Year: 2024

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DOI: https://doi.org/10.1016/j.ecolecon.2023.108048

Originally published at:
Colesanti Senni, Chiara; Goel, Skand; von Jagow, Adrian (2024). Economic and financial consequences of water risks: The case of hydropower. Ecological Economics, 218:108048.
DOI: https://doi.org/10.1016/j.ecolecon.2023.108048

Ecological Economics 218 (2024) 108048

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Economic and financial consequences of water risks: The case of hydropower☆

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ARTICLE INFO

JEL classification:
C21
C23
G3
G12
Q25
Q42

Keywords:
Hydroelectricity generation
Water risks
Risk premia
Geospatial data
Portfolio sorts
Financial risk
Mispricing

ABSTRACT

Reduced water availability poses risks for many economic activities. This paper studies how water risks affect hydroelectricity generation in Europe and the US and whether these risks are priced in by financial markets. To this end, we build a novel dataset for the period 2015–2022, which combines plant-specific hydroelectricity generation with geo-specific water physical risks and equity returns. We find that water risks, measured using model-based aggregate water risk metrics as well as precipitation anomalies, are significantly associated with reduced electricity generation, although the effect disap- pears after two months. We then link the power plants in our sample to the equity returns of their owners to investigate whether financial markets adequately price water risks. Using a portfolio sorts approach, we find weak evidence of a *negative* risk pre- mium. Given the real negative effect of water risks on generation, we conclude that the lack of a positive risk premium amounts to mispricing of water risks by financial markets.

1. Introduction

In the summer of 2022, intense droughts severely hit several locations of the world. The nega- tive effects have been felt, amongst others, in the hydropower sector. In Southwestern China, declining reservoir levels reduced the amount of electricity produced by hydropower plants and the government of Sichuan had to issue a power rationing plan: Energy-intensive indus- try, such as Toyota and the Apple supplier Foxconn, had to halt production for two weeks (Yin, 2022; Langley et al., 2022). In the same summer, the European Drought Observatory reported significant economic impacts from water stress mixed with high temperatures. In particular, hydroelectricity generation in Italy, France and Portugal fell by 11,233 GWh in the first half of 2022 compared to previous years (Toreti et al., 2022). This is equivalent to the amount of hydroelectricity usually produced in Italy in a three-month period.

Academics and policy makers have drawn attention to the fact that a partial collapse of natural ecosystems can have catastrophic consequences for the economic and financial systems (Johnson et al., 2021; Svartzman et al., 2021; Dasgupta, 2021; NGFS, 2022). The widespread disturbance of the hydrological cycle, which is the source of the water risks we describe in this paper, and other examples of nature loss, such as biodiversity loss, are caused by the same anthropogenic drivers, including climate change, land use change, watershed disturbance, pollution, and water resource development (Vorosmarty et al., 2010).

The impact of these drivers, especially of climate change, on water availability affects the feasibility of new hydropower projects (IHA,

☆ The authors gratefully acknowledge two anonymous referees as well as Elena Almeida, Oliver Braun- schweig, Rafael Camargo, Antoine Champetier, Frankie Cho, Yannis Dafermos, Ben Filewod, Alain Naef, Mathilde Salin and Yoshihide Wada for the very useful comments and discussions. We are particularly grate- ful to Edwin Sutanudjaja for his help with water data and detailed comments. Similarly, a special thanks goes to Lukas Zimmermann for the support with the financial data and the very useful comments. This paper has received funding from the Swiss National Science Foundation (SNSF) under the project ``How sustainable is sustainable finance? Impact evaluation and automated greenwashing detection'' (Grant Agreement No. 100018_207800).

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https://doi.org/10.1016/j.ecolecon.2023.108048
Received 31 March 2023; Received in revised form 29 September 2023; Accepted 8 November 2023
Available online 4 January 2024

2019; Paltan et al., 2021).[1] Yet existing plants are also facing the risk of producing less electricity, as changes in water availability reduce their generating capacity. This might hinder the transition to a low-carbon economy, for which hydropower is crucial (Ramiao et al., 2023; IRENA, 2023): existing hydropower plants are the largest source of low-carbon electricity globally and the International Energy Agency (IEA) estimates that hydropower capacity could double by 2050 and cover around 15% of total electricity generation in its net zero scenario (IEA, 2021). The importance of hydropower is further compounded as it is needed as a flexible source of clean electricity to smooth over peaks in generation from solar and wind (Grady and Dennis, 2022).

A reduction in the generating capacity of existing plants also has implications for the financial owners. There are at least two channels through which reduced water availability can impact the economic and financial value of hydropower plants and the viability of hydropower projects (Beilfuss et al., 2012; Van Vliet et al., 2016; Von Randow et al., 2019). First, by reducing the productivity of the plants, water shortages negatively affect their profitability. Possible causes of productivity loss are reduced reservoir inflows due to decreased basin runoff, droughts and increased surface-water evaporation (Beilfuss et al., 2012). Second, reduced water availability might require investments in adaptation measures (Haguma et al., 2017; IHA, 2019). Such additional investments due to changes in water availability increase operating costs. In an extreme scenario, the lack of water can result into stranded assets, driving profits to zero.

This paper contributes to the debate on the impact of nature-related risks on the economy and the financial system, by addressing two questions: (1) What is the impact of reduced water availability, which we refer to as *water risks*, on hydroelectricity generation? (2) Are these risks priced in by financial market?

We rely on two different measures of water risks to quantify the impact of reduced water availability on hydroelectricity generation. First, we use a model-based aggregate water risk metric provided by WRI Aqueduct Water Risk Atlas, which captures exposure to changes in water quantity. Second, we rely on raw hydro-meteorological data from TerraClimate. The dataset was developed by Abatzoglou et al. (2018) and combines high resolution climate nor- mals with coarser time-varying weather data, including precipitation and evapotranspiration. We use this data to construct a time-varying measure of water risks based on precipitation anomalies.

We build a novel dataset that combines the two geo-specific measures of water risks with the locations of hydropower plants and plant-specific characteristics, including plant-level electricity generation and operating capacity. We also add information about the closest reservoir as well as equity returns of power plants' owners. Our sample consists of a subset of hydropower plants in Europe and the United States that we observe over the period 2015–2022. We use our novel dataset to investigate the real effects of water risks on hydroelectricity generation and the pricing of water risks by financial markets.

Our analysis of the real effects is based on three alternative empirical strategies. First, we perform a cross-sectional regression, in which we rely on the aggregate water risk metric provided by WRI. Second, we conduct panel regressions in which we use the time series of location-specific precipitation anomalies as a proxy for water risk. Third, in order to identify the dynamic response of hydroelectricity generation to water risks, we use a structural panel VAR (PVAR) approach.[2] To investigate the pricing of water risks by financial markets, we examine the cross-sectional relationship between water risks and equity returns using a portfolio sorts approach.[3] The flow of analysis is described in Fig. 1.

In terms of the real effects of water risk, our analysis reveals three main findings. First, a one standard deviation increase in water risk is associated with a 9% lower hydroelectric- ity generation for the average plant in 2022, the driest year in our sample, relative to its historical average. Second, the occurrence of a precipitation anomaly (as defined below) is associated with a 18% drop in hydroelectricity generation. Third, our structural panel vector autoregression (PVAR) analysis shows that precipitation anomalies have an immediate effect on generation though the effect fades out after two months. In terms of the financial effects of water risks, we find weak evidence that financial markets provide a negative risk premium on water risk. While we expect water risks to negatively impact hydroelectricity generation, the pricing of these risks is an empirical question. If financial markets price water risks, exposure to such risks is associated with a positive equity risk premium. This implies that investors demand to be compensated for bearing higher risk and leads to more efficient resource al- location in the economy, by increasing the cost of taking risk. However, our findings show that water risks are not priced in, which is reflected in the weak evidence for a negative risk premium.[4] Therefore, either financial markets do not provide plant owners with the right incentives for appropriate risk management or other mechanisms are at work that prevent the water risks at the plant-level to be reflected in the valuation of the assets. Given the evidence of negative real effects of water risks on hydropower generation, we conclude that the absence of a risk premium amounts to a mispricing of water risks by financial markets.

1.1. *Relation to the literature*

Climate-related physical risks - e.g. the increased likelihood of adverse weather events due to climate change - have already been identified as a potential source of economic losses and financial instability (Battiston et al., 2021; Campiglio et al., 2022; Bressan et al., 2022) and several attempts have been made to estimate appropriate damage functions (Nordhaus, 1993; Botzen and van den Bergh, 2012; Diaz and Moore, 2017; Bretschger and Pattakou, 2019; Neumann et al., 2020; Franzke, 2021; Dunyo, 2022; Russell et al., 2022). Moreover, empirical estimates of the economic costs from natural disasters have became increasingly available (Hornbeck, 2012; Parker, 2018; Botzen et al., 2019; Coronese et al., 2019) and studies have emerged on the costs from environmental degradation (Johnson et al., 2021).

At the same time, a related literature has focused on the economic impacts of water risks using both hydro-economic models (Munoz and Sailor, 1998; Harou et al., 2009; Dadson et al., 2017; Turner et al., 2017; Sarzaeim et al., 2018; de Boer et al., 2021; Liao et al., 2021; Turner and Voisin, 2022) and empirical analysis (Eyer and Wichman, 2018; Russ, 2020). Dadson et al. (2017) use a dynamical systems model of water-related investment, risk, and growth to show that without such investment, losses from water-related hazards slow economic growth and may create a poverty trap. Liao et al. (2021) use a calibrated, physically based hydrological model to show that around 10% of China's coal-fired power capacities face low-flow water risks from July to October, and 20% the rest of the year. Empirically, the literature has shown that water risks can significantly impact economic growth, for instance, through changes in water runoff (Russ, 2020), and slow down the transition to a low-carbon economy by tilting the energy mix towards fossil fuels (Eyer and Wichman, 2018).

A specific concern in the context of damages from water risks has been the hydropower sector, which plays an important role in energy

[1] While most regions are likely to see a decrease, some might see an increase in hydropower potential (Ali et al., 2018).

[2] For a detailed description and applications of a PVAR, see the review article by Pedroni (2013).

[3] Note that, due to data availability constraints, throughout our analysis we always look at realized and not expected returns.

[4] Note that an insignificant or a negative risk premium implies that financial markets are not pricing water risks.

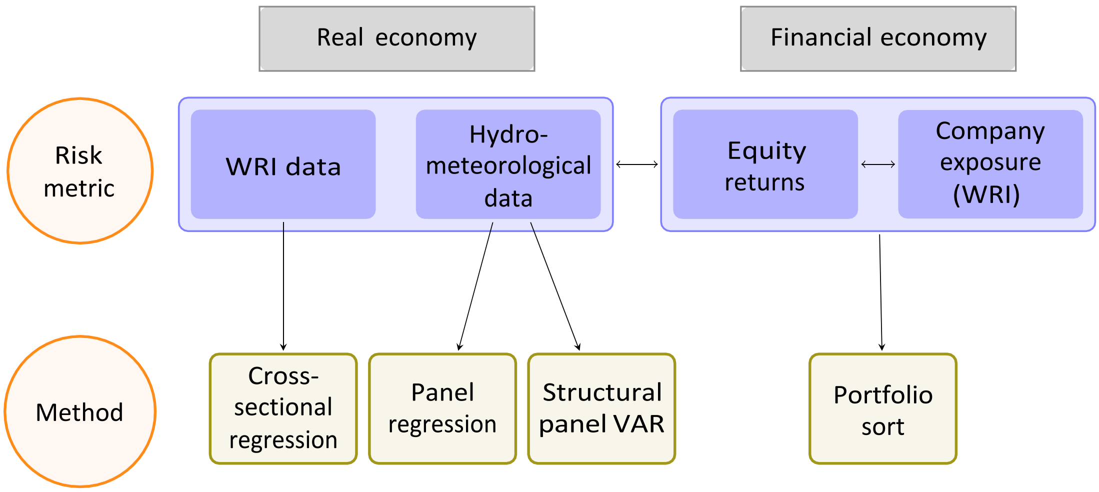

Fig. 1. Flow of the analysis.

security. Our paper builds on the literature on the water-energy nexus (Leck et al., 2015), which highlights the impacts of climate change on the provision of energy and water (Bhave et al., 2022; Pardoe et al., 2018; Siderius et al., 2020). In particular, Munoz and Sailor (1998), Beilfuss et al. (2012), Van Vliet et al. (2016), Turner et al. (2017), Paltan et al. (2018), Von Randow et al. (2019), Paltan et al. (2021) and Zhao et al. (2023) explicitly analyze the impact of climate change on the water cycle and hydroelectricity generation. Van Vliet et al. (2016) project the impact of climate-driven changes in hydrology on the electricity generation of 24,500 hydropower projects globally. They find that between 61 and 74% of plants will see their energy input fall. Beilfuss et al. (2012) and Von Randow et al. (2019) find that frequent droughts increase the variability and reduce the reliability of hydroelectricity generation, reducing total power generation. Paltan et al. (2021) use a multi-model approach to project changing water flows under a 1.5 °C and 2 °C scenario and estimate that about 65% of current installed hydropower capacity will be exposed to risk from recurrent high river flows. While climate change is set to exacerbate water risks (Duran-Encalada et al., 2017; Siderius et al., 2018; Portner et al., 2022; Geressu et al., 2022; Wasti et al., 2022), Lumbroso et al. (2015) find that it is rarely explicitly considered when new hydropower projects are planned.

Another strand of literature considers effects at a more granular level (Conway et al., 2017; Goodarzi et al., 2020; Qin et al., 2020). Conway et al. (2017) look at the river basin configuration in Africa and find that by 2030, 70% and 59% of total hydropower capacity will be located in one cluster of rainfall variability in Eastern and Southern Africa, respectively. This increases the risk of a climate-related concurrent electricity supply disruption in each region. Goodarzi et al. (2020) conduct a microstudy of Seimare Dam in Iran and find that climate change is likely to reduce both water inflow into the dam and electricity generation over a a 30-year horizon. Some recent contributions have made inquiries similar to our paper. Opperman et al. (2022) show that existing and projected dams are predominantly located within river basins that are currently exposed to medium to very high levels of water risk and that climate change will increase the risk for about one third of these plants by 2050. Zhao et al. (2023) study the impact of climate-induced droughts on hydroelectricity generation in China. They find that more than one-fourth of studied plants will experience a 20% reduction in electricity generation under both optimistic and pessimistic climate scenarios vis-a-vis the baseline.

Finally, we build on the literature of pricing of climate and biodiversity risks. Recent work examines such pricing in equities (Hong et al., 2019; Gostlow, 2021; Pastor et al., 2022; Bolton and Kacperczyk, 2021; Hsu et al., 2023; Faccini et al., 2023), corporate bonds (Huynh and Xia, 2021; Seltzer et al., 2022), municipal bonds (Painter, 2020; Goldsmith-Pinkham et al., 2022), options (Ilhan et al., 2021), and real estate (Bernstein et al., 2019; Baldauf et al., 2020; Giglio et al., 2021) or in multiple asset classes (Acharya et al., 2022). Amongst others, Bolton and Kacperczyk (2022) find that higher stock returns are associated with higher levels and growth rates of carbon emissions in all sectors and most countries. Premia related to emission levels are higher in countries with stricter domestic climate policies. Garel et al. (2023) take the analysis explicitly to the context of biodiversity loss and analyze whether the stock prices of firms with a greater biodiversity footprint react to events that signal transition risks, such as the “Kunming Declaration on Biodiversity Conservation”. They find that investors have indeed started to require a risk premium from companies with a higher biodiversity footprint. Coqueret and Giroux (2023) conduct a portfolio sorts analysis based on firm-specific measures of biodiversity loss in US equity markets to investigate the presence of a biodiversity risk premium. They find that the risk premium for biodiversity over the past decade is close to zero and that dimensions of biodiversity closely related to climate change attracting more market attention.

Our paper makes two main contributions to the literature. First, by merging geospatial water data with asset-level economic data, it presents new empirical evidence that water risks are material to hydroelectricity generation. This direct statistical evidence is comple- mentary to the results of hydrological models and can be used to validate simulations from process-based models. The estimates in the paper can be used for planning, as well as for calibrating economy-wide models that endogenize hydroelectricity generation, such as Zhang et al. (2022). Second, the paper contributes to the literature on financial markets pricing climate and biodiversity risks by showing that, despite the real negative effect of water risks on electricity generation, there is only find weak evidence of a negative risk premium for the most exposed plants. This suggests that these risks are not adequately priced in by financial markets.

The remainder of the paper is organized as follows. Section 2 describes the construction of the dataset. In Section 3 we outline our empirical analysis of the real effects of water risk on hydroelectricity generation and present the results of this analysis. In Section 4, we use portfolio sorts analysis to investigate the presence of a water risk premium. Section 5 provides a discussion of our main findings and their implications and highlights directions for future research. Section 6 concludes.

2. Data

For the empirical analysis, we rely on the data sources listed in Table 1 and described below.

Table 1
Sources of the data used in the analysis.

Data	Application	Source
Hydropower plant location and operating capacity	Location data (latitude, longitude), age and operating capacity of 9′498 active hydropower plants (the final sample is much smaller as we only focus on countries with electricity data availability). The location is used to obtain generation, water risk and precipitation data. The operating capacity is used as a control variable.	S&P CapitalIQ Pro Asset Data
Hydroelectricity gener- ation at the plant level	Electricity generation data is aggregated at the monthly level. Average generation per hour in each month is used as the dependent variable in the analysis. Data was reported in MW per 15 minute interval (aggregated at the mean hourly production each month) for Europe and total MWh produced each month for the US	European data comes from ENTSO-E and is downloaded from Fraunhofer Energy Charts. US data comes from the En- ergy Information Administration (EIA)
Water risk factors	For the cross-sectional analysis, we use indicators of water quantity risk (water stress, drought risk and water depletion), which are based on a hydrological model validated on data from 1960 onwards (Sutanudjaja et al., 2018, Hofste et al., 2019).	WRI Aqueduct Water Risk Atlas (World Resource Institute)
Hydro-meteorological data	In the panel analysis, we use data about precipitation (rain), snow-water equivalent (to account for snow cover, which might fill reservoirs too), evapotranspiration and the Palmer Drought Severity Index. The data comes from the analysis of satellite imagery and is available at a resolution of 5 km with missing data taken from separate historical sources.	TerraClimate via Google Earth Engine
Reservoir data	Reservoir size is used as a control variable. The dataset contains the surface water area of 71,208 reservoirs/lakes derived from optical satellite imagery.	The data was compiled by Donchyts et al. (2022)
Ownership data	For the analysis of the risk premium, we use data on plant ownership to connect plants to their owners and/or ultimate parent.	S&P CapitalIQ Pro Asset Data
Revenues data	We use revenues by business activity to infer the importance of the hydroelectricity generation segment for the individual company.	S&P Trucost
Realized returns	We use realized returns to investigate the presence of a risk premium.	S&P Capital IQ Financials

Hydropower plant location and operating capacity. We obtain global data on hy- dropower plants from S&P CapitalIQ Pro Asset Data (CIQ). We extract the location (lat- itude, longitude), operating capacity (in MW) and first year in service for all active hy- dropower plants globally (for a total of 9′498 plants).

Hydroelectricity generation at the plant level. Data on hydroelectricity generation for Europe is taken from the Energy Charts managed by the Frauenhofer Institute for Solar Energy Systems, which is based on 15-min interval electricity generation data from the European association for the cooperation of transmission system operators for electricity (ENTSO-E). We aggregate electricity generation data at the monthly level over the period 2015–2022. Monthly data on plant-level hydroelectricity generation in the US is taken from the Electricity Data Browser provided by the U.S. Energy Information Administration. For Europe, the plant names from the ENTSO-E dataset do not correspond to the names in CIQ. Hence, we manually construct a correspondence table to merge the generation and location data.

Power plant types. The European data includes information on generation from two types of hydropower plants, run of river (ROR) and water reservoir (WR) plants. ROR plants are located directly on or next to active rivers and use water channeled from the riverbed to the facility. Water pressure to operate the turbines is generated by the natural decline of the riverbed. WR plants are located at or below artificial dams or impoundment facilities, which collect the water from rivers and/or precipitation. The pressure to power the turbines is derived from the elevation of the reservoir's surface compared to the turbine. The distinction between ROR and WR plants is not directly available for US data. Instead, we construct a classification table based on the plant's water source ("river"/"rio"/"creek" vs. "reservoir"/"lake"/"dam").

Water risks. Water risk data is taken from the World Resources Institute's Aqueduct Water Risk Atlas. The Water Risk Atlas covers three sources of water risks: water quantity (made up of eight indicators), water quality (two indicators) and reputational/regulatory risks (three indicators). Weights can be adjusted to the user's needs. Our interest are water quantity risks, which are defined as the exposure to changes in water quantity that may impact a company's direct operations, supply chains and/or logistics. For our purposes, we use five out of the eight quantity risks, which are based on the hydrological model PCR-GLOBWB 2 (Sutanudjaja et al., 2018): baseline water stress, baseline water depletion, interannual variability, seasonal variability, and groundwater table decline. In our analysis, we use an aggregated metric of all of the physical quantity risks, which is computed directly within the Aqueduct Water Risk Atlas. This approach leads to an aggregate risk metric that is specific to the water basins,[5] meaning that power plants in the same basin will have the same water risk. We obtain the water risk for the location of each hydropower plant by uploading the longitude and latitude of each plant into Aqueduct. The maps in Figs. 2 and 3 show the aggregate risk metric, expressed in categories of 0–4 (where 4 corresponds to higher risk), of the hydropower plants in our sample. Clusters of high-risk (e.g., Southern California) and low-risk (e.g., Norway and Sweden) locations can be identified. In particular, in Europe we can clearly identify two zones (Northern and Southern Europe) with homogeneous characteristics in terms of water risk. Such a distinction is a bit less clear for the US, although we can identify a cluster of risky locations along the West Coast. However, some high- and low-risk plants are located close to each other, as in the Alps or the South Western US.

Hydro-meteorological data. We rely on hydro-meteorological data to obtain a time- varying proxy for water risks. We use precipitation (the sum of rain and snow-water equiv- alent)[6] and evapotranspiration (in mm) as well the Palmer Drought Severity Index (PDSI) from TerraClimate. The PDSI is a standardized index and uses readily available temperature and precipitation data to estimate relative dryness. Lower values are associated with drier locations. All variables have a resolution

[5] Basins are defined as land areas in which surface water converges.

[6] Note that snow-water equivalent is not a component of precipitation as it is a terrestrial variable, not an atmospheric one. However, for convenience, we refer to the sum of rain and snow-water equivalent as precipitation. We are interested in a measure of the water that is available to fill reservoirs or increase the stream flow of rivers.

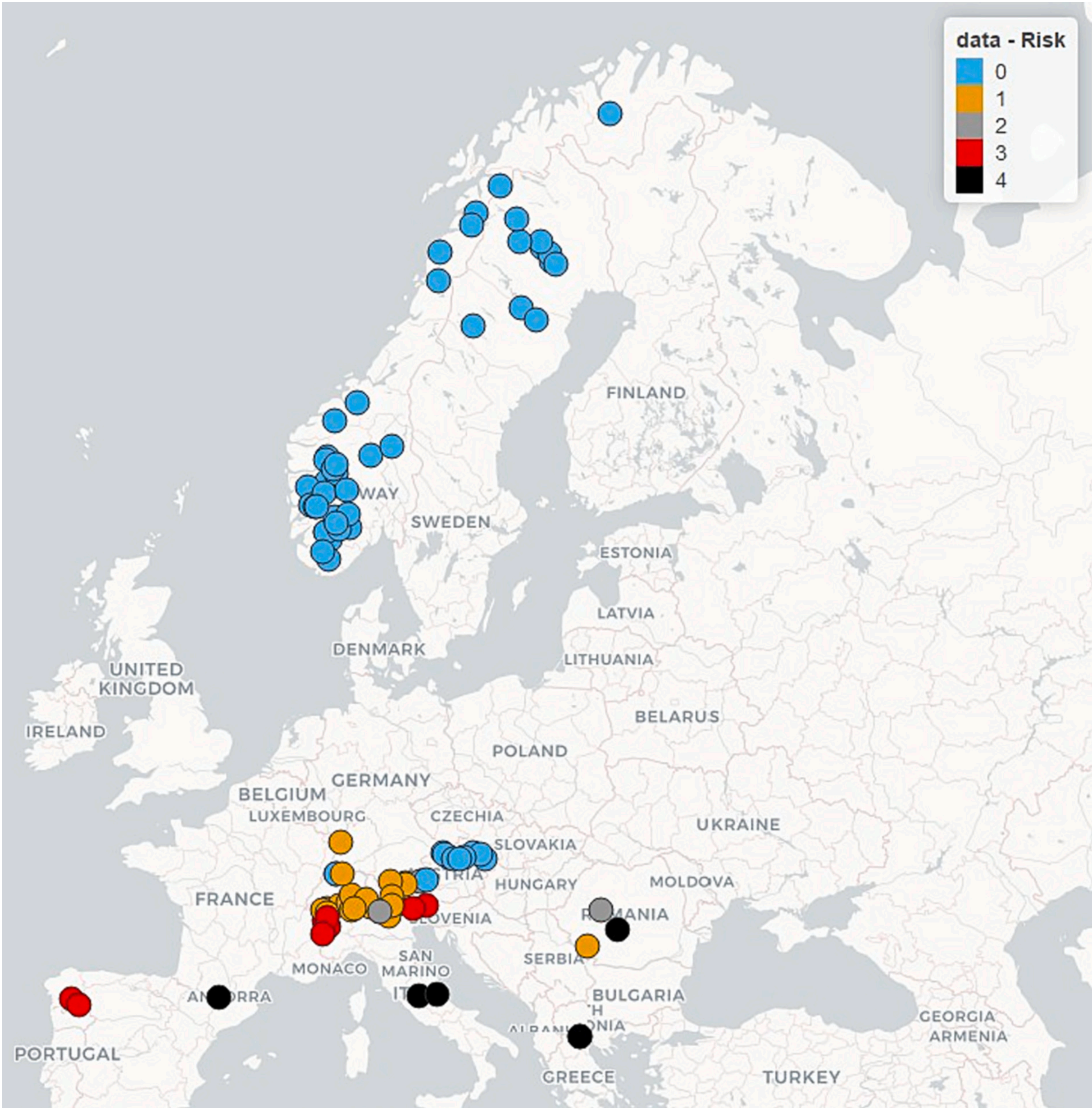

Fig. 2. European hydropower plant locations in our sample and water risk categories (0 - no risk, to 4 - very high risk).

of 1/24° and we aggregate them at the monthly level over the period 2015–2022. The TerraClimate dataset developed by Abatzoglou et al. (2018) combines high-spatial resolution climatological datapoints from the WorldClim dataset with coarser monthly data to create a monthly dataset for the years 1958–2015.[7] The data is obtained based on a 5 km buffer area around the latitude and longitude of the individual power plants.

Reservoir data. Time-varying data on the surface size of reservoirs is obtained from Donchyts et al. (2022). The dataset includes a reservoir's location (in latitude/longitude) and the reservoir's surface area (in ha) for the period 2000–2022. Based on the location, we match each power plant to the closest reservoir - a power plant is considered as connected to a reservoir if their coordinates are within a distance of 20 km.[8]

Financial data. We merge the plant-specific water risk measures with ownership informa- tion available from S&P Capital IQ and the financial performance (i.e. the returns) of the owners. S&P Capital IQ additionally contains information about the ownership percentage of a power plant by a company, which can be the owner of the plant or the

[7] Our final sample covers the period 2015–2022 due to the availability of other variables.

[8] We acknowledge the possibility of heterogeneous measurement error induced by this approach, because there will be spatial variability in temporal behaviour of precipitation within catchments. For smaller catch- ments (e.g. in Europe) this will be less of an issue but for the larger dams/catchments in the US it could be quite important (also important in mountainous areas where precipitation variability is higher).

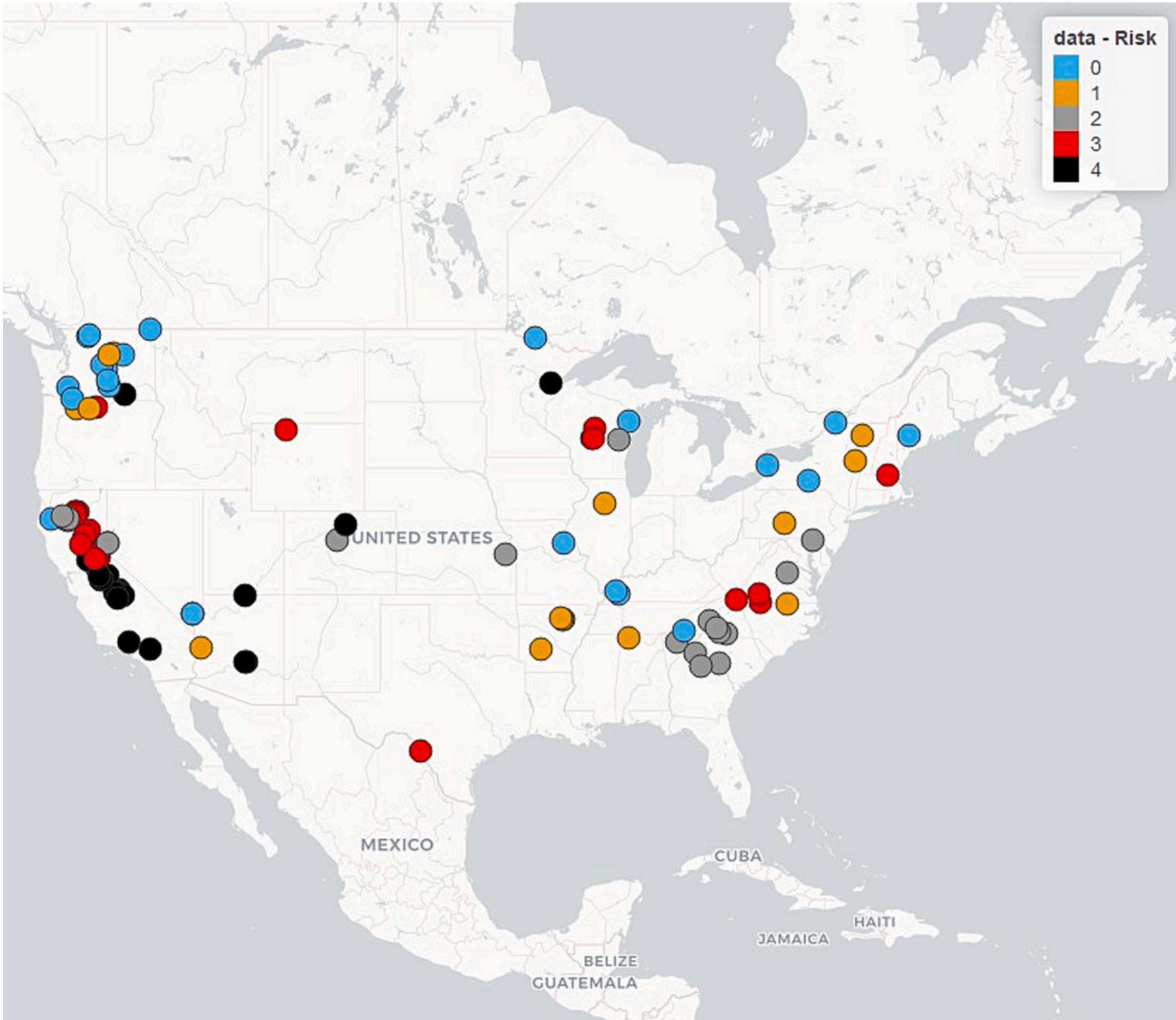

Fig. 3. US hydropower plant locations in our sample and water risk categories (0 - no risk, to 4 - very high risk).

ultimate parent company of the owner.[9] To provide a more accurate picture of the risk faced by companies owning the power plants, we weight the risk of the power plants by the ownership share. Moreover, lower generation might be more relevant for some companies than for others, de- pending on their main activities. We capture this by including in the analysis the company revenue shares from different business segments. The revenue share data is retrieved from the S&P Trucost database. In particular, we look at the revenue share of a company from hydropower generation and pre-multiply this by the ownership share-weighted water risk.[10] The intuition is that for companies deriving a large share of their revenues from hydropower, water risks are more relevant. Finally, data on realized returns is obtained from S&P Capital IQ Financials.

Our final sample includes 1145 power plants in 14 European countries and 47 US states over the period 2015–2022. We report the summary statistics in Table A in the Appendix.

2.1. Precipitation and power generation

To provide some insights about trends, as well as periods of shocks and variability in precip- itation and electricity generation, we show the evolution of these variables over the sample period. Results are reported as monthly averages over different spatial aggregations. Fig. 4 depicts the evolution for the sample of European countries excluding Norway.[11] The figure shows that 2022 is the lowest precipitation year in our sample and reveals the presence of a clear seasonal pattern.[12] Fig. 5 shows that, also for the US, 2022 is the year in which the lowest precipitation was registered.[13] We also see that while average monthly electricity generation is around 40–45 MWh for both European and US plants, it seems to

[9] When available, we use the ultimate parent identifier and retrieve financial information about this company, as the ultimate parent is the guarantor in case of financial losses. For hydropower plants for which only the owner is available or no financial information about the ultimate parent could be retrieved, we rely on the owner.

[10] The Trucost database provides a company's revenue shares from different business activities. As a robustness check, we conduct the same analysis using the total revenue share from "hydropower generation" and "other electricity generation", instead of only "hydropower generation".

[11] We exclude Norway from the analysis as data is only available from 2020 onward. Moreover, Norway experienced unusually large amounts of precipitation in 2021.

[12] To further investigate the variability in precipitation and hydroelectricity generation in European coun- tries, we also plot the monthly averages by country in Figure 9 in the Appendix.

[13] Figure 10 in the Appendix reports the evolution of precipitation and generation for the individual US states.

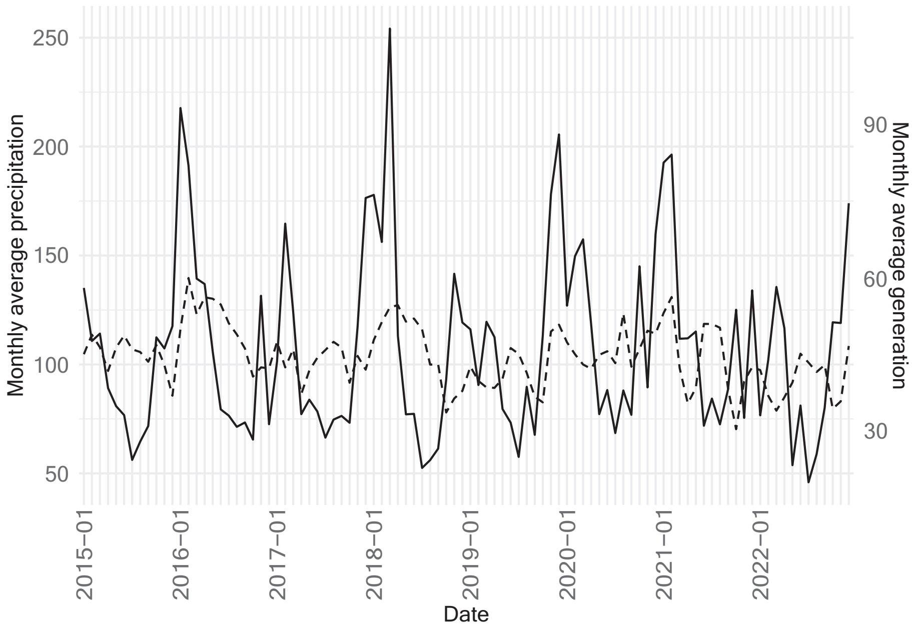

Fig. 4. Monthly average precipitation (solid line) and monthly average electricity gener-ation (dashed line) in Europe, excluding Norway.
Notes: The Pearson correlation coefficient between the two time-series is equal to 0.24.

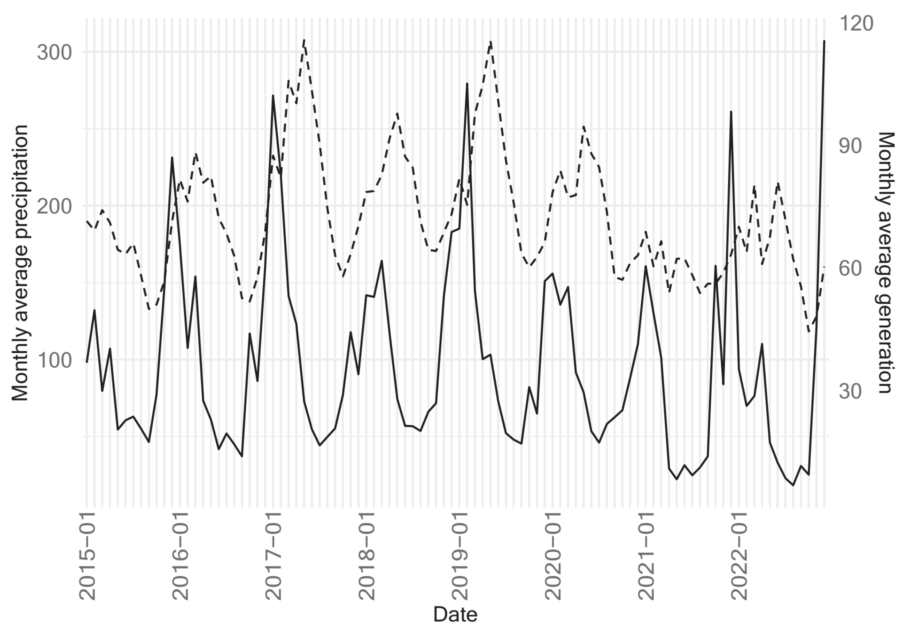

Fig. 5. Monthly average precipitation (solid line) and monthly average electricity gener- ation (dashed line) in the US.
Notes: We have included only generation by the largest plants (≥ 100 MW capacity) in this graph, because for smaller plants data about generation in 2022 is not available yet. The Pearson correlation coefficient between the two time-series is equal to 0.15.

be more volatile in the US. Both plots show a co-movement amongst the variables (especially evident for the US), with generation following precipitation with some delay.

3. Real effect of water risk

We employ three alternative empirical strategies to understand the impact of water risk on hydropower generation. The first strategy uses the cross-sectional water risk from WRI; the second strategy leverages water risk information contained in temporal variation in hydro-meteorological data; the third investigates the dynamic response of hydroelectricity genera- tion to water risks using a structural panel VAR (PVAR) approach. The following subsection describes the methodologies. Subsequently, we discuss results and present some robustness checks.

3.1. Methodology

Cross-sectional analysis. To investigate the impact of water risks using the cross–sectional water risk metric from WRI, we first summarize the time series of electricity generation in the sample period into a single measure. To this end, we construct plant-specific deviations in electricity generation in the low rainfall year 2022, as the ratio of generation in 2022 relative to the historical average (2015–2021). Our regression specification reads

$$\widetilde{y}_i = \beta^{CS} \times Risk_i + \gamma' x_i + \delta_i + \epsilon_i$$

where $\widetilde{y}_i$ is the plant-specific deviation in electricity generation. $Risk_i$ is the standardized WRI aggregated raw physical quantity risk metric in the basin where plant i is located. β^{CS} is our parameter of interest. The vector x includes the following control variables: age, which is defined as the number of years the power plant has been operating,[14] the operating capacity of the power plant, and the surface area of the closest reservoir.[15,16] We also include country fixed effects to control for unobservables at the country level, such as country-specific demand patterns for electricity, management of the electricity grid and water demand, as well as power plant type (WR or ROR) fixed effects (δ_i). Standard errors are clustered at the country level. Except for *Risk*, all variables are in logs and are winsorized at the 5% level. WRI also provides the risk metric on a discrete scale of five categories, running from 0 to 4 (lowest to highest risk). Hence, we also estimate our cross-sectional model using these discrete categories instead of the continuous values of the aggregate risk metric.

Panel data analysis. Next, we are interested in the dynamic effect of water risks on electricity generation. Since the aggregate water risk metric from WRI is time invariant, we use the time series of precipitation to build a time-varying measure of water risk, which we refer to as "precipitation anomaly". To construct this measure, as a first step, we run plant-specific regressions of precipitation on month fixed effects. These regressions account for the average plant-level precipitation as well as plant-level seasonality in rainfall. We then look at the empirical distribution of the regression residuals. These residuals aim to mimic precipitation surprises because we have removed any plant-level average and plant- level seasonal trends. We code events below the 10th and above the 90th percentiles of this distribution as extreme low and extreme high precipitation events, respectively, using dummy variables (we use the same approach for the PDSI).[17] Our focus is on the low precipitation anomalies and we use the constructed low-precipitation dummies as a proxy for high water risk in our panel regression. The intuition behind this exercise is that even if precipitation is not the same as risk, extremely low values of precipitation can be interpreted as realized water risk. Therefore, in the subsequent discussion, we use the term "low precipitation anomaly" interchangeably with "water risk".[18]

Figs. 6 and 7 report the counts of low and high precipitation and PDSI anomalies in our sample.[19] For both Europe and the US, the count of negative precipitation anomalies in 2022 (the red bar) outweighs positive anomalies (in yellow), a situation that only occurred in 2015 (for Europe) and 2016 (for the US) before.[20] This is consistent with 2022 being a lowest precipitation year in our sample.[21]

We estimate the model

$$y_{i,t} = \beta^{\text{Panel}} \times \text{Anomaly}_{i,t} + \gamma' x_{i,t} + \delta_{i,t} + \epsilon_{i,t}$$

where $y_{i,t}$ is the plant-specific average hourly electricity generation per month. The dummy variable $Anomaly_{i,t}$ is the location-specific time series of low precipitation anoma- lies. β^{Panel} is our parameter of interest. The vector $x_{i,t}$ includes plant- and location-specific time-varying control variables (operating capacity, age, area of closest reservoir, evapotranspiration). The vector $\delta_{i,t}$ includes country-by-month, year and type (WR or ROR) fixed effects. The time fixed effects capture the average effect of unobserved time-varying factors that affect the dependent variable across all countries. These factors could include macroe- conomic shocks, global events, or other time-specific influences. Country by month fixed effect account for potential heterogeneous seasonal effects across countries. For example, the effect of higher temperature in some months might be positive for some countries (e.g., through glacier melting) and negative for others (more evapotranspiration). In such cases, the interaction between country and month fixed effects allows us to estimate country-specific time trends. Hence, this specification addresses additional concerns about the results being driven by electricity demand instead of supply shocks, for instance.[22] Standard errors are clustered at the country level to account for any serial correlation in the residuals. Except for $Anomaly_{i,t}$, all variables are expressed in logs and winsorized at the 5% level. **Structural Panel Vector Autoregession.** We also estimate the dynamic response of hydroelectricity generation to water risks using a structural panel VAR (PVAR) approach. The idea is to estimate the joint evolution of hydroelectricity generation and precipitation anomalies using a flexible autoregressive model, imposing a mild theoretical restriction on the model, and using the estimated model to

[14] The rationale for including age is that it could affect the results in two ways: on the one hand, older power plants might have been upgraded to become more efficient over time; on the other hand, older power plants, left without updates, might become less efficient.

[15] Note that we matched the power plants with the closest reservoir both for water reservoir (WR) and run of river (ROR) plants. This is justified by two reasons: First, the available data on reservoirs size does not distinguish between hydropower-specific and other reservoirs. Second, even in the case of ROR plants, a water reservoir nearby increasing in size could have a positive effect on generation that we want to control for.

[16] Due to data availability constraints, we do not include information about storage at the plant level. Our results are likely to underestimate the negative effect of water risks, since we do not control for plants' potential to isolate themselves from water risks through storage. Likewise, we do not control for the endogenous location choice of the power plants or the adoption of adaptation measures. Regarding this second aspect, empirical analysis can, in general, estimate two types of effects: (1) a general equilibrium (or policy) effect, (2) a partial equilibrium effect. In the first case, we would want to obtain an estimate that accounts for the endogenous location choice or for the adoption of adaptation measures. This could be the case, for instance, if we want to provide estimates for choosing a policy that intervenes conditional on location choice or investment decisions of the private sector. In this case, using an effect estimate that disregards private sector decisions might lead to an inefficiently large intervention by the policy maker. In the second case, we could attempt to measure the effect of water risks only, without taking the effect of endogenous location or adaptation into account. If we were to not account for the reduction in the negative effect due to endogenous location choice or the adoption of adaptation measures (or other similar unobservables), we would end up estimating a more negative effect. Hence, our results might represent a lower bound of the effect of water risks.

[17] There are two advantages of this approach. First, the residuals obtained from the plant by plant regression on time fixed effects are noisy. By discretizing the residuals into dummy variables, we can reduce the measurement error. Second, coding the low/high precipitation as dummies allows us to interpret these occurrences as extreme events, which we consider to be a better proxy for risk.

[18] The validity of these proxies for water risks is supported by the fact that the WRI's water risk metric correlates with rainfall, as shown in the Figs. 11, 12 and 13 in the Appendix.

[19] See Figs. 15 and 16 in the Appendix for the occurrence of anomalies by European countries and US states, respectively.

[20] The count for the US is lower in 2021 and 2022 because for 14 states, our precipitation data is only available until 2020.

[21] Figures 12 and 13 in the Appendix show the average monthly precipitation by risk category in Europe and the US. They further confirm that 2022 saw low precipitation, especially for basins exposed to high or very high water quantity risk.

[22] The (i, t) subscript in $\delta_{i,t}$ indicates that there is both cross-sectional and time variation in the fixed effects. Conceptually, the effect is estimated off the within country-season and type variation, controlling for common annual trends and observable plant characteristics.

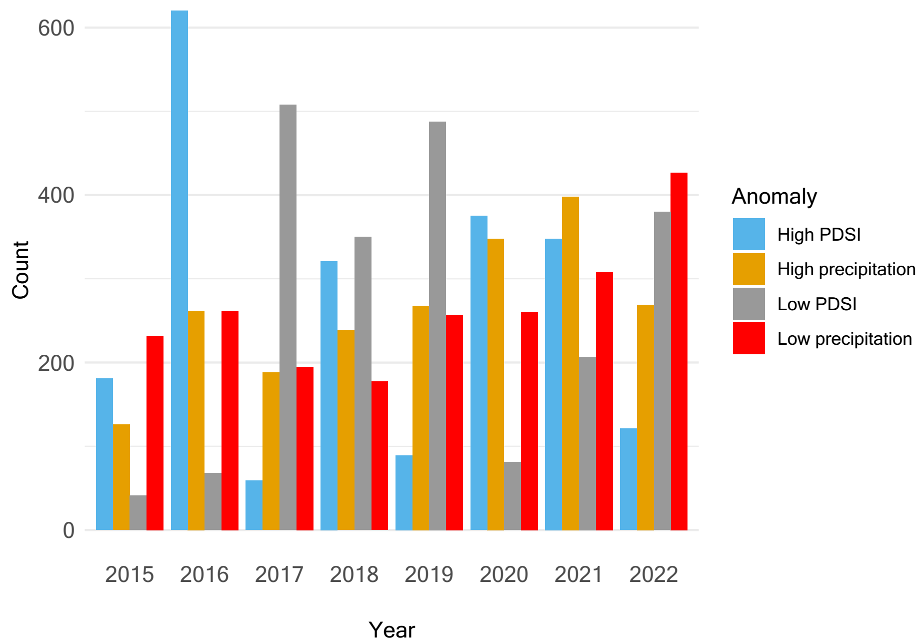

Fig. 6. Count of high and low precipitation and PDSI anomalies in Europe.

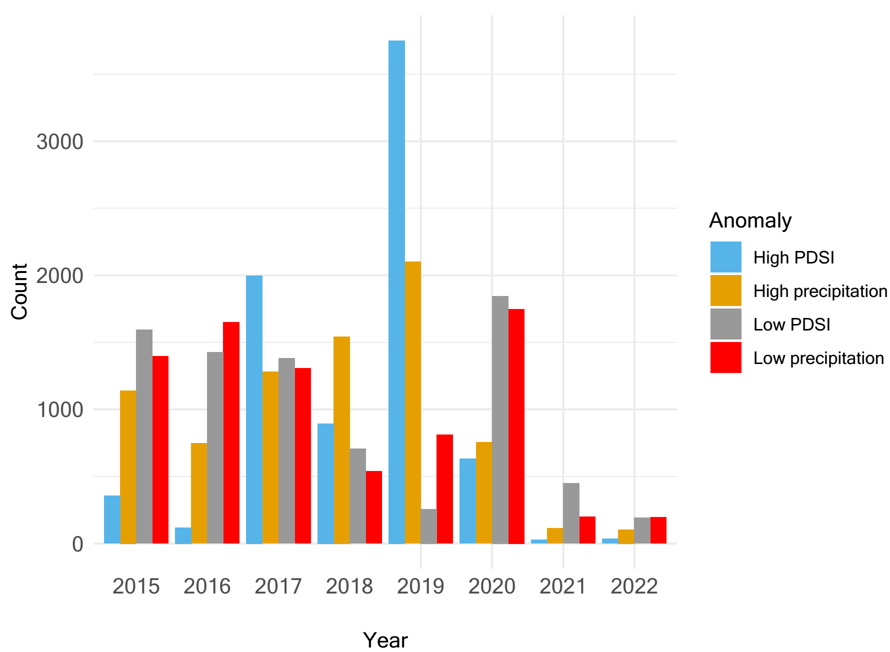

Fig. 7. Count of high and low precipitation and PDSI anomalies in the US.

derive the effect of a one time, exogenous shock to the anomaly on the subsequent evolution of hydroelectricity generation.[23] More precisely, the PVAR model reads

$$\mathbf{y}_{i,t} = \mu_i + \sum_{l=1}^{p} \mathbf{A}_l \mathbf{y}_{i,t-l} + \epsilon_{i,t}$$

where the $\mathbf{y}_{i,t}$ is a 2×1 vector of the two endogenous variables

$$\mathbf{y}_{i,t} = \left[\text{Anomaly}_{i,t}, log(\text{ Generation })_{i,t} \right]^{'},$$

and μ_i is plant fixed effect. Each endogenous variable is expressed as linear combination of l lags of itself and the other endogenous variable. Under stationarity, this PVAR representation has the equivalent panel vector moving averages (PVMA) representation[24] given by

$$\mathbf{y}_{i,t} = \mu_i + \left(\sum_{j=0}^{\infty} \mathbf{A}^j \right) \left[\epsilon_{i,t-j} \right].$$

[23] The panel VAR approach is commonly used in macroeconomic studies to study similar questions. For a detailed description and applications, see the review by Pedroni (2013).

[24] This can be obtained by recursively substituting the VAR representation.

Based on this representation, the impulse response function is defined as

$$\mathrm{IRF}(k,r) = \frac{\partial \mathbf{y}_{i,t+k}}{\partial(\epsilon_{i,t})_r} = \mathbf{A}^k \mathbf{e}_r,$$

where k is the number of periods after the shock to the r-th component of $\epsilon_{i,t}$ with $\mathbf{e}_r$ being a $m \times 1$ vector with a 1 in the r-th column and 0 otherwise. This impulse response, however, does not correctly capture the dynamic response of one endogenous variable to an *exogenous* change in another. This is because the residuals $\epsilon_{i,t}$ are not the same as exogenous shocks to individual endogenous variables. Formally, let $\mathbf{\Sigma}_\epsilon$ be the variance-covariance matrix of $\epsilon_{i,t}$. In general, the off-diagonal elements of $\mathbf{\Sigma}_\epsilon$ will not be 0, which invalidates their interpretation as exogenous shocks. The issue here is similar to that of omitted variable bias. In our case, unobserved shocks to precipitation can be correlated with unobserved shocks to hydropower generation. To find a causal effect, we need to shut down any variation from the latter.

To recover exogenous shocks, we need to impose some restrictions on model parameters. In particular, we impose that $\mathbf{\Sigma}_\epsilon$ is upper triangular (Cholesky decomposition). This amounts to assuming that any exogenous shocks to hydroelectricity generation do not have a contemporaneous effect on precipitation anomalies. This is a defensible assumption since it is unlikely that a shock to generation, e.g. from an exogenous change in electricity demand, has an instantaneous effect on precipitation in the same month.[25] We can use this assumption to adjust the VAR parameters to create a counterfactual where the effect on an exogenous shock to the precipitation anomaly propagates through the system. Formally, note that since $\mathbf{\Sigma}_\epsilon$ is a variance-covariance matrix, it is symmetric positive definite. Therefore, there exists a unique Cholesky decomposition such that $\mathbf{\Sigma}_\epsilon = \mathbf{P}\mathbf{P}^\top$, where $\mathbf{P}$ is a lower triangular matrix. Defining $\Theta_k = \mathbf{A}^k\mathbf{P}$ and $\mathbf{u}_{i,t} = \mathbf{P}^{-1}\epsilon_{i,t}$ we obtain the orthogonal impulse response function:

$$\mathrm{OIRF}(k,r) = \frac{\partial \mathbf{y}_{i,t+k}}{\partial(\mathbf{u}_{i,t})_r} = \mathbf{\Theta}_k \mathbf{e}_r$$

Here $\mathbf{u}_{i,t}$ has the interpretation of an exogenous shock and the the orthogonal impulse re- sponse function traces out the response path of an endogenous variable to an exogenous shock. In our case, we are interested in the impulse response of hydropower generation to an identified precipitation anomaly shock. We implement the structural PVAR using the panelvar package in R (Sigmund and Ferstl, 2021).[26]

3.2. Results

Cross-sectional analysis. The cross-sectional analysis shows that a higher water risk metric is indicative of greater deviation in hydropower plants' electricity generation in a dry year. Table 2 displays our results. We find a significant negative relationship between the aggregate water risk metric and hydroelectricity generation. Specifically, in our baseline regression (Model (1)), one standard deviation increase in the risk metric is associated with 9% lower electricity generation in 2022 relative to the historical average. In Model (2), we use the discrete water risk categories instead of the continuous water risk metric. The coefficients have to be interpreted as the percentage difference in generation compared to the no-risk category (category 0), which is our benchmark. The results show that plants located in higher risk category basins see larger and more significant reductions in electricity generation in 2022 relative to their historical average. Specifically, a plant located in a very high risk basin (category 4), experiences an estimated 31% larger reduction in generation over its average in a dry year, compared to a plant located in a no-risk basin.

Table 2
Cross sectional regression of electricity generation in 2022 compared to the histor- ical average at the plant level. Model (1) uses the continuous risk score. Model (2) uses the categorical risk score, where the benchmark is the risk category 0 (no risk.

Dependent variable:	Generation deviation	
Model:	(1)	(2)
Independent variables:		
Water risk	−0.0914***	
	(0.0102)	
Operating capacity	−0.0241	−0.0304
	(0.0135)	(0.0180)
Age	0.0365	0.0498
	(0.0755)	(0.0751)
Reservoir size	0.0009	0.0007
	(0.0129)	(0.0145)
Risk category 1		−0.1390**
		(0.0613)
Risk category 2		−0.3321***
		(0.0642)
Risk category 3		−0.2678***
		(0.0488)
Risk category 4		−0.3116***
		(0.0427)
Fixed-effects		
Country	Yes	Yes
Type	Yes	Yes
Fit statistics		
Observations	165	165
R^2	0.17738	0.20288
Within R^2	0.05846	0.08765

Clustered by country standard-errors in parentheses Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.
Notes: The cross-sectional model has a sample of only 165 plants as US plants with less 100 MW capacity have not reported generation data for 2022 yet.

Panel data analysis. Our results from the panel data analysis are

Table 3
Baseline panel regression with precipitation anomalies.

Dependent variable:	log(Generation)
Independent variables:	
Precipitation anomaly	−0.1799***
	(0.0359)
Age	0.2268
	(0.1491)
Reservoir size	0.0377**
	(0.0179)
Operating capacity	0.9244***
	(0.0796)
Evapotranspiration	0.0995**
	(0.0386)
Fixed-effects	
Country by Month	Yes
Year	Yes
Type	Yes
Fit statistics	
Observations	69,700
R^2	0.32533
Within R^2	0.20810

Clustered by country standard-errors in parentheses Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

[25] Besides the Cholesky decomposition adopted here, there are several other types of theoretical restrictions that can be imposed to recover exogenous, or structural, shocks from residuals. The term "structural" refers to the idea that these shocks are the main exogenous drivers of the economic system and they are propagated through the system via relationships between the endogenous variables. As such, the problem of identification, or recoverability, of structural shocks has been extensively studied in macroeconometrics. A more detailed discussion is beyond the scope of this paper; a textbook treatment can be found in Kilian and Lutkepohl (2017).

[26] The package is available at https://cran.r-project.org/web/packages/panelvar/.

displayed in Table 3. The occurrence of a negative precipitation anomaly reduces electricity generation by 18%. Hence, when water risks materialize as unexpectedly low water availability, the electricity generation by affected plants is significantly reduced. While a direct comparison of this estimate size with the cross-sectional estimate is not straightforward, we can still consider the following ballpark numbers. As defined, a negative precipitation anomaly has a 10% chance of occurring. Assuming a normal distribution for precipitation surprises, this is 1.72 standard deviations away from the mean. Scaling the estimated 18% effect, we get a 10.5% effect of the one standard deviation shock. In line with our expectations, the coefficients on operating capacity and the area of the reservoir are positive and significant.[27,28]

We conduct several robustness checks for the panel data setting, which are reported in Table 4. First, to account for potential autocorrelation in the measure of water risk that we have constructed, we run our baseline regression controlling for up to six lags of the shocks. Model (1) in Table 4 reports the results when including lags of the anomalies. As expected, the coefficient capturing the impact of the contemporaneous anomaly is smaller in magnitude, but the sign and statistical significance are not affected. This implies that the effect of precipitation anomalies cumulates over time, leading to a persistent effect, although the effect seems to disappear after three months. Second, we test an alternative measure of water risk, namely anomalies to the Palmer Drought Severity Index (PDSI) (Palmer, 1965).[29] We find that a PDSI anomaly is associated with an even stronger (33%) reduction in electricity generation. This might be due to the fact that the PDSI is a more comprehensive measure of water availability, including for instance surface air temperature, which could be correlated with hydroelectricity generation. These results are reported in Model (2) of Table 4. Third, in Model (3), we include country and month fixed effects separately. Finally, in our baseline regression we control for the type of plants (WR or ROR), but include all the plants in the sample. The intuition behind plant types fixed effects is that precipitation anomalies are more relevant for plants situated on a river than for plants with reservoirs, which can use storage to manage anomalies in the short term. To test this hypothesis, we run two separate regressions for WR and ROR plants in Models (4) and (5), respectively. Our results show that run of river plants are more sensitive to water risks, with a larger and more significant reduction in electricity generation following the occurrence of a precipitation anomaly. In particular, a negative anomaly reduces hydroelectric generation for ROR plant by 17.25%, which is equal to a 6.38 GWh reduction in electricity generation for an average ROR plant (in our sample) that produces 36.56 GWh of power. On the other hand, an average WR plant, which produces 39.01 GWh of power monthly, witnesses at 15.04% reduction (equal to 5.87 GWh) following a similar event. This confirms the conventional wisdom that storage offered by reservoirs reduces the sensitivity to lower precipitation. However, surprisingly, we only find a positive effect of the reservoir size for ROR plants. This could be due to the smaller number of observations for WR power plants. Moreover, the reservoir size only refers to the surface of the reservoir and does not account for the volume.

Structural Panel Vector Autoregession. Finally, we present the results from the struc- tural PVAR. Fig. 8 shows the estimated impulse response of *log(Generation)* to a precipi- tation anomaly from a structural PVAR with 6 lags. Precipitation anomalies have an effect on hydropower generation for up to two months, beyond which the effect fades out.

4. Financial markets' pricing of water risks

Next to the real effects of water risks on electricity generation, we are interested in whether such water risks are priced in by financial markets. Hence, we link the power plants in our sample with the equity returns of their owners. Considering the real effect of water risks identified in the previous section, investors should demand a positive equity risk premium for holding companies owning riskier power plants. In other words, we expect to find a positive cross-sectional relationship between water risks and stock returns. If such a relationship exists, financial markets are pricing in water risks and investors are trading off risks and returns, as well as and demanding to be compensated for bearing higher water risks. However, if this relationship does not exist, water risks are not priced in, and financial markets might not be providing plant owners the right incentives for appropriate risk management.

While most owners of larger hydropower plants are utilities, many of these firms are listed and partially traded companies. For instance, in our sample, Enel, Fortum, Energias de Portugal, Iberdola and PG&E are stock-listed and traded, while Electricite de France, a publicly traded company, was traded until recently fully nationalized. The subsample of publicly-traded companies gives us the opportunity to study the pricing of the water risks by financial markets.

4.1. Methodology

A positive cross-sectional relationship between water risk and excess equity returns is evidence of a risk premium for water risk. We use the portfolio sorts approach to investigate the presence of a risk premium. This is a non-parametric method for studying cross-sectional relationships between two variables - in our case, excess stock returns and water risk.

To apply the portfolio sorts approach, we construct a company-level measure of exposure to water risk. This is a weighted average of the risk of all plants owned by a company, with weights defined as the ownership percentage of the company in each plant. For each company i, we define a water exposure metric.

$$\mathrm{Exp}_{i,t} = \mathrm{Rev}_{i,t} \times \frac{\sum_{j\in\mathcal{J}} \mathrm{Risk}_j \times Own\%_j}{\sum_{j\in\mathcal{J}} Own\%_j.}$$

where $Rev_{i,t}$ is the revenue percentage from hydroelectricity generation for company i in year t. J is the set of all power plants owned by a company i and $Own\%_j$ is the share in power plant j owned by company i.

Given our metric of exposure to water risk, we proceed in four steps. First, we partition the sample into groups based on the exposure to water risk of the companies. More concretely, companies are sorted based on their water risk level and then partitioned into terciles. Second, companies in each tercile are used to create tercile portfolios (stocks in the lowest risk tercile will form the least risky portfolio). We use two alternative ways of forming these portfolio: (i) we create value-weighted (VW) portfolios, with the weights given by the market capitalization of each company (for a given tercile) in a month. This is equivalent to buying stocks in proportion to their market capitalization of the company and rebalancing the portfolio at the beginning of each month; (ii) we create equally-weighted (EW) portfolios. This amounts to buying an equal number of stocks in each company, without rebalancing. For every

[27] Note that the coefficient for operating capacity is significant, unlike in the cross-sectional regression. A possible explanation is that a ratio is not affected by the operating capacity, whereas when we want to explain changes to the overall generation, operating capacity plays a more important role. The same might apply for the size of the reservoir.

[28] An alternative analysis could focus on empirically measuring the risk for plant i as a time series correlation between generation and precipitation. This would give a time invariant measure of plant-specific risk (namely, the coefficient in the time series regression). In other words, with a sufficiently long time-series of electricity generation and precipitation anomalies, we could investigate plant-specific βs, as e.g. in (Keane and Neal, 2020). This approach can also be used to estimate plant-specific adaptation under some theoretical restrictions.

[29] The PDSI is a standardized index and uses readily available temperature and precipitation data to estimate relative dryness. Lower values are associated with drier locations. Alternatively, we could have used the Standardized Precipitation Index (McKee et al., 1993).

Table 4
Panel regression robustness checks. Model (1) includes 6 lags of the precipitation anomalies, Model (2) looks at the impact of PDSI anomalies, Model (3) includes country and month fixed effects separately, Model (4) and (5) only includes the results for the subsamples of WR and ROR power plants, respectively.

Dependent variable:			log(Generation)		
Model:	(1)	(2)	(3)	(4)	(5)
Independent variables:					
Precipitation anomaly	−0.1337***		−0.1722***	−0.1504*	−0.1725***
	(0.0355)		(0.0539)	(0.0849)	(0.0511)
Precipitation anomaly, 1 lag	−0.1157***				
	(0.0424)				
Precipitation anomaly, 2 lags	−0.0976***				
	(0.0347)				
Precipitation anomaly, 3 lags	−0.0937***				
	(0.0296)				
Precipitation anomaly, 4 lags	−0.0294				
	(0.0259)				
Precipitation anomaly, 5 lags	0.0042				
	(0.0322)				
Precipitation anomaly, 6 lags	−0.0263				
	(0.0418)				
Age	0.2039	0.2264	0.2268	0.0022	
	(0.1471)	(0.1470)	(0.1472)	(0.1733)	
Reservoir size	0.0342*	0.0377**	0.0382**	−0.0578	0.0443**
	(0.0179)	(0.0179)	(0.0179)	(0.0521)	(0.0201)
Operating capacity	0.9307***	0.9274***	0.9273***	0.6627**	1.012***
	(0.0844)	(0.0820)	(0.0820)	(0.2804)	(0.0527)
Evapotranspiration	0.0425	0.0379	0.0849**	0.0465	0.0310
	(0.0285)	(0.0282)	(0.0324)	(0.0566)	(0.0253)
PDSI anomaly		−0.3291***			
		(0.0774)			
Fixed-effects					
Month	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
Type	Yes	Yes	Yes		
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	64,576	69,700	69,700	16,352	53,348
R^2	0.31174	0.30819	0.30731	0.15119	0.40037
Within R^2	0.20680	0.20475	0.20375	0.05424	0.28015

Clustered (country fe) standard-errors in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

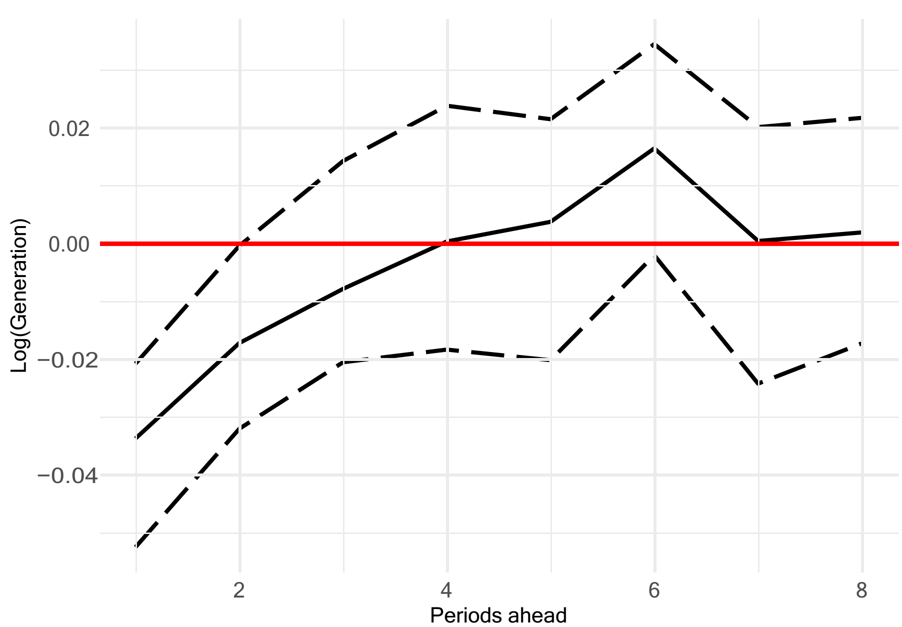

Fig. 8. Impulse response function of log*(Generation)* to a precipitation anomaly.
Notes: The dark line plots the estimate of the impulse response and the dotted lines represent a 90% confidence band. The confidence interval is based on a bootstrapping approach as described in Sigmund and Ferstl (2021).

tercile, we calculate the monthly excess return for both portfolio types (VW and EW). Excess return is defined as the difference between the realized return and the risk-free return for a given month. As a result, for each portfolio type (VW and EW), we have three time-series of excess returns, each corresponding to a tercile. In the third step, we create a hybrid portfolio, which buys (shorts) the high-risk portfolio and sells (goes long on) the low-risk portfolio and calculate its monthly excess return. The excess return on this hybrid portfolio is equal to the excess return on the high-risk portfolio minus the excess return on the low risk portfolio. This gives us an aggregate time-series "risk factor" (one for each portfolio type, VW and EW), which captures the excess return from maximal exposure to water risk in a given month. This risk factor represents the systematic water risk in the economy from the perspective of financial markets (Fama and French (2015)). Finally, to estimate the premium on water risk, we take a time-series average of this risk factor, that is, the unconditional average return of the long-short portfolio. We obtain two estimates - one for the VW portfolio and another the EW portfolio.

One of the central insights of asset pricing theory is that excess returns on any individual traded asset or security should be explained, on average, by its exposure to systematic risk factors. Therefore, we might still be concerned that any estimated water risk premium can be explained by the exposure of assets to other systematic risks in the economy. In other words, water risk might not, in fact, be an independent source of systemic risk in financial markets. To address this concern, we examine whether our findings persist even after controlling for sensitivity of the long-short portfolio returns to known systematic risk factors. We consider three alternative choices of systematic risk factors, or risk models, that are common in the literature. First, as suggested by CAPM (Sharpe, 1964; Lintner, 1965), we consider excess return on the market portfolio as the only source of systematic risk in the economy. To this end, we run the following regression

$$r_t = \alpha + \beta_{MKT}(Mkt - RF) + \epsilon_t$$

where r_t is the water risk factor and $Mkt - RF$ is the excess return on the market portfolio. Second, we extend the set of predictors to include the five factors proposed by Fama and French (2015). In addition to $Mkt - RF$, the authors add four more independent measures of systematic risk. These include: *SMB*, or small minus big, which represents the return spread between small- and large-cap stocks; *HML*, or high minus low, which measures the return spread between high book-to-market and low book-to-market stocks; *RMW*, or robust minus weak, which compares the returns of firms with high, or robust, operating profitability, and those with weak, or low, operating profitability, and lastly, *CMA*, or conservative minus aggressive, which gauges the difference between companies that invest aggressively and those that do so more conservatively. These variables are maintained by Ken French and are available for download on his website.[30] This leads to our second regression specification

$$r_t = \alpha + \beta_{MKT}(Mkt - RF) + \beta_{SMB}SMB + \beta_{HML}HML + \beta_{RMW}RMW + \beta_{CMA}CMA + \epsilon_t,$$

Finally, we also add the well-known momentum factor (Jegadeesh and Titman, 1993) to this list. This gives us the following model

$$r_t = \alpha + \beta_{MKT}(Mkt - RF) + \beta_{SMB}SMB + \beta_{HML}HML + \beta_{RMW}RMW + \beta_{CMA}CMA + \beta_{Mom}Mom + \epsilon_t$$

Table 5
Water risk premium with revenues from hydroelectricity generation and value-weighed portfolios.

Dependent variable:	*Water risk factor*			
Model:	(1)	(2)	(3)	(4)
Independent variables:				
Constant	−0.086	−0.088	−0.087	−0.087
	(−2.816)	(−2.895)	(−2.831)	(−2.835)
Mkt-RF		0.002	0.002	0.002
		(1.650)	(1.279)	(0.959)
SMB			0.001	0.000
			(0.206)	(0.158)
HML			−0.000	−0.001
			(−0.123)	(−0.399)
RMW			−0.002	−0.002
			(−0.342)	(−0.347)
CMA			−0.001	0.000
			(−0.136)	(0.007)
Mom				−0.002
				(−0.703)
Observations	202	202	202	202

Notes: t-statistics in parentheses. Standard errors are adjusted following Newey and West (1987) using six lags.

In all three regressions above, α represents the water risk premium after controlling for exposure to systematic risks. Therefore, it is our parameter of interest and we will compare the estimates of α with the unconditional average return of the long-short portfolio, i.e. the average of the water risk factor for the VW portfolio and another the EW portfolio.

4.2. Results

Model (1) in Table 5 (6) shows the unconditional average excess return of the VW (EW) long-short portfolio over our sample period. This is an estimate of the water risk premium. The t-statistics are in parentheses below and can also be interpreted as Sharpe ratios. The average excess return is negative. Moreover, it is larger in magnitude and has a higher Sharpe ratio for the value-weighted portfolio. The results from the factor regressions, which estimate the risk premium after controlling for exposure to other systematic risk factors, are presented in Models (2)–(4) of Tables 5 and 6, for value-weighted and equal-weighted portfolios, respectively.

For the three factor regression specifications considered, we consistently find a negative estimate α, which would imply that the water risk factor earns a negative premium. The value of the risk premium is negative 9% when looking at value-weighted portfolios and reduces to negative 6–7% when using equal-weighted portfolios. Moreover, the t-statistics for equal- weighted portfolio are much smaller compared to those for value-weighted portfolios. This has two implications. First, the large magnitude of the risk premia for the value-weighted portfolio is driven by a few large firms. Second, given the proliferation of papers seeking new factors to explain the cross-section of returns raises data mining concerns, the evidence of negative risk premium itself is quite weak. To address this problem, the literature has proposed alternative multiple hypothesis testing frameworks. In this scenario, the typical cutoff values for t-statistics that are needed to reject the null hypothesis are considered too low. As a result, most of these frameworks result in a higher hurdle for the t-statistics to guard against the likelihood of false positive discoveries. As an example, Harvey et al. (2016) and Chordia

[30] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 6
Water risk premium with revenues from hydroelectricity generation and equally- weighed portfolios.

Dependent variable:	*Water risk factor*			
Model:	(1)	(2)	(3)	(4)
Independent variables:				
Constant	−0.083	−0.076	−0.061	−0.062
	(−2.232)	(−1.949)	(−1.449)	(−1.474)
Mkt-RF		−0.009	−0.009	−0.008
		(−2.161)	(−2.104)	(−1.771)
SMB			−0.020	−0.019
			(−2.262)	(−2.267)
HML			0.010	0.013
			(1.293)	(1.348)
RMW			−0.026	−0.026
			(−1.650)	(−1.640)
CMA			−0.028	−0.031
			(−1.521)	(−1.526)
Mom				0.005
				(0.765)
Observations	202	202	202	202

Notes: t-statistics in parentheses. Standard errors are adjusted following Newey and West (1987) using six lags.

et al. (2020) propose using t-stat hurdles of 3 and 3.84, respectively. Our t-stats are too low compared to these benchmarks, especially for the EW portfolio. Therefore, on the whole, we find that there is weak evidence of a negative risk premium. This implies that the markets do not price in the water risks for these assets. However, given the real negative effect on generation of water risks, our factor should earn a positive premium. We conclude that the lack of a premium amounts to mispricing of water risks by financial markets.

5. Discussion

Our findings align with the intuition that increasing negative precipitation anomalies, which are expected consequences of climate change, will reduce hydropower generation. However, when testing whether financial markets reflect these implications, we find weak evidence that investors are willing to accept lower returns from firms with higher exposures to water risk. This divergence between real and financial effects suggests that financial markets do not fully internalize the externality imposed by water risk. This can lead to excessive risk-taking by the hydropower sector as well as asset managers, leading to a suboptimal allocation of resources as well as instability in the financial system. Note that it is not a theoretical necessity that financial markets cannot price environmental externalities. As discussed above, several papers found risk premia for climate-related risks. Therefore, the empirical relevance of nature-related risk pricing needs to be established for specific risks and specific asset classes. If externalities are not properly priced, government policy interventions such as taxes and quotas, as well as financial policies are necessary to correct the mispricing. While the discussion of such policies is beyond the scope of this paper, this highlights the relevance of our empirical results.

There are several limitations to our approach. For example, a potential bias in our cross- sectional model could stem from an omitted variable, such as regional weather patterns, which affect both water risk factors and deviations in electricity generation. Another limitation is that our study does not consider the propagation of shocks to the hydropower sectors to other sector of the economy. This implies that the overall effect of water risks on the economy might be larger than what we estimate.

Future research should analyze the heterogeneity across regions and basins. Following Conway et al. (2017), follow-up studies could investigate the location of hydropower plants by spatial clusters with coherent temporal rainfall variability. Extensions of the models presented in this paper may include additional control variables, relating to reservoir characteristics such as volume and dual use for irrigation. Finally, future research should analyze cascading effects by looking at spillovers across sectors and ownership relationships to help translate water risks into financial losses.

6. Conclusion

There is increasing awareness about the impact of climate change and the decline of natural ecosystems on the economy and the financial system. The disturbance of the hydrological cycle, which is the source of the water risks we describe in this paper, and other examples of nature-related risks, such as biodiversity loss, are interdependent and share the same anthropogenic drivers (Vorosmarty et al., 2010).

Reduced water availability poses risks for many economic activities. This paper studies how water risks affect hydroelectricity generation in Europe and the US and whether these risks are priced in by financial markets. To this end, we build a novel dataset for the period 2015–2022, which combines plant-specific hydroelectricity generation with geo-specific water physical risks and equity returns. We show that water risks are material for hydroelectricity, a crucial energy source in the transition to a low-carbon economy. Higher water risk is associated with a 9% lower hydroelectricity generation for the average plant in 2022, the driest year in our sample, relative to the historical average. At the same time, the occurrence of a negative precipitation anomaly is associated with a 18% drop in hydroelectricity generation, although the effect disappears after two months. These findings can be used to inform the design of the low-carbon transition and the role of hydroelectricity. To understand the financial effects of water risks, we use plant owners' financial returns and investigate whether financial markets adequately price water risks. Using a portfolio sorts approach, we find weak evidence of a *negative* risk premium. Given the real negative effect of water risks on electricity generation, we concluded that the lack of a positive risk premium amounts to mispricing of water risks by financial markets. This calls for closer scrutiny by financial supervisors.

Declaration of Competing Interest

The authors, Chiara Colesanti-Senni, Skand Goel and Adian von Jagow have no conflicts of interests to declare.

Data availability

The authors do not have permission to share data.

Appendix A. Summary statistics

Our sample includes 13 European countries, 47 US states, 1145 power plants of two types (run of river or ROR and reservoir or WR) and spans the period 2015–2022. Summary statistics are reported for the datasets used in the regressions (winsorized at the 5% level).

Table 7
Summary statistics.

Variable	Unit	Min.	Max.	Mean	Std dev.
Cross section					
Generation change	*ratio*	0.26	1.35	0.84	0.26
Age	*years*	24	104	59	21.71
Operating capacity	*MW*	3.1	960.0	193.37	186.3
Risk	*numeric*	0.3618	3.6	1.27	0.82
Reservoirs' size	*ha*	53.01	320,674.6	10,095.37	37,492.83
Panel regression					
Generation	*GWh*	0	3944.18	36.56	133.19
Operating capacity	*MW*	0.4	441	83.66	125.27
Age	*years*	1	111	67.36	27.93
Precipitation and snow-water equivalent	*mm/month*	0.00	321.34	105.75	85.9
Evapotranspiration	*mm*	0.00	1200.6	498.22	386.71
PDSI	*index*	−791.44	564.02	46.52	295.56
Reservoirs' size	*ha*	0.92	36,758.92	4963.27	9457.54

Appendix B. Precipitation and generation

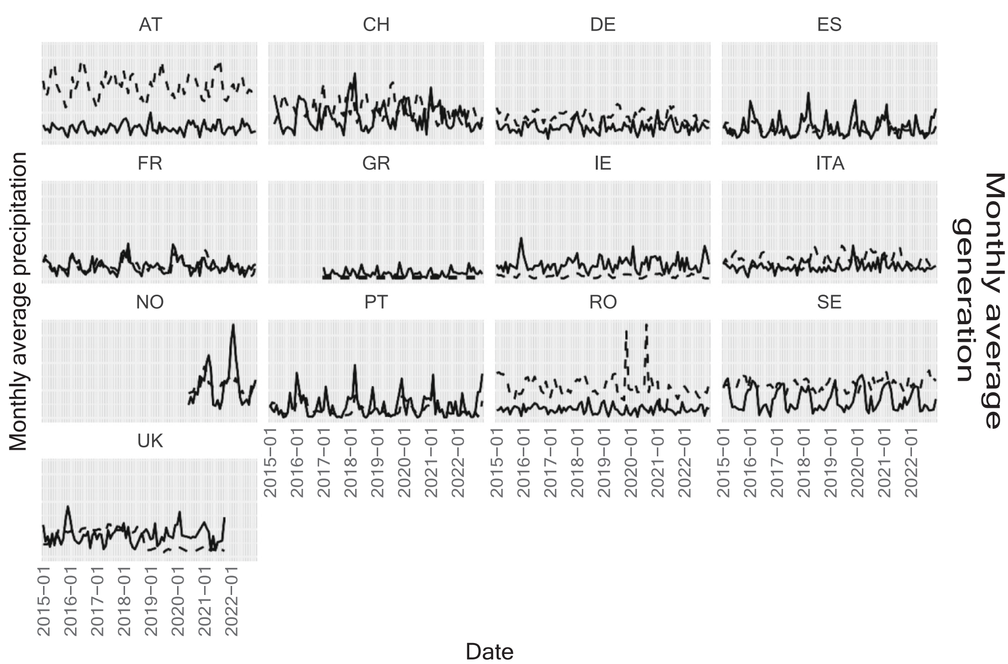

Fig. 9. Monthly average precipitation (solid line) and monthly average electricity gener-ation (dashed line) in European countries.

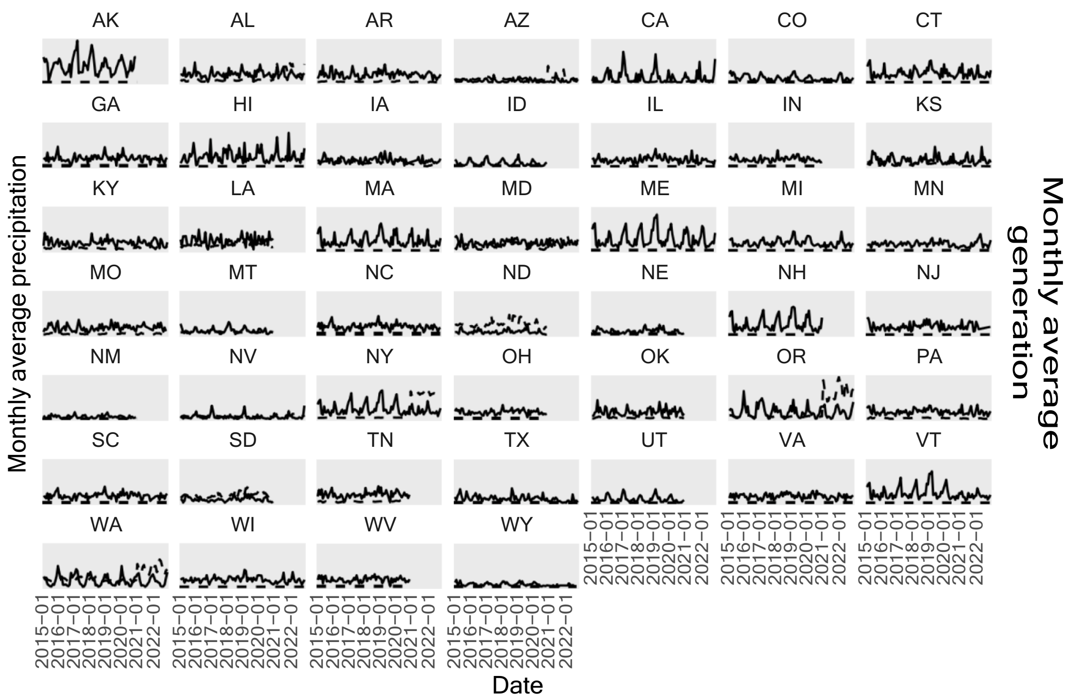

Fig. 10. Monthly average precipitation (solid line) and monthly average electricity generation (dashed line) in US states.

Appendix C. Hydroelectricity generation shares

Table 8 reports the average share of electricity generated from hydropower and other renew- able energy sources (excluding nuclear and waste) in Europe and the US as well as total electricity generated for 2022.

Table 8
Share of hydropower and other renewables in the total electricity generation of countries in our sample. (*UK Data from 2019) Source: ENTSO-E/Fraunhofer Energy Charts/IEA.

	Share hydropower	Share other renewables	Total (TWh)
Austria	56.16%	21.37%	49.93
France	10.05%	13.64%	428.02
Germany	3.45%	45.40%	490.33
Italy	10.76%	21.88%	244.92
Norway	88.36%	10.60%	143.54
Portugal	13.31%	46.06%	40.88
Romania	25.45%	16.03%	55.16
Spain	8.32%	36.26%	261.43
Sweden	43.29%	20.31%	161.27
Switzerland	51.64%	6.28%	55.44
UK*	1.41%	25.79%	252.98
US	6.17%	15.34%	4243

Appendix D. Correlation between precipitation and the water risk metric

Fig. 11 shows average yearly precipitation and water risk at the plant level, differentiating by type of the power plant (water reservoir (WR) and run of river (ROR)) and color coded by risk category. Higher water risk is associated with lower precipitation.

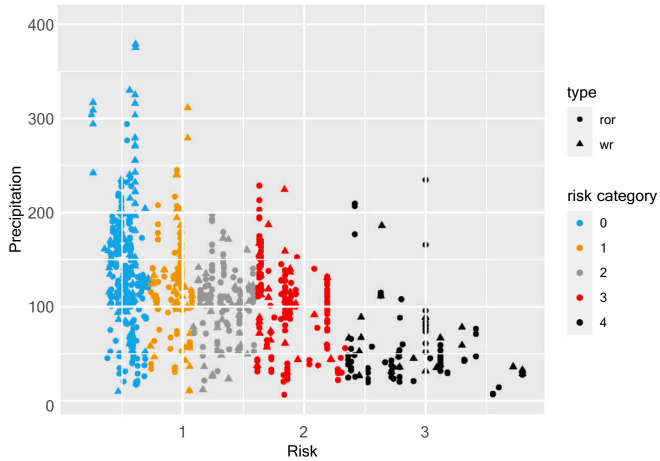

Fig. 11. Correlation between precipitation and water risk, by risk category.

Appendix E. Precipitation

Figs. 12 and 13 show the average monthly precipitation disentangled by water risk categories for European and US plants, respectively.

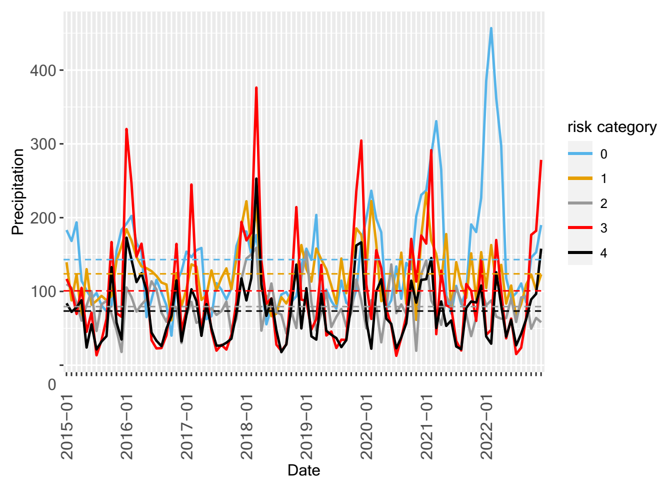

Fig. 12. Average monthly precipitation by water risk category at European plants. The dashed line shows the mean per risk category for the European sample.

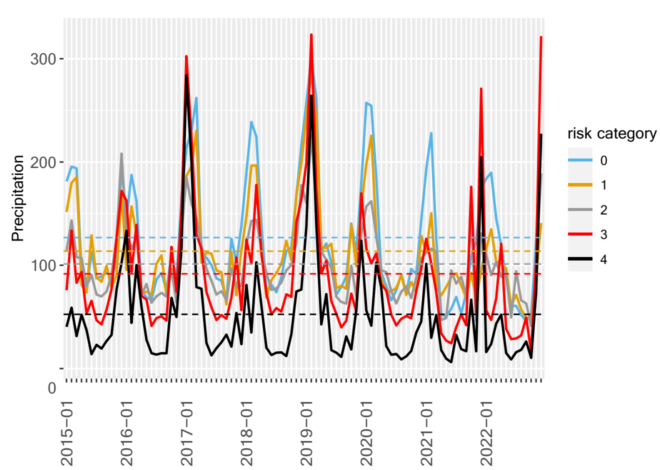

Fig. 13. Average monthly precipitation by water risk category at US plants. The dashed line shows the mean per risk category for the US sample.

Appendix F. Generation ratio

Fig. 14 displays the deviation of electricity generation in 2022 (a low-rainfall year) rela- tive to the historical average by plant. The different colours reflect the different water risk categories. Some of the plants located in the high risk category generate more electricity in 2022 relative to the historical average. However, the figure documents that 2022 saw lower average hydroelectricity generation vis-a-vis the previous years (horizontal lines) across all risk categories, with stronger effects in higher categories (2–4).

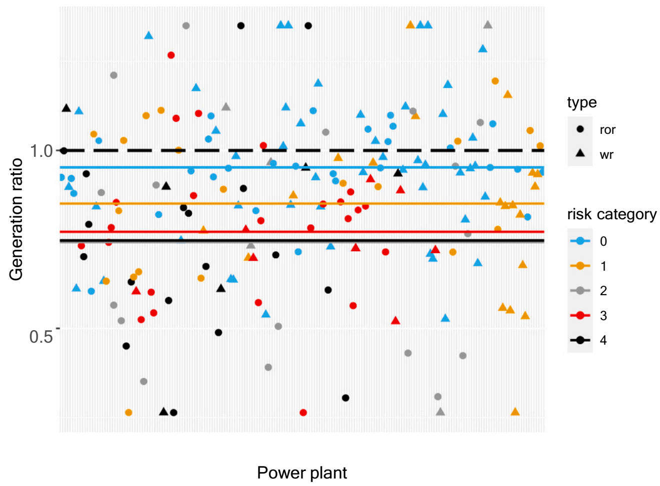

Fig. 14. Deviation of electricity generation in 2022 relative to the historical mean by plant and risk category.

Appendix G. Water anomalies

Figs. 15 and 16 report the counts of precipitation and PDSI anomalies each year in the sampled European countries and US states, respectively. Note that in the US, the data for 2021–2022 is only available in 14 states.

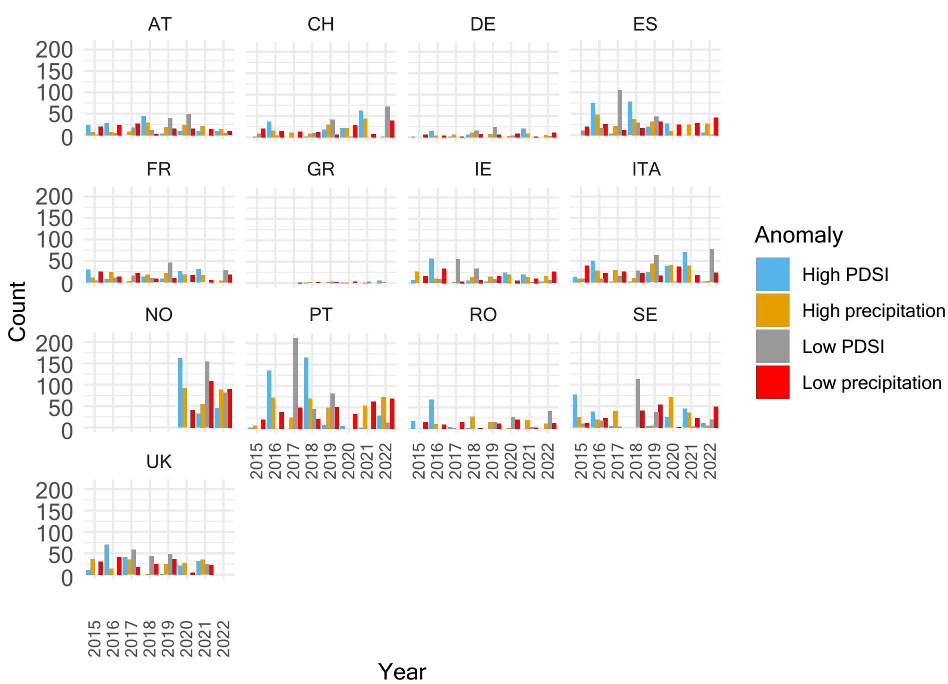

Fig. 15. Count of high and low precipitation and PDSI anomalies in individual European countries.

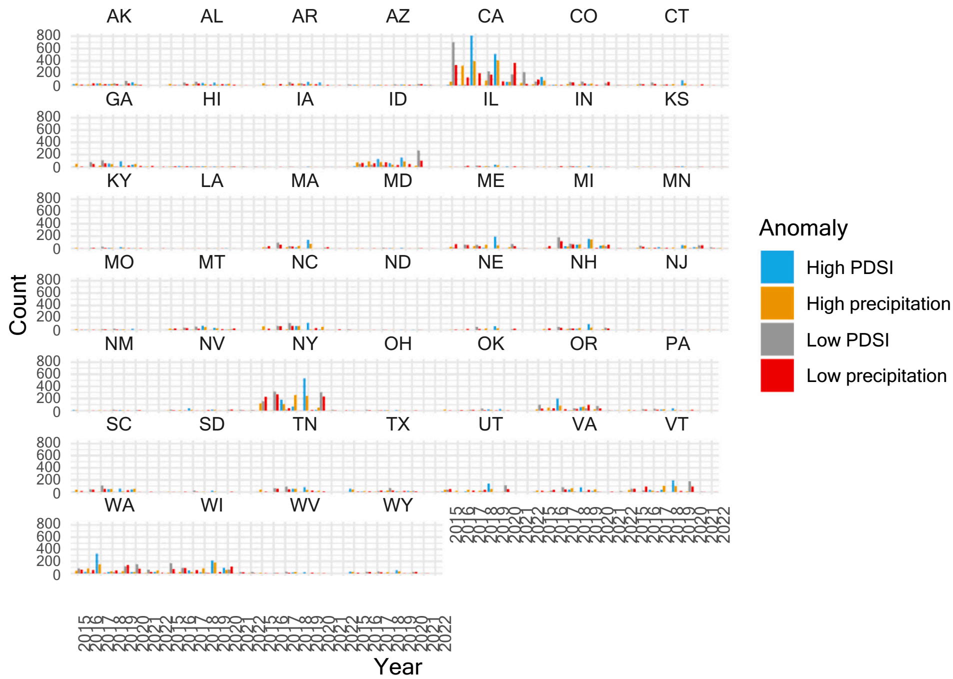

Fig. 16. Count of high and low precipitation and PDSI anomalies in individual US states.

Appendix H. Portfolio sorts analysis using an alternative revenue- share definition

As a robustness check, we use a different measure for the revenues when computing the company-specific exposure to water risks. In particular, we do not only include the revenues from hydroelectricity generation, but also the one from electricity distribution. Results are reported in Tables 9 and 10 for value-weighted and equal-weighted portfolios, respectively. In the first case, results are very close to the baseline including only revenues from hydro- electricity generation. In the second case, the values are slightly bigger. We prefer to rely on the specification in the main text as we think it provides a more accurate picture of the relevance of hydroelectricity generation for the companies analyzed.

Table 9
Water risk premium with revenues from hydroelectricity generation and distribu- tion and value-weighted portfolios.

Dependent variable:	*Water risk factor*			
Model:	(1)	(2)	(3)	(4)
Independent variables:				
Constant	−0.089	−0.090	−0.089	−0.089
	(−2.983)	(−3.015)	(−2.943)	(−2.946)
Mkt-RF		0.001	0.001	0.000
		(0.812)	(0.717)	(0.270)
SMB			−0.001	−0.002
			(−0.421)	(−0.517)
HML			0.001	−0.001
			(0.302)	(−0.155)
RMW			−0.000	−0.000
			(−0.051)	(−0.056)
CMA			−0.003	−0.002
			(−0.562)	(−0.293)
Mom				−0.003
				(−1.230)
Observations	202	202	202	202

Notes: t-statistics in parentheses. Standard errors are adjusted following Newey and West (1987) using six lags.

Table 10
Water risk premium with revenues from hydroelectricity generation and distri- bution and equally-weighted portfolios.

Dependent variable:	*Water risk factor*			
Model:	(1)	(2)	(3)	(4)
Independent variables:				
Constant	−0.102	−0.102	−0.099	−0.099
	(−3.117)	(−3.134)	(−2.703)	(−2.706)

(continued on next page)

Table 10 (*continued*)

Dependent variable:	*Water risk factor*			
Model:	(1)	(2)	(3)	(4)
Mkt-RF		0.001	−0.001	−0.000
		(0.089)	(−0.085)	(−0.017)
SMB			−0.011	−0.011
			(−1.344)	(−1.333)
HML			0.021	0.022
			(2.362)	(2.166)
RMW			0.012	0.012
			(0.721)	(0.724)
CMA			−0.030	−0.030
			(−1.535)	(−1.471)
Mom				0.002
				(0.263)
Observations	202	202	202	202

Notes: t-statistics in parentheses. Standard errors are adjusted following Newey and West (1987) using six lags.

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