (WWF, 2022; Freyman et al. 2015; Money et al. 2014; Davies, 2023) :

Operational risk directly impacts sectors heavily dependent on water, such as food and beverage, energy, and semiconductors. Water scarcity poses risks, including stranded assets and increased operational costs, like water importation or disruptions to maritime transport due to low river levels. Nike's closure of four Thai factories due to flooding underscores the real-world consequences, with growing concerns over cotton harvests and prices.

Capital markets risk is an offshoot of operational risks, stemming from diminished sales and heightened costs in an uncertain production environment. This can lead to adverse outcomes, including the loss of corporate contracts, exemplified by K+S Germany, or temporary production curtailment, as witnessed in the case of EDF during a 2020 heatwave with low water levels. The financial metrics employed by equity analysts to gauge a company's value and future growth are consequently influenced when profits dwindle due to water-related issues.

Industrial water usage presents a significant challenge, as it competes with essential societal needs for limited water resources, exposing companies to potential reputational risks. An illustrative case is Coca-Cola's loss of an operating license in north India in 2014 due to water disputes with local farmers. Similarly, the semiconductor industry, exemplified by Taiwan Semiconductor Manufacturing Co. Ltd. (TSMC), grapples with water scarcity, leading to competition with local communities and farmers. With TSMC's substantial daily water consumption exceeding 150,000 tons and the release of wastewater containing heavy metals and toxic solvents, these issues underscore the complexities faced by such industries.

Regulatory and litigation risks take on various forms and contexts. Notably, EDF, a prominent energy utility heavily reliant on nuclear power, was compelled to cease electricity generation at its 2,600-megawatt Golfech nuclear power plant in France due to elevated ambient and water temperatures.

These examples underscore the intricate and multifaceted nature of regulatory and litigation risks in today's business landscape. The impact of climate change and water uncertainty have resulted in the adaptation of business practices across industry sectors.

2.2 Evaluation of financial implications from water

2.2.1 Corporate water risk disclosures

Corporations routinely disclose their water data in annual sustainability reports, including critical metrics like total water usage, withdrawal, and details about their water management practices. Notably, the United States places substantial emphasis on comprehensive water risk assessment across industry sectors, exemplified by the GICS framework used in the S&P 500 index. Contemporary approaches to water risk reporting and ratings draw guidance from a variety of frameworks, including the Global Reporting Initiative (GRI), the Sustainable Accounting Standards Board (SASB), the Task Force on Climate-Related Financial Disclosures (TCFD), and the Carbon Disclosure Project (CDP)'s Water Disclosure Initiative. These frameworks collectively empower organizations to better comprehend and communicate their water-related impacts, enhancing informed decision-making and the adoption of sustainable practices.

Reports focusing on water security play a pivotal role in compelling companies to not only disclose their environmental impact but also to take measures to mitigate it (Burritt et al. 2016; Reig et al. 2013). This call to action leverages the influence of investors and customers, fostering a sense of corporate responsibility. The motivations underpinning voluntary corporate disclosure are of paramount importance, as they have a profound impact on the quality of these disclosures and their reliability for various stakeholders in making informed decisions (Deegan et al., 2019). The data collected through these initiatives provides influential decision-makers with the necessary information to effectively manage risks, seize strategic opportunities, and drive efforts towards a more sustainable world. By delivering high-quality water-related business and financial insights, these reports enable investors and creditors to gain a comprehensive understanding of the risks and opportunities associated with pressing issues like water scarcity, pollution, and other critical challenges (Ben-Amar and Chelli, 2018; Zhang et al., 2021; Botha et al., 2022).

Nevertheless, there is a notable void in comprehending the economic dimensions of voluntary water disclosure at the corporate operations and market performance impact level. The existing frameworks, while valuable, exhibit limitations in their capacity to effectively gauge water risk exposure and understand corporate responses for mitigating these risks (KPMG, 2013; Larson et al., 2012; Leong et al., 2014; Squillace et al., 2012). These frameworks typically offer partially quantitative insights and, aside from the CDP Global Water Reports, do not sufficiently establish the connection between physical water risk and its financial ramifications in corporate operations.

To meet the growing need for financially-material water data, there is a compelling call for standardized frameworks, expanded data coverage, and heightened data quality to facilitate more robust assessment and informed decision-making (WWF, 2022). It is regrettable that, despite the increasing recognition of the scarcity of natural resources and the importance of sustainable environmental management, many companies still do not disclose the ramifications of climate-related water risks or their strategies for risk mitigation, thus constraining their ability and decisions to address these risks during periods of climate transition (Larson et al., 2012; Sokolov et al., 2021; Kotsantonis et al., 2019, Zhang et al., 2021). Burritt et al. (2016) highlighted the importance of firm size, water sensitivity, and ownership concentration as key indicators influencing water disclosures among Japanese companies. Regarding capital market implications, Zhou et al. (2018) observed a significant influence of water information disclosure on the cost of capital in China. Likewise, Zeng et al. (2020) identified a substantial inverse correlation between water disclosure and a firm's systematic risk.

2.2.2 Corporate Financial Metrics to Account for Water Risk

With corporate water risks manifesting themselves both at the watershed and corporate governance level, investment decision-making needs to be informed by a valuation of the opportunity cost of the impacted industry (e.g., Blacconiere and Northcut, 1997; Dowell et al., 2000; McKinsey et al., 2009). Before utilizing an evaluation tool, it is crucial to scrutinize the various indicators for measuring water risks in manufacturing companies and the financial sector.

The water risk exposure at the company level arises from the interplay of external (basin water risk) and internal (operational water risk) factors within the company's operations and value chain (Orr et al., 2014).

Basin water risk factors are external events and developments that lie beyond a company's production facilities. Nevertheless, they can have a significant impact on operations due to their reliance on water resources. The evaluation of basin water risk aims to gauge the probability of specific water-related risk exposures. Key indicators include physical water risks (water stress, scarcity, drought, water quality, and flooding), regulatory water risks (laws, policies, enforcement, and infrastructure conditions), and reputational water risks (local water conflicts and negative media coverage). These indicators provide a comprehensive framework for assessing and managing water-related risks in a company's operations. Especially the water intensity offers valuable insights into a company's water dependency.

Operational water risk factors are closely tied to a company's response to climate impacts, including risk avoidance, mitigation, acceptance, or transfer strategies. These risks can lead to reduced revenues and increased costs, impacting accounting metrics such as operating profit and earnings (net profit). Banks are particularly susceptible to credit default risks arising from water-related events that impact companies exposed to water risk, which no longer have the capacity to meet their debt obligations. Investors, on te other hand, focus on changes in a company's expected future cash flows, affecting its fair market value, as water risks impact profit margins, return on equity, and return on asset ratios (WWF, 2019). Companies with higher Environmental, Social & Governance (ESG) ratings generally outperform those with lower ratings. Indeed, extensive literature indicates a positive, though moderate, relationship between environmental and financial performance (Griffin and Mahon, 1997; USEPA, 2000; Williams and Siegel, 2001; Orlitzky and

Benjamin, 2001; Orlitzky et al., 2003). Numerous studies confirm a positive association between environmental performance and a company's market value, as seen by Dowell et al. (2000) and Cohen et al. (1995). A wide array of empirical studies has explored the effects of corporate environmental performance either on accounting-based profitability measures or on market performance. However, these studies provided mixed results, in which environmental performance either positively or negatively impacted market performance or where corporate accounting metrics behaved in the opposite direction market indicators (e.g., Lewandowski, 2017; Misani and Pogutz, 2015; Iwata and Okada, 2011).

Traditionally, government water pricing has been at the center of the policy toolbox to impact corporate water stewardship. However, the materiality of this cost to corporate operations has not resulted in significant shifts of water risk management strategies. Hence, a wide range of approaches and financial risk models have been proposed to translate the impact of water on businesses and the capital markets, in attempts to extract a signal that can be used for policy design, including water accounting standards as proposed by the Alliance for Water Stewardship.

Water-related risks are often assessed using WRI's Aqueduct and WWF's Water Risk Filter (WRF), though companies often combine multiple tools to address recognized limitations related to localized geospatial risks. Both Aqueduct and WRF rely on global hydrologic models and datasets, offering global coverage but are inherently biased towards regions with available calibration and validation data, introducing uncertainties in model inputs and parameters (Döll et al., 2016).

Water risk valuation tools have been reviewed in Ceres' Investor Water Toolkit (Figure2.1), which aggregates metrics to quantify the financial value of water value for equities, indexes, private equity investments and fixed income products (loans and bonds). A comprehensive list of such tools can be found in WWF's Valuing Water Database (WWF, 2020). Water valuation tools face challenges in generating accurate outputs due to limitations in available data and the generally simple models used to quantify the opportunity cost from water exposure. They often fail to adequately consider risks associated with events like floods or droughts and lack sufficient insight into a company's risk mitigation strategies for water quantity and quality issues (Bonnafous et al., 2017). Furthermore, there is a lack of clarity regarding how reputational and regulatory risks can manifest and impact a company's financial standing. These issues are common across various water valuation tools (Xu et al., 2021).

CHARACTERISTICS OF WATER TOOLS, DATASETS & RESOURCES

Tool/Dataset/Resource	Best Suited For	Type of Tool	Evaluates Corporate Response to Risk	Corporate Locations Embedded in Tool	Financial Data in Output	Price
CDP Corporate Water Database	Equities	Questionnaire & Dataset	●	◐	◐	Free $*
Ceres Aqua Gauge™	Equities	Questionnaire	●	○	○	Free
Ceres Feeding Ourselves Thirsty	Equities	Dataset	●	◐	○	Free
Earth Genome	Private Equity	Maps & Datasets, Services	◐	○	◐	Free $*
Ecolab Water Risk Monetizer	Equities	Model & Datasets	◐	○	●	Free
Equarius waterBeta	Equities	Financial Model, Services	◐	◐	●	$*
NCFA Bank Drought Stress Test Tool	Bank Credit Portfolios	Scenario Models, Datasets	○	○	●	Free
NCFA Corporate Bonds Water Credit Risk Tool	Corporate Bonds	Model & Datasets	○	◐	●	Free
Oxford Earth Observation (OxEO)	Equities	Model & Datasets	○	◐	◐	$*
Princeton Climate Institute	Equities & Bonds	Model & Datasets	○	○	◐	Free $*
Sustainable Water Management Profiling	Municipal Bonds	Assessment Standard	●	n/a**	n/a**	Free
WRI Aqueduct™	Equities	Maps & Datasets, Services	○	◐***	○	Free $*
WWF Water Risk Filter	Equities	Maps & Datasets, Models	◐	○	◐	Free

● Has information ◐ Some information ○ No information

Figure 2.1: Financial tools to compute the impact of water risk in stocks, bonds, corporate debt, and investment portfolios (Source. Ceres, 2021).

2.3 Machine Learning Tools to Uncover Water-Based Risk Pricing and Market Performance

In spite of the availability of valuation tools, access to climate data, and intricate models of climate change non-linear behavior (Alonso-Robisco et al., 2022), substantial mathematical challenges remain when assessing climate impact on corporate activities and the broader economy. In part the limitations are due to the need for advanced statistical tools to their increasing complexity of the datasets, incomplete information, and the lack of microeconomic (company level) data (López de Prado et al., 2019).

These limitations are compounded by the current corporate disclosure approaches lacking financial depth, resulting in largely physical water risk disclosures (Josset and Larrauri, 2021). This poses substantial challenges for both corporate water risk management and economic policy. Financial risk exposures extend beyond sustainability, a recognized issue in ESG scholarship. This limitation hampers investors ability to accurately assess risk and return, and corporate risk managers access to quantitative insights for risk transfer, internal risk management, and climate transition cost and investment decisions (Alshehhi et al., 2018; Gangi et al., 2020; Khaled et al., 2021; Chan et al., 2022; Ortas et al., 2019; Zhou et al., 2021).

Machine learning methods have gained prominence in the realm of climate finance (Rolnick et al. 2022; Kumar et al. 2022). In sustainable finance, machine learning approaches leverage diverse datasets encompassing accounting metrics, physical risk attributes, and market performance indicators to establish relationships between relevant independent variables (Bolton et al, 2016; Alareeni et al., 2020; Lewandowski, 2017; Busch et al., 2020). These relationships enable the creation of models that predict or impute outcome variables, addressing the challenges of limited data disclosure. The convergence of financial data with climate machine learning (ML) models represents a promising frontier, building upon earlier research. For example, Raza et al. (2022) explored the reliability of Environmental, Social, and Governance (ESG) scores for asset managers, by utilizing ML tools to assess how financial data influences ESG scores for non-financial public companies in the USA, UK, and Germany (2008 to 2020). Plakandaras et al.(2018) harnessed ML techniques to model climate change as a geopolitical risk, predicting its impact on various financial assets. Rolnick et al. (2022) illustrated the substantial influence of deep learning in climate investments, facilitating the selection of low carbon-emitting companies for portfolios and optimizing investment timing. Nguyen et al. (2021) leveraged machine learning to refine the forecast of corporate carbon emissions, a pivotal element in investors' risk evaluations, while establishing links to financial performance metrics.

2.4 Knowledge Gaps and Dissertation Structure

Academic literature has shown that financial materiality and capital markets risk have been addressed from a theoretical input-output, resource competition, and theoretical stakeholder perspective. Yet, there is limited empirical evidence on the relationship between water intensity and financial metrics, either using operational accounting indicators or from a corporate financial performance perspective in the capital markets. This information is important to help understand (1) whether companies are rewarded for taking action on their risk exposures and better water stewardship, (2) whether capital markets-based water risk assessment can serve to incentivize sustainable corporate behavior, and (3) which metrics should be used in financial disclosures to indicate water sustainability under new recommended SEC (Securities and Exchange Commission) policies, or TCFD (Task Force on Climate-Related Financial Disclosures) regulation.

The literature gap has informed our hypothesis that quantitative empirical relationships can be constructed between water use intensity and corporate financial or market performance to understand the material risks experienced by companies, and to facilitate corporate decision-making for economic and societal benefit. In turn, this work can lead to empirically tested theoretical frameworks for further academic inquiry. Our approach to testing this hypothesis is three-fold:

Objective 1. Development of a methodology on the use of causal inference to investigate how water use intensities are related to financial performance metrics of corporations. This causal inference is based on binary treatment variables (high-low water intensity companies), based on water use data as a continuous variable. The machine learning method was used to evaluate the relationship between corporate financial fundamentals and water intensities standardized by sales, operating profit and investment in fixed assets, thus bridging the gap between the financial and environmental assets. The rationale for standardization is that water is used for industrial production, resulting in revenue generation and operating profit, and thus allows for company-to-company comparison. The fixed asset denominator is an indicator of how efficiently a facility or plant uses water for production and provides a benchmark for the return on fixed assets. The limitation of this objective is that very few companies (e.g., 20% of S&P 500-listed companies) disclose water-related information, hence, a machine learning based imputation model will need to be developed.

Objective 2. Testing and application of machine learning methods to impute missing water risk data for public companies that are not disclosing any information related to their climate-water related exposures. The input metrics are derived from widely available corporate accounting data, and imputed water intensity metrics are tested using known corporate disclosures. The intent is to extract the financial metrics that are most predictive for water intensity indicators, and to use these metrics to impute missing values across industry sectors. Despite the broad availability of financial metrics from quarterly disclosures, missing data limits our capacity to explore long term trends for water intensity and to develop robust panel data for temporally dynamic market impact analysis from water risks. Hence, imputation models will be tested for financial metrics, and regression models will be used for market impact analysis.

Objective 3. Development of multiple regression tools to assess the impact of water intensity on firm performance indicators in the market, while controlling for various confounding factors such as size, financial leverage, beta, and other indicators. To evaluate the overall influence of water intensity on market performance, confounding variables will be derived from the Barra risk model, extensively employed for predicting corporate performance based on a wide array of financial indicators. Outcome variables include share price return, return on assets (ROA) and return on equity (ROE), as well as Tobin's Q, a proxy for long term value of the firm. Overall, our approach and results are consistent with the interpretation that investors are seeking compensation for the potential impacts of water risk in their investment decisions. The regressions will be tested for two time periods, comprising before and after promulgation of the Task Force for Climate-Related Financial Disclosures (TCFD), a financial regulation that compels companies to disclose their climate risks. The investigation was structured around the primary research questions, following a three-step process outlined in Figure 2.2.

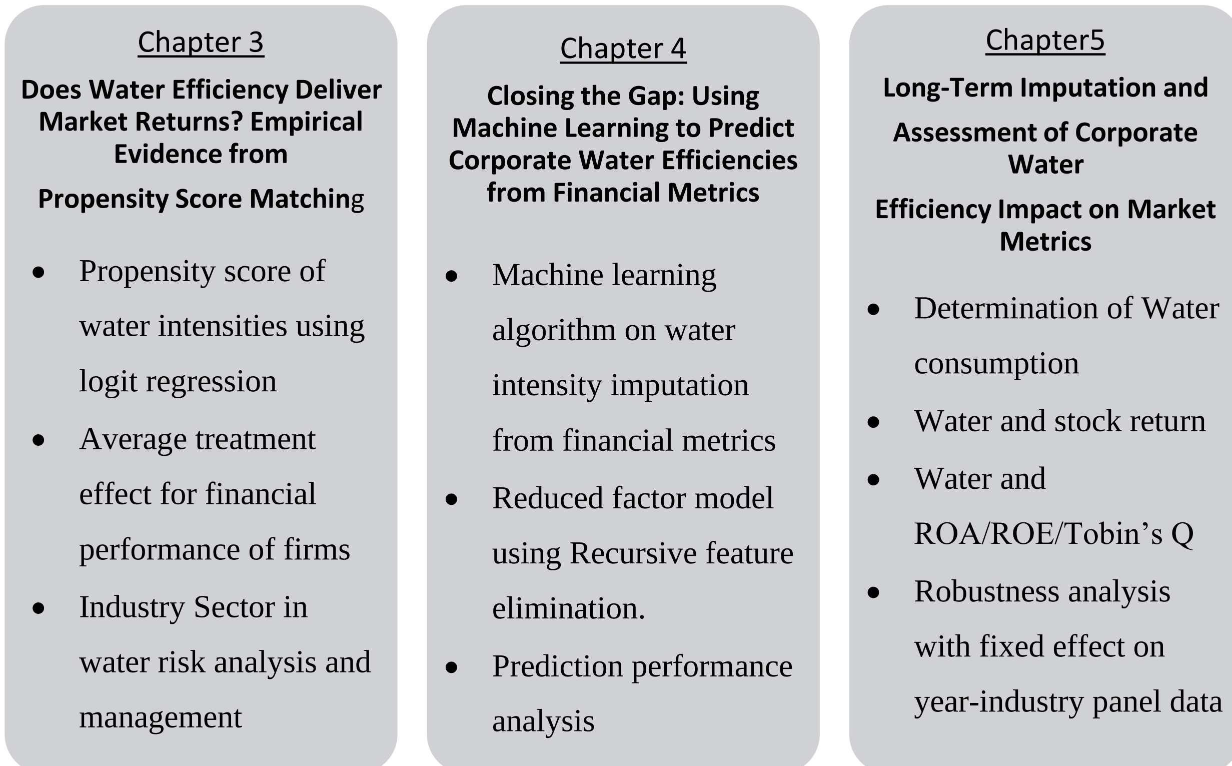


Figure 2.2: Dissertation Organization

This dissertation explores quantifying the effect of water intensity indicators on corporate financial performance in Chapter 3. Chapter 4 proposes a methodology for the development of econometric models to predict water intensity metrics based on machine learning models. Then in Chapter 5, a multiple regression analysis of water impact on US stock return and other performance with 10-year panel data is carried out for internal decision-making and externally facing investor needs. Chapter 6 concludes and discusses future research stemming from this dissertation.

Chapter 3 Does Corporate Water Efficiency Deliver Market Returns? Empirical Evidence from Propensity Score Matching

This chapter is submitted to the International Journal *Finance Research Letter.*

3.1 Introduction

Unpredictable water availability leads to increased water competition, resulting in social and economic conflict. The natural environment is a critical commodity input for sustained operational performance of firms, as water constraints limit the capacity to maintain a competitive advantage (Hart, 1995; Hart and Dowell, 2011; Christ and Burritt, 2015). Current business operations are already witnessing substantial financial impacts due to water resource challenges and the resulting ecosystem degradation. Project risks stemming from environmental, social, health, and safety concerns have demonstrated increased operating costs and amplified investor risk (e.g., Zhou et al., 2018; CDP, 2023 Daniel and Sojamo, 2012; Christ and Burritt, 2017, Burritt et al., 2016). At the same time, a growing number of investors is recognizing the materiality of climate-related financial risks across their investment portfolios and is demanding information to help them evaluate these risks (WEF, 2020; SEC,2022). As a result, an increasing number of firms is disclosing its water use in financial reporting (Yu et al., 2020; Zhang et al., 2021), and the Bloomberg Terminal is tracking water intensity metrics. Academic literature has explored water disclosure from economic, firm strategy, and accounting perspectives. Kuo et al. (2021) showed that firms with more effective risk management strategies have been shown to be more willing to conduct social corporate responsibility (CSR) strategies, including natural resource management. This paper tests the hypothesis that disclosing firms with better water resource management indicators are rewarded by the market.

The reasoning behind this is rooted in financial theory, suggesting that risk premiums stem from three primary sources: compensation for shouldering risk, behavioral biases influenced by investor preferences, and market constraints such as limited liquidity (Cornell, 2021). The premise is that if investors care about corporate management of competitive and irreplaceable resources like water, these risks can be priced in expected stock returns or other market performance metrics. Empirical research on CSR disclosures (Ting, 2021) has shown significant relationships with firm profitability (e.g. ROA), and corporate value (e.g. Tobin's Q) for small firms, but not for large companies. Other findings indicate a positive, but weak relationship between environmental and financial performance (e.g. Griffin and Mahon, 1997; USEPA, 2000; Williams et al., 2001; Orlitzky et al., 2001; Orlitzky et al., 2003), and a positive link between environmental and the market value of companies (Dowell et al., 2000; Nagy et al., 2016). These results, however, tend to be based on literature reviews or corporate strategy (Alshehhi et al., 2018; Gangi et al., 2020; Khaled et al., 2021; Chan et al, 2022), contributing to limited guidance and standards for corporate disclosures on the choice of metrics for corporate water impact and risk to financial performance (Hart and Milstein, 2003; Larson et al., 2012).

Business water footprint accounting, the use of water for a unit production of goods, is considered most commonly as an indicator of water stress for production and consumption of water resources in operations (Wang et al., 2021), but the use of this metric in a financial risk context is limited (Christ and Burritt, 2017). Moreover, Hain et al. (2022) and Bingler et al. (2022) showed that different physical metrics can lead to heterogenous results and cause problems when testing whether financial markets price physical risks or CSR actions. Hence, the choice of metric to quantify water impact on corporate financial performance and to support decision-making in firm disclosures must be carefully considered (Unit, 2015; Snijder, 2017; Arnold et al., 2020). Guidance from the literature on climate risk impacts and firm performance indicates that carbon intensity relative to sales serves as a useful proxy for climate transition risk (Gurvich and Creamer, 2022). Similar metrics for water are being reported on the Bloomberg terminal.

This paper makes two major contributions to literature. First, it shows that water intensity of firms has significant impacts on Tobin's Q, alpha and ROA, but is not significantly priced in share performance. The closest related reference is Pan and Qiu (2022) who showed that climate-induced floods impacted firm performance particularly based on ROA and Tobin's Q metrics for firms with more tangible asset investment. Relatedly, Zhang (2022) documented that carbon intensity is priced in stock returns, and Acharya et al. (2022) showed that physical climate risk from heat (related to droughts) affected a stock price premium. Second, it demonstrates that intra-sector firms cannot necessarily be compared in terms of water risk impacts, as differences in firm fundamentals need to be considered. Industry classifications (e.g. NAICS, GICS) reflect production activities (Phillips and Ormsby, 2016), not operational financials, and thus relational inference with financial accounting performance should not be implied (Krishnan and Press, 2003).

3.2 Data and Metrics

Water intensity indicators were standardized to sales (WIPS), operating margins (WIPE), and fixed asset investments (WIPPE), in accordance with Bloomberg reporting metrics. The firm universe is based on S&P 500 index components exported from Bloomberg environmental and financial datasets between 2017 and 2019. The cutoff date is based on delayed availability of information, the dearth of corporate water disclosures before 2017, and to avoid market volatility impacts from the Covid-19 outbreak.

Since the PSM method is binary, two cohorts were defined. Based on histogram analysis, the treated group comprised 30% of companies with low water intensities and the untreated group as the remaining 70% of firms with high water intensities. This allowed for comparison between leader and laggard companies (Table 3.1). Similar 30:70 splits have been used in firm analysis of carbon emissions (Görgen, 2019). Essential control variables were selected from the Barra Risk Factor model after correlation analysis (Bender, 2013; Giese et al, 2016), and after recursive feature elimination which allowed for removal of the least sensitive variables (Gunduz, 2021). The final set comprises inventory turnover ratio, fixed asset turnover, size, financial leverage, dividend yield, and volume. These variables are similar to those used by Bolton and Kacperczyk (2021) using firm-level assessment of carbon emissions impact on share price return, and by Zhang (2022) to explain the impact of carbon intensity on country GDP. In addition to financial confounders, there are dummy variables for disclosure year and GICS industry sector classification.

Table 3.1. Mean firm-year water intensities classified by industry.

Sector	WIPS (n = 302)		WIPE (n = 350)		WIPPE (n = 344)	
	High WI	Low WI	High WI	Low WI	High WI	Low WI
Communication Services	0.245	0.085	1.635	-	0.842	0.074
Consumer Discretionary	0.700	0.020	5.501	0.173	2.278	0.177
Consumer Staples	0.972	-	7.311	0.378	4.048	-
Energy	2.541	0.005	29.322	0.014	2.530	0.045
Financials	-	0.024	-	0.051	0.764	0.236
Health Care	0.367	0.024	3.485	0.248	1.363	0.176
Industrials	0.208	0.060	1.700	0.439	1.022	0.334
Information Technology	0.363	0.040	2.287	0.216	1.616	0.209
Materials	7.738	-	50.742	-	13.398	-
Real Estate	0.324	-	2.078	-	-	0.153
Utilities	94.497	-	466.044	-	56.029	0.252

Financial performance metrics selected as outcome variables include share price return, volatility, return on equity (ROE), cash flow growth, alpha and Tobin's Q. These indicators have been widely used to assess the financial performance of firms based on environmental risk or natural resource efficiency. For example, Cohen (1995) studied the relationship between pollution and share price return and volatility to demonstrate that the environmental leader portfolio equaled or exceeded that of the environmental laggards for S&P 500 companies during the period 1987-1990. Konar and Cohen (2001) found a positive relationship between environmental performance and Tobin's Q. Nagy et al. (2016) analyzed the impact of ESG ratings performance on alpha as an indicator, relative to unrated firms.

Table 3.2. Descriptive statistics

Variables	N	Mean	Std. Dev.	Min	Median	Max
LOG_WIPS	681	-0.806	2.825	-9.938	-1.352	7.669
LOG_WIPE	621	1.198	2.816	-8.184	0.835	10.068
LOG_WIPPE	675	0.252	2.216	-8.188	-0.045	7.524
Volume	1475	2.88E+08	5.54E+08	3.41E+04	1.52E+08	9.19E+09
Financial Leverage	1489	6.760	49.176	1.108	2.885	1813.000
Inventory Turnover Ratio	1024	24.469	126.045	0.463	5.717	2214.000
Dividend Yield	1198	2.369	1.443	0.020	2.148	14.257
Size	1480	10.164	1.008	7.820	9.972	13.902
Fixed Asset Turnover Ratio	1357	8.267	12.944	0.148	5.280	145.808
Share Price Return Rate	1460	0.153	0.293	-0.576	0.144	1.484
Volatility	1450	24.879	7.911	10.851	23.374	72.403
Cash Flow Growth	1494	59.654	1126.480	-289.965	8.478	41800.000
Return On Equity (ROE)	1486	27.405	60.404	-71.709	16.394	1048.622
Alpha	1426	-1.314	61.248	-372.048	-4.475	727.485
Tobin's Q	1482	2.663	2.137	0.806	1.980	23.563
Communication Services	1515	0.051	0.221	0	0	1
Consumer Discretionary	1515	0.121	0.326	0	0	1
Consumer Staples	1515	0.063	0.244	0	0	1
Energy	1515	0.050	0.217	0	0	1
Financials	1515	0.129	0.335	0	0	1
Health Care	1515	0.125	0.331	0	0	1
Industrials	1515	0.145	0.352	0	0	1
Information Technology	1515	0.145	0.352	0	0	1
Materials	1515	0.055	0.229	0	0	1
Real Estate	1515	0.061	0.240	0	0	1
Year_2017	1515	0.333	0.472	0	0	1
Year_2018	1515	0.333	0.472	0	0	1
Year_2019	1515	0.333	0.472	0	0	1

3.3 Statistical Methods

The propensity score matching (PSM) method was applied to estimate the causal relationship between water intensity indicators and market performance metrics. This method has seen recent applications in finance research (e.g. Wang ,2022; Leong ,2021; Nazarova, 2022; Nekhili et al, 2021; Reber et al, 2022; Darnall et al, 2022; Mu et al, 2023) and has several advantages over Ordinary Least Square (OLS) regression, including elimination or reduction of endogeneity effects and improved randomization of variables to test the treatment effect (e.g. Mu et al., 2006; Varvara et al., 2022; Kim and Park). In this work, the PSM method provides the average treatment effect on the treated (ATT) population to inform how water use intensity affect financial market performance metrics when both the treatment group and the control group are considered. Multiple propensity score matching algorithms were used to address the self-selection problem and to demonstrate robustness (Smith and Todd, 2005).

3.4 Empirical Results

The logit regression (LR) results are shown in Table 3.3. The baseline results of positive values and significance of fixed asset turnover for all water intensity metrics indicate that firms with higher turnover ratios are more likely to exhibit better water use performance relative to their sales. From a water intensity per EBIT (WIPE) perspective, the size indicates that larger firms perform better. Dividend yield and financial leverage coefficients are negative for WIPE and WIPS, respectively, indicating lower profitability and debt for firms with elevated water intensities relative to operating margins and sales. These effects are not consistent across all sectors and years.

The estimated propensity scores were then used in the matching algorithms to quantify the impact of the treatment effects of firms exhibiting low water use intensity compared to the control group. Empirical analysis of the impact of low water intensity on financial market performance metrics using the three sets of water intensity indicators on six market metrics show that impacts on ROE, Tobin's Q and alpha are significant (Table 3.4). Lower water intensities relative to sales have a negative effect on ROE, while those standardized to operating profit positively impact ROE. Positive and significant ATT results on ROE suggest a significant beneficial effect the more efficient a company is with using water as an input for profit generation. The effect is reversed with respect to sales (WIPS), which indicates that industry sectors whose production and revenue generation relies heavily on water resources, such as energy, utilities and industrials, are negatively impacted by lower water use.

Table 3.3. Logistic estimates of propensity scores for water intensities

	WIPS		WIPE		WIPPE	
Volume	3.89E-10		-6.64E-11		3.13E-10	*
Financial Leverage	-0.146	*	-0.015		-0.069	
Inventory Turnover	-0.002		-0.002		-0.001	
Dividend Yield	0.102		-0.187	*	0.006	
Size	0.065		0.483	***	0.010	
Fix Asset Turnover Ratio	0.281	***	0.039	***	0.025	**
Communication Services	0.325				1.836	*
Consumer Discretionary	-0.373		-0.631		0.679	
Consumer Staples			-2.743	***		
Energy	-0.098		-1.439	**	0.683	
Financials					3.019	*
Health Care	0.220		-0.310		0.577	
Industrials	-0.920	*	-1.540	***	-0.889	
Information Technology					0.478	
Materials						
Year_2017	-0.740	*			-0.776	**
Year_2018	-0.507				-0.597	*
Year_2019						
LR chi2(12)	117.920		87.720		37.440	
Prob > chi2	0		0		0.001	
Log likelihood	-129.098		-162.723		-166.645	
Pseudo R2	0.314		0.212		0.101	
Observations	302		350		344	

Note: Constant terms are included but not reported. Robust standard errors in parenthesis. “***”, “**” and “*” refer to two-tailed significance at the 1%, 5% and 10% level, respectively.

While no prior research on the relationship between water intensity and ROE is available, a positive relationship between environmental performance or ESG improvement and ROE has been shown (Buallay, 2019; Alareeni and Hamdan, 2020; Nguyen et al., 2022). Alareeni et al.(2020) showed that environmental and CSR disclosure are negatively correlated with both ROA and ROE. While negative correlations with profitability have been interpreted as the result of higher financial costs and lower operational and financial performance associated with environmental strategy implementation, the positive ATE of WIPE on ROE indicates that more efficient water use benefits firm profitability. While no significant share price return benefit has been seen yet in response to lower water intensities, the ROE benefit serves as interpretive guidance for future estimates of share price growth rate and that of the firm's dividends.

Table 3.4. Summary of PSM analyses on the impact of water intensity on financial performance

			Stock Price Return	Volatility	Cash Flow Growth	ROE	Alpha	Tobin's Q
WIPS	Nearest Neighbor	N(1)	2.335%	1.033	4.648	-10.068*	5.917	0.442*
		N(3)	-0.131%	0.807	5.707	-10.086*	6.768	0.393*
	Kernel	EPAN(0.02)	0.987%	0.571	6.342	-9.282*	6.199	0.443
		Normal	2.241%	1.006	2.989	-8.938*	9.809	0.556*
WIPE	Nearest Neighbor	N(1)	1.479%	0.432	-7.177	22.817**	4.305	0.574**
		N(3)	2.290%	1.366	-5.122	15.247*	4.319	0.374
	Kernel	EPAN(0.02)	1.095%	0.594	-7.344	13.512	6.558	0.380
		EPAN(0.025)	3.349%	0.511	-8.359	14.282	5.22	0.401*
WIPP	Nearest Neighbor	N(1)	3.568%	1.477	9.964	-1.281	15.859***	0.229
		N(3)	2.211%	0.406	4.101	2.935	11.463*	0.389
	Kernel	EPAN(0.02)	-0.394%	1.221	1.946	-3.348	9.376*	0.223
		EPAN(0.025)	-1.302%	0.753	2.589	3.211	9.15	0.292
		Normal	-2.026%	1.089	2.298	1.136	9.599*	0.252

Notes: For the nearest neighbor matching, using the caliper=0.025 and for 3-nearest neighbor matching, using caliper=0.02 for three indicators for comparison. The Epanechinikov kernel bandwidth uses 0.02 and 0.025 for kernel matching. The t-statistics are reported in parentheses. "***", "**" and "*" refer to two-tailed significance at the 1%, 5% and 10% level, respectively.

The impact of WIPS and WIPE on Tobin's Q are positive and significant in most matching algorithms, indicating that lower water intensity and operational efficiency results in higher firm valuations. Pan and Qiu (2022) showed that climate-induced floods impacted firm performance particularly based on ROA and Tobin's Q metrics for firms with more tangible asset investment (PP&E). Positive effects on firm valuation have been reported for ESG performance and certification (Wong et al., 2021, Konar and Cohen, 2001). Nguyen et al. (2022) found that the magnitude of the influence of the ESG practice on Tobin's Q is significantly higher than that of paired ESG-ROA and ESG-ROE effects. Alareeni and Hamdan (2020) showed that environmental and CSR disclosures are positively related to Tobin's Q, which may infer that good water resource governance benefits firm value.

The water intensity normalized by fixed asset investment (WIPPE) only exhibits significantly positive effects on the firm's alpha returns, based on most matching algorithms. Since alpha is a risk factor, the positive effect of water efficiency on excess returns may indicate that the markets price in the lower risk of assets becoming less productive, and returns less volatile, under water resource constraints. Similar results were observed by Arnold et al. (2020) for firms with high fixed asset investments such as energy utilities. Kazdin et al. (2021) showed that companies with low carbon emission intensities have high excess alpha returns, which may reflect more efficient operations. Madhavan et al. (2021) discovered positive correlations between alphas and factor ESG scores. The results are robust given their significance across multiple matching methods. Fixed effect regression of matching groups (data not shown) indicated similar significance of paired relationships.

3.5 Cross-Sector Pairs in Matching Treatment Effects

A general assumption in sustainability accounting, by using production metrics such as water footprints as a water stress measure, is that water security, dependency and operational risks can be classified by industry sector or subsector (CDP, 2016; Ceres, 2015; SASB, 2015; Wang et al., 2021).The assumption of intra-sector performance as a benchmark was tested using the proposed water intensity indicators. By analyzing the nearest neighbor matching pairs, the treated-untreated matching pairs for the three water intensity indicators were analyzed by sector distribution (exemplified for WIPS in Figure 3.1). When corrected for financial fundamentals and sector biases, water intensity factor matching does not strictly follow NAICS production classifications. Information technology, health care and consumer discretionary firms dominate matching pairs for all water intensity effects, with approximately one third of companies matching within sector. The paired companies in the control group are in multiple industry sectors. Since PSM compares companies based on water intensity metrics but matches them based on similarities in their (financially-focused) propensity scores, cross-sectoral panel comparisons are less biased than sector-based sampling. For example, Amgen Inc (Health Care) and Hanesbrands (Consumer Discretionary) are a treated-untreated WIPS match because of similar financials. On the other hand, Microchip Technology Inc and HP Enterprises are a WIPS match within the IT industry. These results have implications for sustainability accounting and indexing strategies based on water risk exposures (Larson et al., 2012; Adriaens et al., 2014). According to Zhang (2022), employing cross-sectional stock return regression analysis, significant cross-country, cross-firm, and cross-time impacts of carbon risk pricing were observed.

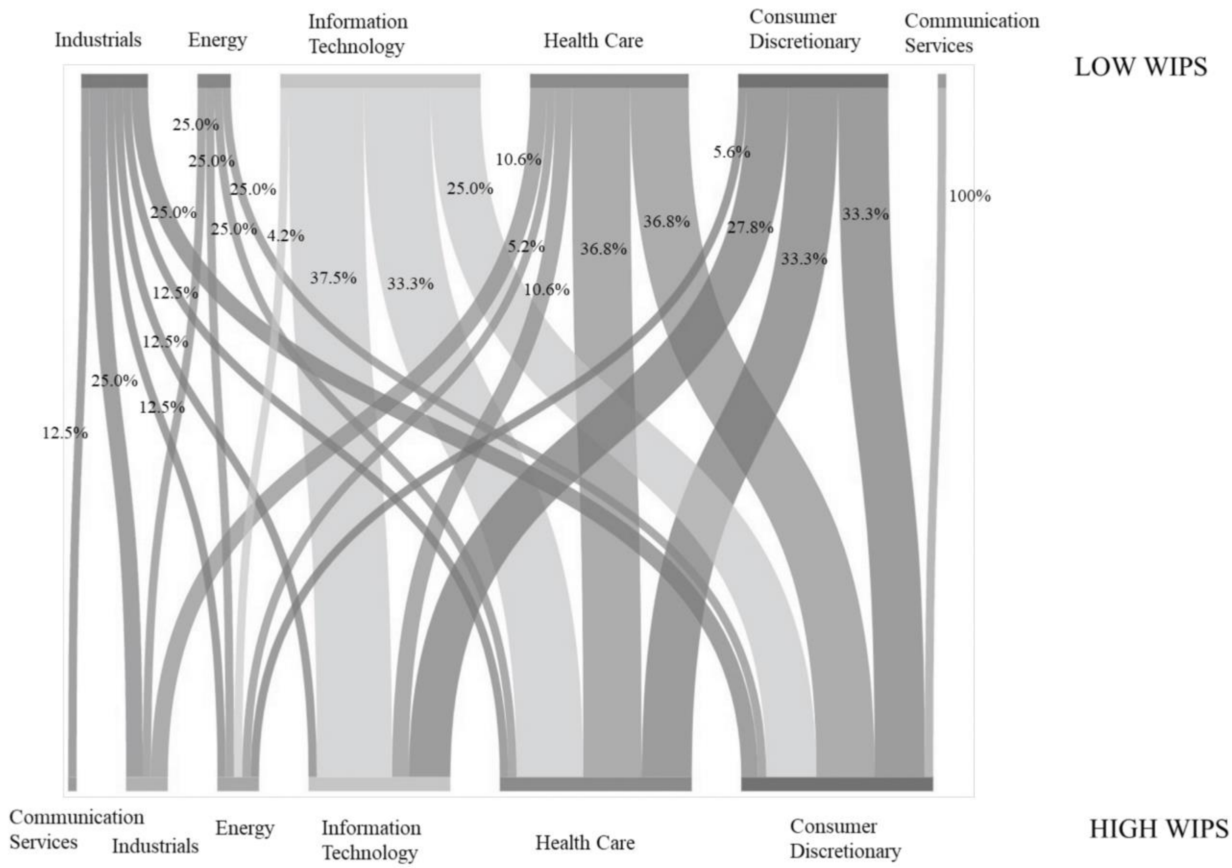


Figure 3.1: Paired industry sector composition for propensity score matching analysis of water Intensity per Sales (WIPS), after correction for confounding financial variables.

3.6 Conclusion

This paper sought to test the hypothesis that water use intensity is priced in the market through share price returns, similar to what has been observed with carbon intensity metrics. No discounts or penalties were observed. However, while water intensity indicators based on sales and operating margin impacted ROE and Tobin's Q, the indicator based on investment in fixed assets only had significant impact on alpha. The positive impact on ROE may portend future share price behaviors in response to water intensity management. Further, it posits that industry sector classification is not a useful benchmark for financial water intensity performance, given differences in fundamentals. While these findings may have been impacted by data distribution bias resulting from the pooled binary treatments of limited disclosures, the size of the dataset is similar to other studies (Zheng et al., 2022). Future work should explore the use of machine learning to impute water intensity metrics from financial fundamentals for non-disclosing firms to enable analysis on expanded datasets.

Chapter 4 Machine Learning to Predict Corporate Water Efficiencies from Financial Accounting Metrics

4.1 Introduction

Climate change is an economically disruptive force for companies (CDP, 2016; Daniel & Sojamo, 2012; Christ et al., 2017; Burritt et al., 2016). From the analysis of the largest 500 global companies, it was reported that the potential financial implications from climate change-related impacts were nearly a trillion dollars (Ceres, 2019). Water scarcity and the uncertainty related to availability are key issues driving the need for investment in climate resilience. To address the needs of a growing world population of $9.7 billion, water demands are expected to increase by 55% by 2050, straining industrial operations, affecting supply chain risks, resulting in increasing commodity price volatility, and decreasing supply reliability. The World Bank approximated that water scarcity could potentially lead to regions losing up to 6% of their GDP. Based on the natural resource-based view of the firm, the natural environment is a critical commodity input for sustained operational performance of firms, as water constraints limit the capacity to maintain a competitive advantage (Hart et al. , 1995; Hart & Dowell, 2011; Christ & Burritt, 2015). Businesses are currently grappling with significant financial implications stemming from the competition for water resources and the resultant degradation of ecosystems. These risks are at multiple scales, with impacts from the corporate level to industry and sector scale, impacting systemic risk. An increasing cohort of investors is acknowledging the materiality of climate-related financial risks within their investment portfolios and is seeking information to effectively evaluate and quantify these risks. (Moody's, 2019; WEF, 2020).

Despite the growing awareness of natural resources scarcity and the importance of sustainable environmental management, many companies do not disclose the impacts of climate-related water risk or their risk management strategies, thus impairing the opportunity to hedge or mitigate these risks during climate transitioning (Larson et al., 2012; Sokolov et al. , 2021; Kotsantonis et al. 2019). To understand the exposure of companies to climate water risks, analysts rely on raw data from voluntary environmental, social and governance (ESG) risk disclosures, sustainability reports, and compliance reports under the task force on climate related financial disclosures (TCFD). Since the majority of corporate directors (Pinney et al., 2019) still do not believe that disclosures on sustainable governance and operations are important in helping investors make informed decisions on climate risk exposures, the incorporation of external data sources for additional validation is necessary. From a public policy perspective, the lack of standardization of water risk reporting, combined with the data gaps leads to incomplete assessments, biases, and potential greenwashing of risks (Kotsantonis et al. 2019). At the same time, financial policy increasingly requires more stringent due diligence on financial risk exposures to climate change and its impacts, including water-related risks.

This data gap in support of the fiduciary duties of corporate and investment managers presents new opportunities for innovative data fusion and imputation approaches to link financial and physical risks from water through machine learning models (Tian et al., 2023a; 2023b). The monitoring of highly granular and temporal data will be necessary for water risk pricing, disclosure requirements, and design of risk management strategies (WWF, 2022). Economically speaking, water-related natural disasters remain the leading cause of loss of life and property (UN, 2021), and are the primary risk in insurance portfolios (Marchal et al., 2023). Climate water risk information, especially financially-material water data disclosures, call for standardized frameworks, expanded data coverage, and improved data quality to enhance assessment and decision-making. Current approaches to water risk reporting and ratings are guided by various frameworks such as the Global Reporting Initiative (GRI), the Sustainable Accounting Standards Board (SASB), the Task Force on Climate-Related Financial Disclosures (TCFD), and CDP's Water Disclosure Initiative. However, these frameworks are limited both in terms of appropriately capturing water risk exposure and corporate response to mitigate this risk. Moreover, these assessments often lean towards semi-quantitative approaches and, with the exception of the CDP Global Water Reports, frequently do not establish a direct connection between physical water risk and the financial risks within corporate operations.

The impact of climate water risk is a more complex issue than carbon, mainly because water is local and risk exposures manifest themselves in the context of supply chains, logistics, floods and as an input in manufacturing operations (Larson et al., 2012; Tian et al., 2023b). Water availability fluctuates daily, while groundwater and climate patterns undergo changes over decades. Water withdrawals or contamination at specific sites have far-reaching impacts across vast watersheds and global product footprints. These variations, compounded by supply chain complexities and climate signals, could prompt resilience investments, or worsen scarcity. (Davis et al., 2021; Lawrence et al., 2020; Josset et al., 2021). These attributes exhibit substantial variation between industrial sectors and across types of water risks, underscoring their site-specific nature (Alcamo et al., 2000; WWF, 2022). Moreover, existing disclosure methods lack financial depth, leading to water data that holds limited significance beyond the realm of physical risks (Josset and Larrauri, 2021). This raises many challenges from a corporate water risk management and economic policy perspective, as financial risk exposures transcend sustainability imperatives, a recognized issue among ESG scholars. For investors, this leads to an inability to accurately evaluate risk and return implications of investments, and for corporate risk managers, the lack of quantitative knowledge impacts decisions on risk transfer, internal risk management and climate transitioning costs (Ortas et al., 2019; Zhou et al. 2021).

Corporate water intensities have been used as financial proxies for climate transition risk (e.g. Tian et al., 2021; 2023a), as they relate water intensities in an operational and financial asset risk context. This information is generally not disclosed in financial or sustainability accounting reports and is difficult for investors or regulators to assess, and for risk managers to address, as required by the Task Force for Climate-Related Financial Disclosures (e.g. Busco et al., 2020; Demaria & Rigot, 2021). While water intensities have not been used in financial reporting, a corollary exists with carbon intensities which have been used in regression models to assess impacts on corporate efficiency, profitability and valuation (Andersson et al., 2016; Cheema-Fox et al., 2023; Harris et al. , 2015; Hao et al., 2018; Heaps et al., 2014; Matsumura et al., 2014; Gurvich et al., 2022; Alex et al., 2022; Shameek et al., 2001). However, the development of econometric models to predict carbon- or water-based financial indicators from corporate fundamentals has not been attempted, despite the need to link climate change with the financial system that is impacted by carbon and water risks (Monasterolo et al. , 2020).

Machine learning methods have been used to develop quantitative relationships for a wide range of financial applications in the context of climate finance (Rolnick et al., 2022; Kumar et al., 2022). The basic premise of machine learning in sustainable finance is to employ datasets reflecting accounting or risk and return values to train relationships between variables of interest to develop models that can be used to impute or predict outcome variables where limited data disclosure is available. For example, Nguyen et al. (2021) use machine learning to improve the prediction of corporate carbon emissions for risk analyses by investors. Established calculation methods such as environmental input-output (I/O) models, process analysis or hybrid approaches require intensive data up to the level of emission sources, activities, raw materials, and emission factors, most of which are not publicly available (Wiedmann et al. , 2009). Additionally, the (un)reliability of self-reported emissions, especially in the absence of independent audits, is a complex issue, heightened by firms' strong motives to avoid environmental controversies (OECD, 2020).

Although there's rising demand from investors and regulators, research on estimating corporate carbon emissions or water use methodologies is still in its early stages. So far, financial data providers such as MSCI ESG Metrics or Thomson Reuters ESG provide estimated data for non-disclosure firms. Traditional estimation models often rely on extrapolation from historical data, production records, or peer companies. Subsequently, researchers have adopted advanced regression techniques, such as Ordinary Least Squares (OLS) or Gamma Generalized Linear Model (GLM), for empirical analysis (CDP, 2016; Goldhammer et al., 2017; Griffin et al. 2017). Empirical models typically utilize either manually collected predictors like industry and location-specific revenue (e.g., CDP) or focus on specific index-based sample universes (e.g. S&P 500 US firms; Griffin et al., 2017), or to a specific industry (EU chemical, engineering and industrial firms; Goldhammer et al., 2017).

Due to these limitations, the need for more flexible and robust models that can predict corporate carbon emissions and water risk exposures on a broader coverage of firms remains elusive, restricting disclosures to investors and corporations for management decision-making (Sun & Scanlon, 2019). Machine learning applications and deep learning have allowed for uncovering trends between physical risk exposures and corporate financial fundamentals. Since financial data are reported on a quarterly basis, while water use data are scarcer, ML models open the opportunity to predict water risk from financial performance metrics. Because research has shown that ESG data and financial metrics are positively correlated (Sharma et al. , 2022), the identification of corporate financial variables that affect ESG scores has become an attractive area of research (Giesy et al., 2019; D'Amato et al., 2021). In corporate financial accounting, balance sheet and income statement data have been used as predictors of carbon emissions and ESG performance. For example, CDP estimated corporate carbon emissions from financial accounting metrics, by using a linear regression model. Chen et al. (2020) suggested a machine learning method to measure a company's ESG risk premium and alpha, integrating ESG and corporate financial data. The results showed that alternative datasets capture ESG premiums better than traditional financial indicators, even when considering that ESG metrics are variable across data vendors (Henriksson et al., 2019).

Given these knowledge gaps, and the lack of corporate water disclosures, this chapter explores whether ubiquitously available financial accounting metrics can be used as the basis for econometric models to predict water intensity indicators of growth companies across eleven industry sectors listed on the S&P 500 index. The hypothesis is that, since water intensity is an efficiency measure of how much water a company uses relative to sales (revenue), to operating income (EBIT; earnings before interest and taxes), and to fixed asset investment (PP&E; plant, property, and equipment), it may be possible to predict these indicators from corporate fundamentals. These metrics provide insight in how efficiently a company is able to generate revenue or profit from its water use, how water intensive a physical asset or plant is, or whether a production facility is at risk of becoming stranded due to insufficient water resources for production. The use of linear regression, Lasso, Random Forest, and Adaptive boosting models was used to predict water intensity indicators by training models on financial and water data from disclosing companies for 2,550 company years (2017-2021) in 11 sectors of the economy.

Since only approximately 20% of S&P500 index companies disclose water use information, financial factor models were developed using this training set, using water intensity indicators as the dependent variable. A final 3- or 6-factor model was developed for the three different water intensity metrics, resulting in predictive capacity (R2) of 0.67-0.75. Financial metrics were derived from the Barra model, a multi-factor model that measures the overall risk of a public company relative to the broad market (Dunn et al. , 2018, Giese et al. , 2019). These factors include inventory turnover ratio (ITR), financial leverage, net fixed asset turnover (FAT), price-to-book ratio (PBR), and size. This study expands on the literature on water risk disclosures by linking physical measures to financial indicators in support of regulatory requirements under TCFD, and to allow for corporate decision-making within and across sectors. The RF factor models proposed here provide new perspectives on the measurement of water risk impacts on financial performance.

The remainder of this paper is organized as follows. Section 2 lays out the data and methodology. Section 3 presents the estimation results. The final section carries the main findings, the conclusion, and the limitations of this paper.

4.2 Data and Feature Selection

We quantified the water intensity indicators disclosed by companies listed on the S&P 500 index relative to a range of financial accounting fundamentals (sales, operating profit, and net fixed asset investment). The rationale for these three metrics is that if companies are to reduce their water use in operations, financial water use efficiencies indicate the dependency of the company and its facilities on water to generate sales, manage their costs and deliver returns on investments in fixed assets. The water uses and indicators, as well as financial accounting data were exported from the Bloomberg Terminal environmental and financial dataset, using a 5-

year time horizon between 2017 and 2021. The corporations on the index comprise eleven industry sectors (Global Industry Classification System) as shown in Table 4.1, which also includes the distribution of companies disclosing water intensity metrics to investors.

Table 4.1. Distribution of water-disclosing vs non-disclosing companies across industry sectors

Sector	Disclosure	Non-Disclosure	TOT_CompanyYear
Communication Services	42	88	130
Consumer Discretionary	133	172	305
Consumer Staples	94	66	160
Energy	65	60	125
Financials	82	243	325
Health Care	180	135	315
Industrials	132	233	365
Information Technology	179	186	365
Materials	104	36	140
Real Estate	116	39	155
Utilities	73	67	140

It notes that firms with water disclosure data are represented in a wide range of industries. In Table 4.1, it presents the distribution of firms in our sample with respect to the Global Industry Classification (GIC) with the highest and the lowest water disclosure ratio. Real Estate and Materials are the most represented industries, with each one having more than 70% firms in S&P 500 index disclosing their water use. Financial, Communication Services, and Industrial sectors have the lowest reporting ratio. The ranking is similar when we rank industries with respect to the recent frequency of disclosure. Health Care and Information Technology sectors comprise the most disclosing industries, while the least disclosing industry is Communication Services. In general, the disclosing rate increases annually, indicating the increasing response from the public listed companies to climate risks and investor demands. For industry annual disclosure rate, Materials and Real Estate sectors lead, while the laggards are comprised in the Finance, Communication Services and Industrials sectors.

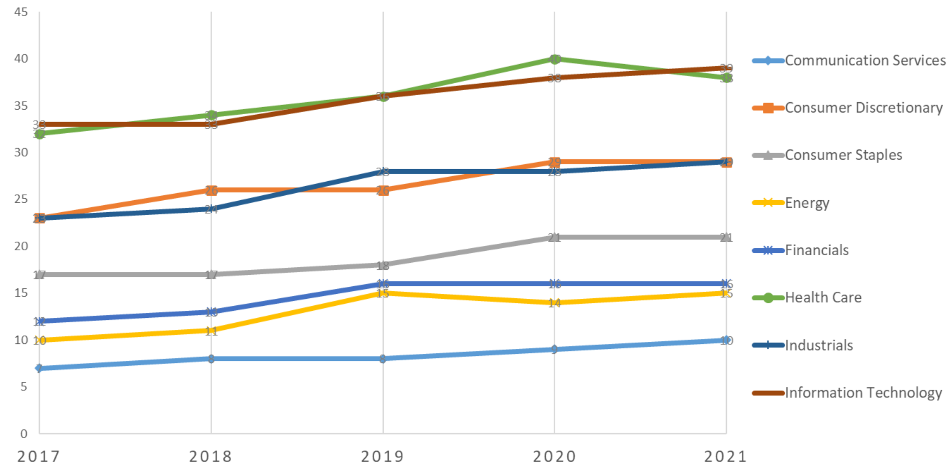


Figure 4.1: Distribution of water-disclosing companies across industry sectors by year

4.2.1 Feature Selection

Financial metrics (features) that are widely available across publicly listed firms since they need to be disclosed under financial regulation by the SEC. These features are used in the Barra Risk Factor model to forecast performance risk based on the firm's microeconomic characteristics, and were incorporated in our models (Lu et al. , 2018; Bender et al. , 2010; Nielsen et al. , 2010). The Barra model includes 38 fundamental factors, including accounting and financial statement variables, in addition to market valuation metrics. Based on Giesy et al. (2019), who used financial factors to predict the impact of ESG ratings on corporate financial performance, a subset of the Barra factors was selected from three subgroups of descriptors: corporate efficiency metrics; metrics capturing corporate profitability; and factors indicative of financial strength and market performance (Table 4.2). Examples of the first category include inventory turnover rate, fixed asset turnover rate, cash flow growth, sales growth and price-to-book ratio. Examples of the second group include earnings-per-share (EPS) growth, operating return on invested capital (ROIC), and EBIT (operating profit). Finally, illustrative features of the third group comprise financial leverage (corporate debt), volume, momentum, size, and beta (market volatility). For further description, please see table legend.

Table 4.2 Descriptive statistics for the variables used in the analysis including the number of observations, mean, standard deviations, and minimum and maximum values.

Variable	Observations	Mean	Std.Dev.	Median
		Financial Fundamental Variables		
Inventory Turnover	1617	14.314	30.306	5.408
Financial Leverage	2429	7.304	46.019	2.954
PE	2409	35.651	86.799	22.136
EPS Growth, %	2464	6.898	2153.721	13.412
Cash Flow Growth, %	2273	49.082	915.793	8.039
Sales Growth, %	1836	8.516	20.656	6.150
Operating Margin, %	2490	12.529	27.185	11.559
Volatility	1661	31.157	13.149	27.655
Fixed asset turnover	2254	7.446	11.712	4.642
Price-to-book ratio	2361	10.453	48.156	3.567
Beta	2382	1.236	2.935	1.125
Momentum	2439	-0.615	15.262	-1.217
Volume	2440	317.40E6	622.26E6	161.68E6
Operating ROIC, %	2488	14.308	16.289	10.841
EBIT, $M	2312	3217.428	7714.135	1286.500
Size, $M	1633	10.293	1.086	10.106
		Water Intensity Variables		
LOG_WIPE	1084	0.996	2.943	0.581
LOG_WIPS	1200	-0.950	2.887	-1.466
LOG_WIPPE	1191	-0.039	2.396	-0.338

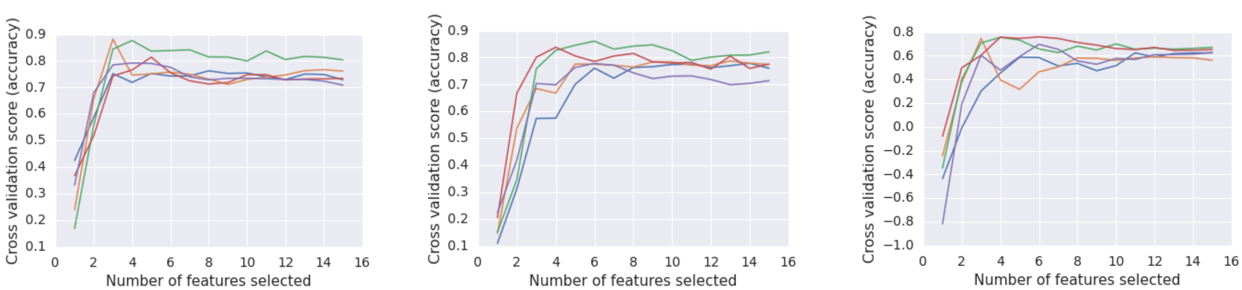
Note: Size is the natural logarithm of market capitalization; Beta (β) is a measure of the volatility (or systematic risk) of a security compared to the market as a whole (usually the S&P 500) calculated over a one-year period; Volatility is the annual stock return volatility calculated over the one-year period; ROIC, return on invested capital; EBIT, Earnings before interest and taxes, a profitability metric; Momentum is the empirically observed tendency for share prices to rise or fall; EPS, earnings per share; PE, price to earnings ratio, a metric that indicates future growth potential of the company.

To understand the relationships between the predictive features described here and the target outcome variables (water intensity indicators), the initial examination is the feature correlation matrix to develop an initial understanding of the Pearson correlation coefficients between features (financial indicators) and target water intensity indicators. Multicollinearity between features exposes the model to excess noise that may negatively affect model predictions. Tree-based models, which are rule-based, are relatively resistant to the noise introduced through predictive feature multicollinearity (Friedman & Popescu 2008). As such, most features are kept throughout each model to understand which are most successful at predicting the water intensity indicators. The summary statistics for the variables selected after correlation analysis of the original Barra Risk Metrics are shown in Table 4.2.

Table 4.3 Correlation Matrix

	INVENTURY TURNOVER	FINANCIAL LEVERAGE	PE	EPS GROWTH	CASH FLOW GROWTH	SALES GROWTH	PROFIT MARGIN	VOLATILITY	FIX ASSET TURNOVER	PRICE TO BOOK RATIO	BETA	MOMENTUM	VOLUME	OPERATING ROIC	SIZE	WIPS	WIPE	WIPPE
INVENTURY TURNOVER	1.000																	
FINANCIAL LEVERAGE	-0.019	1.000																
PE	0.019	-0.010	1.000															
EPS GROWTH	0.010	-0.004	-0.045	1.000														
CASH FLOW GROWTH	-0.012	0.002	-0.012	0.003	1.000													
SALES GROWTH	0.084	-0.041	-0.008	0.102	0.036	1.000												
PROFIT MARGIN	0.018	-0.010	-0.021	0.056	-0.011	0.224	1.000											
VOLATILITY	-0.005	-0.009	0.043	-0.040	0.025	-0.158	-0.292	1.000										
FIX ASSET TURNOVER	0.008	0.003	-0.038	0.020	0.021	0.060	0.010	-0.043	1.000									
PRICE TO BOOK RATIO	-0.031	0.278	0.004	-0.002	0.002	0.002	0.058	0.020	0.012	1.000								
BETA	-0.016	0.018	-0.013	-0.028	-0.004	0.065	-0.044	0.065	0.045	0.015	1.000							
MOMENTUM	0.016	-0.006	0.040	-0.024	0.013	-0.006	0.063	0.050	0.039	0.006	0.061	1.000						
VOLUME	-0.006	-0.007	-0.011	0.015	0.000	-0.020	-0.032	0.132	-0.051	0.012	-0.034	0.038	1.000					
OPERATING ROIC	0.091	0.088	-0.085	0.041	-0.025	0.146	0.254	-0.196	0.125	0.167	-0.038	0.092	-0.023	1.000				
SIZE	0.105	0.030	-0.002	0.051	-0.001	0.116	0.129	-0.178	-0.059	0.142	-0.041	0.121	0.429	0.144	1.000			
WIPS	-0.091	0.012	0.018	-0.009	-0.032	-0.003	-0.063	-0.045	-0.356	-0.059	0.011	-0.020	-0.084	-0.205	-0.192	1.000		
WIPE	-0.106	0.005	0.008	-0.009	-0.007	-0.003	-0.142	-0.045	-0.266	-0.071	0.020	-0.029	-0.106	-0.313	-0.271	0.967	1.000	
WIPPE	-0.129	0.056	-0.075	-0.014	-0.025	0.024	-0.031	-0.080	-0.090	-0.022	-0.026	0.024	-0.071	-0.028	-0.121	0.862	0.883	1.000

Since multicollinearity can introduce bias in linearized models, resulting in overfitting or increased prediction errors, recursive feature elimination (RFE) was applied to arrive at selected. features that represent both financially relevant metrics, for each of the models and water intensity indicators. Recursive feature elimination does not make prior assumptions about the most relevant features but rather fits the model to all the features recursively and eliminates the least predictive feature after repeatedly removing the least significant metrics until the desired number of features is obtained. This technique is useful to eliminate interdependencies and collinearity that may exist between the model features and to reduce noise within the data (Pedregosa et al., 2011). The model was applied initially to the training data with all features fitting to the three water intensity indicators. As shown in Figure 4.2, the RFE technique indicated that three features (independent metrics) were sufficient to design our regression models for each water intensity per sale indicator.



WIPS WIPE WIPPE

Figure 4.2: REF Selection with accuracy of cross validation score analysis (RF Model)

4.3 Regression Models

To predict the water intensity metrics (WIPE, WIPS, WIPPE) from corporate financial fundamental factors, multiple quantitative regression and machine learning models were constructed. These include advanced machine learning models, Random Forest, AdaBoost, LASSO, and regression models such as OLS and GLM models. Ordinary Least Squares (OLS) Regression is commonly used to analyze financial data and estimate the relationship between features and targets by minimizing the sum of squares between the observed and predicted values. Generalized Linear Models (GLM), as applied by CDP for carbon emissions prediction from financial data, use a multi-variable Gamma-Generalized Linear Model (Gamma-GLM) using revenue and production activity information (CDP, 2020). The aim of the machine learning model is to be able to produce predictions using widely reported financial features as well as industry-based classifications (Serafeim et al. , 2022).

Ensemble methods represent a class of non-parametric machine learning algorithms formulated to make predictions through the concerted contributions of multiple estimators. Among these methods, tree-based ensemble techniques exhibit notable qualities, including resistance to overfitting, immunity to the multicollinearity phenomenon among input features, and robust performance in the presence of noisy datasets, even in scenarios where outliers are prominent. Notably, in contrast to linear models, tree-based ensemble regressors require minimal data preprocessing and exhibit insensitivity to the effects of scaling and normalization. The subsequent models employ decision tree (CART) base estimators to construct adaptable models characterized by diminished bias and variance (Maclin & Optiz 1999). The Random Forest algorithm is a parallel ensemble learning meta-estimator primarily designed to mitigate model bias through the utilization of bagging (Breiman et al. 2001). Within ensemble algorithms, Random Forest employs bagging techniques to construct a randomized forest of decision tree estimators by selecting random subsets from the original training set with replacement. These individual estimators' predictions are then aggregated to produce a final prediction. These methods effectively mitigate variance and overfitting associated with decision trees by introducing randomness during construction and subsequently forming an ensemble through prediction averaging. The Adaptive Boosting algorithm (AdaBoost) functions as a sequential ensemble learning meta-estimator with the principal objective of mitigating model bias through the application of boosting techniques (Freund & Schapire,1996). Boosting accomplishes the reduction of training errors by amalgamating a sequence of weak base learners, thereby forming a more potent predictor that strives to minimize the sum of squared error residuals in its predictions. Least Absolute Shrinkage and Selection Operator (LASSO), a regression analysis technique, enhances both prediction accuracy and the interpretability of statistical models through variable selection and regularization.

The models are trained on a set of companies comprising 75% of the total sample universe considered in this study (Table 4.1). All predicted metrics are assessed based on a holdout test set comprised of 25% of the total samples not previously seen by the model. The model performance was evaluated on three metrics: R2 (Regression Score), MAPE (Mean Absolute Percentage Error) and MSE (Mean Squared Error). The R2 regression score function represents the proportion of variance in the target or dependent variable, that can be attributed to the independent variables, or input features, in the model. It provides a measure of the goodness of fit between the data and the model and serves as a measure of how well-unseen test samples are likely to be predicted by the model, through the proportion of explained variance. The mean absolute percentage error (MAPE) calculates a measure of prediction accuracy as a ratio of relative error between the ground truth value and the predicted value (Pedregosa et al., 2011). The difference is divided by the corresponding ground truth value and this ratio is summed for every predicted sample. The Mean Squared Error (MSE) represents a risk function, aligned with the anticipated value of the squared error loss.

After recursive feature elimination, feature importance was tested as a measure used to calculate the relative predictive performance score of each input feature in a model for each target. The score is indicative of the predictive strength of an input feature. Features with a higher feature importance have a larger impact on the model predictions relative to the other input features.

4.4 Results and Discussion

4.4.1 Feature Selection for Regression /ML models

To highlight features that drive model performance, Table 4.4 shows the important features that were selected using RFE by applying the different algorithms (OLS, GLM, Random Forest, etc.) in our analysis. As the results show, the OLS and GLM models exhibit limited efficacy in reducing factors during the analysis process, given the larger number of factors included. Conversely, the LASSO model demonstrates effective factor reduction, albeit with relatively weaker overall performance. Notably, the tree-based models consistently outperform other approaches in terms of both feature reduction and prediction accuracy. Specifically, the random forest model emerges as the optimal choice, minimizing the number of prediction factors required. The impact is dependent on the water intensity indicator (dependent variable) that was selected. For example, for water intensity per sales (WIPS), the model comprises three key variables: inventory turnover, fixed asset turnover, and financial leverage. The WIPE-based reduced factor model incorporates these variables alongside additional metrics, namely price-to-book ratio, return on invested capital (ROIC), and size. Lastly, the WIPPE model encompasses the inventory turnover, fixed asset turnover, financial leverage, along with price-to-book ratio, volume, and size, for a comprehensive evaluation of water index performance prediction.

Table 4.4. Feature selection variables resulting from RFE for five regression/ML models.

		WIPS		
OLS	GLM	LASSO	RF	ADA
INVENT_TURN	INVENT_TURN	INVENT_TURN	INVENT_TURN	INVENT_TURN
FNCL_LVRG	FNCL_LVRG	FNCL_LVRG	FNCL_LVRG	FNCL_LVRG
PE	PE	PE	NET_FIX_ASSET_TURN	PE
EPS_GROWTH	SALES_GROWTH	SALES_GROWTH		EPS_GROWTH
CASH_FLOW_GROWTH	PROFIT_MARGIN	PROFIT_MARGIN		CASH_FLOW_GROWTH
SALES_GROWTH	VOLATILITY_360D	VOLATILITY_360D		SALES_GROWTH
PROFIT_MARGIN	NET_FIX_ASSET_TURN	NET_FIX_ASSET_TURN		PROFIT_MARGIN
VOLATILITY_360D	PX_TO_BOOK_RATIO	PX_TO_BOOK_RATIO		VOLATILITY_360D
NET_FIX_ASSET_TURN	OVERRIDE_RAW_BETA	OVERRIDE_RAW_BETA		NET_FIX_ASSET_TURN
PX_TO_BOOK_RATIO	REL_SHR_MOMENTUM	REL_SHR_MOMENTUM		PX_TO_BOOK_RATIO
OVERRIDE_RAW_BETA	OPERATING_ROIC	Size		OVERRIDE_RAW_BETA
REL_SHR_MOMENTUM	Size			PX_VOLUME
PX_VOLUME				Size
OPERATING_ROIC				
Size				
		WIPPE		
OLS	GLM	LASSO	RF	ADA
INVENT_TURN	INVENT_TURN	INVENT_TURN	INVENT_TURN	INVENT_TURN
FNCL_LVRG	FNCL_LVRG	PE	FNCL_LVRG	FNCL_LVRG
PE	PE	EPS_GROWTH	NET_FIX_ASSET_TURN	NET_FIX_ASSET_TURN
EPS_GROWTH	SALES_GROWTH	CASH_FLOW_GROWTH	PX_TO_BOOK_RATIO	EPS_GROWTH
CASH_FLOW_GROWTH	PROFIT_MARGIN	SALES_GROWTH	PX_VOLUME	PX_TO_BOOK_RATIO
SALES_GROWTH	VOLATILITY_360D	PROFIT_MARGIN	Size	PX_VOLUME
PROFIT_MARGIN	NET_FIX_ASSET_TURN	VOLATILITY_360D		
VOLATILITY_360D	PX_TO_BOOK_RATIO	NET_FIX_ASSET_TURN		
NET_FIX_ASSET_TURN	OVERRIDE_RAW_BETA	PX_TO_BOOK_RATIO		
PX_TO_BOOK_RATIO	REL_SHR_MOMENTUM	OVERRIDE_RAW_BETA		
OVERRIDE_RAW_BETA	OPERATING_ROIC	REL_SHR_MOMENTUM		
REL_SHR_MOMENTUM	Size	PX_VOLUME		
PX_VOLUME		OPERATING_ROIC		
OPERATING_ROIC		Size		
Size				
		WIPE		
OLS	GLM	LASSO	RF	ADA
INVENT_TURN	INVENT_TURN	INVENT_TURN	INVENT_TURN	INVENT_TURN
FNCL_LVRG	FNCL_LVRG	NET_FIX_ASSET_TURN	FNCL_LVRG	FNCL_LVRG
PE	PE	PX_TO_BOOK_RATIO	NET_FIX_ASSET_TURN	PE
EPS_GROWTH	SALES_GROWTH	Size	PX_TO_BOOK_RATIO	EPS_GROWTH
CASH_FLOW_GROWTH	PROFIT_MARGIN		OPERATING_ROIC	CASH_FLOW_GROWTH
SALES_GROWTH	VOLATILITY_360D		Size	PROFIT_MARGIN
PROFIT_MARGIN	NET_FIX_ASSET_TURN			NET_FIX_ASSET_TURN
VOLATILITY_360D	PX_TO_BOOK_RATIO			PX_TO_BOOK_RATIO
NET_FIX_ASSET_TURN	OVERRIDE_RAW_BETA			OVERRIDE_RAW_BETA
PX_TO_BOOK_RATIO	REL_SHR_MOMENTUM			PX_VOLUME
OVERRIDE_RAW_BETA	PX_VOLUME			OPERATING_ROIC
REL_SHR_MOMENTUM	OPERATING_ROIC			Size
PX_VOLUME	Size			
OPERATING_ROIC				
Size				

4.4.2 Regression Results

The prediction metrics for tree-based ensemble methods models alongside general models are shown in Table 4.5, based on the financial features selected in Table 4.2. The visual representation of the models for each water intensity indicator are shown in Figure 4.3. Tree-based models include Random Forest and Adaptive Boosting (AdaBoost) algorithms. To compare these models, we report general model statistics for linear regression estimators using ordinary least squares model, gamma general linear model and LASSO model with alpha is 0.1.

Table 4.5 Comparison of prediction performance of water intensity indicators from financial features.

		OLS	GLM	LASSO	RF	ADA
WIPPE	R2	0.342	0.256	0.302	0.660	0.522
	MAPE	8.607	10.077	8.221	8.581	14.651
	MSE	3.685	4.188	3.902	1.914	2.697
WIPE	R2	0.577	0.467	0.575	0.744	0.663
	MAPE	2.352	2.393	1.931	1.372	2.906
	MSE	3.639	4.662	3.848	2.201	1.810
WIPS	R2	0.600	0.446	0.555	0.752	0.693
	MAPE	1.396	1.063	1.469	0.901	1.278
	MSE	3.679	5.121	3.935	2.281	2.846

Note: The R2 measures the regression score; MAPE standards for the mean absolute percentage error and MSE is the mean squared error of prediction performance.

The results show that across all water intensity indicators, the average predictive capacity of all water intensity indicators is the highest when the Random Forest and AdaBoost models are used. In addition, the margin of prediction error (the maximum and minimum relative errors), and the average relative error of full samples are superior to the other models. The predicted accuracy of the RF model based on the suite of financial features from Table 4-5 results is 66.0% for WIPPE, 74.4% for WIPE and 75.2% for WIPS, indicating that corporate efficiency and profitability factors better predict water intensities based on revenue (sales) and operating income than those based on investments in fixed assets. The R2 of the ordinary linear regression method could be argued to be second best. The R2 of GLM models are much lower than that of OLS regression, with values of 0.256 for WIPPE, 0.467 for WIPE, and 0.446 for WIPS. The LASSO model demonstrates the lowest performance in terms of R2 and error analysis among all the models. The MSE is 2.266 (WIPS), 2.208 (WIPE) and 1.920 (WIPPE) respectively. The lower MSE indicates that the model's predictions are closer to the actual water intensity values on average, suggesting better performance and accuracy. In this context, the MAPE values of 0.909 (WIPS), 1.384 (WIPE), and 8.583 (WIPPE) suggest that, on average, the models' predictions differ from the actual values by approximately 0.909%, 1.384%, and 8.538% respectively.

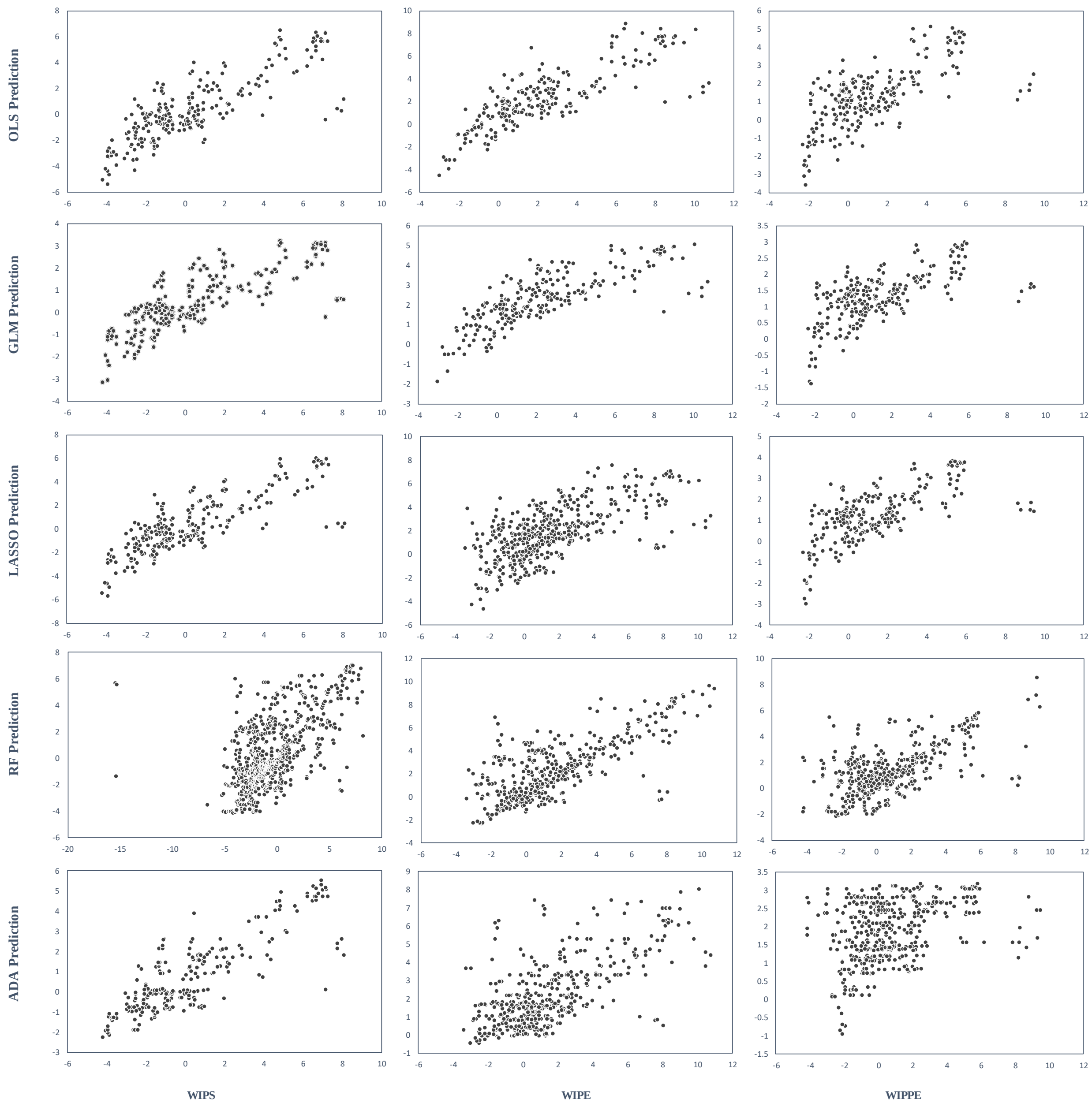
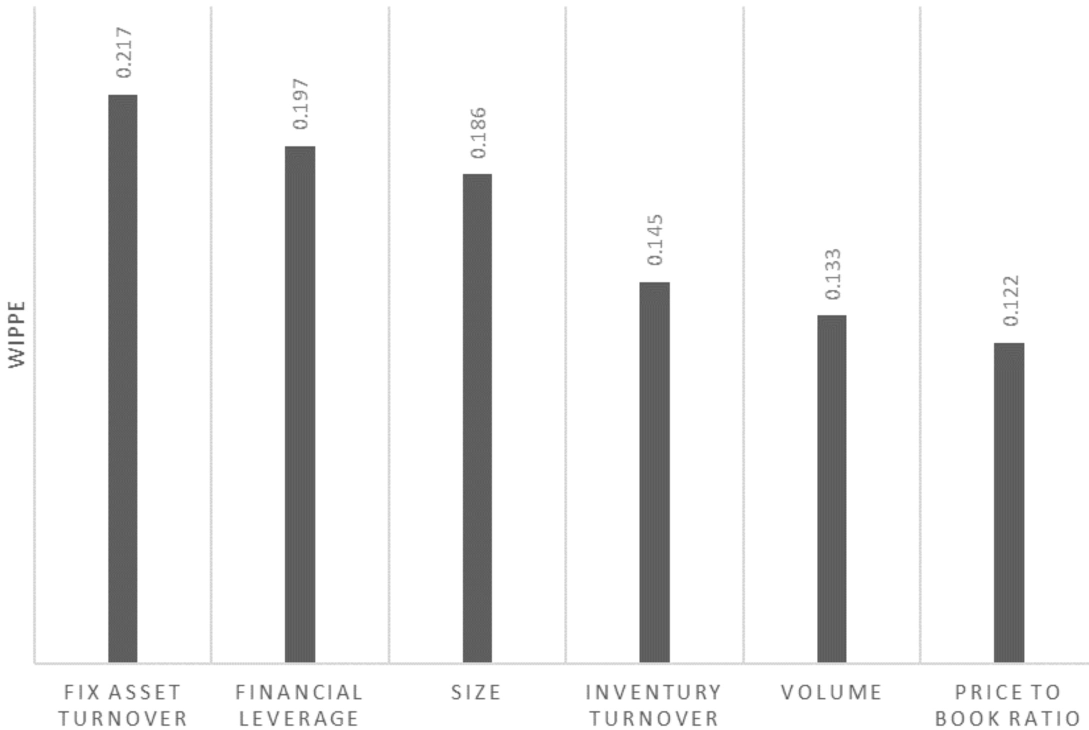


Figure 4.3: Factor Model Performance of Water Intensity Prediction

4.4.3 Feature Contribution to Random Forest Model Prediction

Since the Random Forest model showed the best results overall in its capacity to predict water intensity indicators, their feature contribution was assessed. The result of the variable importance measures is shown in Fig. 4.4 in the order of importance score. Fixed asset turnover ratio, inventory turnover and financial leverage stand out as the most important predictive features for all water intensity indicators. The fixed asset turnover ratio (dimensionless) reveals how efficient a company is at generating sales from its existing fixed assets, namely its property, plants, and equipment. This includes for example production, manufacturing or energy generating facilities. A higher ratio indicates more sales relative to its assets; however, it also indicates higher water intensity behaviors.

Up to 37.5% of water intensity can be explained by this financial accounting factor, based on the random forest model. The inventory turnover ratio represents the rate at which inventory stock is sold, or used, and replaced, whereby a higher ratio indicates strong sales. Not surprisingly because water is an input (direct or indirect) in inventory production, higher ratios result in higher water intensities. Nearly 20% of water intensity is explained by inventory turnover ratios. Last, financial leverage refers to the ratio of short- and long-term debt the company takes on to invest in plants and other fixed assets, relative to the company's net worth (equity or assets minus liabilities). Increase in the debt-to-equity ratio portends more investment in assets and production capacity, resulting in a positive relation between this ratio and water intensity. Up to 26% of corporate water intensity can be explained by this ratio. In addition, the feature analysis indicates that other financial metrics such as size, price-to-book, trading volume, and ROIC are significant contributors to predicting selected water intensity indicators.


WIPPE
0.217
0.197
0.186
0.145
0.133
0.122
FIX ASSET TURNOVER
FINANCIAL LEVERAGE
SIZE
INVENTURY TURNOVER
VOLUME
PRICE TO BOOK RATIO

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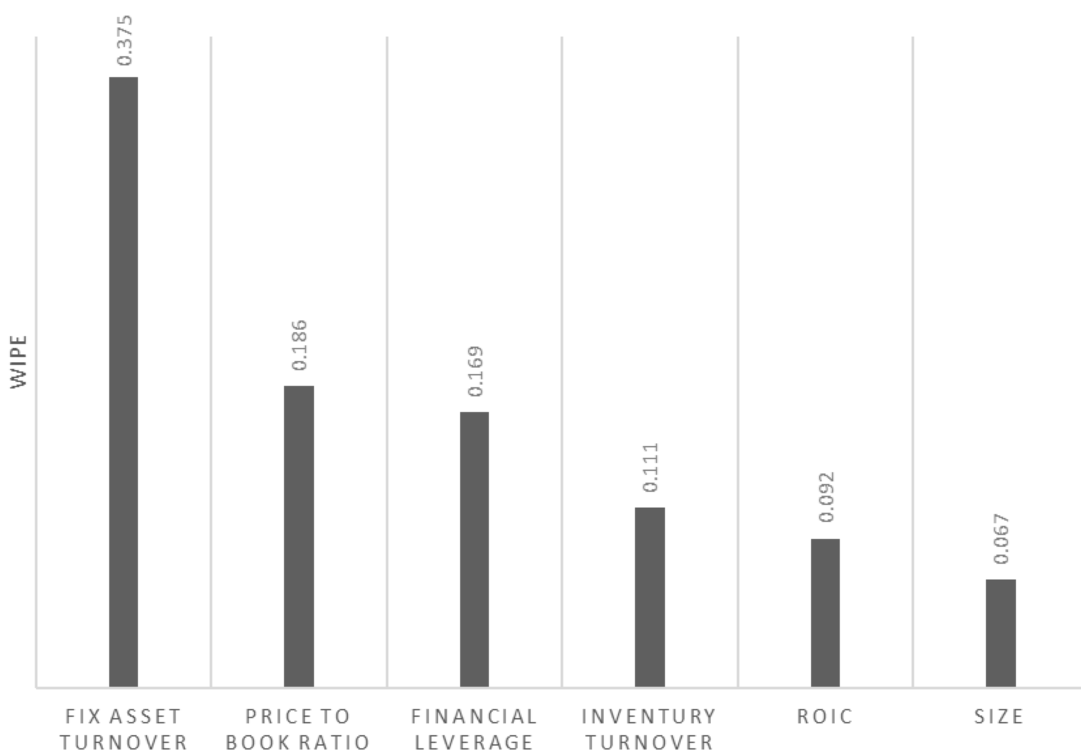

WIPE
0.375
0.186
0.169
0.111
0.092
0.067
FIX ASSET TURNOVER
PRICE TO BOOK RATIO
FINANCIAL LEVERAGE
INVENTURY TURNOVER
ROIC
SIZE

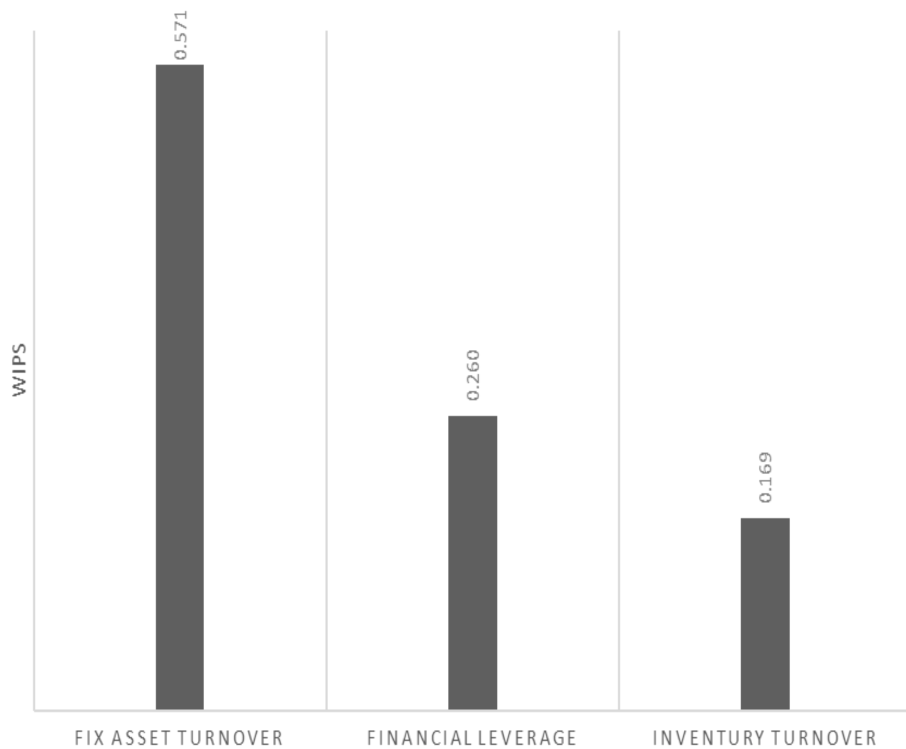


Figure 4.4: Random Forest Factor Model Feature Importance

4.4.4 Factor Model Prediction Performance

The predicted water intensities cannot be independently verified because the majority of companies do not disclose their water risk (Table 4.1). Hence, the predicted outputs from the Random Forest model for non-disclosing companies were compared to disclosed water intensities available from the Bloomberg Terminal and organized by industry sector (Figure 4.5).

When comparing predictive trend values relative to known sector disclosures, random forest predicted correctly for companies in industries with the highest water intensity values, namely Materials, Utilities and Energy sectors. While the model has weak performance in the following sectors. For WIPS, the Random Forest (RF) simulation replicates the underlying trend observed in actual performance, with the exception of communication services, which exhibit an opposite direction. Foe WIPPE, Weak predictions manifest in the consumer discretionary, healthcare, and industrials sectors. For WIPE, RF demonstrates weak performance in the communication services, healthcare, industrials, and information technology sectors, while it performs well in the remaining sectors.

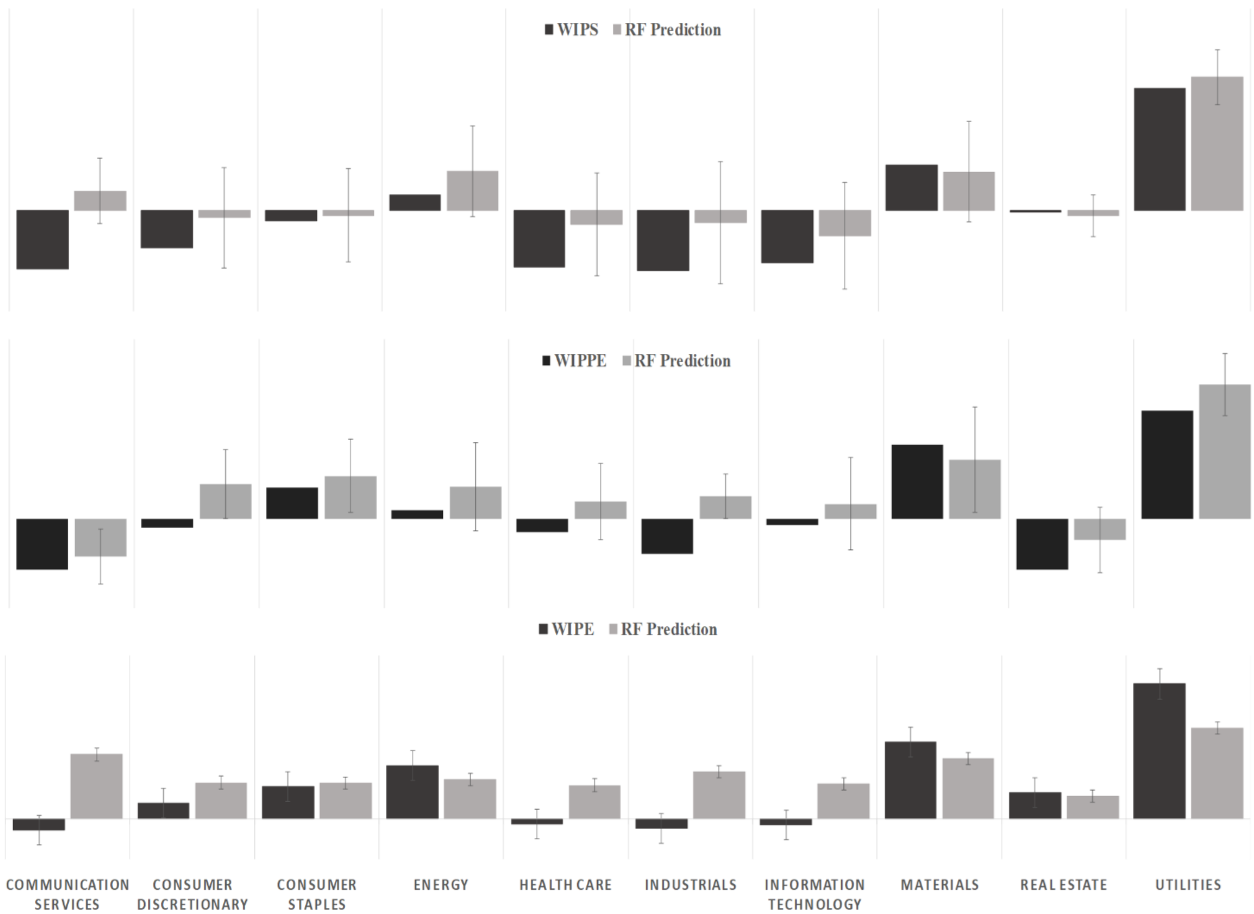


Figure 4.5: Summary of Factor Model Prediction Performance. Top-WIPS; Mid- WIPPE ; Bottom- WIPE. The error bar stands for the standard error deviation of factor model prediction.

4.5 Discussion and Conclusions

Current limitations within reported corporate water data include inconsistent and partial reporting of water risk metrics (WWF, 2022). Moreover, most firms lack the resources and ability to measure water risk, given lack of data, control over decisions made by their suppliers or customers, and difficulty in calculating the financial implications of water risks and inefficiencies (Josset et al., 2021). Hence, water risk measurements and disclosures are completed mostly by large and resource-rich firms. The primary objective of the machine learning approach outlined in this paper is two-fold: (1) how can financially benchmarked water use intensities be correlated to financial accounting metrics, and (2) which statistical tools are best suited to estimate water intensities for non-disclosing companies, based on available data from disclosing companies. It showed that machine learning and regression models can be a promising approach to close the data gap on estimates of corporate water intensities.

Financial risks associated with water tend to be linked to short or long-term opportunity costs that have not generally been disclosed in corporate accounting and thus this information is difficult for investors to evaluate. This paper explores the development of econometric models to predict water intensity metrics from financial accounting data, following multi-correlation and recursive feature elimination (RFE) to keep the indicators that are most predictive. Since water intensities are financial metrics, accounting and market data can be used as independent variables. Linear regression, Lasso, Random Forest, and Adaptive boosting models were used to predict the metrics based on data from disclosing companies for 2,550 company years (2017-2021) in eleven sectors of the economy. A final 3- or 6-factor random forest model for the three different water intensity metrics resulted in R2 values of 0.67-0.75. Financial indicators common across the models include inventory turnover ratio, financial leverage, net fixed asset turnover, price-to-book ratio, and size, indicating that production-oriented companies with higher inventory turnover are more water intensive across all indicators. A statistical comparison of RF estimated water intensities for non-disclosing companies across all industry sectors with those that disclose water use indicates reasonable estimates for asset-intensive sectors such as Energy, Materials and Utilities, with more mixed results in the other sectors.

Several issues limit the applicability of this approach. While water and accounting data can be easily accessed from public reports or financial databases, they are aggregated, and the regression/ML models do not take into account regional water risk exposures and availability for production. Most of the companies considered and listed on the S&P500 index are global and operate facilities in a wide range of climate regimes. Hence, a regionally weighted approach should be considered to inform the impact of water risk on production, supply chains and other operations. Hence, the external validation of the predictions for non-disclosing firms derived from the machine learning models may be limited if some companies have physical water restriction and production features that materially differ from those in the dataset on which the models are trained. Despite these limitations, the application of machine learning models to build out a complete water intensity data set is a cost-effective method to help construct first approximations of water use intensities for benchmarking and index construction. It allows companies, and the public agencies that lack the resources to conduct detailed assessment of corporate water needs to set financial risk targets for efficiency improvement and risk management strategies. In addition, a machine learning approach can enable impact and ESG investors that need data on a very large number of companies for portfolio construction and benchmarking purposes, to evaluate operational improvements and assess natural resource constraints of their holdings.

Chapter 5 Long-Term Imputation and Assessment of Corporate Water Efficiency Impact on Market Metrics

5.1 Background

Climate change is an economically disruptive force for companies (CDP, 2016; Daniel & Sojamo, 2012; Christ et al., 2017; Burritt et al., 2016). From the analysis of the largest 500 global companies, estimates suggest that the potential financial implications from climate change-related impacts reached nearly a trillion dollars (Ceres, 2019). While researchers widely agree that climate change imposes significant economic costs (e.g., Stern, 2007; R.S.J., 2009; Burke et al., 2015; Dietz et al., 2016; Diaz et al. 2017), the impact of climate change on the financial markets has received scant attention up to this point. Especially, the impact of water scarcity and the uncertainty related to its availability are key issues driving the need for corporate investment in climate resilience to remain competitive.

Investors are increasingly tracking information related to water risk exposure of listed firms and engage with companies to understand the risk management strategies employed to mitigate these risks. These exposures are typically associated directly or indirectly with businesses operational risks and therefore with the financial position of financial stakeholders, as financial materiality is the underpinning for risk transfer or strategic investment decisions (Coulson and Dixon 1995). Direct water resource impacts result from their use as essential raw materials for business production and operational processes and represent a geography-dependent instability risk factor for business operations, impacting various stages of the supply chain. Water-dependent sectors which rely on a water or commodity supply chain (e.g. the food industry) may have high exposure to various operational and production risks due to unstable water resource conditions (e.g. drought, floods) in different geographic regions their suppliers operate in (e.g. the agriculture sector). In the latter case, stakeholders might face financial risks and challenges because of the unpredictable changes in water resources resulting in uncertain cash flows, profitability and earnings, which in turn affect market performance.

Despite the abundance of studies focusing on linking market-based performance to broad-based environmental performance (Dixon-Fowler et al.,2013; Chapple et al., 2013), in-depth studies are required to understand climate water risk impacts on water resources and the intensity of their use. Because climate change is a critical concern for multinational companies, it contributes to the dearth of research on the impact of water on firm value in a global context. This work investigates how water use intensity affects market metrics such as firm value, stock price and return on equity (ROE). Based on a sample of the S&P 500 listed corporations, our results show that market metrics are responding to water use intensity, particularly when standardized to balance sheet metrics. These results relate to institutional theory which teaches how changes in societal values, technology improvements, and legislation influence decisions about "green" sustainable activities and environmental management (Greve and Argote, 2015). Scholars advocate for markets and states as effective institutional mechanisms to address externalities linked to collective goods like water, forests, and fisheries. Market forces are instrumental in driving the adoption of environmental measures in business practices, leveraging pricing signals for the most efficient resource utilization. The corollary with our results is that firms with higher water consumption face social pressure and are likely subject to stricter climate regulations, and thus higher cost or compliance. Further evidence shows a significant positive effect of water use efficiency relative to high water dependency industries, suggesting that investors are more concerned about environmental issues in high water intensity industries such as industrials, consumer staples and utilities. Additionally, while water performance positively relates to a company's return on assets (ROA) and return on equity (ROE), negative impacts are seen on Tobin's Q, a proxy metric for long-term corporate valuation. These results indicate that less efficient water use (high intensity) drives increased production, but negatively affects the future value of the company given the uncertainty of water availability on a forward basis.

This study makes several contributions to the literature on water performance and firm value. First, it focuses on the relationship between climate change effects, especially water risks, and firm financial outcomes (Blanco et al., 2020; Kabir et al., 2021; Lee and Min, 2015; Matsumura et al., 2014; Tian and Adriaens, 2023). We draw on extant literature to explore the value relevance of environmental risks and examine the effect of water performance on investors' perceptions of firm valuation. Second, we build on literature research of the effect of water intensity on the firm value and financial performance.

The remainder of this chapter is organized as follows. Section 5.3 presents literature and the development of hypotheses. Section 5.4 presents the sample and methodology followed in the study, with results and discussion covered in Section 5.5. Section 5.6 presents the conclusions.

5.2 Literature and Hypotheses

The correlation between a firm's water management practices and its financial performance can be elucidated through instrumental stakeholder theory, as proposed by Jones in 1995. This theory advocates that for sustained long-term success, firms must prioritize the interests of their stakeholders. Applications of the theory have shown that the two most commonly used measures for measuring the effect of corporate sustainability on financial performance are accounting and market measures. Gentry and Shen (2010) assert that the most prevalent accounting measures employed by firms to gauge financial performance encompass return on equity, return on assets, return on sales, and market-based measures like market return and Tobin's Q. Previous research with market measures for corporate financial performance indicates diversity of results in the corporate sustainability-financial performance relationship such as asymmetry and trade-offs (Grewatsch and Kleindienst, 2015).

Accounting measures serve as indicators of historical data, while short-term financial performance measures based on market data, such as ROE and ROA, are seen as reflections of a company's performance in the distant future (Hoskisson et al., 1994). Stakeholders encompass any group or individual who can influence or is influenced by the attainment of an organization's objectives (Freeman, 1984). Neglecting the concerns of stakeholders can impede a firm's progress towards its objectives. This is because adverse reactions from stakeholders are prone to escalate costs (Berman et al., 1999; Jensen, 2001).

The rise of climate regulations and the evolving preferences of environmentally aware stakeholders have elevated water intensity as a significant risk for firms in the shift towards a low-water economy. The strategic response, or lack thereof, by companies to these factors can have profound effects on their performance, subsequently influencing market metrics and financial outcomes. As an extension of this theory, the theory of the 'natural resource-based view of the firm' argues that the natural environment is a critical commodity input for sustained operational performance of firms, as water constraints limit the capacity to maintain a competitive advantage (Hart et al., 1995; Hart & Dowell, 2011; Christ & Burritt, 2015).

Numerous studies have delved into the impact of corporate environmental performance on either accounting-based profitability measures or market performance. However, these inquiries produce mixed and diverse results (e.g., Lewandowski, 2017; Misani et al., 2015; Iwata et al., 2011). Drawing upon nearly four decades of empirical data (Günther et al., 2012), the analysis unveils a positive yet subtle connection between corporate environmental performance and financial performance, a finding consistent with Russo and Minto's research in 2012. While numerous environmental studies concentrate on carbon risk, the connection between water management practices and financial performance remains an underexplored research domain. Numerous studies have examined the impact of carbon emissions on corporate operating performance. Hart et al. (1996) and Fujii et al. (2013) demonstrate the positive effect of carbon efficiency on ROA, while Iwata et al. (2011) reach analogous conclusions for return on investments (ROI) and ROA. This research underscores that emissions reduction enhances efficiency in production systems, offering a competitive edge. Several studies have examined the return on equity shareholders' ratio (ROE). For example, Gallego-Álvarez et al. (2015) and Batae et al. (2021) find a decrease in ROE linked to emissions. Conversely, some studies yield limited evidence that carbon emissions have a significant impact on corporate operational costs (Brouwers et al., 2018; Busch and Hoffmann, 2011) and financial performance (Iwata and Okada, 2011).

Certain scholars have emphasized the divergence between the short-term (accounting) and long-term (market) consequences of carbon risk on financial performance. Lewandowski (2017) notes an immediate enhancement in a firm's return on sales (ROS) attributable to improved corporate carbon performance, although this improvement is accompanied by a decline in the firm's Tobin's Q, a proxy for long term value. In contrast, Delmas et al. (2015) found that enhanced corporate environmental performance is associated with a reduction in short-term financial performance, measured by return on assets (ROA), while yielding superior long-term market performance, as indicated by Tobin's Q. Numerous studies have explored the share price performance response to corporate carbon emissions, revealing that equity investors tend to penalize companies with substantial carbon emissions. (Clarkson et al., 2015; Griffin et al., 2017; Matsumura et al., 2014; Kim et al., 2015). It identifies a negative correlation between greenhouse gas (GHG) emission levels and Tobin's Q (proxy for future value) (Lee et al. 2015; Hassan et al., 2018; Choi et al., 2021). Similarly, regression analysis uncovered a negative association between environmental disclosures and the operational and financial performance of US S&P 500 companies (Chiong et al. 2010, Smith et al. 2007, Karagozoglu et al., 2000; Majumdar et al., 2001; Saleh et al., 2011).

Hsu et al. (2023) conducted a study examining the impact of environmental pollution on stock returns across various firms and determined that highly polluting companies face greater exposure to environmental regulation risk, resulting in higher average returns. Hong et al. (2019) reveals an inadequate pricing of rising drought risk due to climate change in stock markets, with Cheng (2023) observing a negative correlation between drought and share price returns. In summary, existing literature suggests that stock markets tend to reward companies better equipped for stringent regulations and changing consumer preferences (Busch and Lewandowski, 2018; Delmas et al., 2015; Iwata and Okada, 2011). Based on the extant literature, we state the following two research hypotheses for this work:

H1 Accounting-based profitability ratios are positively affected by lower corporate water intensity.

H2 Capital markets metrics are positively impacted by efficient corporate water use.

5.3 Data and Methods

Our primary corporate dataset covers the 2013–2022 period and is drawn from the Bloomberg dataset for US equities. The Bloomberg terminal also provides corporate water intensity metrics, aside from corporate fundamentals, and market performance indicators. Using log-transformation and scale to build the financial and water data for analysis. The ultimate universe of data comprised 3,421 unique companies out of a universe of 3,481 available equities. Hence, our data covers nearly the entire universe of companies with available water data, listed in the S&P 500 index.

5.3.1 Data on corporate water consumption

Firm-level water consumption and efficiency (benchmarked to operational financial metrics) data are assembled by several main providers: Global Reporting Initiative (GRI), Carbon Disclosure Project (CDP) Water Initiative, the Sustainable Accounting Standards Board (SASB), ratings companies such as Sustainalytics and TruCost, and more recently compliance disclosures for the Task Force for Climate Related Financial Disclosures (TCFD), specifically the Climate Disclosures Standards Board (CDSB) application guidance for water-related disclosures. The accessible data from ESG (Environmental, Social and Governance) providers covers themes such as water use intensity, water stress, toxic effluents/emissions/water quality, and then broader issues such as community conflict, human rights, monitoring, reporting. However, ESG data tends to explore only one linear dimension of water risk exposure and lacks standardized temporal and spatial scales. In addition, counter to the corporate use of carbon as a proxy for climate risks, water risk mitigation addresses only a limited scope of value chain impacts. Given that more and more companies disclose their physical water information in their annual or sustainability reports, and most large corporations report more granular water risks to

CDP, there is an opportunity to capture water risk exposure, corporate risk response, and assessment of financial materiality. This opportunity addresses the need to enhance the transparency of financial risk exposures from water to investors and other stakeholders.

Because of the lack of standardization, we structured all water-related data in three groups of indicators: water consumption (volume), water use growth (year-on-year ratio) and water use efficiency (or intensity). Water intensity metrics are water use standardized to a financial unit, like sales, EBIT (earnings before interest and taxes, a profit margin), and PP&E (property, plant and equipment, the collective investment of the company in fixed assets). The Bloomberg database reports all water data and metrics. The description and correlation of the water variables is in Table 5.1 and Table 5.2.

Table 5.1 Description of water variables

Index		Definition	Method
Water Intensity	WIPS	Water Intensity per Sales	Total water use/ Sales
	WIPE	Water Intensity per EBIT	Total water use/ EBIT
	WIPPE	Water Intensity per PP&E	Total water use/ PP&E
Water use Growth	WATER_GR	Annual growth ratio of Water Use	[Water use (t) - Water use (t-1)] over Total water use(t-1)
Water Volume	WC	Total Water Use(Consumption)	Total water use

Table 5.2 Correlation analysis of water risk metrics

Water Indicator(WIs)		WIPS	WIPE	WIPPE	WATER_GR	WC
Water Intensity	WIPS	1.000	0.502	0.492	-0.005	0.927
	WIPE	0.502	1.000	0.879	0.045	0.418
	WIPPE	0.492	0.879	1.000	0.042	0.414
Water Growth	WATER_GR	-0.005	0.045	0.042	1.000	0.001
Water Volume	WC	0.927	0.418	0.414	0.001	1.000

All three groups of water are positively correlated. While the coefficients are relatively high for some indicators, total water growth is poorly correlated to any other metric, indicating that year-on-year changes in water use are not indicative of water intensity or total volume. For our analysis, the water intensity data were transformed to log-scale and normalized to normal distribution prior to linear regression. The summary statistics of the water indicators are shown in Table 5.3.

Table 5.3 Summary statistics for the variables (panel A: Water indicators; panel B: Financial indicators) used for regression analysis. The sample period is 2013–2022. Panel A reports the water variables. WIPE, WIPPE and WIPS are in the log scale. Panel B reports the cross-sectional return variables and the market performance variables.

Variable	Firm# (n)	Mean	Std	Median
		Panel A Water Variables		
LOG_WIPE(10^3m^3/\$M)	2488	1.31	2.89	0.96
LOG_WIPPE(10^3m^3/\$M)	2792	0.26	2.31	-0.06
LOG_WIPS(10^3m^3/\$M)	2924	6.29	2.87	5.89
WATER_GR	2637	0.42	15.58	0
LOG_WC(10^3m^3)	2819	8.70	2.88	8.37
		Panel B Financial Variables		
INVENT_TURN	4367	20.89	110.63	5.69
FIX_ASSET_TURN	5913	7.71	12.06	4.77
FNCL_LVRG	6398	8.68	128.69	2.89
VOLATILITY, %	6245	31.48	18.75	26.62
VOLUME	6310	317,943,900	757,519,100	155,361,600
PX_TO_BOOK	6252	10.20	63.46	3.23
SIZE, $M	6346	9.85	1.24	9.77
SALES_GROWTH, %	6509	8.82	40.14	5.32
EPS_GROWTH,%	6437	30.92	2117.55	10.67
ROE,%	6385	21.02	55.03	14.37
BETA	6116	1.15	3.68	1.06
RD, $M	5611	656.48	2,676.30	12.00
PPE,$M	6448	9,312.64	20,352.17	2,431.67
ROA,%	6490	5.90	8.70	5.21
STOCK_RETURN	6346	0.13	1.12	0.11
TOBIN_Q, %	6383	2.43	2.03	1.79

The average firm in our sample universe consumes 867,267.6 10^3m^3 of water over 10 years. The water intensity of a company is expressed as volume of water equivalent divided by the company's revenues, EBIT and investment in fixed assets (PP&E) in million US dollar units.

The average log water intensity per sales in our sample equals 6.29 10^3m^3/$ MM, while the log water intensity per EBIT and per PP&E are 0.31 10^3m^3/$million and 0.26 10^3m^3/$ MM, respectively.

The autocorrelation coefficients for the different measures of water indicators are presented in Table 5.4. Autocorrelation assesses the correlation between the same variable in successive time intervals, providing insights into recurring patterns. This analysis is a valuable tool for technical analysis in capital markets. The AR(1) measures with the 1 year-lag windows for series data. Water intensity for all three categories is highly persistent, with an autocorrelation coefficient of 0.987 for WIPPE, 0.977 for WIPE, and 0.994 for WIPS. Interestingly, the year-to-year growth in water consumption shows weak on persistent.

Table 5.4 Time series of Autocorrelation of water indicators estimated using the AR(1) model for various measures of water.

	WC 10^3m^3/$M, YEART+1		WATER_GR YEART+1	WIPPE 10^3m^3/$M, YEART+1		WIPE 10^3m^3/$M, YEAR T+1		WIPS 10^3m^3/$M ,YEART+1	
WC, 10^3,m^3/$M,YEART	0.991	***							
WATER_GR,YEART			0.000						
WIPPE, 10^3m^3/$M,YEART				0.987	***				
WIPE, 10^3m^3/$M,YEART						0.977	***		
WIPS, 10^3m^3/$M,YEART								0.994	***
Constant	0.081	***	0.433	-0.552	***	-0.028	*	0.002	
Year F.E.	YES		YES	YES		YES		YES	
Observations	2428		2243	2403		2031		2525	
R-Squared	0.980		0.000	0.959		0.943		0.981	

Note. All regressions include year fixed effects. We cluster standard errors at year dimensions. ***1% significance; **5% significance; *10% significance.

The firms in the high growth S&P 500 sample universe represent a wide range of industries (Appendix A), based on the six-digit Global Industry Classification (GIC 6). The Oil & gas, Insurance, REITs (Real Estate Investment Trusts) and Semiconductor sectors are the most represented industries, with each represented by more than 25 firms in the index. In Table 5.5, we provide a list of industries with the highest and the lowest intensity of water consumption. Electric utilities, Power and Renewable, and Metals & Mining exhibit the highest total water consumption, while Media, Construction & Engineering and Professional Services present the lowest consumption volumes. The ranking is somewhat different when we classify industries with respect to their water intensities, given that intensities are normalized to sales, operating profits and fixed income investments. For those indicators, Independent Power and Renewable, Water Utilities and Electric Utilities are the most intensive industries when normalized to sales, while Media, Construction & Engineering, and Insurance have the lowest values. In turn, Electric Utilities, Metals & Mining and Independent Power and Renewable are the three most EBIT-intensive industries. Media, Banks, and Capital Markets sectors are the three least EBIT-intensive industries. Water intensity per PPE shows that the most water-intensive sectors are Metals & Mining, Independent Power and Renewable and Electric Utilities, while the least water-intensive GICS sectors are Media, Passenger Airlines and Wireless Telecommunication Services.

5.3.2 Variables in cross-sectional return regressions

Empirical analysis of market metrics employs an annual measure of returns as a dependent variable. In our cross-sectional return regressions, the dependent variable is the annual share price return of an individual company on S&P 500. Control variables are based on previous research on the impact of carbon and ESG (Khan et al. 2019; Gibson et al., 2021; Bolton et al., 2021), defined as follows: SIZE is the natural logarithm of firm market capitalization (price times shares outstanding) at the end of year; FNCL_LVRG is the book leverage of the company; ROE is the firm’s earnings performance, given by the ratio of firm net yearly income divided by the value of its equity; PPE is the natural logarithm, of the firm’s property, plant, and equipment;

BETA is the market beta, calculated over the one year period using daily data; VOLAT is the standard deviation of re-turns based on the past 12 months of monthly returns; SALESGR is the dollar change in annual firm revenues normalized by last month's market capitalization; EPSGR is the dollar change in annual earnings per share, normalized by the firm's equity price. The summary statistics of these variables are in Panel A of Table 5.3.

5.3.3 Variables in cross-sectional performance regressions

The study evaluated how the efficiency of water use influences firm performance based on three dimensions, including the firm's operational, financial and market performance, using ROA, ROE and Tobin's Q, respectively. Return on assets (ROA) is a financial ratio that signifies a company's profitability in relation to its total assets, providing insight into how efficiently the company utilizes its assets to generate a profit. Return on equity (ROE) is a measure of a company's net income divided by its shareholders' equity, serving as an indicator of a corporation's profitability and the efficiency with which it generates profits. Tobin's q is a ratio between the market value of a firm relative to its replacement value and has been extensively used as a proxy for the future operating performance of a firm. These dimensions were employed as dependent variables to evaluate the optimal regression model for assessing the relationship between the study variables. Because we are exploring the impact of water use and water intensity on form performance, this effect needs to be net of key firm performance metrics such as firm size (SIZE), financial leverage (FNCL_LVRG), inventory and fixed asset turnovers (INVENT_TURN; FIX_ASSET_TURN) and asset growth as control variables. The choice of these control variables is supported by studies indicating the significance of firm size, financial leverage, asset turnover, and asset growth as essential factors when assessing the impact of ESG scores on firm performance (Andersen et al., 2011; Han et al., 2016b; Margoliset al., 2009;

Pasquini-Descompset al., 2014a; Hamdan et al., 2017; Hamdan, 2018). The summary statistics of these variables is in Panel B of Table 5.3.

Table 5.5 Water intensity by industry. Panel A reports the top 10 of GIC 6 industries in terms of average water consumption (Total water use/consumption(WC), WIPS, WIPE, WIPPE). Panel B reports on the bottom 10 GIC6 industries in terms of average water consumption (Total water use, WIPS, WIPE, WIPPE). The sample period is 2013–2022 See text and Appendix A for explanation of GIC codes.

Panel A: Largest Water Intensity Sectors (avg.)							
GIC6	WC(10^3m^3)	GIC6	WIPPE (10^3m^3/\$M)	GIC6	WIPE (10^3m^3/\$M)	GIC6	WIPS (10^3m^3/\$M)
551010	7,258,880.064	151040	867.254	551010	2,667.049	551050	477,766.879
551050	5,663,355.000	551050	251.985	151040	2,542.951	551040	372,855.602
151040	5,621,904.421	551010	168.014	551050	2,322.941	551010	354,997.103
551030	1,730,278.573	151020	122.652	551040	1,118.701	151040	273,046.709
551040	1,314,998.000	551040	74.433	551030	994.423	551030	151,001.573
151020	788,070.000	551030	51.680	151020	803.988	151020	141,938.331
151010	270,106.670	151010	28.177	203040	193.226	151010	20,984.639
253010	108,771.910	253010	14.702	151010	183.544	551020	10,535.188
151030	106,791.750	151030	9.667	151030	74.807	251030	6,150.672
203040	68,987.010	201060	9.261	253010	31.398	151030	5800.507
Panel B: Lowest Water Intensity Sectors (avg.)							
GIC6	WC(10^3m^3)	GIC6	WIPPE (10^3m^3/\$M)	GIC6	WIPE (10^3m^3/\$M)	GIC6	WIPS (10^3m^3/\$M)
502010	5.344	502010	0.001	502010	0.001	502010	0.168
201030	16.982	203020	0.016	401010	0.007	201030	1.200
202020	18.678	501020	0.022	402030	0.014	403010	1.991
403010	41.181	202010	0.023	402020	0.017	402020	5.538
402030	89.235	201030	0.028	201030	0.041	202020	5.644
255010	95.847	501010	0.036	202020	0.047	255010	5.888
255030	126.957	403010	0.039	402010	0.066	402030	6.733
402020	141.389	402020	0.041	452010	0.098	255030	11.317
402010	172.919	255030	0.048	255010	0.101	402010	13.061
202010	308.531	402030	0.051	502030	0.108	203020	13.957

5.4 Results

Our analysis begins by investigating the determinants of corporate water use behavior. Then it turns to the evaluation of the water return premium in the cross-section of stocks. The next step is to explore the market performance of the cross-sectional water premium with respect to well-known financial fundamentals factors. Finally, we test robust with the industry groups and different time scales.

5.4.1 Financial determinants of water intensity

Given that not all companies report their water usage, the initial investigation focuses on comparing firms that report water-related information with those that do not, it assesses quantitative differences in various firm-level characteristics of both populations. The basic summary statistics of the two categories of firms are in Table 5.6. Our findings indicate that larger size and high research and development (RD) active firms tend to exhibit a higher propensity to disclose their water consumption data. Moreover, firms with EPS Growth ratios and higher fixed asset turnover are more prone to report emissions.

Table 5.6. Financial indicators to assess differences between disclosing and non-disclosing firms

Financial Indicators	Non-Disclosing Firms	Disclosing Firms
INVENT_TURN	17.388	24.437
FIX_ASSET_TURN	9.328	5.575
FNCL_LVRG	7.091	10.712
VOLATILITY,%	31.474	31.499
VOLUME	250,988,109.656	403,511,854.631
PX_TO_BOOK	10.946	9.262
SALES_GROWTH, %	9.729	7.627
ROE, %	18.891	23.751
RD, $M	332.252	1,074.490
BETA	1.085	1.239
PPE, $M	6,449.588	13,061.689
EPS_GROWTH, %	59.471	-6.119
SIZE, $M	9.566	10.222

Next, it measures the differences in water consumptions levels, year- by-year changes, and water intensities across firms using a regression framework (Table 5.7). The dependent variables are levels, changes, and intensities of sales, EBIT, and PP&E. Since there is no financial theory that can guide us on what financial accounting metrics influence the level of water consumption, we selected firm-level variables that are included in the Barra Risk Factor Analysis Model as well as literature on the relationship between financial indicators and carbon emissions (Bolton et al. 2021). The Barra Risk Factor Analysis, a multi-factor model by Barra Inc., assesses overall security risk relative to the market, incorporating over 40 data metrics, including earnings growth, share turnover, and senior debt rating. Following the same metrics filtration approach proposed in Bolton et al. (2021), the following indicators were selected: Company size (log market capitalization; SIZE), return on equity (ROE), inventory turnover (INVNT_TURN), net fixed asset turnover (NET_FIX_ASSET_TURN), financial leverage (FNCL_LVRG), investment in fixed assets (PPE), investment in research and development (RD), sales growth (SALESGR), and earnings-per-share growth (EPSGR). To consider the potential concentration of firm-level water risk indicators across firms and over time, standard errors will be clustered at the firm and year levels. Standard errors in all panel regressions become significantly smaller when using specifications that cluster at the firm, industry, time, or industry levels and time series.

The level of consumption and water intensity indicators are notably linked to highly leveraged firms with high volume and significant tangible assets, reflecting the needs of growth-focused and production-intensive companies (Table 5.7). Water usage exhibits negative associations with inventory turnover, price-to-book ratio, and research and development (RD), while water growth rate is positively related to inventory turnover. All three water intensity categories display significant negative associations with inventory turnover, fixed asset turnover, and price-to-book ratio. Intriguingly, all water indicators show negative correlations with the company's size factor, suggesting that the larger the size of the company, the better water use is managed.

Table 5.7 Financial determinants of water intensity indicators

Variables	Water Use		Water Intensity		
	LOG_WC (10^3m^3)	WATER_GR	LOG_WIPE (10^3m^3/\$M)	LOG_WIPPE (10^3m^3/\$M)	LOG_WIPS (10^3m^3/\$M)
INVENT_TURN	-0.048 ***	0.046 *	-0.035 **	-0.056 ***	-0.065 ***
FIX_ASSET_TURN	-0.015	-0.059	-0.206 ***	-0.110 ***	-0.427 ***
FNCL_LVRG	0.094 ***	0.016	0.109 ***	0.059 **	0.078 ***
VOLATILITY,%	0.006	-0.031	0.031	-0.016	0.029
VOLUME	0.046 ***	-0.018	0.021	0.187 ***	0.035 **
PX_TO_BOOK	-0.060 ***	-0.012	-0.087 ***	-0.036	-0.038 *
SALES_GROWTH, %	0.027 **	0.022	-0.075 ***	-0.075 ***	0.044 ***
ROE, %	0.017	0.013	-0.018	0.015	0.007
RD, \$M	-0.077 ***	-0.027	-0.032 **	0.042	-0.077 ***
EPS_GROWTH, %	-0.006	-0.001	-0.003	-0.006	-0.006
BETA	0.003	0.000	-0.002	0.023	0.005
PPE, \$M	0.543 ***	0.065	0.272 ***	0.049	0.082 ***
SIZE,\$M	-0.054 **	-0.068	-0.194 ***	-0.155 ***	-0.054 **
Year/Industry F.E.	Yes	Yes	Yes	Yes	Yes
Observations	2056	1910	1889	1485	2123
R-Squared	0.509	0.008	0.490	0.132	0.505

5.4.2 Evidence from cross-sectional corporate market metrics

For all categories of consumption and water intensity, the analysis relates the level of water consumption, the year-to-year growth rate in consumption, and the companies' water intensity to their corresponding stock returns in the cross-section.

It first estimates the following cross-sectional regression model using pooled ordinary least squares (OLS) regression:

$$RET = a_0 + a_1 LOG(WATER) + a_2 Controls + \epsilon \qquad (1)$$

where RET measures the stock return of a company and WATER is a generic term alternately referring to the water indicators. The control vector encompasses various firm-specific variables selected from Table 5.3, known to predict returns, such as SIZE, INVNT_TURN,

NET_FIX_ASSET_TURN, FNCL_LVRG, PPE, RD, SALESGR, and EPSGR. Year and industry fixed effects are included to control for individual-specific attributes that remain constant over time, ensuring a robust analysis. The coefficient of interest is a_1.

The results are present in Table 5.8. Column 1-2 shows the results for total water consumption (WC); column 3-4 for water growth (WATER_GR, and column 5 to 10 for water intensity indicators. The columns are further differentiated by the use of fixed effects by year or industry. For all categories of water risk indicators, except for water use growth, it shows a positive but weak effect on firms' stock returns. For example, one unit increase in total water use leads to a 2.6% increase in stock returns. These relationships are very similar across all indicators. Since water use and intensity metrics tend to cluster significantly within specific industries (e.g. Tian and Adriaens, 2023), a question of interest is whether the firm-specific differences can be attributed to industry-specific effects. To examine this possibility, we additionally include industry-fixed effects using the GICS industry classification specified earlier. The results presented in the table indicate that industry effects do significantly impact the cross-sectional dispersion of returns due to water use or intensities.

Table 5.8. Impact of water indicators on share price returns of S&P500 companies between 2013-2022 (n=1,485-2,125).

Variables	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)		(10)	
LOG_WC , 10^3m^3	0.026		0.039																	
WATER_GR					-0.024		-0.023													
LOG_WIPPE, 10^3m^3/$M									0.022	**	0.027									
LOG_WIPE, 10^3m^3/$M													0.036		0.022					
LOG_WIPS, 10^3m^3/$M																	0.056	**	0.025	
INVENT_TURN	0.034		0.033		0.009		0.027		0.024		0.017		-0.002		0.000		0.025		0.036	
FIX_ASSET_TURN	-0.071	**	0.027	**	-0.090	**	-0.033		-0.053	**	-0.043		-0.072	**	-0.037		-0.073	**	-0.040	
FNCL_LVRG	-0.028		-0.022		-0.050	*	-0.070	**	-0.045		-0.037		-0.055	**	-0.060	**	-0.059	**	-0.071	**
VOLATILITY, %	0.160	**	0.119	***	0.156	***	0.192	***	0.118	***	0.073	*	0.150	***	0.144	***	0.120	***	0.143	***
VOLUME	-0.072	**	-0.098		-0.038		-0.040		-0.105	**	-0.124	**	-0.033		-0.030		-0.040		-0.043	
PX_TO_BOOK	0.133	***	0.132	***	0.109	***	0.127	***	0.159	***	0.158	***	0.125	***	0.136	***	0.117	***	0.133	***
SALES_GROWTH, %	0.324		-0.039	***	0.177	***	0.167	***	0.126	***	0.121	***	0.154	***	0.149	***	0.193	***	-0.047	*
ROE, %	0.007	***	0.331		0.079	***	0.075	***	-0.028		-0.038		0.020		0.019		0.060	**	0.189	***
RD, $M	-0.038		-0.007		-0.064	**	-0.074	**	-0.028		-0.070	**	-0.055	**	-0.088	***	-0.039	*	0.057	**
EPS_GROWTH, %	0.037	*	0.035	**	0.040	**	0.039	*	0.010		0.009		0.009		0.008		0.037	*	0.036	*
BETA	-0.030	*	-0.036		0.015		0.125		-0.014		-0.022		0.013		0.007		0.018		0.017	
PPE, $M	-0.176	***	-0.175	***	-0.178	***	-0.188	***	-0.116	**	-0.120	***	-0.167	***	-0.162	***	-0.179	***	-0.173	***
SIZE, $M	0.302	***	0.297	***	0.264	***	0.286	***	0.238	***	0.241	***	0.246	***	0.253	***	0.250	***	0.258	***
Year F.E.	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Industry F.E.	No		Yes		No		Yes		No		Yes		No		Yes		No		Yes	
Observations	1543		1543		1,910		1910		1485		1,485		1,889		1,889		2,125		2,125	
R-Squared	0.098		0.270		0.090		0.245		0.067		0.246		0.072		0.235		0.106		0.244	

Notes. The sample period is 2013–2022. The dependent variable is RET. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level (in parentheses). All regressions include year fixed effects and industry-fixed effects. The table reports the results for the natural logarithm of total firm-level water use, the percentage change in total water use and the results for water intensity. ∗∗∗ 1% significance; ∗∗ 5% significance; ∗10% significance.

Water use and stock price exhibit a positive weak correlation. Then, we next estimate the same cross-sectional regression model but replace the level of total water use (LOG WC) with the year-to-year growth in water consumption (WATER_GR). The results are reported in Table 5.9, column 3-4. We find a negative and weak effect of the growth in water use on stock returns. Finally, the cross-sectional regression model for water intensities is reported (Table 5.9, column 5 to 10). The results are positive and significant between WIPPE and WIPS and share price returns. This indicates that greater investment in fixed assets such as production facilities, and the resulting lower efficiency of water use, increase share price return.

Overall, these results reveal that there is a significant water risk premium with respect to the level of water intensity, showing that curbing water use, or improving water use efficiencies are not rewarded in the market, since increased water use and increased water intensity result in higher returns. An alternative interpretation of results where price returns lag relative to water intensity metrics is that investors do not immediately absorb new information about water data at the firm level (Kacperczyk et al., 2016). This is similar to the observation by Hart and Ahuja (1996), who saw a lagging response from investors to emissions data. In that case, water intensity will be gradually reflected over time in returns. An additional consideration is that investors obtain information about water information from multiple sources that are not all available at the same time. For example, a lot of firms disclose their water use first to NGOs such as CDP, whose results are then merged into and combined with other sources in the Bloomberg Terminal.

5.4.3 Imputation of Water Intensity Impact on Share Price Return

The lack of water disclosure by companies listed on US indexes such as S&P500 limits the power of statistical analysis for long-term impact on stock prices. In all, approximately 20%

of the companies have disclosure information. The water intensity was imputed based on their financial fundamentals using the reduced factor models developed in Chapter 4. The factor models for water intensity imputation are:

WIPS: INVENT_TURN, FIX_ASSET_TURN and FNCL_LVRN

WIPPE:INVENT_TURN, FIX_ASSET_TURN, FNCL_LVRN, PX_TO_BOOK, VOLUME and SIZE

WIPE: INVENT_TURN, FIX_ASSET_TURN, FNCL_LVRN, PX_TO_BOOK, ROIC and SIZE

This imputation process followed a two-stage approach. First, we impute missing values for the listed financial fundamentals for companies not disclosing all metrics. Following literature on the topic of financial metric imputation, the K-nearest neighbor algorithm was applied (Imandoust et al., 2013; Yu et al., 2022; Cheng et al. 2019). Second, the water intensities for all companies between 2013-2022. were imputed using the random forest (RF) factor models developed in Chapter 4. The results from the cross-sectional regression model for imputed water intensities are shown in Table 5.9.

When considering all companies on the S&P500 index over a decade, there is a statistically significant effect of water intensity on returns for the three categories of water intensity, whether we control for industry or not. The WIPPE has a significantly negative effect related to the stock price. The effect is also economically significant: a unit increase in WIPPE (water intensity relative to fixed asset investment) leads to a 4.8% decrease in stock returns, or 5.8% if we take out the industry concerns. Hence, investor's view water intensities in high capital asset companies as a risk to corporate returns. On the other hand, for WIPE and WIPS, two metrics related to sales and profitability, we find a positive and statistically significant effect on firms' stock returns. A unit increase in WIPE leads to a 3.0% increase in stock returns, and a unit increase in WIPS increases stock returns by 2.4% annualized. The result has little differences with industries control or not. In other words, because water is an input in economic production, sales and profit generation, more intensive use of water results in higher returns.

Table 5.9 Impact of Imputed Water Intensity on Share Price Returns between 2013-2022 (n = 7,200 company-years)

Variables	(1)		(2)		(3)		(4)		(5)		(6)	
LOG_WIPPE*, $10^3m^3/\$M$	-0.048	***	-0.058	***								
LOG_WIPE*, $10^3m^3/\$M$					0.030	***	0.031	***				
LOG_WIPS*, $10^3m^3/\$M$									0.024	***	0.030	***
INVENT_TURN	-0.047	***	-0.035	***	-0.042	***	-0.045	***	-0.042	***	-0.043	***
FIX_ASSET_TURN	-0.055	***	-0.019		-0.027		-0.009		-0.034	*	-0.009	
FNCL_LVRG	-0.008		-0.034	***	-0.029	**	-0.057	***	-0.016		-0.044	***
VOLATILITY, %	-0.007		0.021		0.013		0.031	*	0.013		0.032	*
VOLUME	-0.041	***	-0.043	***	-0.054	***	-0.053	***	-0.055	***	-0.054	**
PX_TO_BOOK	0.253	***	0.271	***	0.252	***	0.276	***	0.240	***	0.265	***
SALES_GROWTH, %	0.153	***	0.148	***	0.154	***	0.151	***	0.153	***	0.149	***
ROE, %	-0.039	***	-0.037	***	-0.033	***	-0.032	***	-0.036	***	-0.035	***
RD, $M	-0.060	***	-0.065	***	-0.066	***	-0.087	***	-0.065	***	-0.084	***
EPS_GROWTH, %	0.014		0.014		0.015		0.014		0.014		0.014	
BETA	0.042	***	0.042	***	0.044	***	0.041	***	0.044	***	0.042	***
PPE, $M	-0.100	***	-0.058	***	-0.146	***	-0.090	***	-0.149	***	-0.092	***
SIZE, $M	0.145	***	0.134	***	0.201	***	0.184	***	0.191	***	0.174	***
Year F.E.	Yes		Yes		Yes		Yes		Yes		Yes	
Industry F.E.	No		Yes		No		Yes		No		Yes	
Observations	7200		7,200		7,200		7,200		7,200		7,200	
R-Squared	0.151		0.243		0.143		0.238		0.142		0.244	

Note: We report the results of the pooled regression with standard errors clustered at the firm and year level (in parentheses). All regressions include year fixed effects and industry-fixed effects. The table reports the results for the natural logarithm of water intensity. ∗∗∗ 1% significance; ∗∗ 5% significance; ∗10% significance.

5.4.4 Categorization of Industries Impacted by Water Intensity Risks

Based on water foot printing of industrial water use (Hoekstra; 2015; Ercin et al., 2014), it is often pointed out that only a handful of industries are most affected by water risk exposures such as drought or lack of access (Tian and Adriaens, 2021, 2023; Tian et al., 2023). The CDP reports mention Energy (43%), Consumer Staples (43%), Utilities (36%) and Materials (36%)

sectors as the top dependent sectors on water. It is therefore natural to wonder whether our results on share price impacts of water intensities are disproportionately driven by these sectors, and whether our cross-sectional water premium would change significantly if we split these industries in our analysis. In Table 5.10, it reports the results for the subset of firms, by separating low and high dependency groups for imputed water dataset.

In comparing the results in Table 5.10 (Figure 5.1), it becomes evident that employing a comprehensive list of coefficients is an effective strategy to mitigate the influence of industry sectors. Notably, there is a substantial difference in the year-fixed WIPPE results between the High (-0.061) and Low (-0.021) sub-dependency groups. However, after adjusting for the industry effect, the results show a decrease to -0.060 for the low dependency group and -0.044 for the high dependency group. This highlights the significant impact of industry sectors, particularly in the high dependency group, where sector sensitivity is pronounced. In contrast, WIPS and WIPE exhibit less sensitivity to industry sectors, but a higher level of dependency leads to more significant benefits in the stock market. Notably, in the low dependency sectors, these results reinforce the findings regarding the firm-level water premium, particularly in the industry-fixed regression results. These findings suggest that investors tend to categorize companies more broadly within water-dependent industries, resulting in returns that are less responsive to variations in water dependency among firms.

Table 5.10 Regression of High and Low Water Intensity Industries with Stock Returns

Variables	(1)		(2)		(3)		(4)		(5)		(6)	
	Low Dependency											
LOG_WIPPE*,10^3m^3/$M	-0.061	***	-0.060	***								
LOG_WIPS*,10^3m^3/$M					0.016		0.020	**				
LOG_WIPE*,10^3m^3/$M									0.032	***	0.033	***
INVENT_TURN	-0.021	*	-0.020	`	-0.034	***	-0.036	***	-0.035	***	-0.038	***
FIX_ASSET_TURN	-0.025		-0.022		-0.040	*	-0.024		-0.024		-0.011	
FNCL_LVRG	0.001		-0.012		-0.002		-0.020		-0.014		-0.032	**

VOLATILITY, %	0.001		-0.001		0.002		0.012		0.002		0.013	
VOLUME	-0.055	***	-0.057	***	-0.070	***	-0.071	***	-0.071	***	-0.071	***
PX_TO_BOOK	0.237	***	0.248	***	0.217	***	0.236	***	0.229	***	0.247	***
RD, $M	-0.025	*	-0.039	***	-0.043	***	-0.064	***	-0.045	***	-0.066	***
SALES_GROWTH, %	0.133	***	0.135	***	0.135	***	0.135	***	0.135	***	0.134	***
ROE, %	-0.038	***	-0.040	***	-0.038	***	-0.040	***	-0.036		-0.038	***
EPS_GROWTH, %	0.014		0.013		0.014		0.013		0.015		0.014	
BETA	0.007		0.006		0.005		0.004		0.006		0.004	
PPE, $M	-0.117	***	-0.082	***	-0.159	***	-0.117	***	-0.155	***	-0.115	***
SIZE, $M	0.167	***	0.151	***	0.216	***	0.201	***	0.233	***	0.219	***
Year F.E.	Yes		Yes		Yes		Yes		Yes		Yes	
Industry F.E.	No		Yes		No		Yes		No		Yes	
Observations	5270		5270		5270		5270		5270		5270	
R-Squared	0.136		0.260		0.127		0.251		0.129		0.252	

Variables	(1)		(2)		(3)		(4)		(5)		(6)	
	High Dependency											
LOG_WIPPE*,$10^3\text{m}^3/\$\text{M}$	-0.021	**	-0.044	***								
LOG_WIPS*,$10^3\text{m}^3/\$\text{M}$					0.045	***	0.034	**				
LOG_WIPE*,$10^3\text{m}^3/\$\text{M}$									0.031	**	0.019	
INVENT_TURN	-0.137	***	-0.106	***	-0.092	***	-0.086	***	-0.106	***	-0.095	***
FIX_ASSET_TURN	-0.030		0.003		0.025		0.026		0.002		0.002	
FNCL_LVRG	-0.140	***	-0.150	***	-0.171	***	-0.177	***	-0.177	***	-0.182	***
VOLATILITY, %	0.016		0.042		0.037		0.041		0.030		0.039	
VOLUME	-0.012		0.003		-0.005		0.002		-0.003		0.003	
PX_TO_BOOK	0.394	***	0.403	***	0.409	***	0.414	***	0.417	***	0.419	***
RD, $M	-0.141	***	-0.145	***	-0.136	***	-0.150	***	-0.143	***	-0.157	***
SALES_GROWTH, %	0.188	***	0.177	***	0.181	***	0.176	***	0.191	***	0.182	***
ROE, %	-0.007		-0.007		0.001		0.001		0.003		0.002	
EPS_GROWTH, %	0.491		0.440		0.449		0.446		0.532		0.498	
BETA	0.232	***	0.233	***	0.243	***	0.243	***	0.239	***	0.240	***
PPE, $M	0.121	***	0.113	**	0.076		0.071		0.079	*	0.076	
SIZE, $M	0.034		0.041		0.050		0.055	*	0.051		0.056	*
Year F.E.	Yes		Yes		Yes		Yes		Yes		Yes	
Industry F.E.	No		Yes		No		Yes		No		Yes	
Observations	1,840		1,840		1,840		1,840		1,840		1,840	
R-Squared	0.236		0.317		0.236		0.325		0.235		0.323	

Note. All regressions include year fixed effects and industry-fixed effects. The table reports the results for the natural logarithm of all water intensity indicators. The upper reports the results for low water dependency sectors (n =5,270 company-years); the bottom reports the results for high dependency sectors (n = 1,840 company-years); ∗∗∗ 1% significance; ∗∗ 5% significance; ∗10% significance.

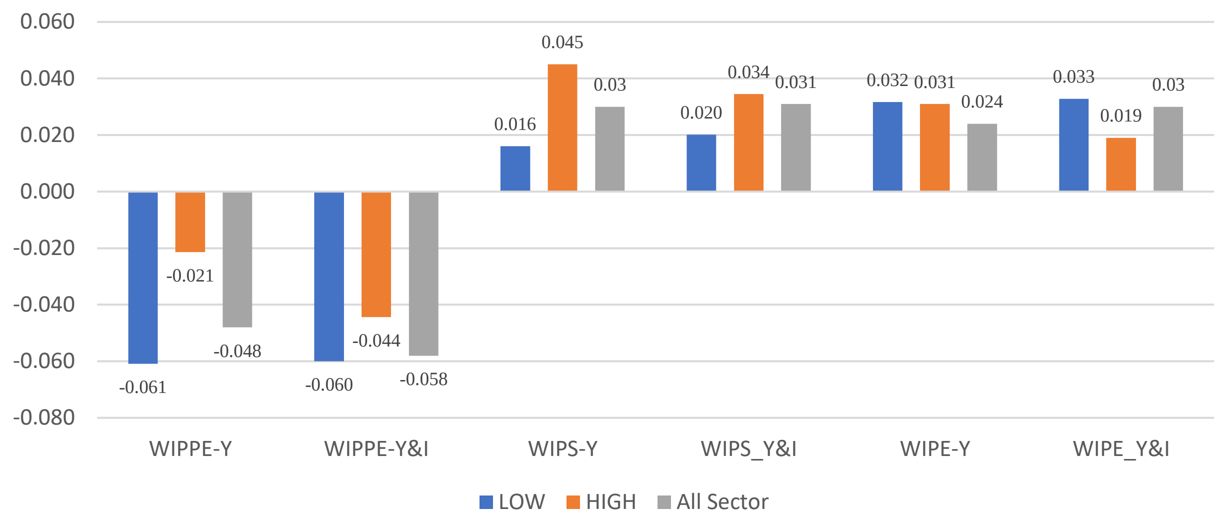


Figure 5.1: Water Intensity Correlation Coefficient to Stock Return in High and Low Dependency Industry (Y: Year fixed; Y & I:Year and Industry fixed)

5.4.5 Temporally Dynamic Shifts in Water Risk Impacts on Share Price Returns

It has been posited that the water premium in share price returns is affected by the changing investor awareness about, or actual physical (climate change) impact of, water use intensities. In particular, one would expect that periods with greater climate change awareness, or when actual physical water risks have manifested themselves, would result in a higher water premium (Pankratz et al. 2023; Sautner et al., 2023; Karydas et al. 2019; Freyman et al. 2015; Reig et al. 2013). We evaluate this hypothesis by comparing the water premium before and after the promulgation of TCFD (Task Force on Climate-Related Financial Disclosures) regulation in 2017 (voluntary until 2021, when disclosure became mandatory in the UK and Europe) using the imputed water intensity for the decade long-term analysis based on their financial fundamentals. The tests offer complementary views on the role of changing investor attention, and the increasing physical risks of climate change.

The objective of TCFD, as stated by the Financial Stability Board, is to provide market transparency regarding climate change's impacts. Through widespread adoption, financial risks and opportunities related to climate change will become an integrated component of corporate risk management and strategic planning processes. As corporate and investor awareness of the financial implications of transitioning to a lower-carbon economy and climate-related risks deepens, decision-useful information will increase. This enhanced understanding will lead to more precise pricing of risks and opportunities, promoting a more efficient allocation of capital. The TCFD implementation is starting to raise both the awareness of risks tied to water use and carbon emissions, and the prospect of regulatory interventions to increase efficiency of water resources. Based on this rationale, one could therefore expect that the water risk premium would decrease after 2017 following the initial release of TCFD proposals. While the market rewards (based on share price returns) higher water intensity, because it means higher sales and profits, the incentive is expected to become attenuated as financial regulation and awareness increases. We report the results in Table 5.11 (Figure 5.2).

The temporal differences of water efficiency impact on financial return can be uncovered by applying the regression model on the two sub-periods: 2013–2017, and 2018–2022. The top-line result is that the impact of time periods has resulted in an attenuation of the impact of water intensity on share price return. For example, the share price rewards of higher WIPS and WIPE which track water use for revenue and profit generation, are nearly 65% lower in 2018-2022 than in 2013-17. Conversely the negative impact of water intensities relative to fixed asset investment (WIPPE), a proxy for capital risk, on share price returns has decreased by 30%. Combined, both trends indicate that companies have shifted towards greater efficiency of water use, and that markets are rewarding lower intensity, thus confirming our hypothesis. For 2013 to 2017, there is a statistically significant effect of water intensity on returns for the three categories of water intensity, whether control for industry or not. The WIPPE has a significant negative related to the stock price: a unit increase in WIPPE leads to a 6.2% decrease in stock returns, or 7.0% by taking out the industry bias. For WIPE and WIPS, a unit increase in WIPE leads to a 3.5% increase in stock returns, and a unit increase in WIPS increases stock returns by 4.2% annualized, which has no difference with the industry control. While for the 2018-2022 periods, there is significant trend with WIPPE and WIPE. The coefficient of WIPPE has changed from -0.062 to -0.040 without industry control and the industry control has increased from -0.070 to -0.53. The WIPE has decreased from 0.042 to 0.017. This could be seen as evidence that investors care more about water risk following the TCFD.

The impact of time period on predictive parameters shows that fixed asset turnover is no longer a significant indicator in the later period, while ROE has become significant. Though not causative, since fixed asset turnover ratio reveals how efficient a company is at generating sales from its existing fixed assets, and the impact water risk per unit fixed assets on share price has decreased, it can be argued that corporate water use efficiency has increased over time, which follows the pattern in Appendix B. Return on equity (ROE), or the return on net assets, is often interpreted as future guidance on share price. Again, without implying causality, it could be argued that higher water use efficiency presents lower risk to sales and profit generation, and thus stable earnings which drive returns. However, the linear regression only measures the contribution of water intensity to the stock price within different time periods. For a more robust test for the future work, the causal inference method could be applied (as I did in Chapter 4), to explore the impact of a binary event (TCFD promulgation) while controlling for the confounders.

Table 5.11 Water intensity and stock returns: Impact of Pre- and Post-TCFD Regulation

Variables	(1)		(2)		(3)		(4)		(5)		(6)	
	2013-2017											
LOG_WIPPE*,$10^3m^3/\$M$	-0.062	***	-0.070	***								
LOG_WIPS*,$10^3m^3/\$M$					0.035	***	0.043	***				
LOG_WIPE*,$10^3m^3/\$M$									0.042	***	0.042	***
INVENT_TURN	-0.050	***	-0.029	**	-0.037	***	-0.033	**	-0.038	***	-0.035	**
FIX_ASSET_TURN	-0.094	***	-0.075	***	-0.049	**	-0.037		-0.040	*	-0.040	*
FNCL_LVRG	0.026	*	-0.006		0.015		-0.017		-0.003		-0.034	**
VOLATILITY, %	-0.027		0.035	*	-0.026		0.021		-0.023		0.022	
VOLUME	-0.047	***	-0.055	***	-0.061	***	-0.063	***	-0.060	***	-0.062	***
PX_TO_BOOK_RATIO	0.223	***	0.238	***	0.215	***	0.237	***	0.233	***	0.252	***
RD, $M	-0.041	***	-0.059	***	-0.041	***	-0.073	***	-0.043	***	-0.076	***
SALES_GROWTH, %	0.124	***	0.112	***	0.125	***	0.115	***	0.125	***	0.116	***
ROE, %	-0.006		-0.004		-0.008		-0.006		-0.004		-0.002	
EPS_GROWTH, %	0.014		0.015	*	0.014		0.014		0.015		0.015	*
BETA	0.305	***	0.296	***	0.312	***	0.304	***	0.309	***	0.300	***
PPE, $M	-0.151		-0.118	***	-0.198	***	-0.144	***	-0.193	***	-0.142	***
SIZE, $M	0.179	***	0.197	***	0.221	***	0.224	***	0.239	***	0.243	***
Year F.E.	Yes		Yes		Yes		Yes		Yes		Yes	
Industry F.E.	No		Yes		No		Yes		No		Yes	
Observations	3600		3600		3600		3600		3600		3600	
R-Squared	0.202		0.282		0.191		0.272		0.193		0.274	

Variables	(1)		(2)		(3)		(4)		(5)		(6)	
	2018-2022											
LOG_WIPPE*,$10^3m^3/\$M$	-0.040	***	-0.053	***								
LOG_WIPS*,$10^3m^3/\$M$					0.013		0.016					
LOG_WIPE*,$10^3m^3/\$M$									0.017	*	0.017	
INVENT_TURN	-0.052	***	-0.049	***	-0.050	***	-0.059	***	-0.150	***	-0.060	***
FIX_ASSET_TURN	-0.011		0.035		-0.009		0.022		0.153		0.023	
FNCL_LVRG	-0.038	**	-0.059	***	-0.045	**	-0.068	***	-0.216	***	-0.075	***
VOLATILITY, %	-0.008		-0.002		0.019		0.021		-0.108		0.020	
VOLUME	-0.051	**	-0.054	***	-0.063	***	-0.065	***	-0.036	***	-0.064	***
PX_TO_BOOK_RATIO	0.288	***	0.309	***	0.273	***	0.298	***	0.381	***	0.304	***
RD, $M	-0.082	***	-0.083	***	-0.091	***	-0.106	***	-0.082	***	-0.107	***
SALES_GROWTH, %	0.172	***	0.165	***	0.172	***	0.167	***	0.276	***	0.169	***
ROE, %	-0.093	***	-0.093	***	-0.084	***	-0.085	***	-0.066		-0.083	***
EPS_GROWTH, %	-0.070		-0.086		-0.048		-0.054		5.456		-0.066	

BETA	-0.041	***	-0.042	***	-0.040	***	-0.043	***	0.261	***	-0.043	***
PPE, $M	-0.040		-0.001		-0.087	***	-0.042		0.193	***	-0.042	
SIZE, $M	0.111	***	0.093	***	0.155	***	0.138	***	-0.079	***	0.143	***
Year F.E.	Yes		Yes		Yes		Yes		Yes		Yes	
Industry F.E.	No		Yes		No		Yes		No		Yes	
Observations	3555		3555		3555		3555		3555		3555	
R-Squared	0.165		0.253		0.161		0.248		0.161		0.248	

Note. The sample period is 2013–2022. The dependent variable is RET. All variables are defined in Table 5.1. We report the results of the pooled regression with standard errors clustered at the firm and year level (in parentheses). All regressions include year fixed effects and industry-fixed effects. The table reports the results for the natural logarithm of water intensity. The upper panel reports the results for the year of 2013-2017 (n = 3,600 company-years); the bottom panel reports the results for the year of 2018-2022 (n = 3,555 company-years); *** 1% significance; ** 5% significance; *10% significance.

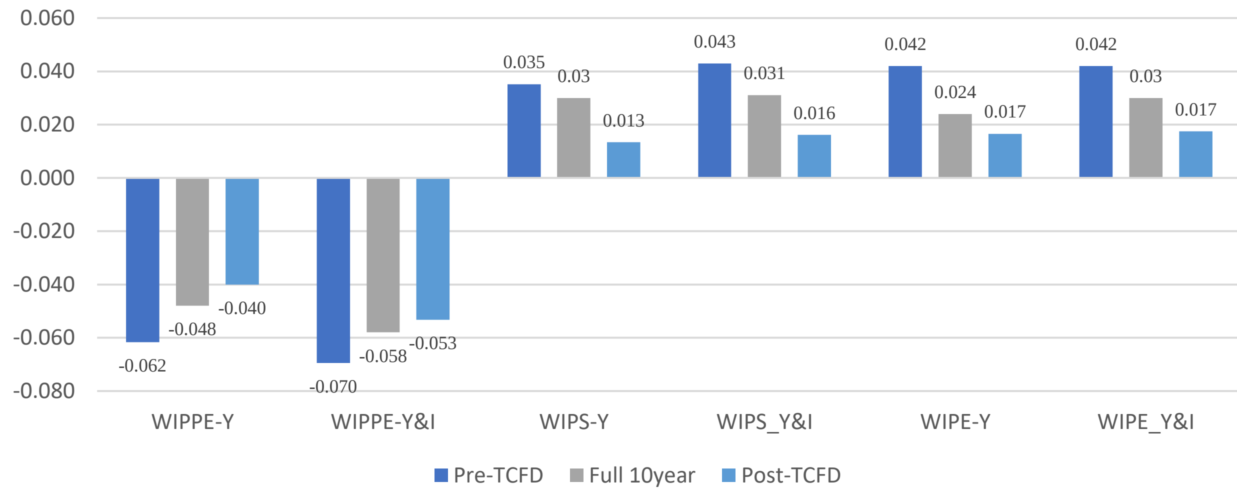


Figure 5.2: Water Intensity Correlation Coefficient with Stock Return Pre- and Post-TCFD Regulation (Y: Year fixed; Y & I:Year and Industry fixed)

5.4.6 Evidence on cross-sectional market performance

While all previous results were focused on the impact of water intensity on share price return, previous work (Tian and Adriaens, 2023; El Khoury et al. 2022; Alareeni et al. 2020; Lewandowski, 2017) has shown ESG or carbon impact on other market metrics including ROA, ROE and Tobin's Q, which reflect business efficiency and valuation metrics. These metrics are also discussed in stakeholder theory on how to measure the moderating effect of corporate sustainability attributes on the financial performance of firms. For all three categories of water, we relate in turn the level of companies' consumption, the year-to-year growth in consumption, and the companies' water intensity to their corresponding market performance in the cross-section.

It estimates the following cross-sectional regression model using pooled OLS:

$$FP(ROA, ROE, TOBIN'S\ Q) = a_0 + a_1 LOG(WATER) + a_2 Controls + \epsilon \qquad (2)$$

where FP measures the financial performance of ROA, ROE and Tobin's Q, standing for firms' operational, financial and market performance and WATER is a generic term alternately standing for the water indicators of this study. The vector of controls includes a host of firm-specific financial variables known to predict returns, such as SIZE, INVNT_TURN, FIX_ASSET_TURN, FNCL_LVRG, RD, and BETA (El Khoury et al. 2022; Alareeni et al. 2020). To address endogeneity issues, we incorporate year and industry fixed effects. Standard errors are clustered at the firm and year levels. The coefficient of interest is a_1. It reports the results in Table 5.12.

Table 5.12 Water Intensity Indicators and Capital Markets Performance Metrics

	TOBINQ(%)									
LOG_WC, 10^3m^3	-0.304***	-0.371***								
WATER_GR			0.007	-0.002						
LOG_WIPPE, 10^3m^3/$M					-0.063**	-0.100***				
LOG_WIPE, 10^3m^3/$M							-0.249***	-0.324***		
LOG_WIPS, 10^3m^3/$M									-0.153***	-0.117***
INVENT_TURN	-0.139***	-0.123	-0.124***	-0.128***	-0.162***	-0.159***	-0.162***	-0.155***	-0.150***	-0.120***
FIX_ASSET_TURN	0.012	-0.018	0.309***	0.126***	0.104***	0.074***	0.032	0.005	0.238***	0.053*
FNCL_LVRG	0.070***	0.069***	0.086***	0.107***	0.031	0.035	0.055***	0.049**	0.081***	0.104***
BETA	-0.041**	-0.043	-0.109***	-0.109***	-0.039**	-0.046**	-0.040**	-0.045**	-0.107***	-0.106***
RD, $M	-0.065**	-0.064**	0.051**	-0.037	0.024	-0.048*	0.010	-0.058**	-0.035*	-0.071***
SIZE, $M	0.386***	0.392***	0.299***	0.299***	0.271***	0.256***	0.235***	0.230***	0.314***	0.306***
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1545	1545	1925	1925	1487	1487	1487	1487	2125	2125
R-Squared	0.207	0.212	0.305	0.268	0.147	0.148	0.182	0.184	0.315	0.284

	ROA(%)									
LOG_WC,10^3m^3	-0.009	-0.031*								
WATER_GR			0.165	0.014						
LOG_WIPPE,10^3m^3/$M					0.068**	0.040				
LOG_WIPE,10^3m^3/$M							-0.150***	-0.247***		
LOG_WIPS,10^3m^3/$M									0.098***	0.036
INVENT_TURN	-0.022**	-0.030**	-19.042*	-0.027	-0.067**	-0.098***	-0.074***	-0.100***	-0.044**	-0.016
FIX_ASSET_TURN	0.028**	0.014	0.227***	0.211***	0.053**	0.057*	-0.014	-0.010	0.337***	0.243***
FNCL_LVRG	-0.015	-0.013	-0.030	-0.042*	-0.053**	-0.032	-0.024	-0.016	-0.040*	-0.045**

BETA	0.002		0.001		-0.001		-0.001		0.000		-0.009		0.001		-0.007		-0.003		-0.001	
RD, $M	0.001		-0.003		-0.023		-0.327		0.038		-0.038		0.022		-0.056		-0.002		-0.015	
SIZE, $M	0.112	***	0.121	***	0.222	***	0.218	***	0.179	***	0.177	***	0.147	***	0.152	***	0.209	***	0.195	***
Year F.E.	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Industry F.E.	No		Yes		No		Yes		No		Yes		No		Yes		No		Yes	
Observations	1586		1586		1925		1925		1514		1514		1514		1514		2125		2125	
R-Squared	0.070		0.093		0.115		0.194		0.044		0.051		0.052		0.058		0.151		0.170	

	ROE(%)																			
LOG_WC, 10^3m^3	-0.031	**	-0.055	***																
WATER_GR					0.016															
LOG_WIPPE, 10^3m^3/$M							0.012		0.008		-0.009									
LOG_WIPE, 10^3m^3/$M													-0.080	***	-0.126	***				
LOG_WIPS, 10^3m^3/$M																	0.028		-0.020	
INVENT_TURN	-0.004		-0.008		-0.070	***	-0.048	**	-0.013		-0.023		-0.015		-0.022		-0.078	***	-0.074	***
FIX_ASSET_TURN	0.019		0.011		0.204	***	0.179	***	0.036	***	0.034	**	0.007		0.004		0.210	***	0.147	***
FNCL_LVRG	0.166	***	0.166	***	0.222	***	0.208	***	0.227	***	0.233	***	0.238	***	0.239	***	0.263	***	0.260	***
BETA	0.014		0.014		0.017		0.018		0.013		0.011		0.013		0.011		0.018		0.018	
RD, $M	-0.021	**	-0.019	*	-0.020		-0.033		0.011		-0.016		0.005		-0.023		-0.042	*	-0.038	
SIZE,$M	0.139	***	0.146	***	0.225	***	0.228	***	0.114	***	0.115	***	0.100	***	0.103	***	0.249	***	0.243	***
Year F.E.	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Industry F.E.	No		Yes		No		Yes		No		Yes		No		Yes		No		Yes	
Observations	1586		1586		1925		1925		1514		1514		1514		1514		2125		2125	
R-Squared	0.199		0.210		0.160		0.167		0.212		0.215		0.223		0.225		0.190		0.195	

Note: Column 1-2 shows the results for total water use; column 3-4 for water change ratio, and column 5-10 for water intensity. The sample period is 2013–2022 (n = 1501-2125). The dependent variable is FP. All regressions include year fixed effects and industry-fixed effects. ∗∗∗ 1% significance; ∗∗ 5% significance; ∗10% significance.

Contrary to the correlation between water risk indicators and share price return, the findings reveal a significant negative association between water consumption (WC) and ROA, ROE, and Tobin's Q. Thus, the hypothesis that water use affects firm market performance across multiple metrics is supported. This signifies that minimizing total water usage positively influences the firm's operational, financial, and market performance. This result aligns with prior research indicating a positive relationship between carbon emission reductions and corporate performance in terms of market and finance metrics (Busch et al, 2020; Delmas et al, 2015; Lewandowski et al. 2017; Gallego-Álvarez et al. 2015; Busch et al, 2018). Van (2021) observes that carbon emissions reduction leads to increases in ROA, ROE, and ROS, with no discernible effect on Tobin's Q and the current ratio (corporate liquidity). Similarly, Ganda (2016) found that, in most instances, carbon emission disclosure correlates positively with ROA (an accounting-based indicator) but exhibits a negative association with market value added (MVA, a market-based shareholder value indicator).

From the Tobin's Q result, reduced water consumption is linked to improved long-term corporate valuation, with industry-specific effects further emphasizing this relationship. Year-to-year growth ratios exhibit weaker associations with Tobin's Q. Water intensity indicators show a statistically significant negative impact on Tobin's Q, which strengthens when industry factors are considered. On the other hand, water use has a significant negative impact on ROE and ROA benefits. The WIPPE and WIPS indicators show a positive relationship with ROA and ROE, while WIPE has the opposite trend compared to other indicators. Lower water efficiency relative to profitability (WIPE) results in lower returns from assets (ROA) and equity (ROE) for companies. While no prior research on the impact of water intensity on market metrics is available, there is arguably some equivalency in the carbon literature. Rokhmawati (2015) finds that carbon intensity has a positive and significant effect on ROA for listed manufacturing firms in Indonesia. Lewandowski (2017) demonstrates that carbon emission mitigation is linearly and significantly positively related to return on sales (ROS) but exhibits a negative association with Tobin's Q. These contradictory findings show that companies have been slow to respond with effective action to tackle climate change beyond marginal efficiency improvements.

In summary, the findings highlight a notable market premium concerning water intensity indicators. Previous regression analyses in the literature have similarly noted a negative association between environmental disclosure and the firm’s operational and financial performance. For instance, a substantial inverse relationship was identified between the level of environmental disclosure and ROA and ROE for US S&P 500 companies (Chiong et al. 2010, Smith et al. 2007, Karagozoglu et al., 2000; Majumdar et al., 2001; Saleh et al., 2011). This result suggests that firms with environmental disclosure practices may face higher costs, potentially resulting in increased product prices and a potential loss of sales in a competitive environment. This emphasizes a more pronounced impact of environmental disclosure on the firm's operational and financial performance. Furthermore, the findings indicate a positive relationship between environmental disclosure and firm market performance, as measured by Tobin’s Q.

While Table 5.12 presented data with companies that are disclosing their water intensities and use (n = 1,501-2,025), the same regression analysis was performed for companies where financial data (K nearest neighbor algorithm) and water intensities (random forest) were imputed as described in Section 5.5.3. This regression analysis allows us to expand our sample universe to 7,110-7,200 company-years, and thus serves as a robustness test of the impact regression (Table 5.13).

Table 5.13 Imputation of Water Intensity and Financial Performance for S&P500 Companies between 2013-2022 (n = 7110-7200)

	TOBINQ (%)											
LOG_WIPPE*,$10^3m^3/\$M$	0.035	**	0.016	**								
LOG_WIPE*,$10^3m^3/\$M$					-0.148	***	-0.138	***				
LOG_WIPS*,$10^3m^3/\$M$									-0.014	*	-0.020	**
INVENT_TURN	0.035	***	0.093	***	-0.006		0.070	***	0.028	**	0.091	***
FIX_ASSET_TURN	0.282	***	0.193	***	0.053	***	0.033	**	0.248	***	0.173	***
FNCL_LVRG	-0.165		-0.086	***	-0.119	***	-0.062	**	-0.150	***	-0.081	***
BETA	-0.080	**	-0.070	***	-0.081	***	-0.069	**	-0.081	***	-0.071	***
RD, $M	0.063		0.016		0.060	***	0.019	*	0.072	***	0.021	*
SIZE, $M	0.206	***	0.213	***	0.120	***	0.131	***	0.198	***	0.207	***
Year F.E.	Yes		Yes		Yes		Yes		Yes		Yes	
Industry F.E.	No		Yes		No		Yes		No		Yes	
Observations	7200		7110		7200		7110		7200		7110	
R-Squared	0.172		0.158		0.219		0.210		0.168		0.156	

	ROA (%)											
LOG_WIPPE* ,$10^3m^3/\$M$	0.028	***	0.019	***								
LOG_WIPE*, $10^3m^3/\$M$					-0.074	***	-0.089	***				
LOG_WIPS*, $10^3m^3/\$M$									0.009		-0.007	
INVENT_TURN	-0.007		0.023	*	-0.027	**	0.011		-0.005		0.024	
FIX_ASSET_TURN	0.256	***	0.218	***	0.137	***	0.116	***	0.257	***	0.212	***
FNCL_LVRG	-0.150	***	-0.141	***	-0.120	***	-0.121	***	-0.136	***	-0.133	***
BETA	-0.017		-0.012		-0.018		-0.011		-0.017		-0.012	
RD, $M	-0.073	***	-0.067	***	-0.071	***	-0.060	***	-0.063	***	-0.060	***
SIZE, $M	0.299	***	0.293	***	0.253	***	0.238	***	0.293	***	0.288	***
Year F.E.	Yes		Yes		Yes		Yes		Yes		Yes	
Industry F.E.	No		Yes		No		Yes		No		Yes	
Observations	7200		7110		7200		7110		7200		7110	
R-Squared	0.162		0.167		0.172		0.176		0.159		0.164	

	ROE(%)											
LOG_WIPPE*,$10^3m^3/\$M$	-0.003	**	-0.011									
LOG_WIPE*,$10^3m^3/\$M$					0.073	***	-0.066	***				
LOG_WIPS*,$10^3m^3/\$M$									0.002		-0.005	
INVENT_TURN	-0.056	***	-0.018		-0.059		-0.023	*	-0.055	***	-0.020	
FIX_ASSET_TURN	0.142	***	0.142	***	0.061	***	0.068	***	0.146	***	0.136	***

FNCL_LVRG	0.175	***	0.189	***	0.183	***	0.190	***	0.173	***	0.183	***
BETA	-0.006		-0.004		-0.006	***	-0.003		-0.006		-0.004	
RD, $M	-0.081	***	-0.075	***	-0.087	***	-0.080	***	-0.082	***	-0.079	***
SIZE,$M	0.276	***	0.280	***	0.243	***	0.244	***	0.276	***	0.283	***
Year F.E.	Yes		Yes		Yes		Yes		Yes		Yes	
Industry F.E.	No		Yes		No		Yes		No		Yes	
Observations	7200		7110		7200		7110		7200		7110	
R-Squared	0.120		0.121		0.129		0.130		0.120		0.121	

Note. All regressions include year fixed effects and industry-fixed effects. The table reports the results for the natural logarithm of water intensity. ∗∗∗ 1% significance; ∗∗ 5% significance; ∗10% significance.

The imputation simulation results are in Table 5.13 closely mirror the observed data series shown in Table 5.12. Both WIPE and WIPS have a significant negative impact on Tobin's Q. Notably, the WIPPE impact is showing a shift, as it is significantly positive in the imputation data, whereas regressions based on disclosed data show a significant negative relationship. Imputation is conducted in an uncertainty framework, and the WIPPE may have been impacted by a tail bias in the distribution. This highlights the need for future research to explore the WIPPE imputation method and its theoretical implications for long-term performance in Tobin's Q. The argument in this chapter is that more investment in real (fixed) assets results in low water use efficiency, and thus negatively impacts the future value of the firm (Tobin’s Q). The result in the imputed table that the long-term value now increases is difficult to reconcile with previous data. Aside from WIPPE and long-term value, both WIPE and WIPPE consistently exert a negative impact on ROE. Additionally, for ROA, a reduction in WIPE and an increase in WIPPE benefit the company, aligns with the trend observed in Table 5.13. The results imply that water intensity is an predictive leading indicator for future financial performance and risk mitigation strategies, and therefore, of considerable importance from a policy perspective.

5.5 Conclusions

How climate change affects the capital markets is a fundamental question in the burgeoning field of climate change and finance and informs policy makers who are seeking to engage investors in the fight against climate change. In fact, it was this question that was considered by the Financial Stability Board of the Bank of England to propose TCFD. Climate change impacts financial stability in the capital markets, and transparency of corporate risk disclosures is a key enabler. This chapter sought to assess whether corporate risk disclosures affect market metrics and whether they are channeled through corporate accounting and their relationship to sustainability metrics such as corporate water use, and water intensity. The rationale is that corporate operations and investor perceptions or expectations of investors to be rewarded for climate risk, have shifted given water availability as an input to corporate operations, profitability and risk of capital assets to become stranded. We posited two hypotheses: H1 Accounting-based profitability ratios are positively affected by lower corporate water intensity; H2 Capital markets metrics are positively impacted by efficient corporate water use.

To address this question, it undertakes a cross-sectional regression analysis with market returns as a dependent variable and corporate accounting as well as water intensity metrics as a firm characteristic, and find robust evidence that water intensity significantly and positively affects share price returns, and generally negatively affects ROA, ROE and Tobin’s Q. The added challenge in this analysis is that few companies disclose their water efficiency (intensity) metrics in public reports and SEC disclosures. For example, of all companies listed on the S&P500 index, approximately 20% of companies provide any information on their water use. Hence, to test these hypotheses with sufficient robustness, imputation methods need to be deployed both for financial and water intensity input data that inform market metrics. This chapter applied K-nearest neighbor and random forest (Chapter 4) imputation algorithms to develop a corporate universe (approx. 7,200 company-years) to complement the disclosing universe (approx. 1,500 company-years).

Whether through the production of their goods and services, or investment in fixed assets to scale revenue growth and profits, firms across eleven (11) industry sectors are differentially affected by internal policies and financial regulation (e.g. TCFD) to use water efficiently and reduce their impact on - and exposure to - climate change. Empirical evidence suggests that investors are discerning these cross-sectional differences and are pricing in water risk, based on the inverse relationship between water intensity indicators and market impacts.

In high water intensity industries such as industrials, energy and commodities, there is a robust, persistent, and significant positive water premium at the firm level for all three categories of water intensity. Higher water intensities result in higher share price return. This result indicates that companies face penalties from investors if they move along the curve towards better water performance. This also implies that companies face little incentive to improve their water performance beyond a minimum level of water performance that brings the opportunity to change from a positive to a negative association and, thereby, benefit financially from a better water performance. The result is in line with those of Keele and DeHart (2011), who find no immediate financial benefits from participation in initiatives such as the United States Environmental Protection Agency (USEPA) Climate Leaders program. Importantly, a comparison of 2013-2017 and 2018-2022 (pre- and post- TCFD promulgation and implementation) shows that market returns are attenuated (the coefficient decreases) in recent years. There is no significant water premium associated with total water use.

By analyzing market performance analysis, our results show that the water efficiency has a significantly negative effect on short-term operating capacity (ROA) and positive effect on long-term market value (Tobin's Q). Hence, the future (replacement) market value of companies is lower when companies are more water intensive, potentially indicating that constrained resources such as water may impact valuation. To avoid contingency bias in our results, we conducted a robustness analysis by incorporating companies with imputed values (n = 7,200 company-years). The results show that while the impact of water intensity per sales and operating profit on Tobin's Q are consistent and negative, the results on water intensity relative to fixed asset investment shifted from a negative to a positive effect. The impact of water intensities on ROA and ROE are robust, but the magnitude of the coefficient decreases in the robustness test. Importantly, our conclusions are not affected by industry selection.

The results of the analysis have important implications for business strategy. Water performance has been recognized by different stakeholder groups as a financially-material business issue. Moreover, an increasing body of empirical research suggests that water performance has a significant positive effect on corporate financial performance (Tian and Adriaens, 2023), including cost of equity. Thus, managers need to explore adequate corporate water strategies (transfer risk, invest in risk, or depreciate assets) to sustain or even enhance competitiveness. This, however, appears to be a very complex process. The results of this chapter suggest that climate water risk mitigation may constitute a source of competitive advantage. While some companies may discover financial benefits in water performance management and opt for a proactive approach, others might find it more financially prudent to adopt a reactive strategy until business uncertainties diminish.

Chapter 6 Conclusions and Future Recommendations

6.1 Machine Learning and Next Generation Analytica Tools for Water Risk Impacts and Valuation

The analytical tools and techniques used in this dissertation produced novel insights to whether the financial markets value corporate water sustainability disclosures, to predict corporate water intensity indicators from financial data inputs, and how corporate water efficiency is related to broader market metrics. These insights inform whether water risks are material to corporate financial performance, which is one of the key inputs in the development of enterprise value-based corporate water stewardship strategies.

While the literature has published ample work on the impact of carbon intensity and emissions on market metrics, water risk, a well-defined component of the Natural Resource Based View of the Firm, a corporate strategy and competitiveness theory, is poorly studied. This despite insurance companies and asset managers arguing that water risk exhibits the greatest direct financial impact of climate change. My work quantifies the effect of water intensity indicators disclosed by high growth companies listed on the S&P 500 index, representing 11 sectors of the economy based on GICS (Global Industry Classification System). The water intensity indicators are normalized relative to income statement and balance sheet metrics such as sales (revenue), operating income (EBIT; earnings before interest and taxes), and fixed asset investment (PP&E; plant, property, and equipment). The impacts was assessed vis a vis a range of market performance metrics, such as share price return, ROE/ROA, and Tobin's Q. Three sets of advanced statistical tools were used in this work: Propensity score matching (PSM), an inference tool, to compare binary universes of companies; Machine learning tools such as Random Forest, Adaboost, and Nearest neighbor algorithms to train statistical relations for imputation purposes of financial and water risk indicators; and Fixed effects regression tools to understand time and industry sector effects, as well as for robustness tests.

In Chapter 3, I used propensity score matching (PSM) to compare the effect of water use efficiency between high (bottom 70% of distribution) and low (top-30 %) intensity companies, while accounting for key confounding financial metrics derived from the Barra financial model and industry sector, over three years. The results show that, after accounting for confounders such as volume traded, dividend yield, financial leverage, size, fixed asset turnover, and inventory turnover, there is a causal inference relationship between water use efficiency (or conversely, water intensity) and corporate financial performance. The impact of the treatment effect on financial performance was highly dependent on the selection of the water intensity metric, and the financial outcome variable. There is significant impact on ROA (a short-term operational metric), alpha (a metric indicating excess returns over the benchmark) and Tobin's Q (a long-term valuation metric for the firm). The results further indicated that industry classification, which is based on business activity, is not a useful benchmark for comparing financial water efficiency performance, because two companies in the same GICS classification exhibit entirely different financial attributes. The limitation of the causal inference tool applied is its requirement for binary-treatment variables (high/low water intensity, based on a probability distribution). Second, the universe of companies was small, because less than 20% of S&P500 companies disclose their water use data.

Chapter 4 addressed one of the shortcomings by expanding the corporate universe for analysis through the development of imputation models of water intensity performance using multiple ML tools, including random forest regression, using corporate financial metrics as an input. The input variables are selected from the Barra Risk Factors models, a multi-factor model that considers 40 financial metrics that are predictive of securities performance. The selection was based on using correlation tables and recursive feature elimination (RFE) to reduce the number of dimensions (financial factors). While five ML regression models were tested, I focused on the random forest model, because it required the least financial input variables and exhibited the best statistical performance on three metrics. After selection, the remaining six input variables for the RF model are volume traded, dividend yield, financial leverage, size, fixed asset turnover, and inventory turnover. The output variables are water intensity per sale (WIPS), water intensity per EBIT (WIPE), and water intensity per PP&E (WIPP). After training and testing the random forest regression over 5 years (2017-2021) of firm data, I was able to combine (disclosed and imputed) water intensities for 2,525 company-years with an R2 of 0.75, 0.74, and 0.66 for WIPS, WIPE, and WIPP respectively. The three most significant variables to predict water intensity indicators are: Fixed Asset Turnover, Inventory Turnover and Financial Leverage. A comparison of companies with known and imputed water intensity indicators resulted in a mixed outcome. The most reliable predictions where imputed values were comparable to peers in the same sector were in the most water intensive industries, including utilities, consumer staples, energy, materials and real estate.

Chapter 5 then empirically investigated the impact of water intensities on the financial variables that may affect the market performance of firms (FP), for up to 10 years (7,200 company-years). It contributes to the expanding literature on empirical premium analysis for water risk by developing and examining a comprehensive set of return prediction factors through various multiple (fixed effect) regression algorithms. It finds that stocks of firms with higher water intensities (and changes in water consumption) earn higher returns, indicating that water use intensities (or access limitations) are not priced in shares. However, the future value of a company (Tobin's Q) and return on equity (ROE) are negatively impacted by water intensity, a signal for forward-looking share prices. In addition, we saw that the impact of corporate water impact before and after promulgation of TCFD, a financial regulatory requirement for companies to disclose their impact from climate change, attenuated the market signals, including tempering short term operational returns (ROA) and further increasing the coefficient of ROE and Tobin's Q. This indicates that financial regulation may reward future corporate action.

This econometric research contributes to our understanding of the financial implications and opportunities of corporate water stewardship and will aid risk management actions in their transition to a climate-induced water resource-constrained world. With insurance companies trying to understand water liabilities from climate change in their portfolios, and corporations needing to make informed water risk management decisions for Enterprise Resource Planning (ERP), there is a need for better data and causal relationships between water risk and quantitative financial implications for their operations and the capital markets. This work is of interest to the market, as evidenced by one of our Center's spinouts, Equarius Risk Analytics, which is focused on climate water risk pricing in equities and invested by corporate strategic partners.

6.2 Which Water Indicator Could be the Signal to Inform the Market?

The environmental indicators pertain to the systematic measurement and reporting of the performance of environmental policies within the framework of sustainable development. Environmental indicators have played a pivotal role in heightening awareness of environmental issues, influencing policy decisions through performance evaluations, spurring strategic planning efforts to mitigate environmental pressures, and serving as catalysts for research and policy actions. Their overarching objective is to convey pertinent information about the environment and its interaction with human activities. This mode of communication is instrumental in emphasizing emerging environmental challenges and shedding light on the effectiveness of existing policy measures. While most research and reporting activity is limited to the physical realm (water the liquidity risk), financial implications for corporate risk managers and asset managers are a lot less well studied, nor reported (water the liquidity risk).

Pioneering work of groundbreaking efforts at the World Resources Institute (WRI) and the World Bank contributed to the development of environmental or "green" national accounting, also known as natural resource accounting. This methodology adjusts national economic accounts to factor in the (social) costs of pollution and the depletion of natural resources (WRI, 1989). This urgency has been further accentuated by impending financial regulations pertaining to climate risk disclosures and the growing integration of sustainability metrics into decision-making processes. For water issues, the OECD (Organization of Economic Cooperation and Development) and UNEP (UN Environment Program) matrices include water resource expenditures and water pricing, while the World bank takes water efficiency into account (Hammond et al. ,1995). In the study of indicator-based sustainability assessment (Juwana et al.,2012), Savenije and Van der Zaag (2002) emphasize the significance of the Dublin Principles for integrated water resource management, as articulated in the International Conference on Water and the Environment (ICWE) (United Nations Conference on Environment and Development, 1992). These principles assert that: (1) Water is an indispensable resource that must be used and managed judiciously; (2) The involvement of all relevant stakeholders is essential in the development and management of water resources; (3) The pivotal role of women in the provision, management, and safeguarding of water resources is recognized and acknowledged. The economic value of water in all its uses should be underscored and factored into the decision-making process. The necessity for the incorporation of water-related issues is also acknowledged by Loucks and Gladwell (1999), who present water sustainability principles. These principles encompass the critical domains of water infrastructure, environmental quality, economics and finance, institutions and society, human health, and well-being, as well as planning and technological considerations.

Specifically, information on the environmental impact on corporate financial performance is considered an Environmental Performance Indicator (EPI). The EPI represents both the quantification of the effectiveness and efficiency of environmental action (Neely et al., 1995), as well as the priority and commitment of firms to quantifying their environmental issues (Henri, 2008). While volumetric measures of water use are relatively simple, physical data do not reflect their impact in terms of financial performance (Christ et al., 2017). On the other hand, the internal economic indicators alone should not replace physical information as the basis for sound decision-making, rather there should be an advanced indicator to present the value of water impact on corporate financial performance to support decision making (Unit, E. I.,2015; Caspar Snijder et al., 2017).

Firm-level water consumption data are assembled by several main providers: GRI, CDP, SASB, Sustainalytics and TCFD (specifically CDSB, Climate Disclosure Sustainability Board) application guidance for water-related disclosures). The accessible data from these ESG data providers covers themes such as water use efficiency, water stress, toxic effluents/emissions/water quality, as well as broader issues such as community conflict, human rights, monitoring, reporting. While some firms incorporate climate risk in terms of emissions or intensity, a specific emphasis on water is uncommon. Given that more and more companies disclose their physical water information and most large corporations report their water risks to

CDP, current ESG methodologies are not configured to capture the spectrum of water risk exposures and corporate risk response options.

In the face of this knowledge gap, my work contributes to the need for enhancing the ability of investors to understand the financial materiality of water. Because of the lack of standardization, we first include all related water data in the paper within three groups: water consumption, water use growth and water use intensity normalized to financial metrics. The first represents both total water consumption and total water withdrawal. The second group encompasses growth of the total water use and growth of the withdrawals over time. The third is the water intensity (or efficiency) relative to sales, EBIT, and fixed assets. The Bloomberg database reports all water data. The description and correlation of the water variables are in Table 6.1 and Table 6.2.

Table 6.1 Description of water variables

Index		Definition	Method
Water Intensity	WIPS	Water Intensity per Sales	Total water use/ Sales
	WIPE	Water Intensity per EBIT	Total water use/ EBIT
	WIPPE	Water Intensity per PPE	Total water use/ PPE
	WIPA	Water Intensity per Assets	Total water use/ ASSETS
	WW_SALES	Water Use/Withdrawal Intensity per Sales	Total water use/ Total water withdraw/ Sales
	WW_EBITDA	Water Use/Withdrawal Intensity per EBITDA	Total water use/ Total water withdraw/ EBITDA
	WW_ASSET	Water Use/Withdrawal Intensity per Assets	Total water use/ Total water withdraw/ ASEET
Water Growth	WATER_GR	Growth Rate of Total Water Use	(Total water use(t)- Total water use(t -1)/ Total water use(t-1)
Water Volume	WATER_USE	Total Water Use	Total amount of water used to support a company's operational process. (unit: 1000 m3)
	WATER_WITHDRAW	Total Water Withdraw	Water withdrawal describes the total amount of water withdrawn from a surface water or groundwater source.

Table 6.2. Correlation between water use and intensity indicators.

The sample period is 2013-2022. The table presents the cross-correlation among water variables. The water variables are defined in table 6-1.

Index		WIPS	WIPE	WIPPE	WIPA	WW_Sales	WW_EBIT	WW_ASSET	WATER_GR	Water TOT	Water_Withdrawal
Water Intensity	WIPS	1.000	0.502	0.492	0.725	0.996	0.417	0.722	0.004	0.927	0.894
	WIPE	0.502	1.000	0.879	0.321	0.502	0.410	0.320	0.045	0.418	0.412
	WIPPE	0.492	0.879	1.000	0.355	0.491	0.168	0.353	0.039	0.414	0.398
	WIPA	0.725	0.321	0.355	1.000	0.725	0.445	1.000	0.006	0.720	0.557
	WW_Sales	0.996	0.502	0.491	0.725	1.000	0.605	0.763	0.004	0.927	0.801
	WW_EBIT	0.417	0.410	0.168	0.445	0.605	1.000	0.597	0.003	0.407	0.520
	WW_ASSET	0.722	0.320	0.353	1.000	0.763	0.597	1.000	0.006	0.720	0.682
Water Growth	WATER_GR	-0.005	0.045	0.042	0.009	-0.002	0.000	-0.001	1.000	0.001	-0.001
Water Volume	Water TOT	0.927	0.418	0.414	0.720	0.927	0.407	0.720	0.001	1.000	0.972
	Water_Withdrawal	0.894	0.412	0.398	0.557	0.801	0.520	0.682	0.001	0.972	1.000

How correlated are these different water variables? The cross-correlations were reported in Table 6.2 for water indicator selection. The levels of all three groups of water are positively correlated and are at times high within each group. Similarly, the level of water consumption is highly positive correlated with total water withdraw and water intensities. Based on the regression analysis and indicator perspective, for water volume group, we choose total water use as proxy. The total water growth is selected in the water growth group. For water intensity and their highly correlated relationship, water-withdraw intensity for indicator is reported in Bloomberg platform and most water use intensities are calculated manually with raw reported data. the work indicated that water use, and water intensity indicators are statistically powerful disclosures for water risk imputation and to understand correlation to short-term and long-term market metrics.

6.3 Limitation

Regrettably, there is a dearth of prior research on the influence of water on financial performance. Existing studies primarily rely on hypothesis testing without delving into the underlying reasons for observed correlations. Limited attention has been given to exploring mediating factors like innovation and operational efficiencies that could enhance corporate performance. Most investment studies lack clear demarcation of the diverse risk-reward outcomes associated with different water behavior integration approaches. Thematic studies are also scarce, although promising insights emerge from climate change research, revealing a robust connection between strategies reducing water intensities and improved corporate performance. This publication addresses these gaps, offering a more comprehensive understanding of the intricate relationship between water dynamics and financial outcomes.

However, due to the limited disclosure of water information (20% of companies) and reliance on imputation methods, potential bias exists of the research, primarily reflecting practices of clean and high-reputation companies. Sensitivity analyses and transparency in reporting were employed to address these limitations.

Research endeavors should enhance their precision in discerning diverse water risk exposures faced by companies to conduct a thorough analysis of financial performance. This study specifically homes in on the direct water intensity associated with production and operation, omitting consideration of indirect water risks originating from supply chains or firm services. The absence of water accounting in measuring the risk of water in these areas poses a notable limitation.

Furthermore, it is imperative to recognize that water risks extend beyond direct operational facets, encompassing regulatory and litigation risks. These external forces significantly impact company performance and should not be disregarded in the broader evaluation of water-related financial risks.

A crucial yet underexplored facet in the current research landscape involves identifying causal factors contributing to improved financial performance in companies with robust sustainability strategies. We advocate for expanded research into various dimensions, including sustainability-driven innovation, employee relations, supplier loyalty, customer demand, risk mitigation, and operational efficiency. This comprehensive examination is essential for a nuanced understanding of the intricate factors influencing corporate success in the context of sustainability strategies.

Nevertheless, intriguing challenges for future research emerge from certain limitations in this study. Firstly, the study's temporal scope is confined, underscoring the need for future investigations to construct more extensive panel data and explore the lag reaction from the market. Additionally, replicating the obtained results with a different environmental measure would bolster the robustness of the findings. Lastly, considering the variations in corporate governance, legal frameworks, and institutional systems based on countries' characteristics is a valuable avenue for further analysis in future research.

6.4 Future Research: Uncovering Hidden Signals for Sustainable Investing Using Big Data

Artificial intelligence (AI) is a groundbreaking technology that enables machines to make human-like decisions and improve over time. Coined by John McCarthy in 1956, AI includes subfields like deep learning, natural language processing, and machine learning, among others (Yaninen, 2017). A Bank of America study predicts significant growth in US ESG or sustainable investments, expanding opportunities in the stock market over the next few decades. Improved data quality and AI's ability to uncover hidden insights make sustainable investing more effective. AI outperforms traditional methods by automating tasks and enhancing analytical capabilities, contributing to cost-efficiency, speed, scalability, accessibility, profitability, and competitiveness in modern finance (Antoncic et al. 2020). Kaack et al. (2020) suggests that recent breakthroughs in machine learning tools have the potential to bring us closer to realizing the United Nations Sustainable Development Goals (UN SDGs), and Kumar et al. (2021) argue that the application of cutting-edge technologies to sustainability assessment can play a pivotal role in facilitating the green transition. Both Al-Sartawi et al. (2021) and Avgouleas (2021) hope that advanced financial technology including AI, ML and blockchain can boost sustainable finance. Inampudi & Macpherson (2020) further posit a great potential for AI to contribute not just to global economic activity, but particularly to ESG investing.

Natural Language Processing (NLP).

Informed Environmental, Social, and Governance (ESG) investments necessitate a means to identify ESG-related markers in companies. The literature highlights the compelling use of Natural Language Processing (NLP)-based analysis to discern the alignment between environmental policy and scientific discourse, to validate their compliance with environmental sustainability objectives (Smith et al., 2021). Amel-Zadeh et al. (2021) identifies that firms aligned with the UN Sustainable Development Goals (SDGs) are identified based on the content within their sustainability disclosures. Sokolov et al.(2021) finds that the use of BERT, a large language model, enhances document assessment in ESG contexts, with implications for automated investment index construction. Pasch et al. (2022) improved ESG sentiment prediction by 11% by combining ESG ratings with annual report text to enhance sentence-level prediction.

By leveraging artificial intelligence (AI) and sentiment analysis, firms can convert qualitative data from news, reports, and filings into quantitative signals for cross-company and industry analysis. Despite limited available ESG data, AI-equipped investors can gain a competitive edge by utilizing sentiment analysis to: Capture news sentiment; Assess a company's alignment with ESG criteria and measure compliance; Make better-informed investment decisions. This approach streamlines data processing, reduces manual reading efforts, and provides transparent, comparable ESG data from diverse sources, ensuring investors stay relevant and competitive in the financial landscape.

Machine Learning with More Diverse Datasets.

Increased access to climate data, despite its limited reliability, and the intricate statistical modeling of climate change's non-linear behavior (Alonso-Robisco et al., 2022) pose formidable mathematical challenges to understand climate impact on corporate activity and the economy (Stephenson et al., 2012). The extensive datasets may demand advanced statistical tools due to their increasing complexity and the growing availability of micro-level data (López de Prado, 2019). Besides, large climate finance datasets enable flexible modeling beyond linear approaches. Machine learning techniques, such as decision trees and neural networks, provide effective tools to model and understand complex financial relationships (Varian 2014, Athey 2018, Athey & Imbens 2019). Data-driven ML approaches accommodate large datasets without imposing rigid assumptions, revealing unanticipated patterns and delivering strong out-of-sample performance (Mullainathan & Spiess, 2017).

Increasingly, advanced ML tools are assuming a pivotal role in climate finance literature, addressing physical and transition risks, as well as corporate and social responsibility aspects, such as ESG factors and climate data. The Conference of the Parts (COP26) conferences have stated that AI and ML can play a key role in important climate-related topics like prediction, mitigation, and adaptation (Clutton-Brock et al. 2021). Linking financial data to climate ML models creates a new opportunity but building on our work. Raza (2022) examines ESG score reliability for asset managers by using ML tools to assess the impact of financial data on ESG scores for non-financial public companies in the USA, UK, and Germany from 2008 to 2020. Plakandaras et al.(2018) leveraged ML techniques to model climate change as a geopolitical risk and predict its influence on various financial assets. Rolnick et al. (2022) shows how deep learning can significantly impact climate investment by helping to select low carbon-emitting companies for portfolios and optimizing investment timing.

The Blockchain Opportunity.

Blockchain is a distributed, decentralized, peer-to-peer database network that allows for fast, secure, and transparent transactions of digital assets. It is a network of ledgers to record information. Each ledger then acts as a node in a network. In blockchain, the veracity of transactions is validated by distributed consensus. The updated transaction is stored in a block. Each block stores a series of transactions and is linked to the previous block of transactions through hashing functions. Through cryptography and complex mathematical puzzles, the blockchain network is virtually immutable, and has been used to track climate (carbon) data in support of TCFD compliance. There are new calls in the literature to utilize blockchain technology to solve the water distribution problems, mitigate the risk involved, and monitor the water management system (Dogo et al.,2019). For recordkeeping, blockchain can help to effectively adjust and monitor the water area, as opposed to with the currently applied techniques (Poberezhna,2018). Besides, the blockchain framework is well equipped to deal with information compromise and reporting, compliance, and audit review on water management (Chung et al., 2023)

6.5 Future Research: Facility-Specific Geospatial Data for Portfolio Risk Management

UN Water advocates investigating water scarcity at the local level, particularly in river basins or sub-basins, aligning with the Aqueduct global water risk mapping methodology (Reig et al., 2013), a product developed by WRI with funding from the Bloomberg Foundation. Norges Bank Investment Management, a sovereign wealth fund, argues for reinsurers (risk underwriters of insurance companies) use of meteorological and geographical models in water risk research and asset risk pricing. These models provide essential statistics for establishing risk thresholds, a key aspect in climate-related risk assessment. Notably, reinsurers are hesitant to disclose their proprietary risk models, hence, independent validation and verification is challenging.

Climate water impact on corporations manifests itself in many forms. First, it encompasses physical risks tied to local water conditions, such as quality and quantity, drought and flood, along with associated reputational and regulatory risks. Second, it considers operational risk, factoring in industry-specific water dependencies, including supply chain, water based logistics and facility-specific geospatial risks, as highlighted by Pan et al. (2012). Consequently, a comprehensive corporate risk transfer strategy may not be the most effective approach. Instead, focusing on facility-level risk profiles for portfolio management strategies is recommended for greater precision and efficiency. Pan et al. (2012) and companies like dClimate emphasizes the need to bridge the information gap in climate risk disclosures using facility-level risk management, as also exemplified in documents such as "CDP - Setting Site Water Targets Informed By Catchment Context: A Guide For Companies." The International Water Stewardship Standard, developed by the Alliance for Water Stewardship (AWS), promotes the equitable, sustainable, and economically beneficial use of water. These standards advocate a stakeholder-inclusive approach, encompassing site- and catchment-based actions.

6.6 Future Work: Corporate Risk Transfer Strategies.

The Investor Water Hub (Prof Adriaens, Advisor), established by Ceres (an NGO), unites 85 investors from various asset classes to explore the impact of water risk on their holdings and how they manage this risk through pricing and asset allocation strategies (Ceres, 2015; Ceres n.d.). The hub argues that due to the intricacies of water risk, encompassing quality, quantity, regulations, and industry sector specificities, it is impractical to derive universally applicable market signals solely from corporate financial data. Thus, a portfolio-based approach has been proposed to assess how environmental risk events affect the market valuation of publicly traded companies.

In a water-constrained world, corporations facing water scarcity and rising business costs for operations often employ risk transfer strategies. These strategies can be financial or infrastructure-focused, aiming for capital efficiency amidst uncertain future cash flows (Heal et al., 2005; Larson et al., 2012; Lanari et al., 2021). While financial instruments like insurance are commonly used to hedge uncertainties, there are limited targeted tools available to address the financial impact of water-related issues. Binary index insurance contracts and reinsurance, as well as insurance-linked securities (ILS), and captive insurance have been explored. Binary index insurance contracts pay out when specific water-measurable quantity thresholds are reached, making the choice of the measurable variable linked to market performance critical. However, in the face of catastrophic risks, traditional insurance can become costly and may surpass its solvency capacity. Indeed, insurance companies will turn to reinsurers to underwrite their risk exposure (Kleindorfer et al., 1999; Froot, 2007; Zhao et al., 2021). A more favorable option is insurance-linked securities, combining uncorrelated insurance and reinsurance with capital market techniques within the Alternative Risk Transfer (ART) market (Securities, I.L., 2009; Hofmann et al., 2017). ART products can expand insurability limits, enhance risk transfer efficiency, increase risk transfer capacity, and reduce insurance premiums through global diversification. Captive insurance essentially means that the company sets aside a portion of free cash flow in a separate line of business, which is managed as an investment arm for the company to grow capital that can be used to address climate/water risks. In a sense, it is risk transfer to another unit within the company, or to a fund management company where multiple companies have partnered in captive products.

An alternative approach to risk transfer involves capacity sharing, a comprehensive global supply-chain network management strategy whereby facilities can be repurposed to address bottlenecks in manufacturing capacity (Huang et al., 2003; Zhao et al., 2020). Originally devised to address asymmetries in demand and supply relationships, this strategy is particularly relevant in sectors like information technology, furniture, and manufacturing. It embodies the concept of 'co-opetition,' where cooperation and competition coexist. The co-opetition dynamic fosters stronger connections between facilities, facilitating the relocation of production capacities and risk assets while optimizing task performance through a division of attention. By treating each facility as a single node in the supply-chain network and a unit in the management portfolio, linkages and action regulations transform the entire system into an agent-dynamic-based (ADB) model. While capacity sharing has not been proposed as a risk management strategy to address climate water risks in the literature, ample discussions in business forums have touched upon this opportunity.

Appendices

Appendix A: Industry representation by number of firms regarding GIC 6 industry classification.

Appendix A. Industry representation by number of firms regarding GIC 6 industry classification.

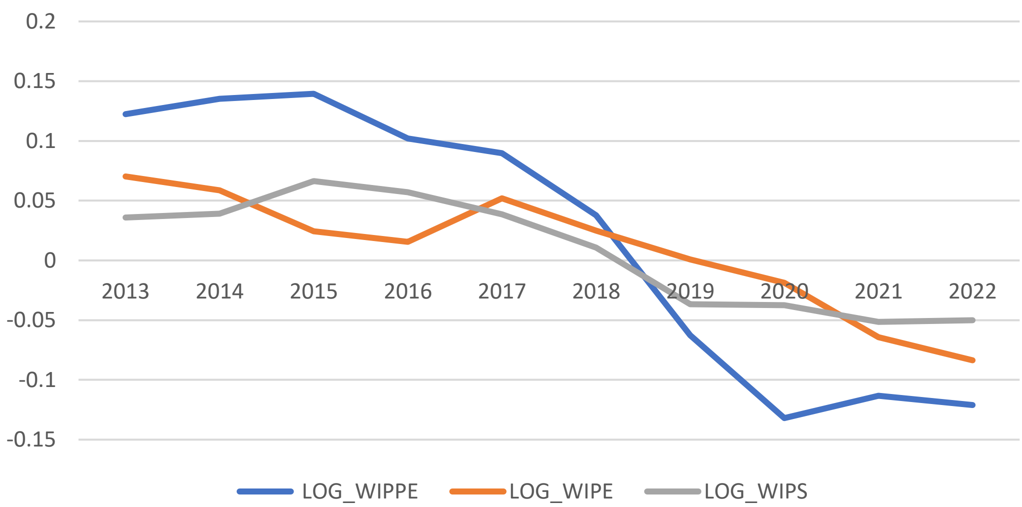
Total represents the total number of firms in our sample. The sample period is 2013–2022.

GICS	GICS6	Industry Name	# of firm
50-Communication Services(44)	501010	Diversified Telecommunication	6
	502020	Entertainment	13
	502030	Interactive Media & Services	7
	502010	Media	17
	501020	Wireless Telecommunication Services	1
25-Consumer Discretionary(86)	251010	Automobile Components	3
	251020	Automobiles	4
	255030	Broadline Retail	7
	255010	Distributors	3
	253020	Diversified Consumer Services	2
	253010	Hotels, Restaurants & Leisure	21
	252010	Household Durables	12
	252020	Leisure Products	2
	255040	Specialty Retail	22
	252030	Textiles, Apparel & Luxury Goods	10
30-Consumer Staples(51)	302010	Beverages	12
	301010	Consumer Staples Distribution	11
	302020	Food Products	16
	303010	Household Products	5
	303020	Personal Care Products	3
	302030	Tobacco	4
10-Energy(54)	101010	Energy Equipment & Services	15
	101020	Oil, Gas & Consumable Fuels	39
40-Financials(93)	401010	Banks	21
	402030	Capital Markets	26
	402020	Consumer Finance	7
	402010	Financial Services	10
	403010	Insurance	29
35-Health Care(89)	352010	Biotechnology	12

	351010	Health Care Equipment & Supplies	24
	351020	Health Care Providers & Services	22
	351030	Health Care Technology	1
	352030	Life Sciences Tools & Services	12
	352020	Pharmaceuticals	18
20-Industrials(100)	201010	Aerospace & Defense	14
	203010	Air Freight & Logistics	4
	201020	Building Products	8
	202010	Commercial Services & Supplies	8
	201030	Construction & Engineering	2
	201040	Electrical Equipment	6
	203040	Ground Transportation	8
	201050	Industrial Conglomerates	4
	201060	Machinery	20
	203020	Passenger Airlines	6
	202020	Professional Services	17
	201070	Trading Companies & Distribution	3
45-Information Technology(83)	452010	Communications Equipment	5
	452030	Electronic Equipment, Instruments & Components	12
	451020	IT Services	11
	453010	Semiconductors & Semiconductor Equipment	27
	451030	Software	19
	452020	Technology Hardware, Storage & Peripherals	9
15-Materials(41)	151010	Chemicals	22
	151020	Construction Materials	2
	151030	Containers & Packaging	10
	151040	Metals & Mining	7
60-Real Estate(40)	601010	Equity Real Estate Investment Trusts (REITs)	39
	601020	Real Estate Management & Development	1
55-Utilities(39)	551010	Electric Utilities	22
	551020	Gas Utilities	2
	551050	Independent Power and Renewable	1
	551030	Multi-Utilities	13
	551040	Water Utilities	1

Appendix B: Water Intensity for 2013-2022

Appendix Figure B: Average Water Intensity for 2013-2022



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