The Pricing of Water Usage

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Abstract

Using Trucost data from 2005 to 2022, we assess whether firms with higher water usage exhibit risk premiums. Our analysis shows a negative relationship between water usage and excess returns, with high-water-usage firms generating lower returns compared with their peers within the same industry. This effect is stronger in high-water-consumption sectors like mining and manufacturing. We also find a positive link between water usage and operating costs, suggesting that investors view water primarily as an operational expense rather than a climate risk factor. We contribute to the understanding of water's role in sustainable investing and highlight its impact on firm performance across diverse industries.

JEL Classification: G11, G12

Keywords: Water Usage; Climate Finance; Sustainable Investing; Stock Market

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1. Introduction

Water and climate change are intrinsically linked. Extreme weather events are making water increasingly scarce, unpredictable, and polluted. In 2022, nearly half the global population experienced severe water scarcity (United Nations World Water Development Report, 2024). More companies now cite water security and scarcity as risk factors in filings (Layne, 2021). Although many studies have examined climate-related financial risks, few have explored how firms' water usage impacts financial markets.

Pricing water scarcity risk is central to discussions on sustainable investing. Water sustainability focuses on managing water resources to support future generations and ecosystems. We examine the relationship between water usage by U.S. firms and stock returns from 2005 to 2022. We investigate whether investors account for water usage risks and how a firm's cash flow relates to its water usage.

Pástor et al. (2021) model ESG-based investing, suggesting that green assets have lower expected returns due to their popularity among investors and their role in hedging climate risk. Research by Hong and Kacperczyk (2009) and Bolton and Kacperczyk (2023) indicates that brown stocks (low ESG scores) often outperform green stocks because investors demand higher compensation for holding them. Hsu et al. (2023) also find a 4.4% annual return from a long-short portfolio based on firms' toxic emissions. However, Pástor et al. (2021) show that green assets can outperform brown ones if the market is not in equilibrium or underestimates the climate risk, as investors shift preferences toward green investments.[1] Furthermore, Zhang (2024) shows that the brown-minus-green carbon returns arise from the forward-looking firm performance information contained in emissions rather than risk premium.

[1] Pástor et al. (2021) argue that it is difficult to separate ex ante from ex post effects of ESG concerns by examining realized returns over periods during which ESG tastes shift. Whether brown or green stocks will offer higher returns, therefore, is an empirical issue.

Like climate risk, the relationship between water usage and stock returns is an empirical question. A positive relationship may occur if the market is in equilibrium and water usage risks are fully priced in. Investors might demand a risk premium to hold stocks of high-water-usage firms, which face higher risks from strict regulations and increasing clean water costs (Ceres, 2024). Moreover, low-water-usage firms can better hedge against these risks, making them more attractive and leading to lower returns (Harasheh et al., 2024).

However, a negative relationship between high water usage and returns is also plausible. If the market fails to fully account for water usage risks, low-water-usage firms may deliver higher returns. The past decade has seen a shift in investor preferences toward sustainability (Pástor et al., 2021), suggesting that markets are still adjusting to reward low-water-usage firms. Hong et al. (2019) find that countries facing high drought risk often experience weaker corporate profit growth, indicating that markets are slow to integrate drought risks. Additionally, investors may view water usage as a basic cost rather than a climate risk.[2] Higher water consumption can increase operating expenses and reduce free cash flows, leading to lower valuations and stock returns.

We show that higher water usage correlates with lower excess returns. A high-minus-low water usage portfolio produces a significant negative annual return of 6.14%, consistent across various asset pricing models. Firms with higher water usage tend to have larger size, greater sales, higher leverage, and higher book-to-market ratios but exhibit lower volatility.

Fama-MacBeth tests indicate that the negative water usage premium is significant only when industry controls are applied, suggesting that high-water-usage firms yield lower returns compared with industry peers. Panel fixed effect regressions confirm these results, indicating that the market may not be fully pricing in water usage risks. We also find that higher water

[2] Recognizing water as a basic utility, Josset and Larrauri (2021) state that fund managers do not receive market signals to integrate water risks, as water is largely seen as an operating expense. ESG reports often fail to reveal the costs of water depletion, cumulative pollution, and low-probability, high-impact events like prolonged droughts and severe floods.

usage is associated with increased operating costs and reduced free cash flow, implying that investors may perceive water more as a basic utility expense than a climate risk factor.

Our analysis of 48 Fama-French industries shows a negative water usage premium in 34 sectors, with Fabricated Products, Business Services, Computers, and Mining exhibiting the largest negative premiums due to high water usage. Real estate, uniquely, shows a significant positive premium, as water scarcity may lower property values in drought-prone areas and restrict construction (Bernstein et al., 2019).[3]

Overall, the absence of a positive risk premium indicates growing awareness of water sustainability among investors, signalling a shift toward better management of water usage. However, achieving equilibrium in water usage returns may take time. During our sample period, investors appear to have viewed water as an operating cost rather than a climate risk. The observed negative returns associated with high water usage suggest an ongoing transition towards a “water sustainability–aware” market, similar to Zhang’s (2024) findings on negative carbon returns. Our findings also highlight the diverse impact of water usage risks across different U.S. industries.

2. Data

We obtain water data from Trucost Environmental datasets by S&P Global, focusing on total water usage, including water from natural sources and utilities, tracked annually since 2005. Our sample includes firms from the intersection of Trucost, the Center for Research for Research in Security Prices (CRSP), and Compustat datasets. We match Trucost data with U.S. stock returns from CRSP and apply these filters: (1) stocks with available water data, limited to domestic common shares on NYSE, AMEX, or NASDAQ; (2) exclude stocks lacking K.

[3] For example, recurring droughts in California have forced the imposition of stringent water restrictions, sending shockwaves through real estate developments, agriculture, and communities alike. See the California state-mandated water conservation measures adopted in July 2014.

French's industry classification; (3) exclude penny stocks (below $1) and those with market caps under $10 million. This yields 3,235 unique firms from 2005 to 2022.

For control variables, we include market capitalization, sales, book-to-market ratio, ROA, leverage ratio (total debt to total assets), investment ratio (capital expenditure to total assets), and asset tangibility (property, plant, and equipment to total assets), all from Compustat at an annual frequency. To meet monthly data needs, we carry forward each year's water usage and fundamentals into monthly observations. We also control for return momentum (average returns over the past 12 months) and return volatility (standard deviation of returns over the past 12 months). Our regressions use lagged fundamentals (momentum and volatility are lagged by one month, while water usage and firm data are lagged by one year) to explain returns.

We create a panel dataset using these variables for all firms in the sample, applying winsorization at the 1% and 99% levels. Table 1 provides summary statistics. Water usage ranges from 24 to 91 million cubic meters at the 5th and 95th percentiles, averaging 60 million cubic meters. Firm size varies from $4 billion to $20 billion, with an average of $10 billion.

3. Empirical results

3.1 Univariate sorting

Following Hsu et al. (2023), we sort stocks into water usage quintiles within each of the 48 Fama-French industries based on their 12-month lagged water usage. These quintiles are then combined across industries, forming low and high portfolios representing firms with the lowest and highest water usage, respectively. We create value-weighted portfolios and a high-minus-low water usage portfolio using the extreme quintiles.

Panel A of Table 2 shows a consistent decline in mean excess returns as water usage increases. The high-minus-low water usage portfolio delivers a significant negative mean return of 0.51% per month (6.14% annually), indicating a strong water usage premium. Panel

B reports alphas from various asset pricing models (CAPM, FF3, FF4, FF5, and q-factor), confirming the persistence of negative high-minus-low water usage portfolio return, averaging –0.50% per month (–6.06% annually).

Table 3 details firm characteristics across quintiles, showing that firms in the highest water usage quintile (Q5) are generally larger, with higher sales, book-to-market ratios, leverage, ROA, and asset tangibility but exhibit lower volatility compared with those in the lowest quintile (Q1).

3.2 Fama-MacBeth tests

In the first step of the Fama-MacBeth tests, we conduct a monthly cross-sectional regression:

$$RET_{i,t} = a_{0,t} + a_{1,t} log(Water\_usage_{i,t-12}) + a_{2,t} Controls_{i,t-12} + a_{3,t} Industry_{i,t} + \varepsilon_{i,t}, \quad (1)$$

where $RET_{i,t}$ is the excess return of firm i at month t, $log(Water\_usage_{i,t-12})$ is the 12-month lagged logarithm of water usage of firm i, and $Controls_{i,t-12}$ is a vector of the control variables. $Industry_{i,t}$ represents industry dummies and $\varepsilon_{i,t}$ are the residuals. We normalize all the continuous independent variables. We collect the estimated coefficients $\{a_{0.t}, a_{1,t}, a_{2,t}, a_{3,t}\}$.

In the second step, we calculate the average of these coefficients and their Newey-West t-statistics. Table 4 shows that the negative water usage premium is significant only when industry controls are applied, indicating that the effect is specific within industries. Firms with higher water usage tend to have lower excess returns compared with their lower-usage peers. A one-standard deviation increase in water usage results in a 0.147% monthly (1.76% annual) drop in excess returns.

These findings challenge the expectation that high-water-usage firms would command a positive risk premium due to potential risks related to excessive water usage. Instead, investors may treat water usage as an operational cost, associating higher consumption with lower profitability and reduced cash flows. Alternatively, the market may not yet be in equilibrium and therefore not fully reflect water usage risks. We will delve more on this in Section 3.4.

Figure 1 illustrates the cumulative water usage risk premium from Equation (1), i.e., the cumulative sum of $a_{1,t}$ coefficients. There is a clear negative trend from January 2009 onward when industry controls are included. Without these controls, the premium is negligible.

3.3 Panel data regressions

We enhance our previous analysis by incorporating panel fixed effect regressions accounting for unobservable differences across industries:

$$RET_{i,t} = \alpha + \beta_1 log\left(Water\_usage_{i,t-12}\right) + \beta_2 Controls_{i,t-12} + \epsilon_{i,t}. \quad (2)$$

Unless noted otherwise, our analysis includes both industry and year-month fixed effects, with residuals clustered by firm and year-month, using control variables from Equation (1). Table 5 presents the results, comparing models with and without industry fixed effects.

The results (Models 1 and 3) are consistent with the Fama-MacBeth regressions, revealing a negative water usage premium only when industry fixed effects are included. Within industries, higher-water-usage firms tend to have lower excess returns than their lower-usage counterparts.[4] We also perform panel regressions using water usage quintile dummies instead of a continuous variable. Unlike the industry-specific quintiles in Table 2, these are based on pooled data. Models 2 and 4 present these results, with the lowest quintile omitted. The results are consistent: firms in Q5 yield lower returns than those in Q1.

To explore industry-specific differences, we interact the water usage variable with 48 industry dummies in Equation (2). Figure 2 illustrates the *t*-statistics of these interactions, and

[4] A one-standard deviation increase in water usage corresponds to a 0.56% monthly reduction in excess returns. This figure is calculated as the natural logarithm of the water usage's standard deviation in Table 1 multiplied by the water usage coefficient in Table 5 (Model 3), –0.056. To strengthen our findings, we follow Zhang's (2024) approach, testing alternative lags of 6 and 18 months for our explanatory variables. The results (reported in Appendix A) remain consistent.

it shows that 34 industries exhibit a negative coefficient. Significant negative premiums at the 5% level are found in Fabricated Products, Business Services, Computers, Non-Metallic and Industrial Metal Mining, and Coal - industries known for heavy water use. For instance, the mining industry uses water for extracting metals and coal.

In contrast, only the real estate industry shows a positive and significant water usage premium. This could be due to the impact of water scarcity on property values in drought-prone areas (Bernstein et al., 2019). Restrictions on new building permits and stricter water policies may contribute to the positive relationship between water usage and returns in real estate.

3.4 Water as a basic utility

The results suggest that investors may view water usage as a basic utility, or that markets have yet to price in water usage risks. Although it is challenging to fully separate these explanations, we test the former by examining water usage's impact on various proxies for firms' cash flows with the following panel regression:

$$CashFlow_{i,t} = \alpha + \beta_1 log\big(Water\_usage_{i,t-12}\big) + \beta_2 Controls_{i,t-12} + \epsilon_{i,t}, \qquad (3)$$

where $CashFlow_{i,t}$ represents the cash flow proxy of firm *i* at month *t*. As cash flow proxies, we use (1) operating expenses (*XOPR*), reflecting expenditures from a firm's routine operations (see, e.g., Ginglinger and Moreau, 2023), (2) free cash flow (*FCF*), calculated as operating cash flow (Compustat *oancf*) minus capital expenditure (Compustat *capx*), and (3) investment ratio (*Invest*), representing the firm's capital investment level.

The findings in Table 6 suggest that investors may view water usage as a basic utility. Firms with higher water consumption exhibit statistically higher operating expenses, lower free cash flow, and consequently, reduced investment.

4. Conclusions

We examine the relationship between a firm's water usage and stock return during 2005-2022. We find a negative association between water usage and excess returns: firms with high water usage generally yield lower returns compared with low-water-usage firms within the same industry. This effect is particularly significant in high-water-consumption industries like mining and manufacturing. Additionally, high water usage is linked to increased operating costs, suggesting that investors view water more as a utility than a climate risk.

References

Bernstein, A., Gustafson, M. T., Lewis, R., 2019. Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics* 134, 253–272.

Bolton, P., Kacperczyk, M., 2023. Global pricing of carbon-transition risk. *Journal of Finance* 78, 3677–3754.

Ceres, 2024. Investor water toolkit, https://www.ceres.org/water/investor-water-toolkit?toolkit=view.

Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116, 1-22.

Ginglinger, E., Moreau, Q., 2023. Climate risk and capital structure. *Management Science* 69(12), 7492–7516.

Harasheh, M., Bouteska, A., Manita, R., 2024. Investors' preferences for sustainable investments: Evidence from the U.S. using an experimental approach. *Economics Letters* 234, 111428.

Hong, H., Kacperczyk, M., 2009. The price of sin: The effects of social norms on markets, *Journal of Financial Economics* 93, 15–36.

Hong, H., Li, F. W., Xu, J., 2019. Climate risks and market efficiency. *Journal of Econometrics* 208, 265–281.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: an investment approach. Review of Financial Studies 28, 650-705.

Hsu, P.-H., Li, K., Tsou, C.-Y., 2023. The pollution premium. *Journal of Finance* 78, 1343–1392.

Josset, L., Larrauri, P. C., 2021. Data for water risks: Current trends in reporting frameworks, shortcomings, and the way forward. In P. Shrivastava & L. Zsolnai (Eds.), *Water risk and its impact on the financial markets and society* (pp. 23–68). Palgrave Macmillan.

Layne, R., 2021. More companies are citing water scarcity as a financial risk in regulatory filings. MoneyWatch, CBS NEWS, July 22.

Pástor, L., Stambaugh, R. F., Taylor, L. A., 2021. Sustainable investing in equilibrium. *Journal of Financial Economics* 142, 550–571.

UN World Water Development Report, UN Water, United Nations, https://www.unwater.org/publications/un-world-water-development-report

Zhang, S., 2024. Carbon returns across the globe. *Journal of Finance*, forthcoming.

Appendix A. Predictive regressions using different lags

This table reports the impact of firms' water usage on stock returns. We regress stock excess returns on the prior h-month, where $h = \{6, 12, 18\}$, water usage in natural logarithm and other controls for firm fundamentals, including (log) market capitalization, leverage ratio, investment ratio, ROA, tangibility ratio, momentum, volatility, book-to-market ratio, and (log) sales. All controls are also lagged by h-month except for momentum and volatility, which are lagged one month. All variables are winsorized at the 1% and 99% levels to reduce the impact of outliers. T-statistics are based on standard errors that are clustered at the year-month and firm levels. The sample period is from January 2005 to December 2022. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	h = 6	*h = 12*	*h = 18*
Lagged log water usage	–0.040**	–0.056***	–0.050***
	(–2.37)	(–3.13)	(–2.73)
Lagged log Mktval	0.161	–0.144	–0.113
	(1.61)	(–1.57)	(–1.33)
Lagged log Sales	–0.111	0.232***	0.183**
	(–1.27)	(2.61)	(2.26)
Lagged BTM	–1.249***	0.092	0.129
	(–6.40)	(0.54)	(0.70)
Lagged Leverage	–0.191	0.068	0.085
	(–0.68)	(0.24)	(0.30)
Lagged Invest	–8.343***	–2.622	–1.020
	(–4.25)	(–1.50)	(–0.60)
Lagged ROA	2.909***	0.328	0.751
	(4.82)	(0.56)	(1.21)
Lagged Tangibility	1.352***	0.364	0.190
	(3.40)	(0.95)	(0.49)
Momentum	–11.338**	–1.304	–2.364
	(–2.27)	(–0.26)	(–0.45)
Volatility	11.693***	4.892	5.278
	(3.80)	(1.56)	(1.64)
Constant	0.419	0.545	0.100
	(0.75)	(0.99)	(0.18)
Observations	221,560	218,143	204,940
R-squared	0.258	0.264	0.272
Industry FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes

Table 1. Statistics and correlations

This table presents summary statistics (Panel A) and correlation matrix (Panel B) for the data in our sample. For the statistics in Panel A, we first take the average over time for each firm and then average them across firms. Similarly, for the correlation in Panel B, we measure correlations among variables for each firm and then average across firms. Obs. is the average monthly number of firms in the cross-section. *Excess_returns* is the monthly stock returns minus the 90-day T-bill. *Water_usage* is the direct water purchase (in thousands cubic meter), *Mktval* is the market capitalization (in $millions), *Sales* is the firm revenue (in $millions), *BTM* is the book-to-market ratio, *Leverage* is the total short- and long-term debt scaled by total asset, *Invest* is the ratio of capital expenditure to total asset, *ROA* is the return on assets, *Tangibility* is the ratio of property, plant, and equipment to total asset, *Momentum* is the 12-month moving average returns, and *Volatility* is the 12-month standard deviation of returns. All variables are winsorized at the 1% and 99% levels. The sample period is from January 2005 to December 2022.

	Excess_returns	*Water_usage*	*Mktval*	*Sales*	*BTM*	*Leverage*	*Invest*	*ROA*	*Tangibility*	*Momentum*	*Volatility*
Panel A: Summary statistics											
Mean	0.007	60,653.63	10,455.28	5,166.41	0.56	0.24	0.04	0.01	0.22	0.01	0.11
Stdev	0.112	20,633.12	4,724.86	1,071.24	0.17	0.06	0.01	0.04	0.03	0.03	0.04
P5	–0.169	24,263.19	4,942.12	3,586.76	0.35	0.16	0.02	–0.07	0.18	–0.03	0.07
P25	–0.064	51,599.73	6,786.30	4,344.15	0.43	0.19	0.03	–0.02	0.20	–0.01	0.09
Median	0.002	61,338.69	9,314.57	5,109.17	0.53	0.23	0.04	0.01	0.22	0.01	0.11
P75	0.073	70,392.96	13,151.44	5,947.34	0.67	0.28	0.05	0.04	0.25	0.03	0.14
P95	0.202	91,259.66	20,254.73	6,938.64	0.86	0.33	0.06	0.07	0.27	0.06	0.18
Obs.	1,034	1,034	1,034	1,034	1,034	1,034	1,034	1,034	1,034	1,034	1,034
Panel B: Correlation											
Excess_returns	1										
Water_usage	–0.03	1									
Mktval	0.09	0.07	1								
Sales	–0.04	0.53	0.19	1							
BTM	0.09	0.00	–0.18	0.00	1						
Leverage	0.02	0.00	0.04	0.07	–0.08	1					
Invest	0.00	0.01	–0.08	–0.04	–0.05	–0.10	1				
ROA	–0.04	0.16	0.08	0.20	–0.21	–0.23	0.09	1			
Tangibility	0.02	–0.01	0.01	–0.02	0.01	0.13	0.28	–0.08	1		
Momentum	–0.09	–0.15	0.27	–0.20	–0.07	0.01	–0.09	–0.10	0.02	1	
Volatility	0.08	–0.02	–0.01	0.03	0.14	0.11	–0.02	–0.12	0.11	0.03	1

Table 2. Portfolio sorting and asset pricing factor tests

This table reports the results from univariate portfolio sorting (Panel A) and asset pricing factor (Panel B) tests for portfolios sorted by water usage, from the lowest (Q1) to highest (Q5). In Panel A, we report the annualized value-weighted portfolio excess returns, *t*-statistics, returns standard deviation, and the Sharpe ratio. In Panel B, we report the regression alpha from various asset pricing factor tests including the CAPM, Fama and French three factors (MKT, SMB, and HML), Fama and French three factors and the Carhart momentum factor (UMD), Fama and French (2015) five factors (MKT, SMB, HML, RMW, and CMA), and the Hou, Xue, and Xhang (2015) *q*-factors (MKT, SMB, IA, and ROE). Figures in parentheses are the Newey-West *t*-statistics. The sample period is from January 2005 to December 2022. *** denotes statistical significance at the 1% level.

	Q1	Q2	Q3	Q4	Q5	Q5–Q1
Panel A: Univariate portfolio sorting						
Excess returns	1.66***	1.51***	1.41***	1.22***	1.15***	–0.51***
T-*stat*	(4.38)	(4.13)	(4.50)	(3.83)	(3.93)	(–3.12)
Std dev	5.21	5.05	4.64	4.53	4.34	2.41
Sharpe ratio	0.32	0.30	0.30	0.27	0.27	–0.21
Panel B: Asset pricing factor tests						
CAPM alpha	0.89***	0.75***	0.69***	0.51***	0.47***	–0.42***
	(6.78)	(5.32)	(7.17)	(6.97)	(6.40)	(–2.74)
FF3 alpha	0.91***	0.75***	0.69***	0.52***	0.45***	–0.46***
	(8.76)	(6.74)	(7.02)	(6.93)	(5.93)	(–3.71)
FF4 alpha	0.92***	0.75***	0.69***	0.52***	0.46***	–0.46***
	(8.90)	(6.67)	(6.94)	(6.96)	(5.94)	(–3.76)
FF5 alpha	0.95***	0.75***	0.68***	0.45***	0.41***	–0.54***
	(7.69)	(5.85)	(7.60)	(6.79)	(6.29)	(–4.03)
HXZ alpha	1.05***	0.81***	0.69***	0.47***	0.41***	–0.65***
	(8.77)	(5.91)	(7.38)	(6.82)	(5.61)	(–5.02)

Table 3. Firm characteristics

This table reports the time-series average of the cross-sectional means of firm characteristics for quintile portfolios sorted by water usage. *Firms* is the average number of firms in each quintile portfolio for each month. *Water_usage* is the direct water purchase (in thousands cubic meter), *Mktval* is the market capitalization (in $millions), *Sales* is the firm revenue (in $millions), *BTM* is the book-to-market ratio, *Leverage* is the total short- and long-term debt scaled by total asset, *Invest* is the ratio of capital expenditure to total asset, *ROA* is the return on assets, *Tangibility* is the ratio of property, plant, and equipment to total asset, *Momentum* is the 12-month moving average returns, and *Volatility* is the 12-month standard deviation of returns. The sample period is from January 2005 to December 2022.

	Q1	Q2	Q3	Q4	Q5
Firms	206	207	208	204	209
Water usage	144.03	783.16	2,137.30	4,562.37	25,358.25
Mktval	1,516.06	2,625.20	4,116.91	6,936.90	13,941.88
Sales	638.28	1,526.46	2,723.48	5,031.62	11,447.81
BTM	0.51	0.54	0.57	0.56	0.57
Leverage	0.19	0.23	0.25	0.26	0.28
Invest	0.04	0.04	0.04	0.04	0.04
ROA	0.01	0.04	0.05	0.05	0.05
Tangibility	0.22	0.25	0.27	0.26	0.29
Momentum	0.01	0.01	0.01	0.01	0.01
Volatility	0.11	0.10	0.09	0.09	0.09

Table 4. Fama-MacBeth regressions

This table reports Fama-MacBeth regressions of individual stock excess returns on their water usage in logarithm and other firm characteristics. We conduct cross-sectional regressions for each month from January 2005 to December 2022. In each month, monthly excess returns of individual stock returns are regressed on water usage in logarithm 12-month prior and different sets of control variables also 12-month prior. Control variables include the logarithm of market capitalization (*log Mktval*), the logarithm of sales (*log Sales*), book-to-market ratio (*BTM*), leverage ratio (*Leverage*), investment ratio (*Invest*), return on assets (*ROA*), tangibility ratio (*Tangibility*), the 12-month moving average returns (*Momentum*), and the 12-month standard deviation of returns (*Volatility*). All variables are winsorized at the 1% and 99% levels. Model 1 excludes industry fixed effect, while Model 2 includes the industry fixed effect. Figures in parentheses are the Newey-West *t*-statistics.

	(1)	(2)
Lagged log water usage	–0.010	–0.147***
	(–0.18)	(–3.61)
Lagged log Mktval	–0.107	–0.087
	(–1.02)	(–0.78)
Lagged log Sales	0.101	0.145
	(0.89)	(1.31)
Lagged BTM	–0.092	–0.040
	(–1.30)	(–0.79)
Lagged Leverage	–0.019	–0.016
	(–0.44)	(–0.41)
Lagged Invest	–0.096	–0.099*
	(–1.47)	(–1.84)
Lagged ROA	0.031	0.058
	(0.69)	(1.26)
Lagged Tangibility	0.048	0.057
	(0.65)	(0.83)
Momentum	0.001	–0.031
	(0.00)	(–0.27)
Volatility	0.096	0.082
	(0.67)	(0.61)
Num. obs.	189,756	189,756
Adj. R^2	–0.23	0.19
Industry FE	No	Yes

Table 5. Panel fixed effect regressions

This table reports the impact of firms' water usage on stock returns. We regress stock excess returns on the prior 12-month water usage in natural logarithm and other controls for firm fundamentals, including (log) market capitalization, leverage ratio, investment ratio, ROA, tangibility ratio, momentum, volatility, book-to-market ratio, and (log) sales. All controls are also lagged by 12 months except for momentum and volatility, which measure the 12-month moving average returns and the 12-month standard deviation of returns, respectively. All variables are winsorized at the 1% and 99% levels to reduce the impact of outliers. In Models 2 and 4, we split the sample by water usage quintiles with Q5 being the quintile with the highest water usage. *T*-statistics are based on standard errors that are clustered at the year-month and firm levels. The sample period is from January 2005 to December 2022. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Lagged log water usage	–0.014		–0.056***	
	(–0.51)		(–3.13)	
Q2 log water usage		–0.017		–0.154
		(–0.11)		(–1.22)
Q3 log water usage		–0.011		–0.211
		(–0.06)		(–1.41)
Q4 log water usage		–0.072		–0.315**
		(–0.35)		(–1.98)
Q5 log water usage		–0.180		–0.503***
		(–0.80)		(–3.16)
Lagged log Mktval	–0.115	–0.113	–0.144	–0.144
	(–1.32)	(–1.31)	(–1.57)	(–1.57)
Lagged log Sales	0.168*	0.171**	0.232***	0.231***
	(1.84)	(2.01)	(2.61)	(2.70)
Lagged BTM	–0.038	–0.041	0.092	0.085
	(–0.19)	(–0.21)	(0.54)	(0.50)
Lagged Leverage	0.101	0.096	0.068	0.065
	(0.36)	(0.35)	(0.24)	(0.23)
Lagged Invest	–3.059*	–3.180*	–2.622	–2.621
	(–1.74)	(–1.84)	(–1.50)	(–1.49)
Lagged ROA	0.282	0.248	0.328	0.304
	(0.48)	(0.42)	(0.56)	(0.52)
Lagged Tangibility	0.267	0.315	0.364	0.370
	(0.68)	(0.85)	(0.95)	(0.98)
Momentum	–1.191	–1.200	–1.304	–1.313
	(–0.24)	(–0.24)	(–0.26)	(–0.27)
Volatility	5.111	5.089	4.892	4.882
	(1.56)	(1.56)	(1.56)	(1.56)
Constant	0.294	0.119	0.545	0.026
	(0.53)	(0.21)	(0.99)	(0.05)
Observations	218,143	218,143	218,143	218,143
R-squared	0.262	0.262	0.264	0.264
Industry FE	No	No	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes

Table 6. Cash flow sensitivity

This table reports the impact of firms' water usage on various proxies for cash flow, including the operating expenses (*XOPR*), free cash flow (*FCF*) measured as net cash flow from operating activities (Compustat *oancf*) minus capital expenditure (Compustat *capx*), and investment ratio (*Invest*). We regress each of the cash flow proxy on the prior 12-month water usage in natural logarithm and other controls for firm fundamentals, including (log) market capitalization, (log) sales, book-to-market ratio, leverage ratio, investment ratio, ROA, tangibility ratio, momentum, and volatility. All controls are also lagged by 12 months except for momentum and volatility, which measure the 12-month moving average returns and the 12-month standard deviation of returns, respectively. All variables are winsorized at the 1% and 99% levels to reduce the impact of outliers. *T*-statistics are based on standard errors that are clustered at the year-month and firm levels. The sample period is from January 2005 to December 2022. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	XOPR	*FCF*	*Invest*
Lagged log water usage	0.012***	–0.020**	–0.002***
	(3.03)	(–2.58)	(–4.96)
Lagged log Mktval	0.086***	0.675***	0.002***
	(4.90)	(34.97)	(3.44)
Lagged log Sales	0.871***	0.369***	–0.002***
	(44.50)	(18.15)	(–2.60)
Lagged BTM	–0.035	0.435***	–0.012***
	(–1.46)	(10.02)	(–7.24)
Lagged Leverage	–0.200***	0.690***	–0.010***
	(–4.82)	(9.22)	(–2.73)
Lagged Invest	–0.339*	–3.884***	
	(–1.76)	(–8.16)	
Lagged ROA	–1.702***	1.636***	0.024***
	(–17.07)	(8.87)	(5.68)
Lagged Tangibility	–0.355***	–0.032	0.136***
	(–6.83)	(–0.32)	(22.79)
Momentum	0.947***	4.238***	–0.018
	(7.60)	(9.16)	(–1.47)
Volatility	0.543***	0.261	0.036***
	(5.07)	(1.10)	(3.39)
Constant	0.191***	–3.292***	0.031***
	(3.77)	(–29.65)	(6.64)
Observations	188,969	147,900	218,128
R-squared	0.960	0.793	0.558
Industry FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes

Figure 1. Cumulative return premiums

This figure plots the cumulative risk premiums of water usage based on the Fama-MacBeth regressions. We report the cumulative risk premiums without industry fixed effects (dashed line) and with industry fixed effects (solid line).

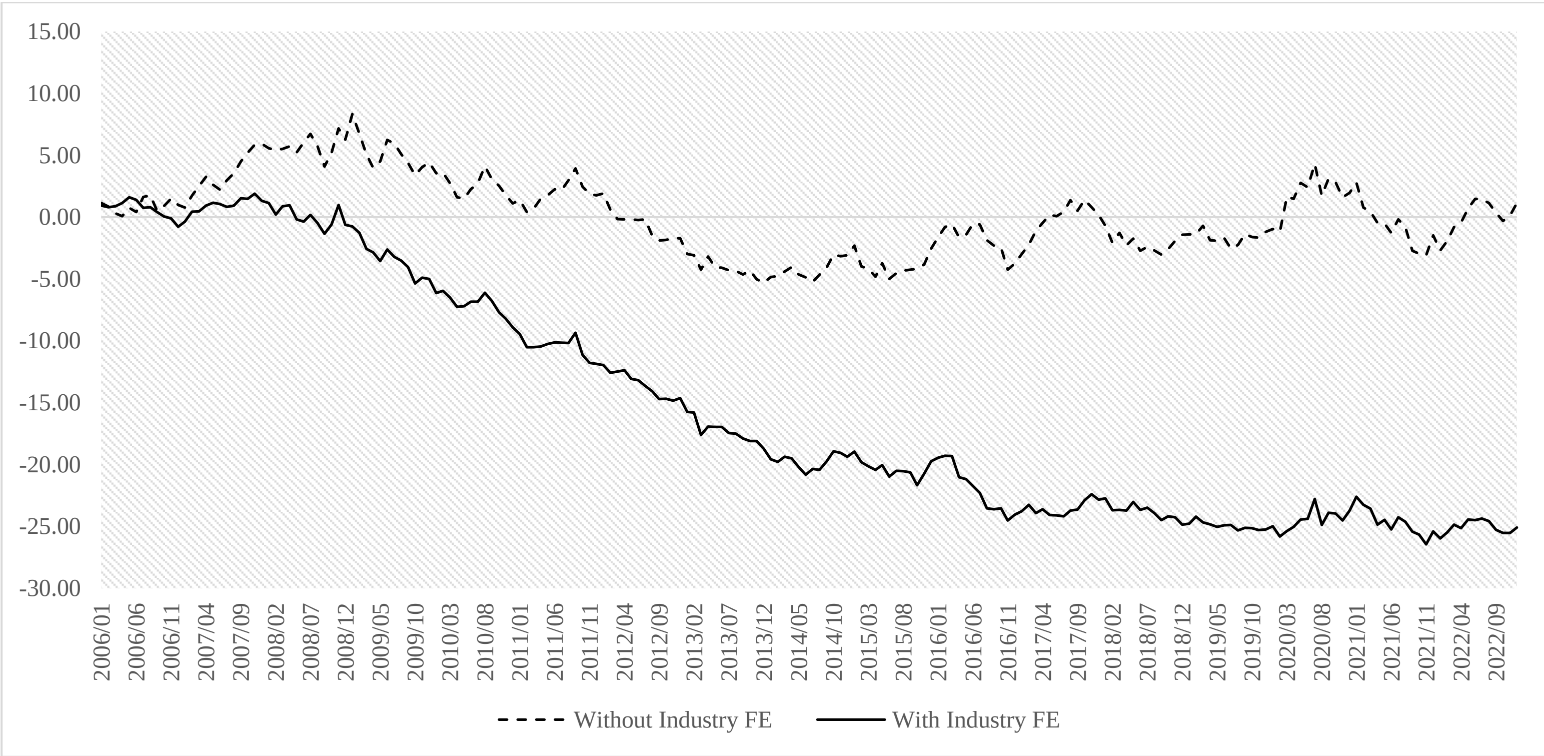

Figure 2. Panel fixed effect regression by industry

This figure plots the *t*-statistics of the interaction coefficients between the water usage and each of the 48 Fama-French industry dummies from a panel fixed effect regression. We regress stock excess returns on the prior 12-month water usage in natural logarithm and other controls for firm fundamentals, including (log) market capitalization, leverage ratio, investment ratio, ROA, tangibility ratio, momentum, volatility, book-to-market ratio, and (log) sales. All controls are also lagged by 12 months except for momentum and volatility, which measure the 12-month moving average returns and the 12-month standard deviation of returns, respectively. We sort the results by the magnitude of the *t*-statistics, from the lowest to the highest. We also plot the critical *t*-statistics at the 10% level.