Thirsty for Returns?
The Impact of Water Risk on the Global Stock Market

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Abstract As freshwater levels decline and economic expansion and population growth place increasing pressure on global freshwater resources, many regions face growing water stress, exposing firms to potential operational disruptions. However, do investors care? This study examines the relation between global stock returns and corporate water use and stress from 2013 to 2024. We construct a novel monthly firm-level water stress measure by combining corporate water use with granular water supply data from NASA satellites. We find a statistically significant positive relation between corporate water use and global stock returns, and show that investors perceive water use as a systematic risk, demanding an annual premium of 2.15% for investing in firms with high water use. Also, indirect and total water use have a higher water use premium than direct water use. These results seem to suggest that investors particularly value water use within supply chains. Furthermore, we provide initial evidence of a potential water stress risk premium for firms in high-water-use industries.

Keywords: water stress, water use, water supply, global stock returns, climate finance, spatial finance

JEL classification: G12, D62, Q25, Q51

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"Water is an essential economic input and our economy is a thirsty system."

— Global Commission on the Economy of Water, *2024*

1. Introduction

The world is facing a growing water crisis. Global water demand is increasing by almost 1 percent each year, driven by shifting consumption patterns, urbanization, and an increase of water in industrial use (Zucchinelli, Spinelli, Corrado, and Lamastra, 2021). Simultaneously, climate change, unsustainable groundwater extraction, and extreme weather events threaten water availability (Gleick, 2023). Together, these dynamics increase the risk of water stress, the notion that water supply does not meet water demand. Companies that rely on water directly in their operations or indirectly through their supply chains may face challenges due to increased water stress, leading to operational disruptions, reduced sales, and lower profitability (UN Water, 2024). Given these potential impacts on company performance, it is important to understand whether water stress will affect global financial markets.

In this paper, we address this question by estimating the relation between water stress and global stock returns from 2013 to 2024. As water stress is a global issue, with an estimated 69 percent of listed firms facing water risks that could substantially change their businesses (Lamb et al., 2022), we test the relation of water stress in global stock markets. The relation between stock markets and water-related risks is complex. For example, Hong, Li, and Xu (2019) and Kim, Jeon, and Kim (2024) find that drought risk is not priced in publicly-traded food companies or the U.S. energy stock market. These findings suggest potential market inefficiencies, or investors do not perceive drought as a risk requiring higher returns. The latter is plausible as the economic consequences of a drought depend on whether it reduces regional water availability below local demand. Drought can only proxy for one side of the water supply-demand story, similar to our water use variable. Therefore, we also focus on water stress. As water stress is a local problem, we use global data to incorporate as many locations as possible. We argue that investors assess the risks of water stress differently from those of droughts. As investors require compensation for risks, we hypothesize that water stress is positively related to stock returns.

We collect water data from three primary sources: the S&P Global Sustainable (2024a) Trucost Environmental dataset provides firm-level water use data, the S&P Global Sustainable (2024b) Trucost Climate Change Physical Risk dataset provides headquarters and asset locations data, and NASA GRACE and GRACE-FO satellite data provide geospatial monthly water level data for a granular global grid (Landerer, 2021, Landerer and Swenson, 2012). As a proxy for a company's water demand, we use direct, indirect and total (direct plus indirect) water use data from the Trucost Environmental Dataset. For our water supply measure, we first consider each company's assets and headquarters locations and match these locations by latitude and longitude with the NASA GRACE and GRACE-FO data. Then, we take the NASA GRACE and GRACE-FO Liquid Water Equivalent (LWE) data, which indicates total water storage (i.e., surface water, like lakes and rivers, groundwater, soil moisture, snow, and ice) at a particular location and point in time. This integration of asset-level geographic exposure with physical satellite observation data allows us to quantify a monthly proxy of water availability for each company's location—an approach that, to the best of our knowledge, has not yet been applied in asset pricing research.

We use the firm's location-specific water supply and direct water use to calculate the firm's water stress. First, we capture seasonal water availability patterns in the LWE measure and calculate how much the observed LWE at each firm's location deviates from its historical monthly average. We then standardize this deviation by calculating a z-score using the location's historical monthly standard deviation. A negative z-score indicates water availability below the location's average, while a positive z-score suggests above-average water availability. Second, we equally weigh the firm's asset locations LWE z-score, so we have one monthly water supply observation per firm. These observations tell us, on average, how the firm's overall water availability is at its asset locations. Third, we obtain the direct water use measure from the Trucost Environmental dataset. We use direct water, as we have no information on the locations of the firm's supply chain; we only have information on the firm's asset locations. Finally, we compute our monthly water stress measure by interacting the monthly geospatial water availability - standardized LWE measure - with the company's direct water use. We end up with a unique firm-specific monthly water stress measure.

We start by analyzing whether water use itself is associated with stock returns. We combine global monthly stock return data from 2013-2024, including 76 countries and 14,650 companies, with our water use variables. We use a panel regression model to estimate the relation and regress the excess stock return on the water use variables and include several stock-level control variables (market beta, size, book-to-market, momentum, leverage, investment, return on equity, plant, property, and equipment (PPE), volatility, and sales growth) to avoid capturing other cross-sectional return predictors. We cluster the standard errors at the firm and month/year levels and include a set of fixed effects that alternately stand for year/month, region×year/month, industry×year/month, or both interaction fixed effects. The interaction fixed effects provide a more conservative specification than separately including time, region, and industry fixed effects. Using region×year/month fixed effects allows the model to absorb regional shocks that occur in a given month—such as droughts, extreme weather events, or sudden regulatory changes. It prevents the model from mistakenly attributing these effects to firm-specific water use and stress measures. We follow the matching technique of Zhang (2025). Thus we always use the last available reported water use information to avoid look-ahead bias.

We find a statistically significant positive relation between water use and excess stock returns after controlling for industry fixed effects. We find that a standard deviation increase in direct and total water use is associated with a 0.93% and a 2.15% p.a. increase in returns, respectively. We observe a sizeable difference between the direct and total water use results. As total water use includes indirect use from supply chains, these results suggest that investors require a higher risk premium for firms with greater total water use, and thus reflect the importance of supply chain water use. When we only control for time and region (or country) fixed effects, we do not find a statistically significant relation between water use and stock returns. Our results suggest that regional differences in water use are not driving return variation. Instead, we argue that the relation comes from the effects between or within industries, as investors typically benchmark firms against industry peers due to similarities in operational and financial risks rather than geographical location. Hence, we include industry fixed effects and observe that water use is priced when we account for heterogeneity across industries.

An intuitive explanation for this positive relation is that investors anticipate water will become more scarce and view these high water-use firms as riskier. Investors demand to be compensated for this risk in the form of higher expected returns, resulting in the observed risk premium. This hypothesis is similar to that of Bolton and Kacperczyk (2023), who hypothesize that investors pay attention to climate risk and that a carbon premium should exist for firms operating in high-carbon emitting countries. Hsu, Li, and Tsou (2023) argue that their positive relation between pollution and stock returns exists because firms with higher emission intensities are subject to greater systematic risk due to potential shifts in environmental regulations. Interestingly, we find a stronger relation for indirect water use, a result which is similar to indirect scope 3 emissions findings by Bolton and Kacperczyk (2023).

Our water use results become statistically significant after controlling for industry fixed effects, a result that is consistent with findings by Fernandez-Perez, Indriawan, and Tse (2024), but also Bolton and Kacperczyk (2023), who underscore the importance of industry adjustment in carbon-transition risk studies. To determine whether our results are driven by industry-level or company-specific water use relative to its industry water use, we follow the empirical approach of Pástor, Stambaugh, and Taylor (2022). For our water use variables, we find a statistically significant positive relation of the *within* industry variation and no significant relation for the *across* industry variation on returns. An increase in standard deviation in within industry total, indirect and direct water use is associated with an 1.86%, 1.98% and 0.86% increase in stock return, respectively. Again, we observe a notably higher premium for total and indirect company water use than for direct water use. Our findings indicate that investors price water use based on company variations in water use within industries rather than broad industry-level differences. We then explore whether these *within* vs. *across* findings differ for companies operating in industries characterized by low water use (e.g., health care and media) compared to those in high water-use industries (e.g., water utilities and food production). Intuitively, for a company in a low-water-use industry, consuming more water than its peers is not an obvious material risk factor. Nevertheless, our primary results remain consistent irrespective of whether a company operates in a low- or high-water-use industry.

The results support our argument that investors typically benchmark firms against industry peers, as they demand a premium even in industries where the risk of using more water might initially seem less material.

Our water use results show that company water use is associated with higher stock returns—an interesting finding that offers insight into how investors price water use. However, when there is ample water supply at the locations where water is needed, there does not necessarily have to be a risk. Therefore, we are interested in the relation between water stress - the notion that water supply cannot meet water demand - and stock returns. We hypothesize that higher water stress is associated with higher stock returns, a water stress premium. Our initial result, in which we use different lags and moving averages to capture different timings in which the potential consequences of water stress come to light, does not provide any statistical evidence for our hypothesis. We observe a negative sign, albeit zero, and an increase in t-statistics when using moving averages rather than monthly lags.

We continue our water stress analyses to explore whether our initial findings differ for companies operating in high or low-water-use industries. Intuitively, experiencing more water stress is a more substantial material risk factor for a company in a high water-use industry. We include a dummy for high direct water-use industries and interact the dummy with our water stress measure. First, we observe a statistically significant negative effect of water stress on stock returns in low water-use industries. A one standard deviation increase in water stress is associated with a 0.55% p.a. decrease in stock return for companies in low water-use industries. Additionally, we find a statistically significant positive coefficient for the interaction term. In terms of economic magnitude, a one standard deviation increase in water stress is associated with a 0.20% p.a. increase in stock return for companies in high water-use industries. An increase in water stress may signal negative cash flow news for companies in low-water use industries (e.g., higher operational costs) or a potential increase in discount rate - in other words, the gradual pricing of water stress and/or preferences. In addition, we find evidence for an economically small water stress premium. However, only for companies in high water-use industries, and this finding suggests that investors differentiate the pricing of water stress risk across industries.

Next, we examine the relation between global stock returns and water stress in light of two climate conferences. Investors may have started incorporating climate variables in their investment decisions after important climate conferences, and therefore, we hypothesize a stronger positive relation between water stress and stock returns after these conferences. The first is the Paris Agreement in 2015, and the second is the UN COP26 in 2021, in which the Glasgow Declaration for Fair Water Footprints was drawn. We find that pre-Paris, a standard deviation increase in water stress is associated with approximately -3.70% p.a. decrease in stock return. However, post-Paris, a standard deviation increase in water stress is associated with -0.30% p.a. in excess stock return. These results seem to suggest that investors price water stress differently after the Paris Agreement. However, we remain careful with our conclusions as the relation is not robust for all our model specifications. Furthermore, we do not find statistical evidence for our hypothesis when focusing on the UN COP26 conference.

Our findings provide evidence for a water use premium for firms using more water than industry peers. This relation remains consistent regardless of whether companies operate in low—or high-water-use industries. Also, indirect and total water use have a higher premium than direct water use. Furthermore, our findings provide initial evidence of a potential, yet small, water stress premium for firms in high-water-use industries.

In climate finance, we typically distinguish between physical and transition risks. Firms exposed to water stress or those with intensive water use may encounter both types of risk. Physical risks refer primarily to disruptions in operations caused by inadequate water availability. Transition risks, in contrast, arise from regulatory measures aimed at managing scarce water resources, potentially leading to increased water costs or mandatory reductions in water use (Petrovic and Cirovic, 2013). Although quantifying these risks separately is challenging, we argue that given water's essential and non-substitutable nature, physical risks likely outweigh transition risks—although definitive conclusions are uncertain.

Our research contributes to a growing body of climate finance research and provides a foundation for ongoing analysis of the relation between water stress and global stock returns. We add to the existing literature of, among others, Hong et al. (2019), Afrin, Peng, and Bowen (2021), Kim et al. (2024), Bolton and Kacperczyk (2023), Fernandez-Perez et al. (2024), and Huynh, Nguyen, and Truong (2020). We make several novel contributions. First, we construct a monthly firm-level water stress exposure measure by combining company-level water use data with location-specific water availability. To the best of our knowledge, prior studies have focused on either firm water use or drought, whereas we are the first to integrate both supply and demand sides of water in analyzing the relation with stock returns. Second, our analysis builds on and differs from Fernandez-Perez et al. (2024), who also examine water use and stock returns. While Fernandez-Perez et al. (2024) find a negative relation, we find a statistically significant positive relation between water use and stock returns. The difference may stem from differences in estimation periods and our global set of companies. Third, we distinguish between direct and indirect firm water use and focus on within-industry and across-industry analyses, thereby exploring different possible mechanisms at play. Fourth, we include the water stress levels of companies' production locations rather than focusing solely on the location of a company's headquarters, so that our water stress measure better captures the actual water stress for a company at its different production sites. Finally, we contribute to the growing literature on spatial finance by integrating geospatial data with financial information (Caldecott, McCarten, Christiaen, and Hickey, 2022, Christiaen, Lockwood, Jackman, and Caldecott, 2025).

Global trends are intensifying pressure on freshwater resources, now and in the future. The green energy transition, for instance, drives demand for water-intensive lithium mining. At the same time, the rapid advancement of artificial intelligence increases dependence on water-based liquid cooling systems in data centers. Considering that water is essentially a non-substitutable resource, our findings should attract the interest of companies and investors alike. From an investor and risk management perspective, firm-level water use is a practical proxy for water risk, as this information is relatively easy to integrate into investment models. However, water stress is the more fundamental determinant of whether firms are at risk of operational disruption or cost increases. Our results indicate that companies' water use is priced, and we find a potential water stress premium for companies operating in high-water-use industries. These insights can potentially spur companies to develop strategies to improve water conservation, use water more efficiently, and adopt sustainable water management practices. Additionally, our results can help investors identify potential operating risks and price environmental exposures more accurately.

2. Background and Hypotheses

2.1. Water use and stock returns

Companies that rely heavily on water in their operations may face several water-related risks. First, not having enough water to operate is a physical risk that will disrupt a company's day-to-day operations. There is some evidence that although companies might hold contracts to obtain water from certain aquifers, lakes, or groundwater wells, municipalities prioritize basic human needs over corporate agreements when water levels run low (Cole, Narayanan, Connors, Tewari, and Onda, 2023), for example, during the prolonged drought in Sicily in the summer of 2024, the government prioritized water to hospitals and the general population—and only made exceptions for businesses that produce key assets (e.g., oxygen) or operate in critical sectors of the economy (e.g., hotels) (Bubola, 2024). Second, companies may also encounter transition risks. Petrovic and Cirovic (2013) argue that governmental interference and regulation in water will undoubtedly increase, potentially impacting the price of water or requiring companies to reduce water consumption in their operations. Finally, the companies can face reputation risks when water use impacts the local population or biodiversity. These physical, transition, and reputation risks might impact firms' operations, sales, and profitability.

The demand for freshwater is projected to increase even more. Li, Yang, Islam, and Ren (2023) explain that the "rise" of artificial intelligence (AI) is expected to demand 4.2 − 6.6 billion cubic meters of water withdrawal for cooling servers and electricity generation in 2027, which is half of the annual water demand of the United Kingdom. In the United States, there are growing concerns about who uses water and for what purpose, as dry conditions are evident across the country (Temple-West, 2025). The global shift towards green energy requires an increase in battery production, which translates to an increase in the mining of lithium, cobalt, and nickel (International Energy Agency, 2024). Lithium mining is very water-intensive and sometimes done in extremely arid regions in Argentina, Chile, and Bolivia, which causes aquifers to deplete (Kaunda, 2020, Heredia, Martinez, and Surraco Urtubey, 2020). The transformation towards a more sustainable, carbon-low future puts pressure on water supplies.

Previous research on water use and stock returns shows that an increase in company water use is associated with lower stock returns (Fernandez-Perez et al., 2024). However, awareness of these water-related pressures has intensified significantly in recent years. Therefore, it is possible that investors now examine the company's water use and demand differently, demanding a water use premium.

- Hypothesis 1 (H1a): Higher company-level water use is associated with higher stock returns.

Furthermore, most companies depend more on water within their supply chains than in direct operations, with agriculture being the main exception.[1] For instance, in the retail sector, 10 to 40 percent of water use typically occurs at the supplier level, 60 to 90 percent among sub-suppliers, while a company's headquarters only consumes around 1 percent (McKinsey and Company, 2009). Given this complexity in water use, investors may not perceive company water use uniformly and instead differentiate between direct operations and supply chain water use exposure. Companies that depend more on indirect water use through global supply chains may be seen as more vulnerable to operational disruptions from droughts, changing regulations, or public scrutiny. Therefore, we argue that the relation between water use and stock returns may be stronger for firms with higher indirect water use.

- Hypothesis 1 (H1b): The relation between company-level water use and higher stock returns is stronger for higher indirect company-level water use.

2.2. Across and within-industry water use

Pástor et al. (2022) analyze the equity greennium, a well-documented outperformance of green stocks over brown in recent years. Their analyses also focus on whether the relation is driven by industry greenness or the relative greenness of the firm within its industry. They find that much of the greennium is owed to industry-level greenness. We argue that investors might also

[1] Agricultural companies are direct water users, particularly those growing crops.

distinguish between industry water use and company water use relative to their peers. On the one hand, investors may demand a premium for companies operating in high-water use industries due to the higher exposure to operational disruptions and regulations when there is insufficient water. On the other hand, investors might focus more on within-industry water use variation, as investors typically benchmark firms against industry peers due to similarities in operational and financial risks rather than geographical location. Furthermore, a recent survey shows that investors are likelier to measure ESG relative to industry peers rather than viewing an ESG rating as an absolute performance (Larcker, Lee, Seru, and Tayan, 2024). Therefore, we argue that the within-water use variation drives our stock return and water use and relation.

- Hypothesis 2 (H2a): The positive relation between company-level water use and stock returns is stronger for companies that use more water than their industry peers.

Water demand varies across industries: in manufacturing, significant water use occurs in raw material extraction, while the textile industry often relies on water for crop production. In contrast, the tech industry's water needs are often indirect for cooling or electricity generation (Cole et al., 2023). In the energy sector, gas, coal, and oil extraction use much water (UN Water, 2024). Several industries, such as media, health care, and consumer services, require little water. For companies where water is a critical input for production, water use should represent a more material operational risk, thus attracting a higher premium from investors.

- Hypothesis 2 (H2b): The positive relation between water use and stock returns is stronger for companies operating in high water-use industries than low water-use industries.

2.3. Water stress and stock returns

Water stress refers to situations where the available water supply fails to meet the regional water demand. Climate change exacerbates the risk of longer dry periods, decreasing the water supply. In addition, global water quality is decreasing due to, for one, the expansion of urban lands (Shi et al., 2024). Water supply cannot keep up with rapid urbanization, changing consumption patterns, and economic growth.

Water stress differs from other sustainability risks, e.g., carbon dioxide emissions, as water stress can have direct repercussions for companies. Byrareddy, Kouadio, Mushtaq, Kath, and Stone (2021), for example, find that robusta coffee yield declines on average 6.5 percent during a drought in Vietnam. In the commodity market, this translates to an increase in the price of robusta beans and, inevitably, in consumer prices of espressos (Kazmin and Savage, 2024). Similar problems occur in the cacao market, increasing consumers' prices for chocolate bars (Savage, 2024). These examples show how water stress may directly impact a company's operations and, consequently, affect a company's profitability and market stability. Water stress represents an additional risk dimension beyond company water use levels. Companies operating in areas with lower water supply face greater disruption risks, and investors might want compensation for these risks.

- Hypothesis 3 (H3): Higher water stress is associated with higher stock returns.

2.4. Industry exposure to water stress

Similar to Hypothesis 2 (H2b), companies in industries highly reliant on water could experience more significant operational disruptions or financial consequences from water stress than industries less dependent on water. Therefore, we argue that investors price water stress more strongly for companies operating in high-water use industries.

- Hypothesis 4 (H4): The positive relation between water stress exposure and stock returns is stronger for companies operating in high water-use industries.

2.5. Measuring impact of climate conferences

Conferences, such as the Conference of the Parties (COP) conferences from the United Nations, are broadcast extensively in the global media. These climate conferences could heighten investors' attention to sustainability and potentially impact investors' inclusion of climate variables in their investment decisions. A notion strengthened by the results of Bolton and Kacperczyk (2023). They find no evidence of a carbon premium before the Paris Agreement but a statistically significant and economically large premium after the Paris Agreement. Similarly, Monasterolo and De Angelis

(2020) find evidence suggesting that, after the Paris Agreement, investors began to view low-carbon assets as attractive opportunities, although without penalizing carbon-intensive assets. In addition, Garel, Romec, Sautner, and Wagner (2024) find evidence of a biodiversity footprint premium after COP15. Specifically, after the Kunming Declaration, a framework for action to protect biodiversity and reverse species loss. Building on these results, we hypothesize that water stress and high water use may similarly become priced into stock returns after global climate conferences. We focus on the Paris Agreement in 2015, and the UN COP26 in 2021, in which the Glasgow Declaration for Fair Water Footprints was drawn.

- Hypothesis 5 (H5): The positive relation between water stress (or water use) and stock returns is stronger in the period following a global climate conference (Paris Agreement and COP26).

3. Data

3.1. Water Demand, Supply and Stress

Our first variable of interest is the company's water demand. In this study, we use the company water use data from the Trucost Environmental Data (S&P Global Sustainable, 2024a) as a proxy for a company's water demand. Within the Trucost Environmental universe, we focus on two variables, namely the "Absolute: Water Direct and Purchased" and "Absolute: Cooling, Process, and Purchased", which we renamed *Direct Water Use* and *Total Water Use* respectively. The direct and total (direct + indirect) water use variables are measured in cubic meters (m^3) and encompass the volume of water a company obtains from natural sources and purchases from utility companies. The total water use variable also contains the company's indirect water usage, including water sourced from upstream suppliers (S&P Global Sustainable, 2024a). We also use the variable *Indirect Water Use*, which we calculated by taking the difference between the total and direct water use reported.

We match the companies' water use data to the returns data following the method of Zhang (2025) to prevent forward-looking bias. In short, we use Trucosts' effective data release dates and take the next calendar day if releases occur after 18:00 hours. We shift weekend releases to the following Monday and then align these adjusted dates with returns data from the subsequent month.

To construct our monthly company water stress measure, we first obtain the water supply variable. We use the Trucost Physical Risk dataset to extract the company's asset and headquarters locations (longitude and latitude) as of fiscal year 2022 S&P Global Sustainable (2024b).[2] We match these locations' coordinates to the NASA Gravity Recovery and Climate Experiment Follow-on (GRACE-FO) data, which provides Liquid Water Equivalent Thickness (LWE) on a 1-degree latitude-by-longitude grid. Each company location is matched to the closest corresponding GRACE-FO grid cell based on its reported coordinates, a procedure that is called nearest neighbor matching. A limitation of this approach is that it does not account for hydrological flow direction—nearby locations may receive the same LWE value even if one lies upstream and the other downstream from a water source. Nonetheless, integrating firm-level location data with satellite-based physical water availability measures gives us a time-varying indicator of local water conditions at company-specific locations. To the best of our knowledge, this is the first attempt to incorporate monthly satellite-derived water supply metrics into asset pricing research at the firm level, combining both headquarters and asset locations.

The LWE indicates the total water storage at a specific location over time, including groundwater, soil moisture, snow, and ice. The LWE variable represents an anomaly with respect to a mean state and can be called a water storage anomaly (Landerer, 2021, Landerer and Swenson, 2012). Positive anomalies indicate more water is stored than in the baseline period, while negative anomalies imply water loss compared to the baseline. The baseline is the location's average computed over all months from 2005-2010. Because the baseline is an average over the years, there might be residual seasonal patterns—different months can have systematically higher or lower anomalies. Therefore, we calculate deviations from the location's long-term monthly average (i.e., the average for each month) to adequately capture the seasonality that is so obvious in water data.

First, we calculate the average LWE ($\bar{x}_{im}$) for asset i in month m over the period (2005–2010).

[2] The dataset does not provide time-varying location data; we assume that asset and headquarters locations remain constant over the sample period.

Second, we calculate the difference between the assets i LWE value in month m in year y with the $\bar{x}_{im}$. Finally, we divide the difference by the standard deviation for asset i in month m over the period (2005–2010) to create a z-score. Even though x is already an anomaly, the further adjustment (subtracting the mean and standardizing) allows us to control for any residual seasonality or heterogeneity in variability across different months and assets. The final company-level z-score, obtained by equally weighting these individual assets i z-scores, represents an average measure of how "unusual" the underlying assets are regarding their water anomaly deviations for that month. In addition to the equally weighted company z-score, we also construct a weighted z-score that assigns greater weight to water-intensive asset types. Specifically, we apply a weighting scheme in which water-intensive assets—coal mines, mine projects, and power plant sites—receive twice the weight of less water-intensive assets, including branches, broadcast stations, headquarters, gas facilities, global branches, LNG facilities, and pipeline facilities. Thus, our unique company-specific final water stress variables effectively capture company-level water supply by considering both overall and water-intensive asset-specific locations.

Our unique and novel monthly company water stress measure is the interaction between the direct water use from S&P Global Sustainable (2024a) and our company-level water supply z-score. We use the direct water use of a company rather than the total water use because we only have information on the company's asset locations, not the supplier's assets location. Hence, we do not want to include the indirect water use of a company. The z-score is negative when the company's asset locations experience lower water supply than usual. When we interact the z-score with the company's direct water use by construction, the water stress variable becomes counterintuitive. The lower the water stress variable (due to negative z-score), the higher the water stress. Therefore, we multiply the water stress variable by -1 to improve the readability of the results. A higher water stress value now indicates a higher water stress level.

3.2. Global stock return data

We create a global database of monthly stock returns and characteristics covering January 2013 to December 2024, using data from the Center for Research in Security Prices (CRSP), Compustat

North America, and Compustat Global. We clean the stock data following Alves, Krüger, and van Dijk (2025). The dataset includes 14,650 unique firms across 75 countries. Following Fama and French (2017), we categorize countries into the regions: North America, Japan, Asia Pacific, and Europe. In addition, we include Emerging Markets as a separate region to account for the presence of developing countries in our data. In our regressions, we include several stock-level control variables: market beta, size, book-to-market, momentum, leverage, investment, return on equity, plant, property, and equipment (PPE), volatility, and sales growth (Bolton and Kacperczyk, 2021). We winsorize the stock returns at 0.1% and 99.9% each month (Jensen, Kelly, and Pedersen, 2023). In addition, we also winsorize the market beta, momentum, leverage, investment, return on equity, volatility, and sales growth control variables at 0.1% and 99.9%, and we use the natural logarithm of the PPE control variable.

3.3. Descriptive statistics

Table 1 shows the summary statistics of the variables in our analyses. The variables *Direct Water Use* and *Total Water Use* are measured in cubic meters (m^3) and display significant outliers among companies and industries. Therefore, we decide to take the natural logarithm of both variables. Before taking the logarithm, we create the *Indirect Water Use* variable, which is simply the difference between the *Total* and *Direct* variable. We also took the natural logarithm of the *Indirect Water Use*. Table 1 shows that all three variables have similar variability, as demonstrated by the standard deviation. The variables *Total* and *Indirect Water Use* have very similar descriptive statistics, and as shown in Table 3, their correlation is 96%.

Although the variables *Water Supply* and *Weighted Water Supply* exhibit nearly perfect correlation, the weighted measure provides additional nuance by explicitly emphasizing locations with higher water use assets (e.g., coal mines and power plants), whereas the unweighted measure gives equal weight to all firm locations. Both are based on standardized anomalies in local water availability (LWE) derived from NASA satellite data matched to firm asset coordinates. Given that our dataset contains relatively few high-water-intensity assets compared to, for example, headquarters (available for all companies), this weighting only somewhat adjusts the variable, leading naturally to similar empirical outcomes. However, we do observe differences between the two variables. The difference between the *Weighted Water Supply* and the *Water Supply* captures how water availability differs between a firm's water-intensive locations and its overall asset locations. A positive difference indicates that the firm's most water-dependent assets are located in areas with more water available than the average across all its locations. In contrast, a negative difference indicates that the firm's water-intensive assets are in areas with less water available. On average, firms in the high-water-use industries "water utilities", "paper and forest products", and "automobiles", have a negative difference between the weighted and non-weighted water supply, indicating that the firm's water-intensive assets are operating in regions with below-average water availability. In contrast, firms in the high-water-use industries "multi-utilities", "electric utilities", and "metals and mining", have, on average, a positive difference, indicating that the water intense assets are located in regions with a positive water supply value. Substituting *Water Supply* with the *Weighted Water Supply* measure enables us to demonstrate that our results remain robust across different weighting approaches.

The *Water Stress* measure ranges from -223.18 to 207.88 with a standard deviation of 8.92. This range indicates that most observations are clustered near the mean, with only a few cases driving the range's extreme ends. Upon examining the extreme values, we notice that the majority of the negative values originate from Japan between 2020 and 2024. The region experienced notably wet conditions in this period, compared to the 2005-2010 baseline (Japan Meteorological Agency, 2025). These wet conditions translate into high *Water Supply* observations; on average, the value of the *Water Supply* variable is 6.5 for Japan from 2020 to 2024. By construction, our *Water Stress* measure is the interaction between the *Water Supply* and *Direct Water Use* variables, multiplied by -1. Some of the firms in Japan operate in high-water-use industries, as seen in Figure 1, such as "auto components", "food products", and "oil, gas and consumable Fuels". The high *Water Supply* observations for these firms in Japan are thus multiplied by the firms' high *Direct Water Use* (and -1, to ensure that higher *Water Stress* values indicate higher water stress), resulting in these high negative values for *Water Stress*. Similarly, we observe that companies operating in high-water-use industries tend to have high water stress values, which explain the positive long tails of the *Water*

Stress distribution.[3]

Figure 1 shows us the average *Direct Water Use* per industry and the average *Water Stress* per industry. We observe that high-water use industries such as "multi-utilities", "paper and forest products", and "water utilities" have, on average, negative water stress. This essentially means that the asset locations of the firms in these industries are located in water-prone regions. In contrast, we observe that firms in low-water-use industries, such as "software", "media and service", and "IT services" have, on average, higher water stress. One possible explanation is that even though the companies do not use much direct water, they are still exposed to water stress because its assets (HQs, data centers) are in drought-prone areas such as California, U.S. (e.g., Alphabet ("Interaction Media & IT services"), Salesforce and Adobe ("Software")). Importantly, these figures highlight that our water stress measure captures geographic exposure to water stress, which may not always align with industry-level water use patterns. This nuance underscores the importance of combining water use and water availability.

Table 3 shows the correlations between our variables. We observe a negative correlation between our *Water Stress* variables and our *RET (%)* variable. Furthermore, we observe a high correlation between the *Total/Indirect Water Use* and the *size* variable of 58% and 59% respectively. This seems to make sense intuitively, the larger the company, the more water it might need to operate. Similarly, we observe a a 70% correlation between the *ln (PPE)* variable and the *Water Use* variables. We control for both *size* and *PPE* in our regression analyses.

4. Empirical Approach

4.1. Water Use

To assess the relation between global stock returns and our water use variables, we estimate the following panel model:

$$\mathrm{RET}_{i,t} = \beta_0 + \beta_1 \log(\mathit{Water\ Use}_{i,t-1}) + \lambda' X_{i,t-1} + \alpha_{\mathrm{FEs}} + \varepsilon_{i,t}, \tag{1}$$

[3]Winsorizing the *Water Stress* variable at 0.1% and 99.9% does not change our findings, therefore we decided to leave the *Water Stress* variable unaltered.

where $RET_{i,t}$ is the monthly excess stock return (%) of firm i in month t. $Water\ Use_{i,t-1}$ is the generic term that alternately stands for *Total Water Use* and *Direct Water Use*. The *Water Use* variables are the company-level natural logarithm of the total and direct water use cubic meters (m^3).[4] α_{FEs} represents a set of fixed effects that alternately stands for year/month fixed effects (α_t), region × year/month fixed effects ($\alpha_{t \cdot r(i)}$), industry × year/month fixed effects ($\alpha_{t \cdot ind(i)}$) or both interaction fixed effects ($\alpha_{t \cdot r(i)} + \alpha_{t \cdot ind(i)}$). The vector of stock-level control variables, $X_{i,t-1}$, includes the following variables: *market beta*, *size*, *book-to-market*, *momentum*, *leverage*, *investment*, *return on equity*, *plant, property, and equipment* (*PPE*), *volatility*, and *sales growth*. We cluster standard errors at the firm and month/year levels. Our coefficient of interest is β_1.

Following Pástor et al. (2022), we are interested in whether the relation between global stock returns and water use is an across or within-industry relation. Hence, we decompose *Water Use* variables into *Water Use Across* and *Water Use Within*, representing across- and within-industry variation. The across-industry component at time t for industry *ind* is calculated as the industry-month average water use:

$$\text{Water Use } Across_{ind,t} = \frac{1}{N_{ind,t}} \sum_{i \in \{ind,t\}} \text{Water Use}_{i,t}, \tag{2}$$

where $N_{ind,t}$ is the number of firms in industry *ind* in month t. The within-industry component measures how much a firm's water use deviates from this industry-month average:

$$\text{Water Use } Within_{i,t} = \text{Water Use}_{i,t} - \text{Water Use } Across_{ind,t}. \tag{3}$$

To assess the relation between our global stock returns and the *Water Use Across* and *Within* variables, we estimate Eq. 1 and substitute the $log(Water\ Use_{i,t-1})$ with the $\log(Water\ Use\ Across_{ind,t-1})$ and $\log(Water\ Use\ Within_{i,t-1})$. Where $Water\ Use\ Across_{ind,t-1}$ and $Water\ Use\ Within_{i,t-1}$ are the generic terms that alternately stand for the *Across* and *Within* variables of *Total Water Use*, *Direct Water Use* and *Indirect Water Use*. As we already separate the industry variation and

[4] To save space in Table 4, we omit the *Indirect Water Use* in this analysis; it will feature in the rest of the water use regressions.

within industry variation, we do not have to include the industry fixed effects, therefore the α_{FEs} in Eq. 1 represents a set of fixed effects that alternately stands for year/month fixed effects (α_t) and region×year/month fixed effects ($\alpha_{t \cdot r(i)}$).

Furthermore, we explore whether the relation between global stock returns and water use differs for companies operating in low-water-use industries (e.g., healthcare and media) compared to those in high-water-use industries (e.g., water utilities and food production). We construct a dummy variable equal to 1 if firm i's industry-average total water use is above the median across all industries (see Table 1 Panel A). We do not interact this dummy with the *Water Use Across* measure, as the dummy already captures across-industry variation. Such an interaction would be redundant since *Water Use Across* inherently reflects industry-level differences in water use. Instead, we interact this dummy with *Water Use Within*, which allows us to examine whether the relation between water use and global stock returns differs for companies operating in industries characterized by low or high water use.

4.2. Fixed effects

We opt for fixed effects interacting year/month with region and year/month with industry for several reasons. First, these interaction terms provide a more conservative specification than including the fixed effects separately as the interaction FE absorbs all variation common to all firms in a particular region/month or industry/month. Including the FE separately implies the assumption that the effect of a region is the same across months and vice versa. Second, using region×year/month fixed effects enables the model to control for every unique combination of region and month in our dataset. This level of control is critical when working with water-related variables, as, for example, water stress is local in nature and does not necessarily follow predictable patterns. For example, Europe may experience severe drought in April 2020 but not in April 2021. This notion differs from other climate finance variables, such as carbon emissions, which do not rely on a fluctuating natural resource input. As a result, Bolton and Kacperczyk (2023) can rely on separate month and industry fixed effects, whereas our setting requires fixed effects interactions. Using the interaction fixed effects prevents the model from mistakenly attributing these local water stress effects to firm-specific water use and stress measures. Third, choosing region×year/month (rather than country×month) fixed effects preserves variation in our water stress measures that would otherwise be removed by country×year/month interactions, given that the country-level fixed effects correlate with our water stress variable. We prefer to use similar fixed effects across our regressions, so we favor the region×year/month fixed effects over the country×year/month. Finally, we hypothesize that investors are likely to make decisions at a regional rather than purely national level. Thus, incorporating these fixed effects aligns more closely with realistic investor decision-making behavior.

4.3. Water Stress

To assess the relation between global stock returns and our water stress variables, we estimate the following panel model:

$$\begin{aligned}\mathrm{RET}_{i,t} = \beta_0 + \beta_1\, \textit{Water Stress}_{i,t-\tau} + \beta_2 \log(\textit{Direct Water Use Within}_{i,t-1}) \\ + \beta_3\, \textit{Water Supply}_{i,t-\tau} + \beta_4 \log(\textit{Direct Water Use Across}_{ind,t-1}) + \lambda' X_{i,t-1} + \alpha_{\mathrm{FEs}} + \varepsilon_{i,t},\end{aligned} \tag{4}$$

where $RET_{i,t}$ denotes the excess stock return (%) of firm i in month t. $\textit{Water Stress}_{i,t-\tau}$ is the interaction between $\textit{log(Direct Water Use Within)}_{i,t-1}$ and $\textit{Water Supply}_{i,t-\tau}$, with higher values indicating greater water stress. To avoid omitted variable bias, both the interaction variables are also included, plus the $\textit{log(Direct Water Use Across)}_{i,t-1}$ as it complements the *log(Direct Water Use Within)* variable. *Direct Water Use Across* and *Direct Water Use Within* capture industry-level and firm-specific deviations in direct water consumption, respectively. The variables *Water Supply* and *Water Stress* are lagged by various horizons ($\tau = 1, 3, 6$ months) or represented as moving averages (3- and 6-months). These different lag structures allow us to capture delayed effects, as reductions in water supply or increases in water stress may not immediately impact firm performance but instead unfold gradually over time. α_{FEs} represents a set of fixed effects that alternately stands for year/month fixed effects (α_t) and region×year/month fixed effects ($\alpha_{t \cdot r(i)}$). X represents the vector of stock-level control variables. We cluster standard errors at the firm and month/year levels. Our coefficient of interest is β_1.

Similar to our water use variables, we explore whether the relation between global stock returns and water stress varies among firms operating in high and low-water-use industries. We construct a dummy variable equal to 1 if firm i's industry-average direct water use exceeds the median direct water use across all industries (see Table 1, Panel A). We specifically choose *Direct Water Use* over *Total Water Use* because our water stress regressions exclusively focus on direct water consumption. We interact this dummy with the variables *Direct Water Use Within*, *Water Supply*, and *Water Stress*. Given that the *Water Stress* variable itself is constructed as an interaction between *Direct Water Use Within* and *Water Supply*, we interact the dummy with all these variables to provide a consistent and comprehensive analysis.

5. Results

5.1. Stock returns and Water Use

Table 4 shows the results of the relation between company water use and global stock returns by estimating Eq. 1. Columns (1)-(2) show the results using year/month fixed effects. Columns (3)-(4) show the relation using region×year/month fixed effects. Columns (5)-(6) display the relation using industry×year/month fixed effects and columns (7)-(8) display the relation using region×year/month and industry×year/month fixed effects.

The results of Table 4 show a positive relation between global stock returns and company water use. The relation becomes statistically significant when we include industry×year/month fixed effects in our model. This result is interesting as it suggests that broad regional differences in water use alone are not driving return variation. Using separate fixed effects instead of interactions or country fixed effects instead of regional fixed effects yields similar results. We hypothesize that the relation comes from differences within industries, which would explain the significant results when including industry-fixed effects. We find that an increase of one standard deviation in *Total Water Use* is associated with 2.15% p.a. increase in stock returns. In comparison, an increase of one standard deviation in *Direct Water Use* is associated with a return increase of 0.93%. Our results suggest that investors require a risk premium for companies with higher water use. In addition, we observe a sizable difference between the direct and total water use results. As total water use includes indirect water use from supply chains, an intuitive interpretation could be that investors require a higher risk premium for firms with greater total water use, reflecting the importance of supply chain water use. However, we cannot directly test this interpretation, so it should be viewed as suggestive rather than conclusive.

We also observe a statistically significant relation between the stock returns and the B/M and *sales growth* variables. A standard deviation increase in B/M is, on average, associated with a 1.78% p.a. increase in stock returns. A standard deviation increase in *sales growth* is associated with a decrease of 0.68% p.a. in stock return.

Given that our water use results become statistically significant after controlling for industry fixed effects—consistent with findings by Fernandez-Perez et al. (2024)—we follow the approach of Pástor et al. (2022) to determine whether our results are driven by industry-level water usage or by company-specific water use relative to its industry peers. Using Eq. 2 and Eq. 3, we construct the *Water Use Across* and *Water Use Within* variables. Where *Across* indicates the average monthly water use of the firm i's industry, the *Within* variable indicates the firm i's deviation from that industry average. We omit industry-fixed effects in all subsequent analyses, as the two variables capture these effects.

Table 5 shows the results of the relation between global stock returns and industry and company water use by estimating Eq.1 with the *Water Use Across* and *Water Use Within* variables. Columns (1)-(4) show the results using year/month fixed effects. Columns (5)-(8) show the relation using region×year/month fixed effects. Columns (1) and (5) show the results for total company water use, columns (2) and (6) for direct company water use, columns (3) and (7) for indirect company water use, and finally, columns (4) and (8) show a "horse race" between direct and indirect company water use.

We find a statistically significant positive relation of the *Water Use Within* variable and no significant relation for the *Water Use Across* variables across all columns and fixed effect specifications. These results also hold when we use country×year/month fixed effects. Table 5 columns (5)-(7) show that a one-standard-deviation increase of *Total, Indirect, and Direct Water Use Within* is associated with 1.68% p.a., 1.98% p.a., and 0.86% p.a. increase in stock return, respectively. Our results suggest that investors demand a water use premium for companies that consume more water than their industry peers but do not require a premium for investing in an industry that consumes more water than other industries. This result aligns with a recent survey that shows investors are more likely to measure ESG relative to industry peers rather than viewing an ESG rating as an absolute performance measure (Larcker et al., 2024). Our results differ from Pástor et al. (2022), who find that much of the greenium (outperformance of green stocks over brown stocks) is owed to industry-level greenness rather than within-industry variation. Furthermore, we observe the importance of considering indirect water use within supply chains, as reflected by the higher premium associated with total and indirect water use and the "horse race" regression results with direct water use. The *Direct Water Use Within* variable is not statistically significant, whereas the *Indirect Water Use Within* is significant with a standard deviation increase associated with a 2.39% p.a. increase in stock return.

We continue our analysis by estimating whether the relation between global stock returns and water use variables varies between companies operating in low- versus high-water-use industries. Intuitively, for a company in a low-water-use industry, e.g., "healthcare", "media", and "entertainment", consuming more water than its peers is not an obvious material risk factor. Table 6 presents results from regressions that include a dummy variable equal to 1 if firm i operates in a high-water-use industry, as well as its interaction with the *Water Use Within* variables. Columns (1)-(3) show the results using year/month fixed effects. Columns (4)-(6) show the relation using region×year/month fixed effects.

We find a statistically significant positive relation for the *Water Use Within* variables for all model specifications. Which, in this regression, should be interpreted as the within-water-use variable for firms operating in industries with low water use. The interaction between the high-water-use industry dummy and the *Water Use Within* variables capture the additional effect of water use for firms operating in high-water-use industries relative to those in low-water-use industries. The coefficient on the interaction term is not statistically significant. These results show no evidence that investors demand a different water use premium regardless of whether firms operate in high- or low-water-use industries. These findings also hold when we use country×year/month fixed effects. The high-water-use dummy is statistically insignificant in most columns, except column (5), providing some suggestive evidence that firms operating in high-water-use industries are associated with, on average, lower returns than those operating in low-water-use industries. However, we remain cautious in our conclusions as the dummy is only statistically significant in one specification.

5.2. Stock returns and Water Stress

Our previous results show that company water use is associated with higher stock returns; however, when there is ample water supply at the locations where water is needed, there does not necessarily have to be a risk. Therefore, we are interested in the relation between global stock returns and water stress—the notion that water supply cannot meet water demand. We hypothesize that an increase in water stress is associated with an increase in stock returns, a water stress premium. Table 7 shows the results of estimating Eq. 4. As *Water Stress* is the interaction between *Direct Water Use Within* and *Water Supply*, both the interaction variables are also included, plus the *Direct Water Use Across* as it complements the *Direct Water Use Within* variable. *Water Supply* and *Water Stress* are lagged by various horizons (τ = 1, 3, 6 months) or represented as moving averages (3- and 6-months). Columns (1)-(3) present the regression results for different lag periods, specifically τ = 1, 3, and 6 months, respectively. Columns (4) and (5) report results based on moving averages over 3-month and 6-month windows. Table 7 Panel A shows the regression results using year/month fixed effects, and Panel B shows the results when we use region×year/month fixed effects.

Our initial result, in which we use different lags and moving averages to capture different timings in which the potential consequences of water stress come to light, does not provide any statistical evidence for our hypothesis. We observe a negative sign for the *Water Stress* variable, albeit close to zero, and an increase in t-statistics when using moving averages rather than monthly lags. Furthermore, in all model specifications, we observe a statistically significant positive coefficient for the log *Direct Water Use Within* variable. Highlighting the robustness of our previous water use findings. Using country×year/month fixed effects or the weighted water stress variable yields similar results.

We continue our water stress analyses to explore whether our initial findings differ for companies operating in high- or low-water-use industries. Intuitively, experiencing more water stress is a more substantial material risk factor for a company operating in a high-water-use industry. We include a dummy for high direct water-use industries—we use direct water use to capture water stress as we know the company's headquarters and asset locations, not its suppliers.[5] We include the *High Direct Water Use* Dummy in Eq. 4 and add the interactions between the dummy and the variables: *Water Use Within*, *Water Supply* and *Water Stress*. Table 8 follows the same structure as Table 7.

We observe a statistically significant negative relation for the water stress variable for the 3- and 6-month moving averages and, in Panel B, also for the 3-month lag model. These results suggest that, for firms operating in low-water-use industries, an increase in water stress is associated with a decrease in stock returns. Specifically, a one standard deviation increase in water stress (3-month lag, Panel B) is associated with 0.55% p.a. decrease in stock return. We observe a significant positive relation between the water stress × dummy interaction for all models. For the firms operating in high-water-use industries, a standard deviation increase in water stress (3-month lag) is associated with approximately 0.20% p.a. increase in stock return. Similarly, for the 3-month moving average and 6-month moving average, the economic magnitude of a one standard deviation increase in water stress for firms operating in high-water use industries is associated with an increase of 0.30% p.a., 0.15% p.a., respectively, in stock return. Our results suggest that an increase in water stress is associated with a decrease in stock returns for firms operating in low-water-use industries. However, a small water stress premium seems to exist for firms operating in high-water-use industries. Moreover, these findings indicate a potential combination of pricing in risk and demanding a risk premium. An increase in water stress may signal negative cash flow news for companies in low-water use industries (e.g., higher operational costs) or a potential increase in discount rate - in other words, the gradual pricing of water stress and/or preferences. The positive relation for companies operating in high-water use industries could indicate a water stress premium as investors want compensation for holding stocks with higher water stress in already high-water

[5]This dummy is different than in Table 6, as the *High Water Use* dummy was constructed using the industries' total water use.

use industries.

We remain cautious in our conclusions as these results are solely visible when including the high direct water use dummy and not by estimating Eq. 4; nevertheless, we do observe a difference in the pricing of water stress for firms operating in low- and high-water use industries and using country×year/month fixed effects or substituting the water stress by the weighted water stress variable yields the same results.

Furthermore, in Panel B, we observe that the high direct water use dummy is not statistically significant in any specification. Our *Direct Water Use Within* variable is statistically positively related to global stock returns, similar to our previous findings. Surprisingly, the interaction of the log *Direct Water Use Within* with the high direct water use dummy is statistically negatively significant in the one-month lag model. These results suggest that firms operating in low-water-use industries have a water-use premium for using more water than their peers. Yet, this premium is lower for firms operating in high-water-use industries. In Panel A, the interaction between log *Direct Water Use Within* with the high direct water use dummy is statistically negatively significant in all model specifications. Indicating a lower water-use premium for firms operating in high-water-use industries. This result suggests that investors demand a lower premium for firms in high-water-use industries, perhaps as the industry already is "known"' for its high water use. For firms operating in low-water-use industries, investors might see higher water use, compared to industry peers, as more of a risk.

Our findings provide evidence of a water use premium for firms using more water than their industry peers, regardless of the industry. However, our results only suggest initial evidence of a potential, albeit small, water stress premium for firms in high-water-use industries. One possible explanation is that firm-level water use is a practical proxy for water-related risks. Corporate water use information is relatively easy to obtain and, therefore, can be more easily integrated into investment models. Although water stress is the essential determinant of whether firms are at risk of operational disruption or cost increases, it is more difficult to measure and evaluate. Our findings suggest that water use serves as a more practical and straightforward proxy for investors when pricing water-related risk.

5.3. Measuring impact of climate conferences

Next, we examine the relation between global stock returns and water use and stress based on two climate conferences. The first conference is the Paris Agreement, adopted by 196 Parties at the UN Climate Change Conference (COP21) in December 2015. The Paris Agreement is often used in finance literature to assess the relation between stock returns and climate variables, as there is evidence that investors began to price climate variables more actively following the agreement (among others, Bolton and Kacperczyk, 2023, Monasterolo and De Angelis, 2020). The other conference is the Glasgow Declaration for Fair Water Footprints for Climate Resilient, Inclusive, and Sustainable Development, a UN Climate Change Conference (COP26) Initiative, held in Glasgow in November 2021. We include this conference as Garel et al. (2024) find evidence of a biodiversity footprint premium after the Kunming Declaration at COP15, a framework for action to protect biodiversity and reverse species loss. Similarly, we identify a COP initiative that specifically addresses water-related issues. We create two dummies, the *Post Paris* Dummy equals 1 for 2016-2024, and the *Post Glasgow* Dummy that equals 1 for the years 2022-2024.

Table 10 shows the result of estimating Eq. 4, including the Post Paris dummy and interactions that equals 1 for the 2016-2024 years, and Table 9 shows the results of the relation between global stock returns and industry and company water use by estimating Eq.1 with the *Water Use Across* and *Water Use Within* variables, with the Post Paris dummy and interactions. Table 11 shows the results of estimating Eq.1 with the *Water Use Across* and *Water Use Within* variables, with the Post Glasgow dummy (that equals 1 for the 2022-2024 years) and interactions, and Table 12 shows the result of estimating Eq. 4, including the Post Glasgow dummy and interactions.

From Table 9 we observe a statistically significant negative relation between the *Water Use Across* variables and stock returns. This result, in column (4), indicates that pre-Paris, a standard deviation increase in *Total Water Use Across* is associated with a decrease in stock returns of approximately -2.570% p.a. In contrast, a standard deviation increase in *Total Water Use Across* after Paris is associated with a 0.26% p.a. increase in stock return. These results suggest a potential combination of the gradual pricing in risk across industries before Paris and demanding a small industry water use risk premium after Paris. For the region$\times$year/month F.E. specification (columns (4)-(6)), we observe a similar relation for the *Water Use Within* variables, a negative relation pre-Paris (albeit not statistically significant) and a statistically significant positive relation after the Paris agreement. These results seem to suggest that the positive relation we find in Table 5 is potentially driven by post Paris attention to climate finance variables.

From Table 10, we observe a significant negative relation for the *Water Stress* variable in Panel A and B in columns (4) and (5). This result indicates that Pre-Paris, a standard deviation increase in water stress (6-month m.a.) is associated with approximately -3.70% p.a. decrease in stock returns. In Panel B, column (5), the water stress interaction with the *Post-Paris dummy* is positive with a coefficient magnitude similar to that of the *Water Stress* variable. Post-Paris, a standard deviation increase in water stress is associated with -0.30% p.a. in stock return. These results seem to suggest that the negative relation pre-Paris between stock returns and *Water Stress* is partially or entirely offset by the positive coefficient on the interaction term, which helps explain why the full-sample estimate, presented in Table 7, yields a near-zero, statistically insignificant coefficient.

This shift in economic magnitude—from a sizeable negative effect pre-Paris to a near-zero effect post-Paris—suggests that investors may have started to recognize and more effectively price water-related variables following the Paris Agreement. From an asset pricing perspective, the pre-Paris negative relation between water stress and stock returns could reflect negative cash flow news if these firms were already suffering from operational or financial constraints tied to water stress or an increase in discount rates specific to high water-stress firms, perhaps due to perceived future regulatory or physical risks. While we cannot directly test these mechanisms, our findings are consistent with the idea that the Paris Agreement marked a shift in how water stress and use is perceived and priced by financial markets.

We also observe a statistically significant negative relation between the *Direct Water Use Across* variable in Panel A and Panel B of Table 10. This result, in Panel B column (5), indicates that pre-Paris, a standard deviation increase in *Direct Water Use Across* is associated with a decrease in stock returns of approximately -3.40% p.a. In contrast, a standard deviation increase in *Direct Water Use Across* after Paris is associated with a 0.68% p.a. increase in stock return. Similar to the results on water stress, these results suggest a potential combination of the gradual pricing in of industry water use and demanding a industry water use premium after Paris.

We observe a similar relation in Panel B for the *Water Supply* variable and interaction with the Post-Paris dummy. An increase in water supply, pre-Paris, is associated with a decrease in stock return. This result is intuitive, as water availability does not hurt a company's operation and even lowers the risk of water stress. The positive and significant interaction term indicates that post-2016, the negative relation is reversed or mitigated, as the interaction term coefficient is similar in magnitude to that of the water supply variable. Although these findings support the hypothesis that the Paris Agreement changed the pricing of water variables, caution is warranted given the relatively short pre-Paris period and the potential for other concurrent global factors confounding the results.

Table 11 shows similar results as Table 9, although the *Water Use Across* variables are not statistically significant in all model specifications anymore. This could be given the relatively short Post-Glasgow period. We do observe a statistically significant relation for the *Water Use Within* variables after Glasgow conference. Similar to our previous results.

Table 12 shows a statistically significant positive relation for the interaction term between the log *Direct Water Use Within* and Post-Glasgow dummy. These results indicate that the positive relation we observe in our previous findings is driven by the later years in our sample. We also observe these statistically significant positive coefficients for the interaction in Table 10. Strengthening the idea that the relation between within-industry water use and stock returns is driven in the later part of our sample period. We cannot draw conclusions for the other variables, as statistical significance is scattered in Panel A and diminishes in Panel B. Table 10 and Table 12 using country×year/month fixed effects or substituting the water stress by the weighted water stress variable yield the same results.

6. Conclusion

The world faces an intensifying water crisis driven by rising global demand and threats to freshwater availability. Companies dependent on water resources may face future operational and financial risks. The primary purpose of our research is to better understand the relation between water stress and global stock returns, contributing to the expanding literature on climate and spatial finance. Our findings can be summarized as follows. Firstly, we find evidence for a water use premium for firms consuming more water than industry peers. This relation remains consistent regardless of whether companies operate in low or high-water-use industries. Secondly, we observe that indirect and total water use have a higher premium than direct water use. These results highlight the importance of including indirect water use within supply chains. Thirdly, investors respond differently to water use and stress after the Paris Agreement. Finally, our findings provide initial evidence of a potential water stress premium for firms in high-water-use industries. While economically small, the statistically significant relation we identify provides a foundation for future research.

Water is a non-substitutable resource, and climate change and human activities—including pollution, the transition to green energy, and advancements in artificial intelligence—increase the pressure on freshwater systems. Therefore, we believe our findings should attract the interest of both companies and investors. Our results indicate that companies' water use is priced, and we find a water stress premium for companies operating in high-water-use industries. These insights can help companies create strategies to improve water conservation, use water more efficiently, and adopt sustainable water management practices. Additionally, our results can help investors make more informed investment decisions. Moreover, we hope our findings will encourage investors and companies to pursue more efficient and responsible water use.

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Tables and Figures

Table 1 Descriptive Statistics

This table presents the summary statistics (the number of observations, mean, standard deviation, median, minimum and maximum values) of the variables used in our research. **Panel A** reports the water variables. The *log (Total Water Use)*, *log (Direct Water Use)* and *log (Indirect Water Use)* are the company-level natural logarithm of total, direct and indirect water use (in m^3) from S&P Global Sustainable (2024a). The *Across* and *Within* variables of the three water use variables are constructed using Eq. 2 and Eq. 3 respectively. **Panel B** reports the water supply and water stress variables. *Water Supply* is the equally weighted z-score, which represents an average measure of how 'unusual' the underlying assets are regarding their water supply deviations for that month. *Weighted Water Supply* is the weighted z-score in which we weigh water-intense asset locations (coal mine, mine project, power plant site) twice. *(Weighted) Water Stress* is the interaction between company *log (Direct Water Use)* and *(Weighted) Water Supply.* The *3 and 6 month m.a.* are the appropriate month moving averages of the *(Weighted) Water Stress* variable. For readability we multiplied all *Water Stress* variables by -1, so that a higher *(Weighted) Water Stress* indicates higher water stress for a company.

VARIABLES	Obs.	Mean	S.D.	Min	P25	Median	P75	Max
Panel A: Water Use								
log (Total Water Use)	994,331.00	16.68	2.33	3.77	15.24	16.66	18.15	25.65
log (Direct Water Use)	994,042.00	13.58	2.85	-13.82	11.86	13.48	15.24	25.64
log (Indirect Water Use)	994,305.00	16.46	2.22	3.38	15.11	16.50	17.91	24.44
log (Total Water Use *Across*)	1,747,549.00	16.95	1.44	12.83	16.05	16.93	17.85	21.89
log (Total Water Use *Within*)	994,331.00	0.00	1.84	-13.75	-1.09	-0.00	1.15	8.73
log (Direct Water Use *Across*)	1,747,549.00	13.89	1.89	8.93	12.87	13.75	15.10	21.53
log (Direct Water Use *Within*)	994,042.00	0.00	2.17	-27.37	-1.21	-0.00	1.28	11.95
log (Indirect Water Use *Across*)	1,747,549.00	16.73	1.35	12.50	15.88	16.75	17.60	21.89
log (Indirect Water Use *Within*)	994,305.00	0.00	1.78	-13.49	-1.07	-0.01	1.11	7.94
Panel B: Water Supply and Water Stress								
Water Supply	1,411,421.00	0.39	4.06	-34.11	-1.76	-0.08	1.58	41.07
Weighted Water Supply	1,411,421.00	0.39	4.07	-34.11	-1.76	-0.07	1.59	41.07
Water Stress	875,399.00	0.39	8.92	-223.18	-1.73	0.03	2.06	207.88
Water Stress (3 month m.a.)	935,072.00	0.36	7.97	-115.74	-1.62	0.03	1.93	137.04
Water Stress (6 month m.a.)	950,734.00	0.35	7.74	-106.20	-1.61	0.03	1.92	129.71
Weighted Water Stress	875,399.00	0.39	8.94	-223.18	-1.74	0.03	2.06	207.88
Weighted Water Stress (3 month m.a.)	935,072.00	0.36	7.99	-115.74	-1.63	0.03	1.94	137.04
Weighted Water Stress (6 month m.a.)	950,734.00	0.35	7.76	-106.20	-1.61	0.03	1.92	129.71

Table 2 Descriptive Statistics: Control Variables

This table presents the summary statistics (the number of observations, mean, standard deviation, median, minimum and maximum values) of the the cross-sectional returns and company characteristics used in our research. *RET* (%) is the monthly excess stock return; log(*Size*) is the natural logarithm of market capitalization (in $ million) as of June of each year and held that value constant until May of the following year; The book-to-market ratio log(B/M) is the natural logarithm of the book value of equity to market capitalization computed every June of each year t, using the last book equity value in June of the previous calendar year and the market capitalization value in December of the previous year; *Beta* is the monthly market beta computed at the end of month t as the regression slope of a regression of monthly excess stock returns on market excess returns over the previous 24 months, where we require at least 12 months of non-NA excess returns data; *Momentum* is computed as the cumulative return during an 11-month period between months $t-1$ and $t-11$, where we require at least 9 months of return data during the 11-month period; *Volatility* is computed as the standard deviation of the returns of a stock i over a 12-month period ($RET_{i,t-12}$, $RET_{i,t-11}, ...,$ $RET_{i,t-1}$, measured at the end of month t, excluding the current period's RET_t) where we require at least 9 non-NA returns observations during the 12-month period; *Leverage* is defined as the ratio of debt to the book value of assets, where we allow the long-term debt or the current debt to be missing, but not both, and we set negative values to missing; *Invest/A* is calculated as the ratio of capital expenditures to the book value of total assets; *log(PPE)* is the natural logarithm of the property, plant, and equipment cost of tangible fixed property used in the production of revenue; *Sales Growth* is defined as the percentage change in net sales; *Return on Equity* is computed every June by taking the net income divided by the market capitalization value in December of the previous calendar year.

VARIABLES	Obs.	Mean	S.D.	Min	P25	Median	P75	Max
RET (%) (winsorized at 0.1%)	1,754,695.00	0.85	13.77	-78.72	-6.11	-0.08	6.37	225.38
log (Size)	1,691,241.00	6.53	1.63	0.05	5.40	6.51	7.57	14.64
log (B/M)	1,299,618.00	-0.61	1.06	-13.19	-1.21	-0.53	0.09	5.43
Beta (winsorized at 0.1%)	1,565,432.00	1.14	0.89	-3.14	0.62	1.08	1.59	6.48
Momentum (winsorized at 0.1%)	1,597,473.00	0.12	0.60	-0.91	-0.20	0.02	0.28	6.74
Volatility (winsorized at 0.1%)	1,582,929.00	0.12	0.08	0.02	0.07	0.10	0.14	0.88
Leverage (winsorized at 0.1%)	1,427,009.00	0.22	0.20	0.00	0.06	0.20	0.34	1.97
Invest/A (winsorized at 0.1%)	1,424,094.00	0.04	0.05	0.00	0.01	0.03	0.06	0.44
log (PPE)	1,424,694.00	5.07	2.35	-9.14	3.75	5.14	6.56	12.76
Sales Growth (winsorized at 0.1%)	1,411,697.00	0.17	1.41	-1.00	-0.06	0.04	0.17	33.48
Return on Equity (winsorized at 0.1%)	1,300,416.00	0.03	0.36	-6.96	0.01	0.04	0.08	2.85

Table 3 Correlation matrix

This table shows the correlations between the variables in our study. We refer to Table 1 for a description of the variables. *TWU* stands for *Total Water Use*, *DWU* stands for *Direct Water Use* and *IWU* stands for *Indirect Water Use*.

	RET (%)	log (TWU)	log (DWU)	log (IWU)	Water Supply	Weighted Water Supply	Water Stress	Water Stress (3m.m.a.)	Water Stress (6m.m.a.)
RET (%)	1.00								
log (TWU)	0.01	1.00							
log (DWU)	0.01	0.88	1.00						
log (IWU)	0.01	0.96	0.77	1.00					
Water Supply	-0.00	-0.07	-0.09	-0.06	1.00				
Weighted Water Supply	-0.00	-0.07	-0.09	-0.06	1.00	1.00			
Water Stress	-0.00	-0.10	-0.10	-0.10	0.10	0.10	1.00		
Water Stress (3m.m.a)	-0.00	-0.10	-0.10	-0.10	0.11	0.11	0.92	1.00	
Water Stress (6m.m.a)	-0.00	-0.10	-0.10	-0.10	0.11	0.11	0.90	0.98	1.00
Weighted Water Stress	-0.00	-0.10	-0.10	-0.10	0.10	0.10	1.00	0.92	0.90
W. Water Stress (3m.m.a)	-0.00	-0.10	-0.10	-0.10	0.11	0.11	0.92	1.00	0.98
W. Water Stress (6m.m.a)	-0.00	-0.10	-0.10	-0.10	0.11	0.11	0.90	0.98	1.00
Beta	0.02	-0.04	-0.03	-0.03	-0.09	-0.09	-0.01	-0.01	-0.01
log (Size)	-0.02	0.58	0.47	0.59	-0.11	-0.11	-0.10	-0.11	-0.10
B/M	0.01	0.29	0.29	0.27	0.07	0.07	-0.02	-0.02	-0.02
Momentum	0.02	0.02	0.02	0.02	-0.01	-0.01	-0.01	-0.01	-0.01
Leverage	-0.00	0.19	0.19	0.16	-0.05	-0.05	-0.04	-0.04	-0.05
Invest/A	0.00	0.11	0.14	0.10	-0.06	-0.06	-0.03	-0.03	-0.03
Return on Equity	-0.00	0.13	0.10	0.13	0.02	0.02	0.00	0.00	0.00
log (PPE)	-0.01	0.79	0.71	0.77	-0.08	-0.08	-0.11	-0.12	-0.12
Volatility	0.02	-0.27	-0.21	-0.27	-0.07	-0.07	0.01	0.01	0.01
Sales Growth	-0.00	-0.11	-0.08	-0.11	-0.02	-0.02	0.00	0.00	0.00

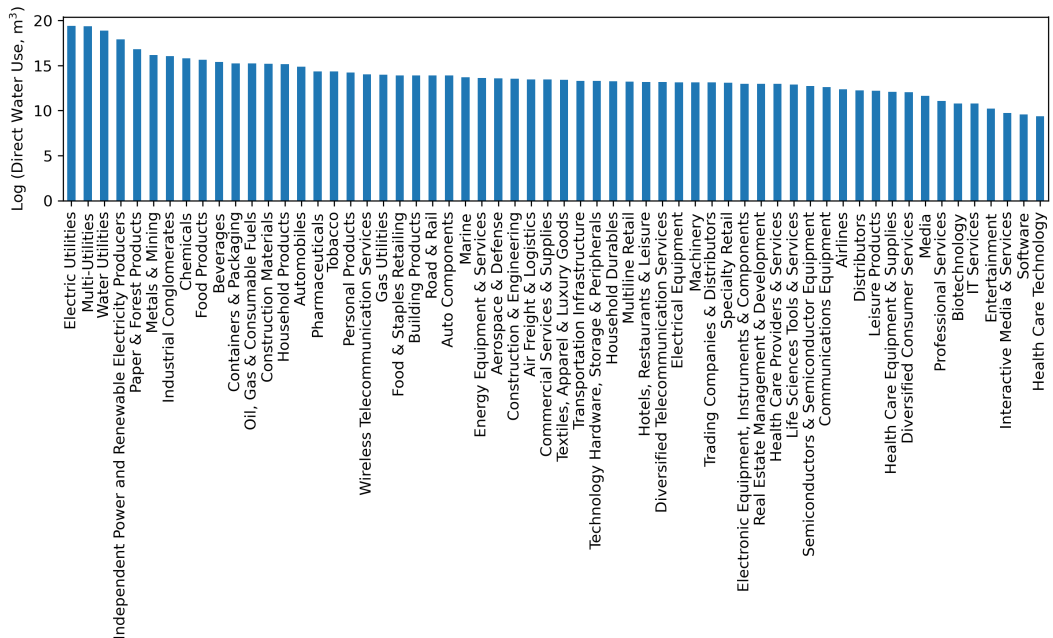
Table 3 continued

This table shows the correlations between the variables in our study. We refer to Tables 1 and 2 for a description of the variables. *TWU* stands for *Total Water Use*, *DWU* stands for *Direct Water Use*, *IWU* stands for *Indirect Water Use*, *Mom.* stands for *Momentum*, *Lev.* stands for *Leverage* and *Vol.* stands for *Volatility*.

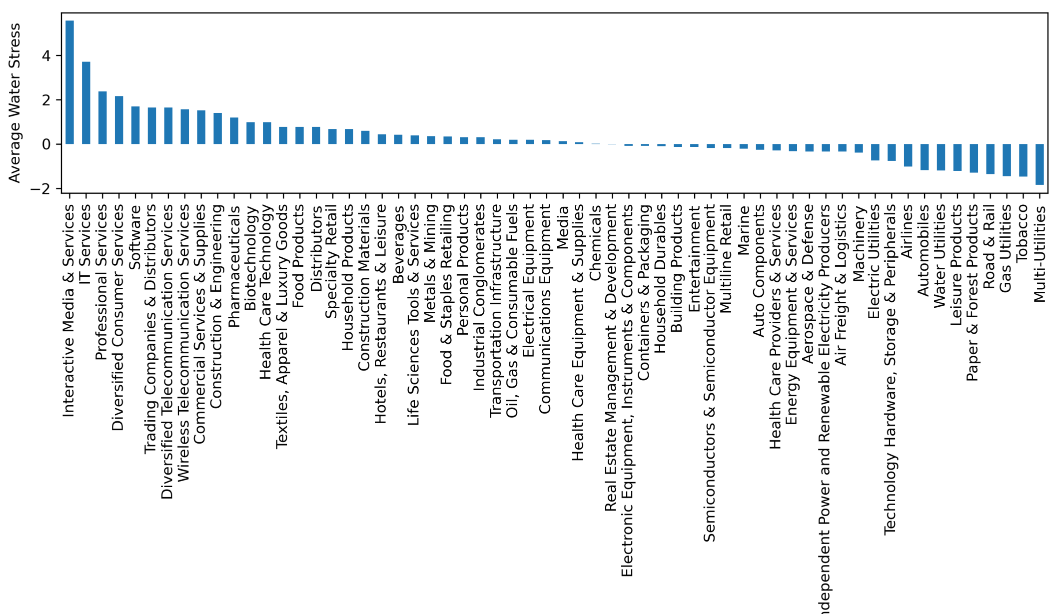
	Weighted Water Stress	W. Water Stress (3m.m.a.)	W. Water Stress (6m.m.a.)	Beta	log (Size)	B/M	Mom.	Lev.	Invest/A	Return on Equity	log (PPE)	Vol.	Sales Growth
Weighted Water Stress	1.00												
W. Water Stress (3m.m.a)	0.92	1.00											
W. Water Stress (6m.m.a)	0.90	0.98	1.00										
Beta	-0.01	-0.01	-0.01	1.00									
log (Size)	-0.10	-0.10	-0.10	-0.00	1.00								
B/M	-0.02	-0.02	-0.02	-0.05	-0.24	1.00							
Momentum	-0.01	-0.01	-0.01	0.03	0.01	-0.01	1.00						
Leverage	-0.04	-0.04	-0.04	0.09	0.04	0.04	-0.00	1.00					
Invest/A	-0.03	-0.03	-0.03	0.04	0.08	-0.05	0.00*	0.09	1.00				
Return on Equity	0.00	0.00	0.00	-0.06	0.15	0.04	-0.00	-0.15	0.02	1.00			
log (PPE)	-0.11	-0.12	-0.12	-0.01	0.62	0.35	-0.06	0.30	0.25	0.09	1.00		
Volatility	0.01	0.01	0.01	0.33	-0.18	-0.18	0.29	0.08	0.01	-0.19	-0.26	1.00	
Sales Growth	0.00	0.00	0.00	0.02	0.00	-0.08	-0.01	-0.01	0.03	0.00	-0.07	0.06	1.00

Figure 1 Direct Water Use and Water Stress by Industry

Figure 1 **Panel A** showcases the average log(*Direct Water Use*) by industry. In addition, **Panel B** shows the *Water Stress* by industry. *Water Stress* is the interaction between log(*Direct Water Use Within*) and *Water Supply*, with higher values indicating greater water stress.



Panel A: log(*Direct Water Use*) by Industry



Panel B: *Water Stress* by Industry

Table 4 Water Use and Stock Returns

This table shows the results of regressions to examine the relation between company water use and global stock returns. The dependent variable is the monthly excess stock return for company i in month t. As independent variables, we include the natural logarithm of our total and direct water use variables and the stock-level control variables. We refer to Tables 1 and 2 for a description of these variables. Columns (1)-(2) show the results of Eq. 1 using year/month fixed effects. Columns (3)-(4) show the relation using region×year/month fixed effects. Columns (5)-(6) display the relation using industry×year/month fixed effects and columns (7)-(8) display the relation using region×year/month and industry×year/month fixed effects. The uneven columns show the relation for the log (*Total Water Use*) variable. The even columns display the relation for the log (*Direct Water Use*). Intercepts are suppressed to conserve space. The t-statistics are double clustered at the firm and month/year level. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable: RET	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log (Total Water Use)	0.0432		0.0451		0.0743*		0.0768**	
	(1.3696)		(1.5113)		(1.9726)		(2.1520)	
log (Direct Water Use)		0.0252		0.0236		0.0285		0.0271*
		(1.1827)		(1.4622)		(1.6126)		(1.6954)
Beta	0.3402	0.3392	0.3785	0.3781	0.3018	0.3010	0.3329	0.3331
	(1.0209)	(1.0180)	(1.1046)	(1.1035)	(0.9374)	(0.9347)	(1.0068)	(1.0071)
Size	0.0317	0.0423	-0.0082	0.0031	0.0105	0.0372	-0.0264	0.0015
	(0.3399)	(0.4809)	(-0.0913)	(0.0361)	(0.1091)	(0.4328)	(-0.2897)	(0.0189)
B/M	0.1539**	0.1604**	0.1317*	0.1390*	0.1274	0.1458*	0.1079	0.1271*
	(1.9926)	(2.0902)	(1.7449)	(1.8393)	(1.6284)	(1.9256)	(1.4053)	(1.7024)
Momentum	0.0805	0.0786	0.2200	0.2181	-0.0135	-0.0174	0.1261	0.1220
	(0.3065)	(0.2996)	(0.8839)	(0.8776)	(-0.0560)	(-0.0723)	(0.5632)	(0.5451)
Leverage	-0.1211	-0.1122	-0.2475	-0.2371	-0.0001	0.0356	-0.1365	-0.0994
	(-0.3474)	(-0.3234)	(-0.9687)	(-0.9342)	(-0.0002)	(0.1040)	(-0.5602)	(-0.4193)
INV/A	0.2146	0.1040	0.1623	0.0515	0.2463	0.0499	0.1789	-0.0216
	(0.1841)	(0.0873)	(0.1571)	(0.0491)	(0.2508)	(0.0481)	(0.2013)	(-0.0233)
Return on Equity	-0.1227	-0.1216	-0.1877	-0.1861	-0.0911	-0.0875	-0.1540	-0.1502
	(-0.9220)	(-0.9105)	(-1.5993)	(-1.5808)	(-0.7296)	(-0.6960)	(-1.4105)	(-1.3691)
ln (PPE)	-0.0304	-0.0243	-0.0257	-0.0170	-0.0299	-0.0128	-0.0310	-0.0120
	(-0.5658)	(-0.4133)	(-0.4946)	(-0.2991)	(-0.6423)	(-0.2511)	(-0.7320)	(-0.2523)
Volatility	-0.1679	-0.2533	-1.8789	-1.9569	-0.4270	-0.5172	-2.0662	-2.1472
	(-0.0892)	(-0.1332)	(-1.1674)	(-1.2057)	(-0.2457)	(-0.2955)	(-1.3974)	(-1.4421)
Sales Growth	-0.0565**	-0.0594**	-0.0563**	-0.0594**	-0.0389*	-0.0430*	-0.0385*	-0.0428**
	(-2.3488)	(-2.3938)	(-2.3598)	(-2.4184)	(-1.7870)	(-1.9620)	(-1.8161)	(-1.9848)
Year/month F.E.	Yes	Yes						
Region*Year/month F.E.			Yes	Yes			Yes	Yes
Industry*Year/month F.E.					Yes	Yes	Yes	Yes
Observations	893,153	892,867	893,153	892,867	893,153	892,867	893,153	892,867
R-squared	0.1439	0.1439	0.1854	0.1855	0.1861	0.1861	0.2242	0.2242

Table 5 Water Use and Stock Returns: Industry variation

This table shows regressions results to examine the relation between company water use and global stock returns within and across industries. The dependent variable is the monthly excess stock return for company i in month t. As independent variables, we include the natural logarithm of our total, direct and indirect water use variables decomposed into *Water Use Across* and *Water Use Within.* and the stock-level control variables. The *Across* and *Within* variables are constructed using Eq. 2 and Eq. 3, respectively. We refer to Tables 1 and 2 for a description of the independent variables. Columns (1)-(4) show the results of Eq.1, with the *Water Use Across* and *Water Use Within* variables, using year/month fixed effects. Columns (5)-(8) show the relation using region×year/month fixed effects. Columns (1) and (5) display the relation between the log (*Total Water Use*) variables, whereas columns (2) and (6) depict the results of log (*Direct Water Use*), columns (3) and (7) show the results for log (*Indirect Water Use*). In columns (4) and (8) we include both the log (*Direct Water Use*) and log (*Indirect Water Use*) variables in the analyses. Intercepts and control variables are suppressed to conserve space.The t-statistics are double clustered at the firm and month/year level. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable: RET (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log (Total Water Use *Across*)	0.0074				0.0100			
	(0.1520)				(0.2298)			
log (Total Water Use *Within*)	0.0750**				0.0760**			
	(2.3610)				(2.4801)			
log (Direct Water Use *Across*)		0.0121		0.0428		0.0116		0.0379
		(0.3282)		(1.1981)		(0.3979)		(1.2036)
log (Direct Water Use *Within*)		0.0358**		-0.0046		0.0329**		-0.0098
		(2.1153)		(-0.2145)		(2.2163)		(-0.8752)
log (Indirect Water Use *Across*)			0.0050	-0.0301			0.0099	-0.0215
			(0.0998)	(-0.5863)			(0.2085)	(-0.4152)
log (Indirect Water Use *Within*)			0.0892**	0.1052**			0.0927***	0.1117***
			(2.3839)	(2.3584)			(2.6584)	(3.0508)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes				
Region*Year/month F.E.					Yes	Yes	Yes	Yes
Observations	893,153	892,867	893,127	892,841	893,153	892,867	893,127	892,841
R-squared	0.1439	0.1439	0.1439	0.1440	0.1855	0.1855	0.1855	0.1855

Table 6 Water Use and Stock Returns: Industry Variation for High and Low Water Users

This table presents regression results examining whether the relation between water use and global stock returns varies between companies operating in low- versus high-water-use industries. The dependent variable is the monthly excess stock return for company i in month t. As independent variables, we include the natural logarithm of our total, direct and indirect water use variables decomposed into *Water Use Across* (constructed using Eq. 2) and *Water Use Within.* (constructed using Eq. 3) and the stock-level control variables. We refer to Tables 1 and 2 for a description of the independent variables. Columns (1)-(3) show the results of Eq. 1 including the *High Water Use (HWU)* Dummy and the interaction with the *Water Use Within* variables, using year/month fixed effects. Columns (4)-(6) show the relation using region×year/month fixed effects. Columns (1) and (4) display the relation between the log (*Total Water Use*) variables, whereas columns (2) and (5) depict the results of log (*Direct Water Use*), columns (3) and (6) show the results for log (*Indirect Water Use*). Intercepts and control variables are suppressed to conserve space. The t-statistics are double clustered at the firm and month/year level. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable: RET (%)	(1)	(2)	(3)	(4)	(5)	(6)
High Water Use Dummy	-0.1582	-0.1694	-0.1269	-0.1550	-0.1627*	-0.1284
	(-1.3284)	(-1.5300)	(-1.1754)	(-1.6083)	(-1.6582)	(-1.4369)
log (Total Water Use *Across*)	0.0517			0.0530		
	(0.9057)			(1.2063)		
log (Total Water Use *Within*)	0.1005***			0.0961***		
	(2.9268)			(2.7453)		
log (Total Water Use *Within*) x HWU	-0.0473			-0.0383		
	(-1.3632)			(-1.2552)		
log (Direct Water Use *Across*)		0.0387			0.0370	
		(0.9675)			(1.3037)	
log (Direct Water Use *Within*)		0.0473*			0.0412*	
		(1.7520)			(1.8697)	
log (Direct Water Use *Within*) x HWU		-0.0253			-0.0198	
		(-0.8739)			(-0.7967)	
log (Indirect Water Use *Across*)			0.0394			0.0443
			(0.7362)			(0.9506)
log (Indirect Water Use *Within*)			0.1069***			0.1048***
			(2.9925)			(2.9057)
log (Indirect Water Use *Within*) x HWU			-0.0438			-0.0332
			(-1.2314)			(-1.0799)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes			
Region*Year/month F.E.				Yes	Yes	Yes
Observations	893,153	892,867	893,127	893,153	892,867	893,127
R-squared	0.1440	0.1440	0.1440	0.1855	0.1855	0.1855

Table 7 Water Stress and Stock Returns

This table shows the results of regressions to examine the relation between company water stress and global stock returns. The dependent variable is the monthly excess stock return for company i in month t. As independent variables, we include the natural logarithm of the direct water use variable decomposed into *Direct Water Use Across* (constructed using Eq. 2) and *Direct Water Use Within* (constructed using Eq. 3), the water supply and water stress variables and the stock-level control variables. *Water Stress* is the interaction between log(*Direct Water Use Within*) and *Water Supply*, with higher values indicating greater water stress. We refer to Tables 1 and 2 for a description of the other variables. **Panel A** show the results of Eq. 4 using year/month fixed effects. **Panel B** depicts the results of Eq. 4 using region×year/month fixed effects. The variables Water Supply and Water Stress are lagged by various horizons (τ = 1, 3, 6 months) or represented as moving averages (3- and 6-months). Columns (1)–(3) present the regression results for different lag periods, specifically τ = 1, 3, and 6 months, respectively. Columns (5) and (6) report results based on moving averages over 3-month and 6-month windows, respectively. Intercepts are suppressed to conserve space. The t-statistics are double clustered at the firm and month/year level. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Year/month F.E.					
Dependent Variable: RET (%)	(1)	(2)	(3)	(4)	(5)
	Lag 1	Lag 3	Lag 6	Mov. Av. 3	Mov. Av. 6
Water Stress	-0.0011	-0.0028	-0.0035	-0.0039	-0.0045
	(-0.3184)	(-0.9658)	(-1.0214)	(-1.1677)	(-1.3270)
log (Direct Water Use *Within*)	0.0394**	0.0385**	0.0396**	0.0392**	0.0402**
	(2.1233)	(2.0492)	(2.1074)	(2.1935)	(2.2923)
Water Supply	-0.0132	-0.0173	-0.0291	-0.0150	-0.0223
	(-0.6214)	(-0.9319)	(-1.4038)	(-0.6686)	(-1.0212)
log (Direct Water Use *Across*)	0.0263	0.0232	0.0243	0.0231	0.0222
	(0.6662)	(0.5922)	(0.6120)	(0.6118)	(0.5982)
Controls	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes
Observations	787,832	777,658	764,233	839,553	853,949
R-squared	0.1454	0.1483	0.1478	0.1471	0.1460

Table 7 continued

Panel B: Region*Year/month F.E.					
Dependent Variable: RET (%)	(1)	(2)	(3)	(4)	(5)
	Lag 1	Lag 3	Lag 6	Mov. Av. 3	Mov. Av. 6
Water Stress	-0.0008	-0.0026	-0.0031	-0.0032	-0.0037
	(-0.2732)	(-1.1119)	(-1.1013)	(-1.1466)	(-1.3180)
log (Direct Water Use *Within*)	0.0357**	0.0313*	0.0366**	0.0342**	0.0350**
	(2.2157)	(1.9026)	(2.2141)	(2.1942)	(2.2832)
Water Supply	-0.0002	0.0010	-0.0035	0.0003	-0.0003
	(-0.0212)	(0.1073)	(-0.4082)	(0.0358)	(-0.0340)
log (Direct Water Use *Across*)	0.0186	0.0171	0.0249	0.0172	0.0178
	(0.5756)	(0.5297)	(0.7694)	(0.5614)	(0.5908)
Controls	Yes	Yes	Yes	Yes	Yes
Region*Year/month F.E.	Yes	Yes	Yes	Yes	Yes
Observations	787,832	777,658	764,233	839,553	853,949
R-squared	0.1869	0.1891	0.1891	0.1887	0.1875

Table 8 Water Stress and Stock Returns: High Direct Water Use Industries

This table presents regression results examining whether the relation between water stress and global stock returns varies between companies operating in low- versus high-water-use industries. The dependent variable is the monthly excess stock return for company i in month t. As independent variables, we include the natural logarithm of the direct water use variable decomposed into *Direct Water Use Across* (constructed using Eq. 2) and *Direct Water Use Within* (constructed using Eq. 3), the water supply and water stress variables and the stock-level control variables. *Water Stress* is the interaction between log(*Direct Water Use Within*) and *Water Supply*, with higher values indicating greater water stress. We refer to Tables 1 and 2 for a description of the other variables. We include a dummy variable *High Direct Water Use Dummy (HDWU)* equal to 1 if firm i's industry-average direct water use exceeds the median direct water use across all industries. We interact the dummy with all variables except the *Across* variable which already captures between industry direct water use. **Panel A** show the results of Eq. 4 using year/month fixed effects. **Panel B** depicts the results of Eq. 4 using region×year/month fixed effects. The variables Water Supply and Water Stress are lagged by various horizons (τ = 1, 3, 6 months) or represented as moving averages (3- and 6-months). Columns (1)–(3) present the regression results for different lag periods, specifically τ = 1, 3, and 6 months, respectively. Columns (4) and (5) report results based on moving averages over 3-month and 6-month windows, respectively. Intercepts are suppressed to conserve space.The t-statistics are double clustered at the firm and month/year level. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Year/month F.E.					
Dependent Variable: RET (%)	(1)	(2)	(3)	(4)	(5)
	Lag 1	Lag 3	Lag 6	Mov. Av. 3	Mov. Av. 6
Water Stress	-0.0036	-0.0052	-0.0055	-0.0075*	-0.0074*
	(-0.8275)	(-1.4126)	(-1.3424)	(-1.7426)	(-1.7416)
Water Stress x HDWU	0.0077**	0.0069*	0.0060*	0.0103***	0.0086**
	(2.0675)	(1.9642)	(1.7919)	(2.6279)	(2.3293)
log (Direct Water Use *Within*)	0.0638**	0.0601**	0.0617**	0.0598**	0.0608**
	(2.4718)	(2.2870)	(2.3437)	(2.3875)	(2.4663)
log (Direct Water Use *Within*) x HDWU	-0.0456**	-0.0408*	-0.0413*	-0.0394*	-0.0388*
	(-2.0502)	(-1.7910)	(-1.7850)	(-1.8356)	(-1.8330)
Water Supply	-0.0134	-0.0127	-0.0274	-0.0131	-0.0210
	(-0.5841)	(-0.6505)	(-1.3320)	(-0.5516)	(-0.9225)
Water Supply x HDWU	0.0013	-0.0123	-0.0042	-0.0043	-0.0028
	(0.1018)	(-0.9374)	(-0.3151)	(-0.3132)	(-0.2007)
log (Direct Water Use *Across*)	0.0534	0.0448	0.0488	0.0512	0.0479
	(1.3381)	(1.1313)	(1.2065)	(1.3356)	(1.2705)
High Direct Water Use Dummy	-0.1253	-0.0964	-0.1122	-0.1315	-0.1199
	(-0.8668)	(-0.6585)	(-0.7633)	(-0.9590)	(-0.8848)
Controls	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes
Observations	787,832	777,658	764,233	839,553	853,949
R-squared	0.1454	0.1483	0.1478	0.1471	0.1460

Table 8 continued

Panel B: Region*Year/month F.E.					
Dependent Variable: RET (%)	(1)	(2)	(3)	(4)	(5)
	Lag 1	Lag 3	Lag 6	Mov. Av. 3	Mov. Av. 6
Water Stress	-0.0033	-0.0051*	-0.0047	-0.0068**	-0.0066**
	(-0.9633)	(-1.7951)	(-1.5559)	(-2.0452)	(-2.0657)
Water Stress x HDWU	0.0075**	0.0069**	0.0049*	0.0100***	0.0082***
	(2.5247)	(2.3521)	(1.7612)	(3.2693)	(2.9233)
log (Direct Water Use *Within*)	0.0560**	0.0503**	0.0552**	0.0517**	0.0523**
	(2.5707)	(2.2556)	(2.4655)	(2.4333)	(2.5093)
log (Direct Water Use *Within*) x HDWU	-0.0383*	-0.0361	-0.0349	-0.0339	-0.0330
	(-1.7728)	(-1.6338)	(-1.5602)	(-1.6219)	(-1.6116)
Water Supply	-0.0003	0.0046	-0.0016	0.0017	0.0008
	(-0.0375)	(0.4124)	(-0.1568)	(0.1599)	(0.0787)
Water Supply x HDWU	0.0010	-0.0097	-0.0049	-0.0032	-0.0027
	(0.0760)	(-0.7419)	(-0.3695)	(-0.2349)	(-0.1932)
log (Direct Water Use *Across*)	0.0449	0.0400	0.0466	0.0445	0.0426
	(1.4738)	(1.2882)	(1.4913)	(1.4993)	(1.4555)
High Direct Water Use Dummy	-0.1251	-0.1053	-0.1004	-0.1304	-0.1179
	(-0.8832)	(-0.7331)	(-0.7000)	(-0.9713)	(-0.8900)
Controls	Yes	Yes	Yes	Yes	Yes
Region*Year/month F.E.	Yes	Yes	Yes	Yes	Yes
Observations	787,832	777,658	764,233	839,553	853,949
R-squared	0.1870	0.1892	0.1892	0.1888	0.1875

Table 9 Water Use and Stock Returns: Paris

This table presents regression results examining the relation between global stock return and water use variables before and after Paris Agreement (2015). The dependent variable is the monthly excess stock return for company i in month t. As independent variables, we include the natural logarithm of our total, direct and indirect water use variables decomposed into *Water Use Across* (constructed using Eq. 2) and *Water Use Within.* (constructed using Eq. 3) and the stock-level control variables. We refer to Tables 1 and 2 for a description of the independent variables. Columns (1)-(3) show the results of Eq. 1 including the *Post-Paris (PP)* Dummy and the interaction with the *Water Use* variables, using year/month fixed effects. Columns (4)-(6) show the relation using region×year/month fixed effects. Columns (1) and (4) display the relation between the log (*Total Water Use*) variables, whereas columns (2) and (5) depict the results of log (*Direct Water Use*), columns (3) and (6) show the results for log (*Indirect Water Use*). Intercepts and control variables are suppressed to conserve space. The t-statistics are double clustered at the firm and month/year level. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable: RET (%)	(1)	(2)	(3)	(4)	(5)	(6)
log (Total Water Use *Across*)	-0.1609*			-0.1488*		
	(-1.8911)			(-1.9244)		
log (Total Water Use *Across*) x PP	0.1738*			0.1640*		
	(1.6734)			(1.7312)		
log (Total Water Use *Within*)	0.0006			-0.0412		
	(0.0062)			(-0.5819)		
log (Total Water Use *Within*) x PP	0.0776			0.1215*		
	(0.7904)			(1.6951)		
log (Direct Water Use *Across*)		-0.1681**			-0.1535**	
		(-2.1384)			(-2.2764)	
log (Direct Water Use *Across*) x PP		0.1865**			0.1711**	
		(2.1029)			(2.2250)	
log (Direct Water Use *Within*)		-0.0303			-0.0627	
		(-0.4642)			(-1.1848)	
log (Direct Water Use *Within*) x PP		0.0688			0.0992*	
		(1.0268)			(1.8169)	
log (Indirect Water Use *Across*)			-0.1480*			-0.1439*
			(-1.6960)			(-1.7976)
log (Indirect Water Use *Across*) x PP			0.1580			0.1588
			(1.4783)			(1.6136)
log (Indirect Water Use *Within*)			0.0129			-0.0272
			(0.1223)			(-0.3756)
log (Indirect Water Use *Within*) x PP			0.0795			0.1242*
			(0.7692)			(1.7009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes			
Region*Year/month F.E.				Yes	Yes	Yes
Observations	892,867	892,867	892,841	892,867	892,867	892,841
R-squared	0.1440	0.1440	0.1440	0.1855	0.1855	0.1855

Table 10 Water Stress and Stock Returns: Paris

This table presents regression results examining whether the relation between water stress and global stock returns changes after the Paris Agreement. The dependent variable is the monthly excess stock return for company i in month t. As independent variables, we include the natural logarithm of the direct water use variable decomposed into *Direct Water Use Across* (constructed using Eq. 2) and *Direct Water Use Within* (constructed using Eq. 3), the water supply and water stress variables and the stock-level control variables. *Water Stress* is the interaction between log(*Direct Water Use Within*) and *Water Supply*, with higher values indicating greater water stress. We refer to Tables 1 and 2 for a description of the other variables. The Post Paris dummy (PP) variable equals 1 during the years 2016-2024. We interact the dummy with all water use and water stress variables. **Panel A** show the results of Eq. 4, including the dummy and interactions using year/month fixed effects. **Panel B** depicts the results of Eq. 4, including the dummy and interactions using region×year/month fixed effects. The variables Water Supply and Water Stress are lagged by various horizons (τ = 1, 3, 6 months) or represented as moving averages (3- and 6-months). Columns (1)–(3) present the regression results for different lag periods, specifically τ = 1, 3, and 6 months, respectively. Columns (4) and (5) report results based on moving averages over 3-month and 6-month windows, respectively. Intercepts are suppressed to conserve space. The t-statistics are double clustered at the firm and month/year level. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Year/month F.E.					
Dependent Variable: RET (%)	(1)	(2)	(3)	(4)	(5)
	Lag 1	Lag 3	Lag 6	Mov. Av. 3	Mov. Av. 6
Water Stress	-0.0201	-0.0155	-0.0357	-0.0408**	-0.0477*
	(-0.8037)	(-1.0593)	(-0.9183))	(-2.0906)	(-1.8395)
Water Stress x PP	0.0192	0.0128	0.0325	0.0373*	0.0437*
	(0.7627)	(0.8729)	(0.8354)	(1.9050)	(1.6811)
log (Direct Water Use *Within*)	0.0175	-0.0368	-0.0025	-0.0205	-0.0222
	(0.1967)	(-0.5129)	(-0.0301)	(-0.3198)	(-0.3387)
log (Direct Water Use *Within*) x PP	0.0227	0.0781	0.0438	0.0625	0.0653
	(0.2504)	(1.0590)	(0.5078)	(0.9489)	(0.9705)
Water Supply	-0.0579	-0.0598	-0.0401	-0.0586	-0.0545
	(-1.1754)	(-1.3087)	(-0.4955)	(-1.2031)	(-1.1306)
Water Supply x PP	0.0452	0.0432	0.0112	0.0443	0.0328
	(0.8434)	(0.8719)	(0.1338)	(0.8230)	(0.6159)
log (Direct Water Use *Across*)	-0.0967	-0.1701*	-0.1596	-0.1677**	-0.1691**
	(-1.1429)	(-1.7471)	(-1.6295)	(-2.1554)	(-2.1620)
log (Direct Water Use *Across*) x PP	0.1263	0.1993*	0.1893*	0.1981**	0.1985**
	(1.3247)	(1.8659)	(1.7615)	(2.2366)	(2.2415)
Controls	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes
Observations	787,832	777,658	764,233	839,553	853,949
R-squared	0.1454	0.1483	0.1478	0.1471	0.1460

Table 10 continued

Panel B: Region*Year/month F.E.					
Dependent Variable: RET (%)	(1)	(2)	(3)	(4)	(5)
	Lag 1	Lag 3	Lag 6	Mov. Av. 3	Mov. Av. 6
Water Stress	-0.0093	-0.0049	-0.0311	-0.0328*	-0.0399*
	(-0.4113)	(-0.2906)	(-1.0771)	(-1.7605)	(-1.8751)
Water Stress x PP	0.0086	0.0023	0.0282	0.0299	0.0365*
	(0.3770)	(0.1343)	(0.9749)	(1.5946)	(1.7092)
log (Direct Water Use *Within*)	-0.0195	-0.0844	-0.0463	-0.0588	-0.0610
	(-0.2800)	(-1.3550)	(-0.6817)	(-1.1189)	(-1.1596)
log (Direct Water Use *Within*) x PP	0.0568	0.1195*	0.0855	0.0969*	0.1000*
	(0.7959)	(1.8640)	(1.2290)	(1.7880)	(1.8443)
Water Supply	-0.0852**	-0.0861***	-0.0713	-0.1079***	-0.1130***
	(-2.3152)	(-3.6718)	(-1.2273)	(-2.9327)	(-2.8530)
Water Supply x PP	0.0863**	0.0886***	0.0688	0.1102***	0.1146***
	(2.2978)	(3.4997)	(1.1711)	(2.9014)	(2.8150)
log (Direct Water Use *Across*)	-0.1100	-0.1561**	-0.1476*	-0.1533**	-0.1552**
	(-1.3705)	(-2.0402)	(-1.7793)	(-2.2675)	(-2.2931)
log (Direct Water Use *Across*) x PP	0.1320	0.1788**	0.1777*	0.1772**	0.1797**
	(1.4711)	(2.0614)	(1.9263)	(2.2737)	(2.3133)
Controls	Yes	Yes	Yes	Yes	Yes
Region*Year/month F.E.	Yes	Yes	Yes	Yes	Yes
Observations	787,832	777,658	764,233	839,553	853,949
R-squared	0.1869	0.1892	0.1892	0.1888	0.1875

Table 11 Water Use and Stock Returns: Glasgow

This table presents regression results examining the relation between global stock return and water use variables before and after Glasgow conference (2021). The dependent variable is the monthly excess stock return for company i in month t. As independent variables, we include the natural logarithm of our total, direct and indirect water use variables decomposed into *Water Use Across* (constructed using Eq. 2) and *Water Use Within.* (constructed using Eq. 3) and the stock-level control variables. We refer to Tables 1 and 2 for a description of the independent variables. Columns (1)-(3) show the results of Eq. 1 including the *Post-Glasgow (PG)* Dummy and the interaction with the *Water Use* variables, using year/month fixed effects. Columns (4)-(6) show the relation using region×year/month fixed effects. Columns (1) and (4) display the relation between the log (*Total Water Use*) variables, whereas columns (2) and (5) depict the results of log (*Direct Water Use*), columns (3) and (6) show the results for log (*Indirect Water Use*). Intercepts and control variables are suppressed to conserve space. The t-statistics are double clustered at the firm and month/year level. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable: RET (%)	(1)	(2)	(3)	(4)	(5)	(6)
log (Total Water Use *Across*)	-0.0980*			-0.0833		
	(-1.7193)			(-1.5217)		
log (Total Water Use *Across*) x PG	0.2430*			0.2154		
	(1.7069)			(1.6516)		
log (Total Water Use *Within*)	0.0189			0.0158		
	(0.5008)			(0.4152)		
log (Total Water Use *Within*) x PG	0.1280**			0.1368**		
	(2.0693)			(2.1161)		
log (Direct Water Use *Across*)		-0.0492			-0.0447	
		(-1.1762)			(-1.2591)	
log (Direct Water Use *Across*) x PG		0.1517			0.1406	
		(1.4835)			(1.5042)	
log (Direct Water Use *Within*)		-0.0062			-0.0087	
		(-0.2652)			(-0.3673)	
log (Direct Water Use *Within*) x PG		0.0974**			0.0965**	
		(2.0839)			(2.1425)	
log (Indirect Water Use *Across*)			-0.1072*			-0.0866
			(-1.8317)			(-1.4685)
log (Indirect Water Use *Across*) x PG			0.2557*			0.2199
			(1.7494)			(1.6418)
log (Indirect Water Use *Within*)			0.0343			0.0324
			(0.8074)			(0.7962)
log (Indirect Water Use *Within*) x PG			0.1265*			0.1373**
			(1.9544)			(2.0138)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes			
Region*Year/month F.E.				Yes	Yes	Yes
Observations	892,867	892,867	892,841	892,867	892,867	892,841
R-squared	0.1442	0.1441	0.1442	0.1857	0.1856	0.1857

Table 12 Water Stress and Stock Returns: Glasgow

This table presents regression results examining whether the relation between water stress and global stock returns varies after the Glasgow conference. The dependent variable is the monthly excess stock return for company i in month t. As independent variables, we include the natural logarithm of the direct water use variable decomposed into *Direct Water Use Across* (constructed using Eq. 2) and *Direct Water Use Within* (constructed using Eq. 3), the water supply and water stress variables and the stock-level control variables. *Water Stress* is the interaction between log(*Direct Water Use Within*) and *Water Supply*, with higher values indicating greater water stress. We refer to Tables 1 and 2 for a description of the other variables. The Post Glasgow dummy (PG) variable equals 1 during the years 2022-2024. We interact the dummy with all water use and water stress variables. **Panel A** show the results of Eq. 4, including the dummy and interactions using year/month fixed effects. **Panel B** depicts the results of Eq. 4, including the dummy and interactions using region×year/month fixed effects. The variables Water Supply and Water Stress are lagged by various horizons (τ = 1, 3, 6 months) or represented as moving averages (3- and 6-months). Columns (1)–(3) present the regression results for different lag periods, specifically τ = 1, 3, and 6 months, respectively. Columns (4) and (5) report results based on moving averages over 3-month and 6-month windows, respectively. Intercepts are suppressed to conserve space. The t-statistics are double clustered at the firm and month/year level. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Year/month F.E.					
Dependent Variable: RET (%)	(1) Lag 1	(2) Lag 3	(3) Lag 6	(4) Mov. Av. 3	(5) Mov. Av. 6
Water Stress	-0.0062	-0.0037	-0.0070	-0.0064	-0.0073
	(-1.2262)	(-0.8610)	(-1.3856)	(-1.2739)	(-1.4644)
Water Stress x PG	0.0092	0.0015	0.0059	0.0045	0.0050
	(1.3836)	(0.2531)	(0.8620)	(0.6658)	(0.7290)
log (Direct Water Use *Within*)	-0.0162	-0.0131	-0.0137	-0.0078	-0.0052
	(-0.5782)	(-0.4588)	(-0.4689)	(-0.3029)	(-0.2074)
log (Direct Water Use *Within*) x PG	0.1153**	0.1061**	0.1075**	0.1032**	0.1012**
	(2.3415)	(2.1154)	(2.1301)	(2.1467)	(2.1201)
Water Supply	-0.0452	-0.0635*	-0.0728*	-0.0562	-0.0620
	(-1.2596)	(-1.8420)	(-1.7863)	(-1.4411)	(-1.6296)
Water Supply x PG	0.0600	0.0865**	0.0802	0.0796	0.0770
	(1.2878)	(2.0253)	(1.6214)	(1.5613)	(1.5353)
log (Direct Water Use *Across*)	-0.0453	-0.0496	-0.0444	-0.0426	-0.0413
	(-0.9695)	(-1.0905)	(-0.9267)	(-0.9762)	(-0.9690)
log (Direct Water Use *Across*) x PG	0.1566	0.1566	0.1456	0.1521	0.1495
	(1.4741)	(1.4791)	(1.3697)	(1.4506)	(1.4362)
Controls	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes
Observations	787,832	777,658	764,233	839,553	853,949
R-squared	0.1457	0.1486	0.1481	0.1474	0.1462

Table 12 continued

Panel B: Region*Year/month F.E.					
Dependent Variable: RET (%)	(1)	(2)	(3)	(4)	(5)
	Lag 1	Lag 3	Lag 6	Mov. Av. 3	Mov. Av. 6
log (Direct Water Use *Across*)	-0.0485	-0.0486	-0.0333	-0.0414	-0.0389
	(-1.1603)	(-1.1648)	(-0.8060)	(-1.0743)	(-1.0382)
log (Direct Water Use *Across*) x Post Glasgow	0.1483	0.1437	0.1252	0.1381	0.1359
	(1.5328)	(1.4862)	(1.3028)	(1.4514)	(1.4375)
log (Direct Water Use *Within*)	-0.0148	-0.0217	-0.0125	-0.0106	-0.0081
	(-0.5238)	(-0.7503)	(-0.4253)	(-0.4094)	(-0.3215)
log (Direct Water Use *Within*) x Post Glasgow	0.1048**	0.1089**	0.0993**	0.0985**	0.0963**
	(2.1735)	(2.2389)	(2.0248)	(2.1086)	(2.0845)
Water Supply	0.0043	-0.0078	-0.0104	-0.0048	-0.0050
	(0.3558)	(-0.6497)	(-0.8031)	(-0.3587)	(-0.3780)
Water Supply x Post Glasgow	-0.0079	0.0174	0.0135	0.0109	0.0102
	(-0.5087)	(0.9681)	(0.7916)	(0.5974)	(0.5649)
Water Stress	-0.0043	-0.0036	-0.0052	-0.0047	-0.0050
	(-1.0020)	(-1.1267)	(-1.4443)	(-1.1908)	(-1.3472)
Water Stress x Post Glasgow	0.0064	0.0015	0.0036	0.0028	0.0024
	(1.1469)	(0.3373)	(0.6661)	(0.5067)	(0.4472)
Controls	Yes	Yes	Yes	Yes	Yes
Region*Year/month F.E.	Yes	Yes	Yes	Yes	Yes
Observations	787,832	777,658	764,233	839,553	853,949
R-squared	0.1870	0.1892	0.1892	0.1888	0.1875